EDA Bank loan analysis

April 16, 2022

[1]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.style as style
import seaborn as sns
import itertools
%matplotlib inline

#setting up plot style
style.use('seaborn-poster')
style.use('fivethirtyeight')
```

[2]:
```
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
# set_option( ) is used to adjust the jupiter view
pd.set_option('display.max_rows',500)
pd.set_option('display.max_rows',500)
pd.set_option('display.width',1000)
pd.set_option('display.expand_frame_repr',False)
```

[4]:
```
application=pd.read_csv(r'C:\Users\abhir\Downloads\28th\28th\application_data.
↪csv')
```

[5]:
```
application.head()
```

[5]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR
FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  …
FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20 FLAG_DOCUMENT_21
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
0      100002       1         Cash loans           M            N
Y             0          202500.0    406597.5      24700.5  …
0                0                0                0                        0.0
0.0                          0.0                          0.0
0.0                          1.0
```

```
1      100003       0        Cash loans          F            N
N             0          270000.0   1293502.5      35698.5  …
0                0                0                0                        0.0
0.0                        0.0                        0.0
0.0                        0.0
2      100004       0    Revolving loans         M            Y
Y             0           67500.0    135000.0       6750.0  …
0                0                0                0                        0.0
0.0                        0.0                        0.0
0.0                        0.0
3      100006       0        Cash loans          F            N
Y             0          135000.0    312682.5      29686.5  …
0                0                0                0                        NaN
NaN                        NaN                        NaN
NaN                        NaN
4      100007       0        Cash loans          M            N
Y             0          121500.0    513000.0      21865.5  …
0                0                0                0                        0.0
0.0                        0.0                        0.0
0.0                        0.0

[5 rows x 122 columns]
```

[6]:
```python
#database dimensions
print('database dimensions',application.shape)
```

```
database dimensions (307511, 122)
```

[7]:
```python
#database size
print('database size',application.size)
```

```
database size 37516342
```

[8]:
```python
#for large dataframes use verbose
application.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 122 columns):
 #    Column                        Dtype
---   ------                        -----
 0    SK_ID_CURR                    int64
 1    TARGET                        int64
 2    NAME_CONTRACT_TYPE            object
 3    CODE_GENDER                   object
 4    FLAG_OWN_CAR                  object
 5    FLAG_OWN_REALTY               object
 6    CNT_CHILDREN                  int64
```

7	AMT_INCOME_TOTAL	float64
8	AMT_CREDIT	float64
9	AMT_ANNUITY	float64
10	AMT_GOODS_PRICE	float64
11	NAME_TYPE_SUITE	object
12	NAME_INCOME_TYPE	object
13	NAME_EDUCATION_TYPE	object
14	NAME_FAMILY_STATUS	object
15	NAME_HOUSING_TYPE	object
16	REGION_POPULATION_RELATIVE	float64
17	DAYS_BIRTH	int64
18	DAYS_EMPLOYED	int64
19	DAYS_REGISTRATION	float64
20	DAYS_ID_PUBLISH	int64
21	OWN_CAR_AGE	float64
22	FLAG_MOBIL	int64
23	FLAG_EMP_PHONE	int64
24	FLAG_WORK_PHONE	int64
25	FLAG_CONT_MOBILE	int64
26	FLAG_PHONE	int64
27	FLAG_EMAIL	int64
28	OCCUPATION_TYPE	object
29	CNT_FAM_MEMBERS	float64
30	REGION_RATING_CLIENT	int64
31	REGION_RATING_CLIENT_W_CITY	int64
32	WEEKDAY_APPR_PROCESS_START	object
33	HOUR_APPR_PROCESS_START	int64
34	REG_REGION_NOT_LIVE_REGION	int64
35	REG_REGION_NOT_WORK_REGION	int64
36	LIVE_REGION_NOT_WORK_REGION	int64
37	REG_CITY_NOT_LIVE_CITY	int64
38	REG_CITY_NOT_WORK_CITY	int64
39	LIVE_CITY_NOT_WORK_CITY	int64
40	ORGANIZATION_TYPE	object
41	EXT_SOURCE_1	float64
42	EXT_SOURCE_2	float64
43	EXT_SOURCE_3	float64
44	APARTMENTS_AVG	float64
45	BASEMENTAREA_AVG	float64
46	YEARS_BEGINEXPLUATATION_AVG	float64
47	YEARS_BUILD_AVG	float64
48	COMMONAREA_AVG	float64
49	ELEVATORS_AVG	float64
50	ENTRANCES_AVG	float64
51	FLOORSMAX_AVG	float64
52	FLOORSMIN_AVG	float64
53	LANDAREA_AVG	float64
54	LIVINGAPARTMENTS_AVG	float64

55	LIVINGAREA_AVG	float64
56	NONLIVINGAPARTMENTS_AVG	float64
57	NONLIVINGAREA_AVG	float64
58	APARTMENTS_MODE	float64
59	BASEMENTAREA_MODE	float64
60	YEARS_BEGINEXPLUATATION_MODE	float64
61	YEARS_BUILD_MODE	float64
62	COMMONAREA_MODE	float64
63	ELEVATORS_MODE	float64
64	ENTRANCES_MODE	float64
65	FLOORSMAX_MODE	float64
66	FLOORSMIN_MODE	float64
67	LANDAREA_MODE	float64
68	LIVINGAPARTMENTS_MODE	float64
69	LIVINGAREA_MODE	float64
70	NONLIVINGAPARTMENTS_MODE	float64
71	NONLIVINGAREA_MODE	float64
72	APARTMENTS_MEDI	float64
73	BASEMENTAREA_MEDI	float64
74	YEARS_BEGINEXPLUATATION_MEDI	float64
75	YEARS_BUILD_MEDI	float64
76	COMMONAREA_MEDI	float64
77	ELEVATORS_MEDI	float64
78	ENTRANCES_MEDI	float64
79	FLOORSMAX_MEDI	float64
80	FLOORSMIN_MEDI	float64
81	LANDAREA_MEDI	float64
82	LIVINGAPARTMENTS_MEDI	float64
83	LIVINGAREA_MEDI	float64
84	NONLIVINGAPARTMENTS_MEDI	float64
85	NONLIVINGAREA_MEDI	float64
86	FONDKAPREMONT_MODE	object
87	HOUSETYPE_MODE	object
88	TOTALAREA_MODE	float64
89	WALLSMATERIAL_MODE	object
90	EMERGENCYSTATE_MODE	object
91	OBS_30_CNT_SOCIAL_CIRCLE	float64
92	DEF_30_CNT_SOCIAL_CIRCLE	float64
93	OBS_60_CNT_SOCIAL_CIRCLE	float64
94	DEF_60_CNT_SOCIAL_CIRCLE	float64
95	DAYS_LAST_PHONE_CHANGE	float64
96	FLAG_DOCUMENT_2	int64
97	FLAG_DOCUMENT_3	int64
98	FLAG_DOCUMENT_4	int64
99	FLAG_DOCUMENT_5	int64
100	FLAG_DOCUMENT_6	int64
101	FLAG_DOCUMENT_7	int64
102	FLAG_DOCUMENT_8	int64

```
 103  FLAG_DOCUMENT_9              int64
 104  FLAG_DOCUMENT_10             int64
 105  FLAG_DOCUMENT_11             int64
 106  FLAG_DOCUMENT_12             int64
 107  FLAG_DOCUMENT_13             int64
 108  FLAG_DOCUMENT_14             int64
 109  FLAG_DOCUMENT_15             int64
 110  FLAG_DOCUMENT_16             int64
 111  FLAG_DOCUMENT_17             int64
 112  FLAG_DOCUMENT_18             int64
 113  FLAG_DOCUMENT_19             int64
 114  FLAG_DOCUMENT_20             int64
 115  FLAG_DOCUMENT_21             int64
 116  AMT_REQ_CREDIT_BUREAU_HOUR   float64
 117  AMT_REQ_CREDIT_BUREAU_DAY    float64
 118  AMT_REQ_CREDIT_BUREAU_WEEK   float64
 119  AMT_REQ_CREDIT_BUREAU_MON    float64
 120  AMT_REQ_CREDIT_BUREAU_QRT    float64
 121  AMT_REQ_CREDIT_BUREAU_YEAR   float64
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

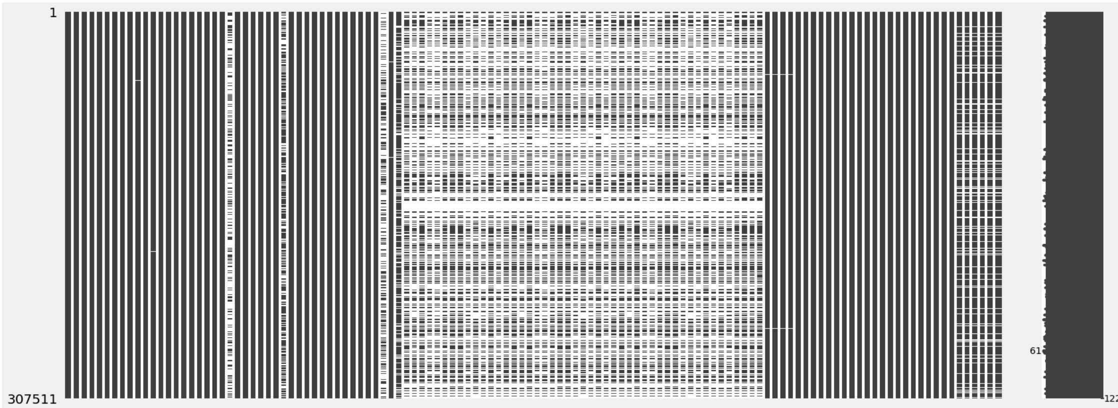
[9]:
```
application.describe()
```

[9]:
```
          SK_ID_CURR         TARGET   CNT_CHILDREN   AMT_INCOME_TOTAL
AMT_CREDIT    AMT_ANNUITY  AMT_GOODS_PRICE  REGION_POPULATION_RELATIVE
DAYS_BIRTH  DAYS_EMPLOYED  …  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19
FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  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
count  307511.000000  307511.000000  307511.000000      3.075110e+05
3.075110e+05  307499.000000      3.072330e+05               307511.000000
307511.000000  307511.000000  …      307511.000000      307511.000000
307511.000000      307511.000000              265992.000000
265992.000000              265992.000000              265992.000000
265992.000000              265992.000000
mean   278180.518577       0.080729       0.417052      1.687979e+05
5.990260e+05   27108.573909      5.383962e+05                    0.020868
-16036.995067   63815.045904  …           0.008130          0.000595
0.000507          0.000335                    0.006402
0.007000                    0.034362                    0.267395
0.265474                    1.899974
std    102790.175348       0.272419       0.722121      2.371231e+05
4.024908e+05   14493.737315     3.694465e+05                    0.013831
4363.988632  141275.766519  …          0.089798          0.024387
0.022518          0.018299                    0.083849
0.110757                    0.204685                    0.916002
```

```
0.794056                    1.869295
min     100002.000000       0.000000       0.000000      2.565000e+04
4.500000e+04     1615.500000     4.050000e+04                    0.000290
-25229.000000   -17912.000000   …          0.000000          0.000000
0.000000          0.000000                    0.000000
0.000000                    0.000000                    0.000000
0.000000                    0.000000
25%     189145.500000       0.000000       0.000000      1.125000e+05
2.700000e+05    16524.000000     2.385000e+05                    0.010006
-19682.000000    -2760.000000   …          0.000000          0.000000
0.000000          0.000000                    0.000000
0.000000                    0.000000                    0.000000
0.000000                    0.000000
50%     278202.000000       0.000000       0.000000      1.471500e+05
5.135310e+05    24903.000000     4.500000e+05                    0.018850
-15750.000000    -1213.000000   …          0.000000          0.000000
0.000000          0.000000                    0.000000
0.000000                    0.000000                    0.000000
0.000000                    1.000000
75%     367142.500000       0.000000       1.000000      2.025000e+05
8.086500e+05    34596.000000     6.795000e+05                    0.028663
-12413.000000     -289.000000   …          0.000000          0.000000
0.000000          0.000000                    0.000000
0.000000                    0.000000                    0.000000
0.000000                    3.000000
max     456255.000000       1.000000      19.000000      1.170000e+08
4.050000e+06   258025.500000     4.050000e+06                    0.072508
-7489.000000   365243.000000   …          1.000000          1.000000
1.000000          1.000000                    4.000000
9.000000                    8.000000                   27.000000
261.000000                    25.000000

[8 rows x 106 columns]
```

[10]:
```python
#application missing vales
import missingno as mn
mn.matrix(application)
```

[10]:
```
<AxesSubplot:>
```



[11]:
```
#sum of null value in each column
application.isnull().sum()
```

[11]:
```
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                         12
AMT_GOODS_PRICE                    278
NAME_TYPE_SUITE                   1292
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
OWN_CAR_AGE                     202929
FLAG_MOBIL                           0
FLAG_EMP_PHONE                       0
FLAG_WORK_PHONE                      0
FLAG_CONT_MOBILE                     0
FLAG_PHONE                           0
FLAG_EMAIL                           0
OCCUPATION_TYPE                  96391
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
EXT_SOURCE_1	173378
EXT_SOURCE_2	660
EXT_SOURCE_3	60965
APARTMENTS_AVG	156061
BASEMENTAREA_AVG	179943
YEARS_BEGINEXPLUATATION_AVG	150007
YEARS_BUILD_AVG	204488
COMMONAREA_AVG	214865
ELEVATORS_AVG	163891
ENTRANCES_AVG	154828
FLOORSMAX_AVG	153020
FLOORSMIN_AVG	208642
LANDAREA_AVG	182590
LIVINGAPARTMENTS_AVG	210199
LIVINGAREA_AVG	154350
NONLIVINGAPARTMENTS_AVG	213514
NONLIVINGAREA_AVG	169682
APARTMENTS_MODE	156061
BASEMENTAREA_MODE	179943
YEARS_BEGINEXPLUATATION_MODE	150007
YEARS_BUILD_MODE	204488
COMMONAREA_MODE	214865
ELEVATORS_MODE	163891
ENTRANCES_MODE	154828
FLOORSMAX_MODE	153020
FLOORSMIN_MODE	208642
LANDAREA_MODE	182590
LIVINGAPARTMENTS_MODE	210199
LIVINGAREA_MODE	154350
NONLIVINGAPARTMENTS_MODE	213514
NONLIVINGAREA_MODE	169682
APARTMENTS_MEDI	156061
BASEMENTAREA_MEDI	179943
YEARS_BEGINEXPLUATATION_MEDI	150007
YEARS_BUILD_MEDI	204488
COMMONAREA_MEDI	214865

```
ELEVATORS_MEDI                  163891
ENTRANCES_MEDI                  154828
FLOORSMAX_MEDI                  153020
FLOORSMIN_MEDI                  208642
LANDAREA_MEDI                   182590
LIVINGAPARTMENTS_MEDI           210199
LIVINGAREA_MEDI                 154350
NONLIVINGAPARTMENTS_MEDI        213514
NONLIVINGAREA_MEDI              169682
FONDKAPREMONT_MODE              210295
HOUSETYPE_MODE                  154297
TOTALAREA_MODE                  148431
WALLSMATERIAL_MODE              156341
EMERGENCYSTATE_MODE             145755
OBS_30_CNT_SOCIAL_CIRCLE          1021
DEF_30_CNT_SOCIAL_CIRCLE          1021
OBS_60_CNT_SOCIAL_CIRCLE          1021
DEF_60_CNT_SOCIAL_CIRCLE          1021
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
AMT_REQ_CREDIT_BUREAU_HOUR       41519
AMT_REQ_CREDIT_BUREAU_DAY        41519
AMT_REQ_CREDIT_BUREAU_WEEK       41519
AMT_REQ_CREDIT_BUREAU_MON        41519
AMT_REQ_CREDIT_BUREAU_QRT        41519
AMT_REQ_CREDIT_BUREAU_YEAR       41519
dtype: int64
```

[12]:
```
application.shape[0]
```

[12]:
```
307511
```

[13]:
```
# % of null values
round(application.isnull().sum()/application.shape[0]*100.00,2)
```

[13]:
```
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                     0.00
AMT_GOODS_PRICE                 0.09
NAME_TYPE_SUITE                 0.42
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
OWN_CAR_AGE                    65.99
FLAG_MOBIL                      0.00
FLAG_EMP_PHONE                  0.00
FLAG_WORK_PHONE                 0.00
FLAG_CONT_MOBILE                0.00
FLAG_PHONE                      0.00
FLAG_EMAIL                      0.00
OCCUPATION_TYPE                31.35
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
```

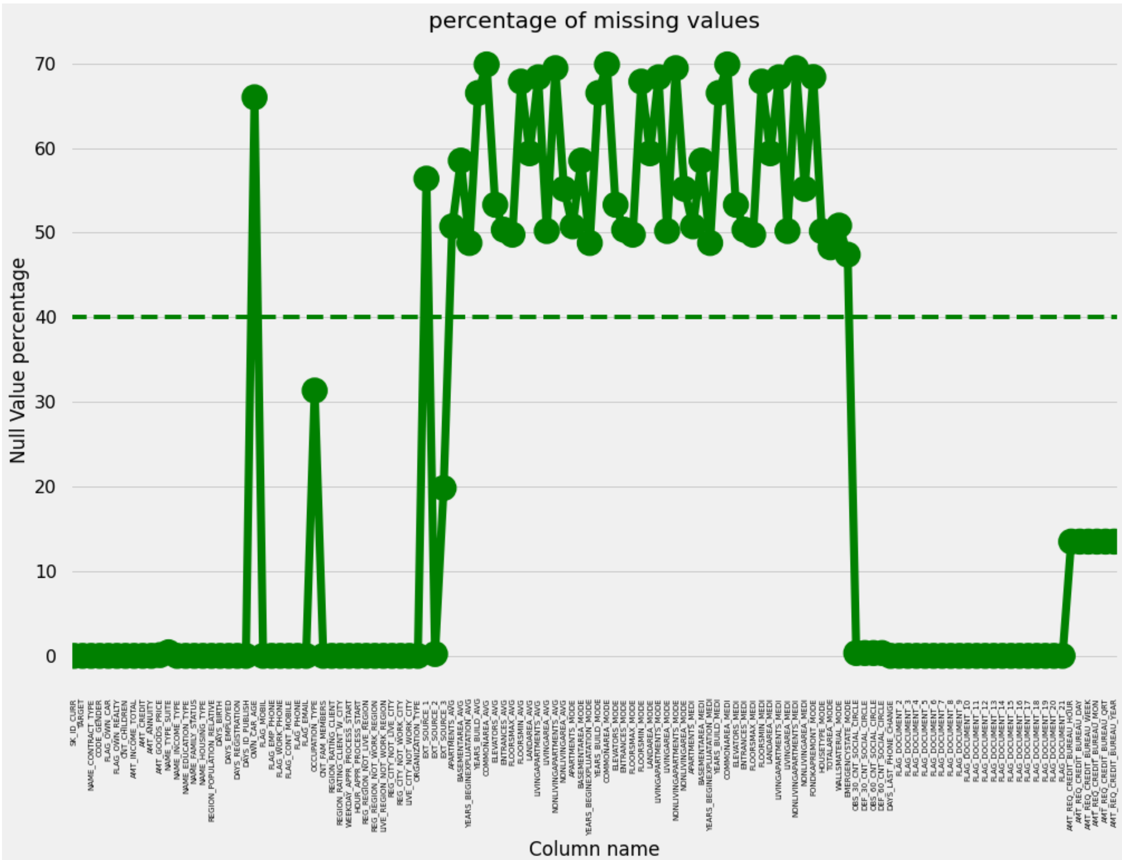
ORGANIZATION_TYPE	0.00
EXT_SOURCE_1	56.38
EXT_SOURCE_2	0.21
EXT_SOURCE_3	19.83
APARTMENTS_AVG	50.75
BASEMENTAREA_AVG	58.52
YEARS_BEGINEXPLUATATION_AVG	48.78
YEARS_BUILD_AVG	66.50
COMMONAREA_AVG	69.87
ELEVATORS_AVG	53.30
ENTRANCES_AVG	50.35
FLOORSMAX_AVG	49.76
FLOORSMIN_AVG	67.85
LANDAREA_AVG	59.38
LIVINGAPARTMENTS_AVG	68.35
LIVINGAREA_AVG	50.19
NONLIVINGAPARTMENTS_AVG	69.43
NONLIVINGAREA_AVG	55.18
APARTMENTS_MODE	50.75
BASEMENTAREA_MODE	58.52
YEARS_BEGINEXPLUATATION_MODE	48.78
YEARS_BUILD_MODE	66.50
COMMONAREA_MODE	69.87
ELEVATORS_MODE	53.30
ENTRANCES_MODE	50.35
FLOORSMAX_MODE	49.76
FLOORSMIN_MODE	67.85
LANDAREA_MODE	59.38
LIVINGAPARTMENTS_MODE	68.35
LIVINGAREA_MODE	50.19
NONLIVINGAPARTMENTS_MODE	69.43
NONLIVINGAREA_MODE	55.18
APARTMENTS_MEDI	50.75
BASEMENTAREA_MEDI	58.52
YEARS_BEGINEXPLUATATION_MEDI	48.78
YEARS_BUILD_MEDI	66.50
COMMONAREA_MEDI	69.87
ELEVATORS_MEDI	53.30
ENTRANCES_MEDI	50.35
FLOORSMAX_MEDI	49.76
FLOORSMIN_MEDI	67.85
LANDAREA_MEDI	59.38
LIVINGAPARTMENTS_MEDI	68.35
LIVINGAREA_MEDI	50.19
NONLIVINGAPARTMENTS_MEDI	69.43
NONLIVINGAREA_MEDI	55.18
FONDKAPREMONT_MODE	68.39

```
HOUSETYPE_MODE                 50.18
TOTALAREA_MODE                 48.27
WALLSMATERIAL_MODE             50.84
EMERGENCYSTATE_MODE            47.40
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
FLAG_DOCUMENT_2                 0.00
FLAG_DOCUMENT_3                 0.00
FLAG_DOCUMENT_4                 0.00
FLAG_DOCUMENT_5                 0.00
FLAG_DOCUMENT_6                 0.00
FLAG_DOCUMENT_7                 0.00
FLAG_DOCUMENT_8                 0.00
FLAG_DOCUMENT_9                 0.00
FLAG_DOCUMENT_10                0.00
FLAG_DOCUMENT_11                0.00
FLAG_DOCUMENT_12                0.00
FLAG_DOCUMENT_13                0.00
FLAG_DOCUMENT_14                0.00
FLAG_DOCUMENT_15                0.00
FLAG_DOCUMENT_16                0.00
FLAG_DOCUMENT_17                0.00
FLAG_DOCUMENT_18                0.00
FLAG_DOCUMENT_19                0.00
FLAG_DOCUMENT_20                0.00
FLAG_DOCUMENT_21                0.00
AMT_REQ_CREDIT_BUREAU_HOUR     13.50
AMT_REQ_CREDIT_BUREAU_DAY      13.50
AMT_REQ_CREDIT_BUREAU_WEEK     13.50
AMT_REQ_CREDIT_BUREAU_MON      13.50
AMT_REQ_CREDIT_BUREAU_QRT      13.50
AMT_REQ_CREDIT_BUREAU_YEAR     13.50
dtype: float64
```

[14]:

```
#to plot the columns Vs missing value % taking 40% as cutoff mark
null_application=pd.DataFrame(application.isnull().sum()/application.
 ↪shape[0]*100).reset_index()
null_application.columns=['Column name','Null Value percentage']
fig=plt.figure(figsize=(15,10))
ax=sns.pointplot(x='Column name',y='Null Value␣
 ↪percentage',data=null_application,color='green')
plt.xticks(rotation=90,fontsize=7)
ax.axhline(40,ls='--',color='green')
plt.title('percentage of missing values')
```

```
plt.xlabel=('columns')
plt.ylabel=('Null values %')
plt.show()
```



[15]:

```
#columns having more than 40% empty rows
nullColumns_40=null_application[null_application['Null Value percentage']>=40]
nullColumns_40
```

[15]:

	Column name	Null Value percentage
21	OWN_CAR_AGE	65.990810
41	EXT_SOURCE_1	56.381073
44	APARTMENTS_AVG	50.749729
45	BASEMENTAREA_AVG	58.515956
46	YEARS_BEGINEXPLUATATION_AVG	48.781019
47	YEARS_BUILD_AVG	66.497784
48	COMMONAREA_AVG	69.872297
49	ELEVATORS_AVG	53.295980
50	ENTRANCES_AVG	50.348768
51	FLOORSMAX_AVG	49.760822
52	FLOORSMIN_AVG	67.848630

```
53               LANDAREA_AVG          59.376738
54       LIVINGAPARTMENTS_AVG          68.354953
55             LIVINGAREA_AVG          50.193326
56    NONLIVINGAPARTMENTS_AVG          69.432963
57          NONLIVINGAREA_AVG          55.179164
58            APARTMENTS_MODE          50.749729
59          BASEMENTAREA_MODE          58.515956
60 YEARS_BEGINEXPLUATATION_MODE        48.781019
61           YEARS_BUILD_MODE          66.497784
62            COMMONAREA_MODE          69.872297
63             ELEVATORS_MODE          53.295980
64             ENTRANCES_MODE          50.348768
65             FLOORSMAX_MODE          49.760822
66             FLOORSMIN_MODE          67.848630
67              LANDAREA_MODE          59.376738
68      LIVINGAPARTMENTS_MODE          68.354953
69            LIVINGAREA_MODE          50.193326
70   NONLIVINGAPARTMENTS_MODE          69.432963
71         NONLIVINGAREA_MODE          55.179164
72            APARTMENTS_MEDI          50.749729
73          BASEMENTAREA_MEDI          58.515956
74 YEARS_BEGINEXPLUATATION_MEDI        48.781019
75           YEARS_BUILD_MEDI          66.497784
76            COMMONAREA_MEDI          69.872297
77             ELEVATORS_MEDI          53.295980
78             ENTRANCES_MEDI          50.348768
79             FLOORSMAX_MEDI          49.760822
80             FLOORSMIN_MEDI          67.848630
81              LANDAREA_MEDI          59.376738
82      LIVINGAPARTMENTS_MEDI          68.354953
83            LIVINGAREA_MEDI          50.193326
84   NONLIVINGAPARTMENTS_MEDI          69.432963
85         NONLIVINGAREA_MEDI          55.179164
86         FONDKAPREMONT_MODE          68.386172
87             HOUSETYPE_MODE          50.176091
88             TOTALAREA_MODE          48.268517
89         WALLSMATERIAL_MODE          50.840783
90        EMERGENCYSTATE_MODE          47.398304
```

[16]:
```
#no of coluns with missing values more than or equal to 40%
len(nullColumns_40)
```

[16]: 49

[17]:
```
previous=pd.read_csv(r'C:\Users\abhir\Downloads\archive␣
↪(1)\previous_application.csv')
```

[18]:
```python
previous.head()
```

[18]:
```
   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  … 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
0     2030495      271877     Consumer loans     1730.430          17145.0
17145.0               0.0          17145.0                   SATURDAY
15  …          Connectivity         12.0            middle  POS mobile with
interest            365243.0          -42.0                       300.0
-42.0            -37.0                       0.0
1     2802425      108129         Cash loans    25188.615         607500.0
679671.0               NaN         607500.0                   THURSDAY
11  …                   XNA         36.0         low_action           Cash
X-Sell: low            365243.0          -134.0                    916.0
365243.0         365243.0                       1.0
2     2523466      122040         Cash loans    15060.735         112500.0
136444.5               NaN         112500.0                    TUESDAY
11  …                   XNA         12.0               high         Cash X-Sell:
high             365243.0         -271.0                     59.0       365243.0
365243.0                       1.0
3     2819243      176158         Cash loans    47041.335         450000.0
470790.0               NaN         450000.0                     MONDAY
7  …                   XNA         12.0             middle       Cash X-Sell:
middle             365243.0          -482.0                   -152.0
-182.0           -177.0                       1.0
4     1784265      202054         Cash loans    31924.395         337500.0
404055.0               NaN         337500.0                   THURSDAY
9  …                   XNA         24.0               high        Cash Street:
high                   NaN            NaN                    NaN            NaN
NaN                       NaN

[5 rows x 37 columns]
```

[19]:
```python
print('data dimensions',previous.shape)
```

```
data dimensions (1670214, 37)
```

[20]:
```python
print('data size',previous.size)
```

```
data size 61797918
```

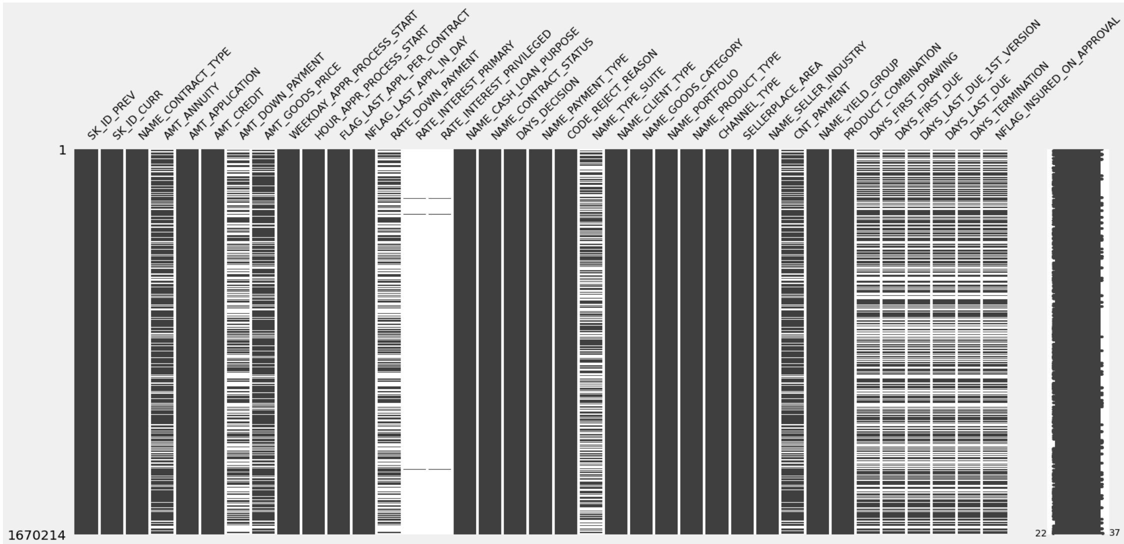
[21]:
```python
previous.info(verbose=True)
```

```
<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
```

[22]:
```
mn.matrix(previous)
```

[22]: <AxesSubplot:>



[23]:
```
#number of null values in each column in previous dataset
previous.isnull().sum()
```

[23]:
```
SK_ID_PREV                           0
SK_ID_CURR                           0
NAME_CONTRACT_TYPE                   0
AMT_ANNUITY                     372235
AMT_APPLICATION                      0
AMT_CREDIT                           1
AMT_DOWN_PAYMENT                895844
AMT_GOODS_PRICE                 385515
WEEKDAY_APPR_PROCESS_START           0
HOUR_APPR_PROCESS_START              0
FLAG_LAST_APPL_PER_CONTRACT          0
NFLAG_LAST_APPL_IN_DAY               0
RATE_DOWN_PAYMENT               895844
RATE_INTEREST_PRIMARY          1664263
RATE_INTEREST_PRIVILEGED       1664263
NAME_CASH_LOAN_PURPOSE               0
NAME_CONTRACT_STATUS                 0
DAYS_DECISION                        0
NAME_PAYMENT_TYPE                    0
CODE_REJECT_REASON                   0
NAME_TYPE_SUITE                 820405
NAME_CLIENT_TYPE                     0
NAME_GOODS_CATEGORY                  0
NAME_PORTFOLIO                       0
NAME_PRODUCT_TYPE                    0
CHANNEL_TYPE                         0
```

```
SELLERPLACE_AREA                     0
NAME_SELLER_INDUSTRY                 0
CNT_PAYMENT                     372230
NAME_YIELD_GROUP                     0
PRODUCT_COMBINATION                346
DAYS_FIRST_DRAWING              673065
DAYS_FIRST_DUE                  673065
DAYS_LAST_DUE_1ST_VERSION       673065
DAYS_LAST_DUE                   673065
DAYS_TERMINATION                673065
NFLAG_INSURED_ON_APPROVAL       673065
dtype: int64
```

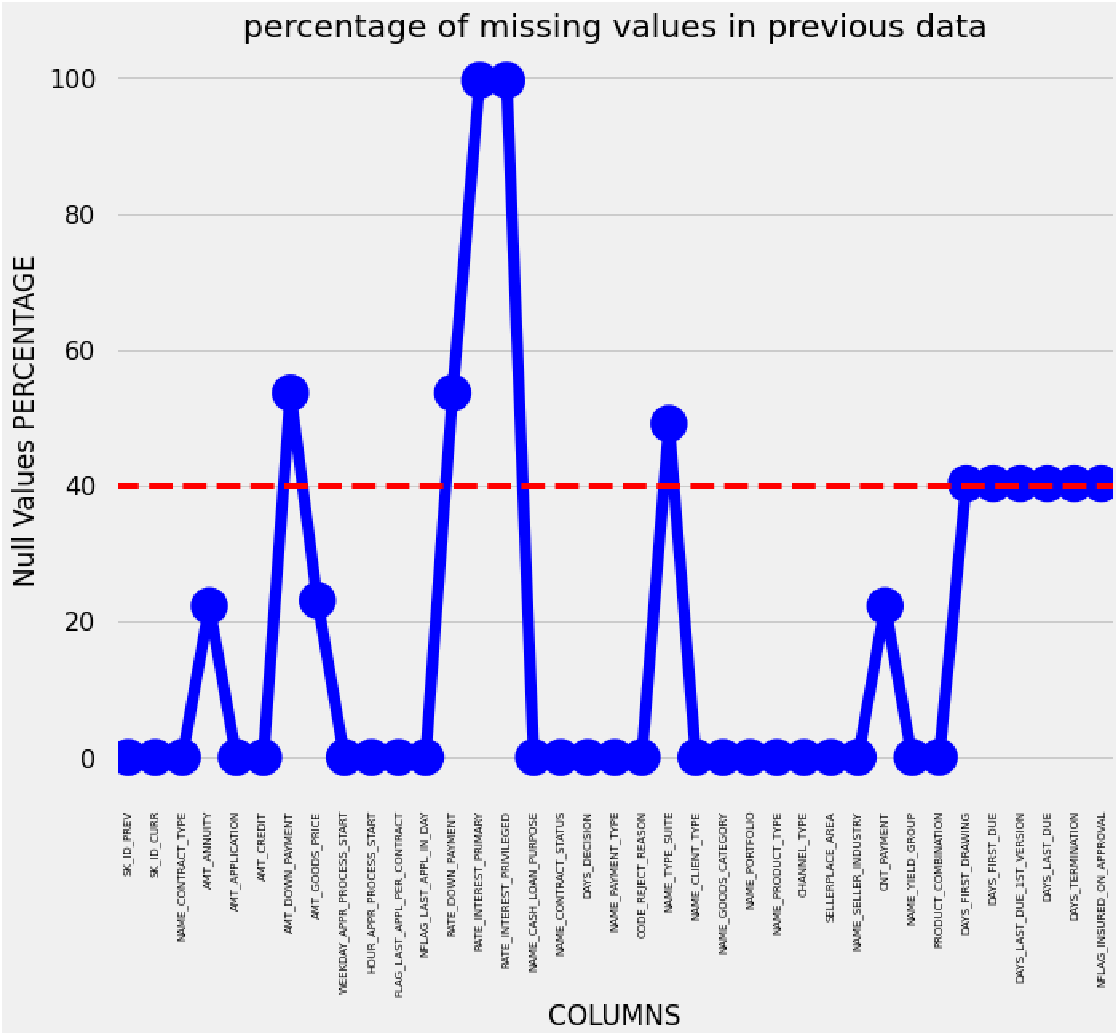
[24]:
```
# % of null values in each columns
round(previous.isnull().sum()/previous.shape[0]*100.00,2)
```

[24]:
```
SK_ID_PREV                      0.00
SK_ID_CURR                      0.00
NAME_CONTRACT_TYPE              0.00
AMT_ANNUITY                    22.29
AMT_APPLICATION                 0.00
AMT_CREDIT                      0.00
AMT_DOWN_PAYMENT               53.64
AMT_GOODS_PRICE                23.08
WEEKDAY_APPR_PROCESS_START      0.00
HOUR_APPR_PROCESS_START         0.00
FLAG_LAST_APPL_PER_CONTRACT     0.00
NFLAG_LAST_APPL_IN_DAY          0.00
RATE_DOWN_PAYMENT              53.64
RATE_INTEREST_PRIMARY          99.64
RATE_INTEREST_PRIVILEGED       99.64
NAME_CASH_LOAN_PURPOSE          0.00
NAME_CONTRACT_STATUS            0.00
DAYS_DECISION                   0.00
NAME_PAYMENT_TYPE               0.00
CODE_REJECT_REASON              0.00
NAME_TYPE_SUITE                49.12
NAME_CLIENT_TYPE                0.00
NAME_GOODS_CATEGORY             0.00
NAME_PORTFOLIO                  0.00
NAME_PRODUCT_TYPE               0.00
CHANNEL_TYPE                    0.00
SELLERPLACE_AREA                0.00
NAME_SELLER_INDUSTRY            0.00
CNT_PAYMENT                    22.29
NAME_YIELD_GROUP                0.00
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
```

[25]:
```
#added this as I got error as 'str' object is not callable
import matplotlib.pyplot as plt
from importlib import reload
plt=reload(plt)
```

[26]:
```
#to plot the columns Vs missing value % and taking 40% as cutoff mark
null_previous=pd.DataFrame(previous.isnull().sum()/previous.shape[0]*100).
 ↪reset_index()
null_previous.columns = ['Column Name', 'Null Values Percentage']
fig=plt.figure(figsize=(10,8))
ax = sns.pointplot(x="Column Name",y="Null Values␣
 ↪Percentage",data=null_previous,color ='blue')
plt.xticks(rotation=90,fontsize=7)
ax.axhline(40,ls='--',color='red')
plt.title('percentage of missing values in previous data')
plt.ylabel("Null Values PERCENTAGE")
plt.xlabel("COLUMNS")
plt.show()
```



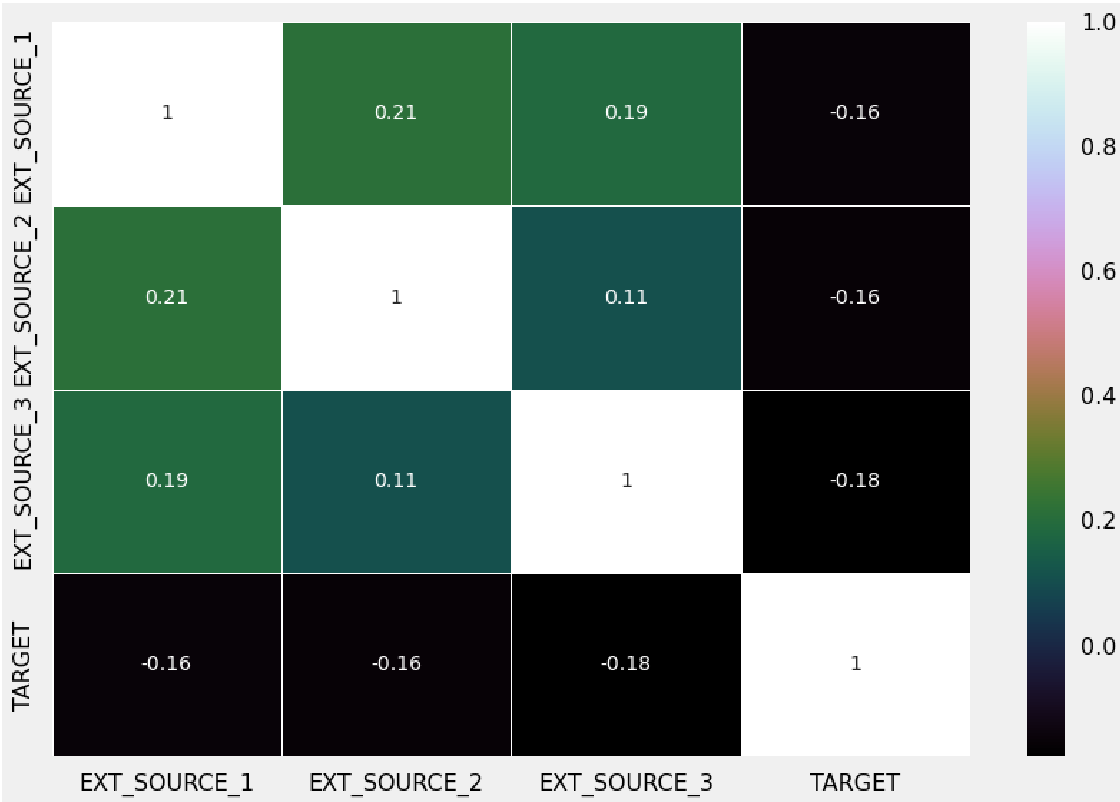
[27]:
```python
#columns having more than 40% empty rows
nullColumns_40prev=null_previous[null_previous['Null Values Percentage']>=40]
nullColumns_40prev
```

[27]:

	Column Name	Null Values Percentage
6	AMT_DOWN_PAYMENT	53.636480
12	RATE_DOWN_PAYMENT	53.636480
13	RATE_INTEREST_PRIMARY	99.643698
14	RATE_INTEREST_PRIVILEGED	99.643698
20	NAME_TYPE_SUITE	49.119754
31	DAYS_FIRST_DRAWING	40.298129
32	DAYS_FIRST_DUE	40.298129
33	DAYS_LAST_DUE_1ST_VERSION	40.298129
34	DAYS_LAST_DUE	40.298129
35	DAYS_TERMINATION	40.298129

```
36  NFLAG_INSURED_ON_APPROVAL                 40.298129
```

[28]:
```
#verfying whether EXT_SOURCE is correlated with target
source_corr=application[['EXT_SOURCE_1','EXT_SOURCE_2','EXT_SOURCE_3','TARGET']]
ax=sns.heatmap(source_corr.corr(),xticklabels=source_corr.columns,␣
↪yticklabels=source_corr.columns,cmap='cubehelix',annot=True,linewidth=1)
```



[29]:
```
#creating a list with columns having >40% null values and adding the EXT_SOURCE
#.list() is used to convert a series to list
unwanted_columns=nullColumns_40['Column name'].
↪tolist()+['EXT_SOURCE_2','EXT_SOURCE_3']
len(unwanted_columns)
```

[29]: 51

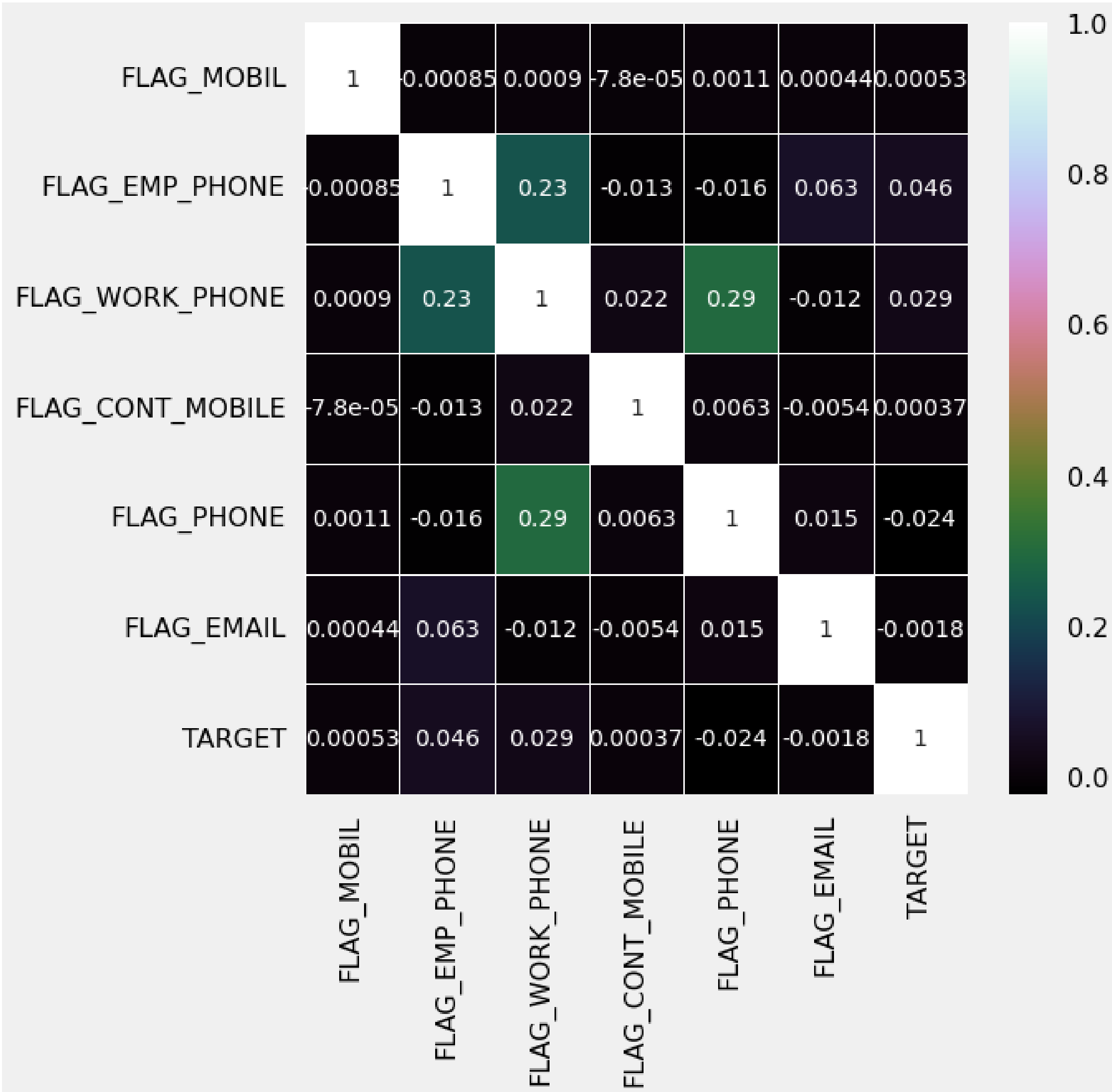
[30]:
```
#added this as I got error 'str' object is not callable
import matplotlib.pyplot as plt
from importlib import reload
plt=reload(plt)
```

[31]:
```python
#checking wether the submitted flag_docments is related with loan repayment␣
↪status
col_Doc = [ '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_flag = application[col_Doc+["TARGET"]]
df_flag["TARGET"] = df_flag["TARGET"].replace({1:"Defaulter",0:"Repayer"})
fig = plt.figure(figsize=(25,20))
j=0
for i in col_Doc:
    plt.subplot(4,5,j+1)
    ax = sns.countplot(df_flag[i],hue=df_flag["TARGET"],palette=["r","g"])
    plt.yticks(fontsize=0.1)
    plt.title(i)
    plt.yticks(fontsize=8)
    plt.xlabel("")
    plt.ylabel("")
    j=j+1
```

[32]:
```
col_Doc.remove('FLAG_DOCUMENT_3')
unwanted_columns = unwanted_columns + col_Doc
len(unwanted_columns)
```

[32]: 70

[33]:
```
#checking the correlation b/w contact details
contact_col = ['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',␣
↪'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL','TARGET']
Contact_corr = application[contact_col].corr()
fig = plt.figure(figsize=(8,8))
ax = sns.heatmap(Contact_corr, xticklabels=Contact_corr.
↪columns,yticklabels=Contact_corr.columns,annot = True,cmap␣
↪="cubehelix",linewidth=1)
```



[34]:
```
#adding contact details to unwanted columns
contact_col.remove('TARGET')
unwanted_columns=unwanted_columns+contact_col
len(unwanted_columns)
```

[34]: 76

[35]:
```
unwanted_columns
```

[35]:
```
['OWN_CAR_AGE',
 'EXT_SOURCE_1',
 'APARTMENTS_AVG',
 'BASEMENTAREA_AVG',
```

```
'YEARS_BEGINEXPLUATATION_AVG',
'YEARS_BUILD_AVG',
'COMMONAREA_AVG',
'ELEVATORS_AVG',
'ENTRANCES_AVG',
'FLOORSMAX_AVG',
'FLOORSMIN_AVG',
'LANDAREA_AVG',
'LIVINGAPARTMENTS_AVG',
'LIVINGAREA_AVG',
'NONLIVINGAPARTMENTS_AVG',
'NONLIVINGAREA_AVG',
'APARTMENTS_MODE',
'BASEMENTAREA_MODE',
'YEARS_BEGINEXPLUATATION_MODE',
'YEARS_BUILD_MODE',
'COMMONAREA_MODE',
'ELEVATORS_MODE',
'ENTRANCES_MODE',
'FLOORSMAX_MODE',
'FLOORSMIN_MODE',
'LANDAREA_MODE',
'LIVINGAPARTMENTS_MODE',
'LIVINGAREA_MODE',
'NONLIVINGAPARTMENTS_MODE',
'NONLIVINGAREA_MODE',
'APARTMENTS_MEDI',
'BASEMENTAREA_MEDI',
'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BUILD_MEDI',
'COMMONAREA_MEDI',
'ELEVATORS_MEDI',
'ENTRANCES_MEDI',
'FLOORSMAX_MEDI',
'FLOORSMIN_MEDI',
'LANDAREA_MEDI',
'LIVINGAPARTMENTS_MEDI',
'LIVINGAREA_MEDI',
'NONLIVINGAPARTMENTS_MEDI',
'NONLIVINGAREA_MEDI',
'FONDKAPREMONT_MODE',
'HOUSETYPE_MODE',
'TOTALAREA_MODE',
'WALLSMATERIAL_MODE',
'EMERGENCYSTATE_MODE',
'EXT_SOURCE_2',
'EXT_SOURCE_3',
```

```
 'FLAG_DOCUMENT_2',
 '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',
 'FLAG_MOBIL',
 'FLAG_EMP_PHONE',
 'FLAG_WORK_PHONE',
 'FLAG_CONT_MOBILE',
 'FLAG_PHONE',
 'FLAG_EMAIL']
```

[36]:

```
#removed all unwanted columns from the application set
application.drop(labels=unwanted_columns,axis=1,inplace=True)
```

[37]:

```
application.columns
```

[37]:

```
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', 'OCCUPATION_TYPE',
'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',
'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3', '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')
```

[38]:
```
application.shape
```

[38]:
```
(307511, 46)
```

[39]:
```
application.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 46 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   SK_ID_CURR                   307511 non-null  int64
 1   TARGET                       307511 non-null  int64
 2   NAME_CONTRACT_TYPE           307511 non-null  object
 3   CODE_GENDER                  307511 non-null  object
 4   FLAG_OWN_CAR                 307511 non-null  object
 5   FLAG_OWN_REALTY              307511 non-null  object
 6   CNT_CHILDREN                 307511 non-null  int64
 7   AMT_INCOME_TOTAL             307511 non-null  float64
 8   AMT_CREDIT                   307511 non-null  float64
 9   AMT_ANNUITY                  307499 non-null  float64
 10  AMT_GOODS_PRICE              307233 non-null  float64
 11  NAME_TYPE_SUITE              306219 non-null  object
 12  NAME_INCOME_TYPE             307511 non-null  object
 13  NAME_EDUCATION_TYPE          307511 non-null  object
 14  NAME_FAMILY_STATUS           307511 non-null  object
 15  NAME_HOUSING_TYPE            307511 non-null  object
 16  REGION_POPULATION_RELATIVE   307511 non-null  float64
 17  DAYS_BIRTH                   307511 non-null  int64
 18  DAYS_EMPLOYED                307511 non-null  int64
 19  DAYS_REGISTRATION            307511 non-null  float64
 20  DAYS_ID_PUBLISH              307511 non-null  int64
 21  OCCUPATION_TYPE              211120 non-null  object
 22  CNT_FAM_MEMBERS              307509 non-null  float64
 23  REGION_RATING_CLIENT         307511 non-null  int64
 24  REGION_RATING_CLIENT_W_CITY  307511 non-null  int64
 25  WEEKDAY_APPR_PROCESS_START   307511 non-null  object
 26  HOUR_APPR_PROCESS_START      307511 non-null  int64
 27  REG_REGION_NOT_LIVE_REGION   307511 non-null  int64
 28  REG_REGION_NOT_WORK_REGION   307511 non-null  int64
 29  LIVE_REGION_NOT_WORK_REGION  307511 non-null  int64
 30  REG_CITY_NOT_LIVE_CITY       307511 non-null  int64
 31  REG_CITY_NOT_WORK_CITY       307511 non-null  int64
 32  LIVE_CITY_NOT_WORK_CITY      307511 non-null  int64
```

```
 33  ORGANIZATION_TYPE            307511 non-null  object
 34  OBS_30_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 35  DEF_30_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 36  OBS_60_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 37  DEF_60_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 38  DAYS_LAST_PHONE_CHANGE       307510 non-null  float64
 39  FLAG_DOCUMENT_3              307511 non-null  int64
 40  AMT_REQ_CREDIT_BUREAU_HOUR   265992 non-null  float64
 41  AMT_REQ_CREDIT_BUREAU_DAY    265992 non-null  float64
 42  AMT_REQ_CREDIT_BUREAU_WEEK   265992 non-null  float64
 43  AMT_REQ_CREDIT_BUREAU_MON    265992 non-null  float64
 44  AMT_REQ_CREDIT_BUREAU_QRT    265992 non-null  float64
 45  AMT_REQ_CREDIT_BUREAU_YEAR   265992 non-null  float64
dtypes: float64(18), int64(16), object(12)
memory usage: 107.9+ MB
```

[40]:
```
#columns having more tha 40% null values converting to unwanted list
unwanted_previous=nullColumns_40prev['Column Name'].tolist()
unwanted_previous
```

[40]:
```
['AMT_DOWN_PAYMENT',
 'RATE_DOWN_PAYMENT',
 'RATE_INTEREST_PRIMARY',
 'RATE_INTEREST_PRIVILEGED',
 'NAME_TYPE_SUITE',
 'DAYS_FIRST_DRAWING',
 'DAYS_FIRST_DUE',
 'DAYS_LAST_DUE_1ST_VERSION',
 'DAYS_LAST_DUE',
 'DAYS_TERMINATION',
 'NFLAG_INSURED_ON_APPROVAL']
```

[41]:
```
#removing some unnecessary columns
Unnecessary_previous =␣
 ↪['WEEKDAY_APPR_PROCESS_START','HOUR_APPR_PROCESS_START','FLAG_LAST_APPL_PER_CONTRACT','NFLA
```

[42]:
```
unwanted_previous=unwanted_previous+Unnecessary_previous
len(unwanted_previous)
```

[42]:
```
15
```

[43]:
```
previous.drop(labels=unwanted_previous,axis=1,inplace=True)
```

[44]:
```
previous.shape
```

[44]:
```
(1670214, 22)
```

[45]:
```
previous.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 22 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_GOODS_PRICE          1284699 non-null  float64
 7   NAME_CASH_LOAN_PURPOSE   1670214 non-null  object
 8   NAME_CONTRACT_STATUS     1670214 non-null  object
 9   DAYS_DECISION            1670214 non-null  int64
 10  NAME_PAYMENT_TYPE        1670214 non-null  object
 11  CODE_REJECT_REASON       1670214 non-null  object
 12  NAME_CLIENT_TYPE         1670214 non-null  object
 13  NAME_GOODS_CATEGORY      1670214 non-null  object
 14  NAME_PORTFOLIO           1670214 non-null  object
 15  NAME_PRODUCT_TYPE        1670214 non-null  object
 16  CHANNEL_TYPE             1670214 non-null  object
 17  SELLERPLACE_AREA         1670214 non-null  int64
 18  NAME_SELLER_INDUSTRY     1670214 non-null  object
 19  CNT_PAYMENT              1297984 non-null  float64
 20  NAME_YIELD_GROUP         1670214 non-null  object
 21  PRODUCT_COMBINATION      1669868 non-null  object
dtypes: float64(5), int64(4), object(13)
memory usage: 280.3+ MB
```

[46]:
```
previous.describe()
```

[46]:
```
         SK_ID_PREV    SK_ID_CURR   AMT_ANNUITY  AMT_APPLICATION    AMT_CREDIT
 AMT_GOODS_PRICE  DAYS_DECISION  SELLERPLACE_AREA   CNT_PAYMENT
count  1.670214e+06  1.670214e+06  1.297979e+06     1.670214e+06  1.670213e+06
1.284699e+06   1.670214e+06      1.670214e+06  1.297984e+06
mean   1.923089e+06  2.783572e+05  1.595512e+04     1.752339e+05  1.961140e+05
2.278473e+05  -8.806797e+02      3.139511e+02  1.605408e+01
std    5.325980e+05  1.028148e+05  1.478214e+04     2.927798e+05  3.185746e+05
3.153966e+05   7.790997e+02      7.127443e+03  1.456729e+01
min    1.000001e+06  1.000010e+05  0.000000e+00     0.000000e+00  0.000000e+00
0.000000e+00  -2.922000e+03     -1.000000e+00  0.000000e+00
25%    1.461857e+06  1.893290e+05  6.321780e+03     1.872000e+04  2.416050e+04
5.084100e+04  -1.300000e+03     -1.000000e+00  6.000000e+00
50%    1.923110e+06  2.787145e+05  1.125000e+04     7.104600e+04  8.054100e+04
```

```
1.123200e+05  -5.810000e+02      3.000000e+00  1.200000e+01
75%     2.384280e+06  3.675140e+05  2.065842e+04     1.803600e+05  2.164185e+05
2.340000e+05  -2.800000e+02      8.200000e+01  2.400000e+01
max     2.845382e+06  4.562550e+05  4.180581e+05     6.905160e+06  6.905160e+06
6.905160e+06  -1.000000e+00      4.000000e+06  8.400000e+01
```

[47]:
```
#converting negative to positive as days can't be negative
#abs() to return positive value
date_col=['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH']
for col in date_col:
    application[col]=abs(application[col])
```

[48]:
```
#Categorize the client income variable into bins
#pd.cut to seperate the array elements into different bins
application['AMT_INCOME_TOTAL']=application['AMT_INCOME_TOTAL']/100000
bins=[0,1,2,3,4,5,6,7,8,9,10,11]
slots=['0-100K','100K-200K','200K-300K','300K-400K','400K-500K','500K-600K','600K-700K','700K-
 ↪Above']
application['INCOME_RANGE']=pd.
 ↪cut(application['AMT_INCOME_TOTAL'],bins,labels=slots)
```

[49]:
```
#range of incomes
application['INCOME_RANGE']
```

[49]:
```
0         200K-300K
1         200K-300K
2            0-100K
3         100K-200K
4         100K-200K
            …
307506    100K-200K
307507       0-100K
307508    100K-200K
307509    100K-200K
307510    100K-200K
Name: INCOME_RANGE, Length: 307511, dtype: category
Categories (11, object): ['0-100K' < '100K-200K' < '200K-300K' < '300K-400K' …
'700K-800K' < '800K-900K' < '900K-1M' < '1M Above']
```

[50]:
```
#calculating the percentage in the range of salary
#IF normalize is true then the object returns the relative frequencies of the␣
 ↪unique values
#More than 50% loan applicants have income amount in the range of 100K-200K.␣
 ↪Almost 92% loan applicants have income less than 300K
application['INCOME_RANGE'].value_counts(normalize=True)*100
```

[50]:
```
100K-200K    50.735000
200K-300K    21.210691
0-100K       20.729695
300K-400K     4.776116
400K-500K     1.744669
500K-600K     0.356354
600K-700K     0.282805
800K-900K     0.096980
700K-800K     0.052721
900K-1M       0.009112
1M Above      0.005858
Name: INCOME_RANGE, dtype: float64
```

[51]:
```
#Categorize the client credit amount into bins
application['AMT_CREDIT']=application['AMT_CREDIT']/100000
bins=[0,1,2,3,4,5,6,7,8,9,10,100]
slots = ['0 to 100K','100K to 200K', '200k to 300k','300k to 400k','400k to␣
↪500k','500k to 600k','600k to 700k','700k to 800k','800k to 900k','900k to␣
↪1M', '1M Above']
application['LOAN_AMT']=pd.cut(application['AMT_CREDIT'], bins,labels=slots)
```

[52]:
```
#calculating the percentage of loan amount
application['LOAN_AMT'].value_counts(normalize=True)*100
```

[52]:
```
200k to 300k    17.824728
1M Above        16.254703
500k to 600k    11.131960
400k to 500k    10.418489
100K to 200K     9.801275
300k to 400k     8.564897
600k to 700k     7.820533
800k to 900k     7.086576
700k to 800k     6.241403
900k to 1M       2.902986
0 to 100K        1.952450
Name: LOAN_AMT, dtype: float64
```

[53]:
```
#Categorize the client age into bins
application['AGE']=application['DAYS_BIRTH']//365
bins=(0,20,30,40,50,100)
slots=['0 to 20','20 to 30','30 to 40','40 to 50','50 above']
application['AGE_GROUP']=pd.cut(application['AGE'],bins,labels=slots)
```

[54]:
```
#checking for which age group people are major
application['AGE_GROUP'].value_counts(normalize=True)*100
```

[54]:
```
50 above    31.604398
30 to 40    27.028952
40 to 50    24.194582
20 to 30    17.171743
0 to 20      0.000325
Name: AGE_GROUP, dtype: float64
```

[55]:
```
#Categorize the clients working years into bins
application['YEARS_EMPLOYED'] = application['DAYS_EMPLOYED']//365
bins = [0,5,10,20,30,40,50,60,150]
slots = ['0-5','5-10','10-20','20-30','30-40','40-50','50-60','60 above']
application['WORKING_YEARS']=pd.
 ↪cut(application['YEARS_EMPLOYED'],bins=bins,labels=slots)
```

[56]:
```
application['WORKING_YEARS'].value_counts(normalize=True)*100
```

[56]:
```
0-5         55.582363
5-10        24.966441
10-20       14.564315
20-30        3.750117
30-40        1.058720
40-50        0.078044
50-60        0.000000
60 above     0.000000
Name: WORKING_YEARS, dtype: float64
```

[57]:
```
#Checking the number of unique values each column possess to identify␣
 ↪categorical columns
application.nunique().sort_values()
```

[57]:
```
LIVE_CITY_NOT_WORK_CITY          2
TARGET                           2
NAME_CONTRACT_TYPE               2
REG_REGION_NOT_LIVE_REGION       2
FLAG_OWN_CAR                     2
FLAG_OWN_REALTY                  2
REG_REGION_NOT_WORK_REGION       2
LIVE_REGION_NOT_WORK_REGION      2
FLAG_DOCUMENT_3                  2
REG_CITY_NOT_LIVE_CITY           2
REG_CITY_NOT_WORK_CITY           2
REGION_RATING_CLIENT             3
CODE_GENDER                      3
REGION_RATING_CLIENT_W_CITY      3
AMT_REQ_CREDIT_BUREAU_HOUR       5
NAME_EDUCATION_TYPE              5
AGE_GROUP                        5
```

```
NAME_FAMILY_STATUS                 6
NAME_HOUSING_TYPE                  6
WORKING_YEARS                      6
WEEKDAY_APPR_PROCESS_START         7
NAME_TYPE_SUITE                    7
NAME_INCOME_TYPE                   8
AMT_REQ_CREDIT_BUREAU_WEEK         9
AMT_REQ_CREDIT_BUREAU_DAY          9
DEF_60_CNT_SOCIAL_CIRCLE           9
DEF_30_CNT_SOCIAL_CIRCLE          10
LOAN_AMT                          11
INCOME_RANGE                      11
AMT_REQ_CREDIT_BUREAU_QRT         11
CNT_CHILDREN                      15
CNT_FAM_MEMBERS                   17
OCCUPATION_TYPE                   18
HOUR_APPR_PROCESS_START           24
AMT_REQ_CREDIT_BUREAU_MON         24
AMT_REQ_CREDIT_BUREAU_YEAR        25
OBS_60_CNT_SOCIAL_CIRCLE          33
OBS_30_CNT_SOCIAL_CIRCLE          33
AGE                               50
YEARS_EMPLOYED                    51
ORGANIZATION_TYPE                 58
REGION_POPULATION_RELATIVE        81
AMT_GOODS_PRICE                 1002
AMT_INCOME_TOTAL                2548
DAYS_LAST_PHONE_CHANGE          3773
AMT_CREDIT                      5603
DAYS_ID_PUBLISH                 6168
DAYS_EMPLOYED                  12574
AMT_ANNUITY                    13672
DAYS_REGISTRATION              15688
DAYS_BIRTH                     17460
SK_ID_CURR                    307511
dtype: int64
```

[58]:
```
#checking the data type of columns and correcting them
application.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 52 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   SK_ID_CURR                   307511 non-null  int64
 1   TARGET                       307511 non-null  int64
```

```
2   NAME_CONTRACT_TYPE          307511 non-null  object
3   CODE_GENDER                 307511 non-null  object
4   FLAG_OWN_CAR                307511 non-null  object
5   FLAG_OWN_REALTY             307511 non-null  object
6   CNT_CHILDREN                307511 non-null  int64
7   AMT_INCOME_TOTAL            307511 non-null  float64
8   AMT_CREDIT                  307511 non-null  float64
9   AMT_ANNUITY                 307499 non-null  float64
10  AMT_GOODS_PRICE             307233 non-null  float64
11  NAME_TYPE_SUITE             306219 non-null  object
12  NAME_INCOME_TYPE            307511 non-null  object
13  NAME_EDUCATION_TYPE         307511 non-null  object
14  NAME_FAMILY_STATUS          307511 non-null  object
15  NAME_HOUSING_TYPE           307511 non-null  object
16  REGION_POPULATION_RELATIVE  307511 non-null  float64
17  DAYS_BIRTH                  307511 non-null  int64
18  DAYS_EMPLOYED               307511 non-null  int64
19  DAYS_REGISTRATION           307511 non-null  float64
20  DAYS_ID_PUBLISH             307511 non-null  int64
21  OCCUPATION_TYPE             211120 non-null  object
22  CNT_FAM_MEMBERS             307509 non-null  float64
23  REGION_RATING_CLIENT        307511 non-null  int64
24  REGION_RATING_CLIENT_W_CITY 307511 non-null  int64
25  WEEKDAY_APPR_PROCESS_START  307511 non-null  object
26  HOUR_APPR_PROCESS_START     307511 non-null  int64
27  REG_REGION_NOT_LIVE_REGION  307511 non-null  int64
28  REG_REGION_NOT_WORK_REGION  307511 non-null  int64
29  LIVE_REGION_NOT_WORK_REGION 307511 non-null  int64
30  REG_CITY_NOT_LIVE_CITY      307511 non-null  int64
31  REG_CITY_NOT_WORK_CITY      307511 non-null  int64
32  LIVE_CITY_NOT_WORK_CITY     307511 non-null  int64
33  ORGANIZATION_TYPE           307511 non-null  object
34  OBS_30_CNT_SOCIAL_CIRCLE    306490 non-null  float64
35  DEF_30_CNT_SOCIAL_CIRCLE    306490 non-null  float64
36  OBS_60_CNT_SOCIAL_CIRCLE    306490 non-null  float64
37  DEF_60_CNT_SOCIAL_CIRCLE    306490 non-null  float64
38  DAYS_LAST_PHONE_CHANGE      307510 non-null  float64
39  FLAG_DOCUMENT_3             307511 non-null  int64
40  AMT_REQ_CREDIT_BUREAU_HOUR  265992 non-null  float64
41  AMT_REQ_CREDIT_BUREAU_DAY   265992 non-null  float64
42  AMT_REQ_CREDIT_BUREAU_WEEK  265992 non-null  float64
43  AMT_REQ_CREDIT_BUREAU_MON   265992 non-null  float64
44  AMT_REQ_CREDIT_BUREAU_QRT   265992 non-null  float64
45  AMT_REQ_CREDIT_BUREAU_YEAR  265992 non-null  float64
46  INCOME_RANGE                307279 non-null  category
47  LOAN_AMT                    307511 non-null  category
48  AGE                         307511 non-null  int64
49  AGE_GROUP                   307511 non-null  category
```

```
 50   YEARS_EMPLOYED                307511 non-null   int64
 51   WORKING_YEARS                 224233 non-null   category
dtypes: category(4), float64(18), int64(18), object(12)
memory usage: 113.8+ MB
```

[59]:

```python
#converting the datatype to categorical
categorical_columns=['NAME_CONTRACT_TYPE','CODE_GENDER','NAME_TYPE_SUITE','NAME_INCOME_TYPE','
␣
 ↪'REG_CITY_NOT_LIVE_CITY','REG_CITY_NOT_WORK_CITY','REG_REGION_NOT_WORK_REGION','LIVE_REGION
 ↪'REGION_RATING_CLIENT_W_CITY' ]
for col in categorical_columns:
    application[col]=pd.Categorical(application[col])
```

[60]:

```python
application.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 52 columns):
 #    Column                        Non-Null Count    Dtype
---   ------                        --------------    -----
 0    SK_ID_CURR                    307511 non-null   int64
 1    TARGET                        307511 non-null   int64
 2    NAME_CONTRACT_TYPE            307511 non-null   category
 3    CODE_GENDER                   307511 non-null   category
 4    FLAG_OWN_CAR                  307511 non-null   category
 5    FLAG_OWN_REALTY               307511 non-null   category
 6    CNT_CHILDREN                  307511 non-null   int64
 7    AMT_INCOME_TOTAL              307511 non-null   float64
 8    AMT_CREDIT                    307511 non-null   float64
 9    AMT_ANNUITY                   307499 non-null   float64
 10   AMT_GOODS_PRICE               307233 non-null   float64
 11   NAME_TYPE_SUITE               306219 non-null   category
 12   NAME_INCOME_TYPE              307511 non-null   category
 13   NAME_EDUCATION_TYPE           307511 non-null   category
 14   NAME_FAMILY_STATUS            307511 non-null   category
 15   NAME_HOUSING_TYPE             307511 non-null   category
 16   REGION_POPULATION_RELATIVE    307511 non-null   float64
 17   DAYS_BIRTH                    307511 non-null   int64
 18   DAYS_EMPLOYED                 307511 non-null   int64
 19   DAYS_REGISTRATION             307511 non-null   float64
 20   DAYS_ID_PUBLISH               307511 non-null   int64
 21   OCCUPATION_TYPE               211120 non-null   category
 22   CNT_FAM_MEMBERS               307509 non-null   float64
 23   REGION_RATING_CLIENT          307511 non-null   category
 24   REGION_RATING_CLIENT_W_CITY   307511 non-null   category
 25   WEEKDAY_APPR_PROCESS_START    307511 non-null   category
 26   HOUR_APPR_PROCESS_START       307511 non-null   int64
 27   REG_REGION_NOT_LIVE_REGION    307511 non-null   int64
```

```
 28  REG_REGION_NOT_WORK_REGION   307511 non-null  category
 29  LIVE_REGION_NOT_WORK_REGION  307511 non-null  category
 30  REG_CITY_NOT_LIVE_CITY       307511 non-null  category
 31  REG_CITY_NOT_WORK_CITY       307511 non-null  category
 32  LIVE_CITY_NOT_WORK_CITY      307511 non-null  category
 33  ORGANIZATION_TYPE            307511 non-null  category
 34  OBS_30_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 35  DEF_30_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 36  OBS_60_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 37  DEF_60_CNT_SOCIAL_CIRCLE     306490 non-null  float64
 38  DAYS_LAST_PHONE_CHANGE       307510 non-null  float64
 39  FLAG_DOCUMENT_3              307511 non-null  int64
 40  AMT_REQ_CREDIT_BUREAU_HOUR   265992 non-null  float64
 41  AMT_REQ_CREDIT_BUREAU_DAY    265992 non-null  float64
 42  AMT_REQ_CREDIT_BUREAU_WEEK   265992 non-null  float64
 43  AMT_REQ_CREDIT_BUREAU_MON    265992 non-null  float64
 44  AMT_REQ_CREDIT_BUREAU_QRT    265992 non-null  float64
 45  AMT_REQ_CREDIT_BUREAU_YEAR   265992 non-null  float64
 46  INCOME_RANGE                 307279 non-null  category
 47  LOAN_AMT                     307511 non-null  category
 48  AGE                          307511 non-null  int64
 49  AGE_GROUP                    307511 non-null  category
 50  YEARS_EMPLOYED               307511 non-null  int64
 51  WORKING_YEARS                224233 non-null  category
dtypes: category(23), float64(18), int64(11)
memory usage: 74.8 MB
```

[61]:
```
#converting negative days to positive for previous dataset
#abs() to convert into whole number
previous['DAYS_DECISION']=abs(previous['DAYS_DECISION'])
```

[62]:
```
previous.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 22 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_GOODS_PRICE         1284699 non-null  float64
 7   NAME_CASH_LOAN_PURPOSE  1670214 non-null  object
 8   NAME_CONTRACT_STATUS    1670214 non-null  object
 9   DAYS_DECISION           1670214 non-null  int64
```

```
 10   NAME_PAYMENT_TYPE       1670214 non-null  object
 11   CODE_REJECT_REASON      1670214 non-null  object
 12   NAME_CLIENT_TYPE        1670214 non-null  object
 13   NAME_GOODS_CATEGORY     1670214 non-null  object
 14   NAME_PORTFOLIO          1670214 non-null  object
 15   NAME_PRODUCT_TYPE       1670214 non-null  object
 16   CHANNEL_TYPE            1670214 non-null  object
 17   SELLERPLACE_AREA        1670214 non-null  int64
 18   NAME_SELLER_INDUSTRY    1670214 non-null  object
 19   CNT_PAYMENT             1297984 non-null  float64
 20   NAME_YIELD_GROUP        1670214 non-null  object
 21   PRODUCT_COMBINATION     1669868 non-null  object
dtypes: float64(5), int64(4), object(13)
memory usage: 280.3+ MB
```

[63]:
```
bins=[0,400,800,1200,1600,2000,2400,2800,3200]
previous['DAYS_DECISION_GROUP']=pd.cut(previous['DAYS_DECISION'],bins)
```

[64]:
```
previous['DAYS_DECISION_GROUP'].value_counts(normalize=True)*100
```

[64]:
```
(0, 400]        37.574526
(400, 800]      22.900299
(800, 1200]     12.426012
(1200, 1600]     7.899646
(2400, 2800]     6.292188
(1600, 2000]     5.791174
(2000, 2400]     5.689750
(2800, 3200]     1.426404
Name: DAYS_DECISION_GROUP, dtype: float64
```

[65]:
```
#Checking the number of unique values each column possess to identify␣
 ↪categorical columns
previous.nunique().sort_values()
```

[65]:
```
NAME_PRODUCT_TYPE          3
NAME_CONTRACT_TYPE         4
NAME_CLIENT_TYPE           4
NAME_PAYMENT_TYPE          4
NAME_CONTRACT_STATUS       4
NAME_YIELD_GROUP           5
NAME_PORTFOLIO             5
DAYS_DECISION_GROUP        8
CHANNEL_TYPE               8
CODE_REJECT_REASON         9
NAME_SELLER_INDUSTRY      11
PRODUCT_COMBINATION       17
NAME_CASH_LOAN_PURPOSE    25
```

```
NAME_GOODS_CATEGORY           28
CNT_PAYMENT                   49
SELLERPLACE_AREA            2097
DAYS_DECISION               2922
AMT_CREDIT                 86803
AMT_GOODS_PRICE            93885
AMT_APPLICATION            93885
SK_ID_CURR                338857
AMT_ANNUITY               357959
SK_ID_PREV               1670214
dtype: int64
```

[66]:

```
previous.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 23 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_GOODS_PRICE         1284699 non-null  float64
 7   NAME_CASH_LOAN_PURPOSE  1670214 non-null  object
 8   NAME_CONTRACT_STATUS    1670214 non-null  object
 9   DAYS_DECISION           1670214 non-null  int64
 10  NAME_PAYMENT_TYPE       1670214 non-null  object
 11  CODE_REJECT_REASON      1670214 non-null  object
 12  NAME_CLIENT_TYPE        1670214 non-null  object
 13  NAME_GOODS_CATEGORY     1670214 non-null  object
 14  NAME_PORTFOLIO          1670214 non-null  object
 15  NAME_PRODUCT_TYPE       1670214 non-null  object
 16  CHANNEL_TYPE            1670214 non-null  object
 17  SELLERPLACE_AREA        1670214 non-null  int64
 18  NAME_SELLER_INDUSTRY    1670214 non-null  object
 19  CNT_PAYMENT             1297984 non-null  float64
 20  NAME_YIELD_GROUP        1670214 non-null  object
 21  PRODUCT_COMBINATION     1669868 non-null  object
 22  DAYS_DECISION_GROUP     1670214 non-null  category
dtypes: category(1), float64(5), int64(4), object(13)
memory usage: 281.9+ MB
```

[67]:

```
previous_Cat= ␣
↪['NAME_CASH_LOAN_PURPOSE','NAME_CONTRACT_STATUS','NAME_PAYMENT_TYPE','CODE_REJECT_REASON','
```

```
        ␣
↪'NAME_GOODS_CATEGORY','NAME_PORTFOLIO','NAME_PRODUCT_TYPE','CHANNEL_TYPE','NAME_SELLER_INDU
        ␣
↪'PRODUCT_COMBINATION','NAME_CONTRACT_TYPE','DAYS_DECISION_GROUP']
for col in previous_Cat:
    previous[col]=pd.Categorical(previous[col])
```

[68]:
```
previous.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 23 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  category
 3   AMT_ANNUITY             1297979 non-null  float64
 4   AMT_APPLICATION         1670214 non-null  float64
 5   AMT_CREDIT              1670213 non-null  float64
 6   AMT_GOODS_PRICE         1284699 non-null  float64
 7   NAME_CASH_LOAN_PURPOSE  1670214 non-null  category
 8   NAME_CONTRACT_STATUS    1670214 non-null  category
 9   DAYS_DECISION           1670214 non-null  int64
 10  NAME_PAYMENT_TYPE       1670214 non-null  category
 11  CODE_REJECT_REASON      1670214 non-null  category
 12  NAME_CLIENT_TYPE        1670214 non-null  category
 13  NAME_GOODS_CATEGORY     1670214 non-null  category
 14  NAME_PORTFOLIO          1670214 non-null  category
 15  NAME_PRODUCT_TYPE       1670214 non-null  category
 16  CHANNEL_TYPE            1670214 non-null  category
 17  SELLERPLACE_AREA        1670214 non-null  int64
 18  NAME_SELLER_INDUSTRY    1670214 non-null  category
 19  CNT_PAYMENT             1297984 non-null  float64
 20  NAME_YIELD_GROUP        1670214 non-null  category
 21  PRODUCT_COMBINATION     1669868 non-null  category
 22  DAYS_DECISION_GROUP     1670214 non-null  category
dtypes: category(14), float64(5), int64(4)
memory usage: 137.0 MB
```

[69]:
```
#checking null value percentage in each column
round(application.isnull().sum()/application.shape[0]*100.00,2)
```

[69]:
```
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	0.00
AMT_GOODS_PRICE	0.09
NAME_TYPE_SUITE	0.42
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	31.35
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
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
FLAG_DOCUMENT_3	0.00
AMT_REQ_CREDIT_BUREAU_HOUR	13.50
AMT_REQ_CREDIT_BUREAU_DAY	13.50
AMT_REQ_CREDIT_BUREAU_WEEK	13.50
AMT_REQ_CREDIT_BUREAU_MON	13.50
AMT_REQ_CREDIT_BUREAU_QRT	13.50
AMT_REQ_CREDIT_BUREAU_YEAR	13.50
INCOME_RANGE	0.08
LOAN_AMT	0.00
AGE	0.00
AGE_GROUP	0.00
YEARS_EMPLOYED	0.00

```
WORKING_YEARS                        27.08
dtype: float64
```

[70]:
```python
#NAME_TYPE_SUITE as only 0.42%null value
application['NAME_TYPE_SUITE'].describe()
```

[70]:
```
count             306219
unique                 7
top        Unaccompanied
freq              248526
Name: NAME_TYPE_SUITE, dtype: object
```

[71]:
```python
#imputing the null values with most occuring value by mode()
application['NAME_TYPE_SUITE'].fillna((application['NAME_TYPE_SUITE'].
 ↪mode()[0]),inplace=True)
```

[72]:
```python
#imputing the null values with new category
application['OCCUPATION_TYPE']=application['OCCUPATION_TYPE'].cat.
 ↪add_categories('Unknown')
application['OCCUPATION_TYPE'].fillna('Unknown',inplace=True)
```

[73]:
```python
application[['AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CREDIT_BUREAU_W
               'AMT_REQ_CREDIT_BUREAU_QRT','AMT_REQ_CREDIT_BUREAU_YEAR']].
 ↪describe()
```

[73]:
```
       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
count                 265992.000000              265992.000000
265992.000000              265992.000000              265992.000000
265992.000000
mean                       0.006402                   0.007000
0.034362                   0.267395                   0.265474
1.899974
std                        0.083849                   0.110757
0.204685                   0.916002                   0.794056
1.869295
min                        0.000000                   0.000000
0.000000                   0.000000                   0.000000
0.000000
25%                        0.000000                   0.000000
0.000000                   0.000000                   0.000000
0.000000
50%                        0.000000                   0.000000
0.000000                   0.000000                   0.000000
1.000000
75%                        0.000000                   0.000000
```

```
0.000000                        0.000000                        0.000000
3.000000
max                           4.000000                        9.000000
8.000000                       27.000000                      261.000000
25.000000
```

[74]:

```python
#imputing with median as mean is in decimal
amount=['AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CREDIT_BUREAU_WEEK',
               'AMT_REQ_CREDIT_BUREAU_QRT','AMT_REQ_CREDIT_BUREAU_YEAR']
for col in amount:
    application[col].fillna(application[col].median(),inplace=True)
```

[75]:

```python
round(application.isnull().sum()/application.shape[0]*100.0,2)
```

[75]:

```
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                     0.00
AMT_GOODS_PRICE                 0.09
NAME_TYPE_SUITE                 0.00
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                 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
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
FLAG_DOCUMENT_3                0.00
AMT_REQ_CREDIT_BUREAU_HOUR     0.00
AMT_REQ_CREDIT_BUREAU_DAY      0.00
AMT_REQ_CREDIT_BUREAU_WEEK     0.00
AMT_REQ_CREDIT_BUREAU_MON      0.00
AMT_REQ_CREDIT_BUREAU_QRT      0.00
AMT_REQ_CREDIT_BUREAU_YEAR     0.00
INCOME_RANGE                   0.08
LOAN_AMT                       0.00
AGE                            0.00
AGE_GROUP                      0.00
YEARS_EMPLOYED                 0.00
WORKING_YEARS                 27.08
dtype: float64
```

[76]:

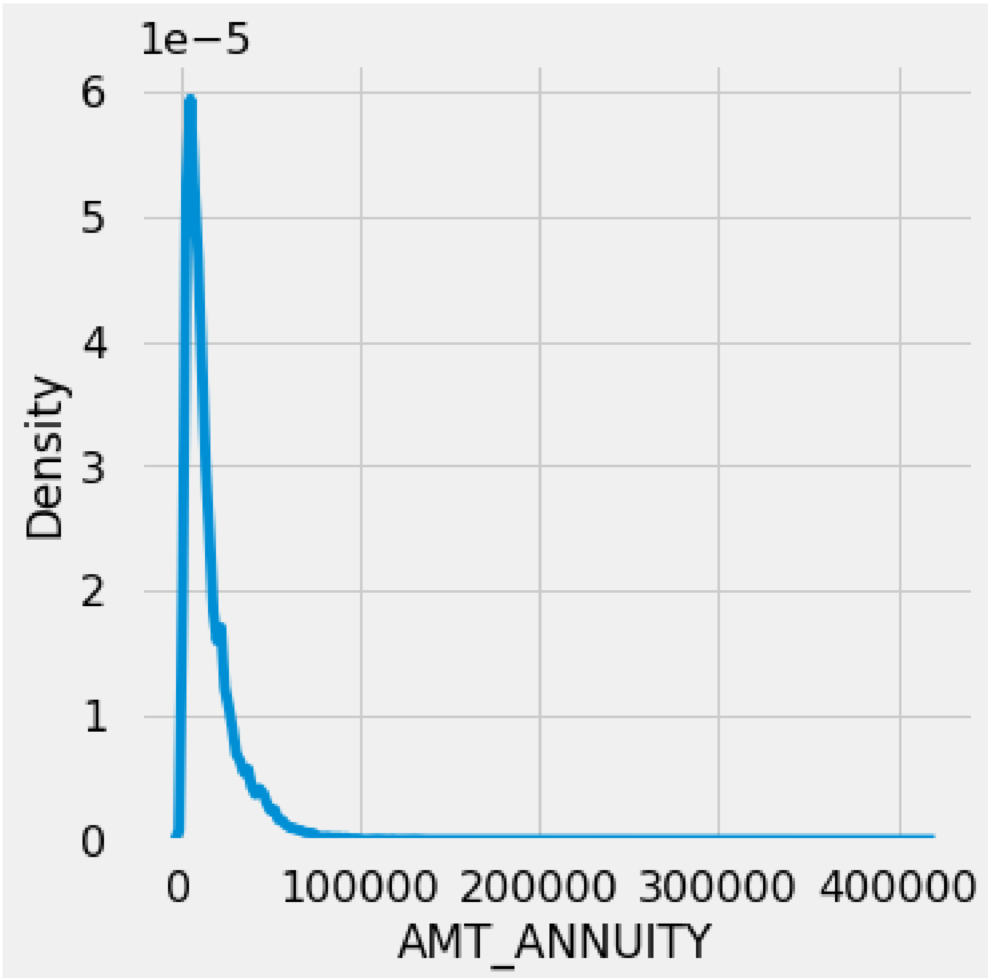
```python
#percentage of null values in previous
round(previous.isnull().sum()/previous.shape[0]*100.00,3)
```

[76]:

```
SK_ID_PREV                 0.000
SK_ID_CURR                 0.000
NAME_CONTRACT_TYPE         0.000
AMT_ANNUITY               22.287
AMT_APPLICATION            0.000
AMT_CREDIT                 0.000
AMT_GOODS_PRICE           23.082
NAME_CASH_LOAN_PURPOSE     0.000
NAME_CONTRACT_STATUS       0.000
DAYS_DECISION              0.000
NAME_PAYMENT_TYPE          0.000
CODE_REJECT_REASON         0.000
NAME_CLIENT_TYPE           0.000
NAME_GOODS_CATEGORY        0.000
NAME_PORTFOLIO             0.000
NAME_PRODUCT_TYPE          0.000
CHANNEL_TYPE               0.000
SELLERPLACE_AREA           0.000
NAME_SELLER_INDUSTRY       0.000
CNT_PAYMENT               22.286
NAME_YIELD_GROUP           0.000
PRODUCT_COMBINATION        0.021
DAYS_DECISION_GROUP        0.000
```

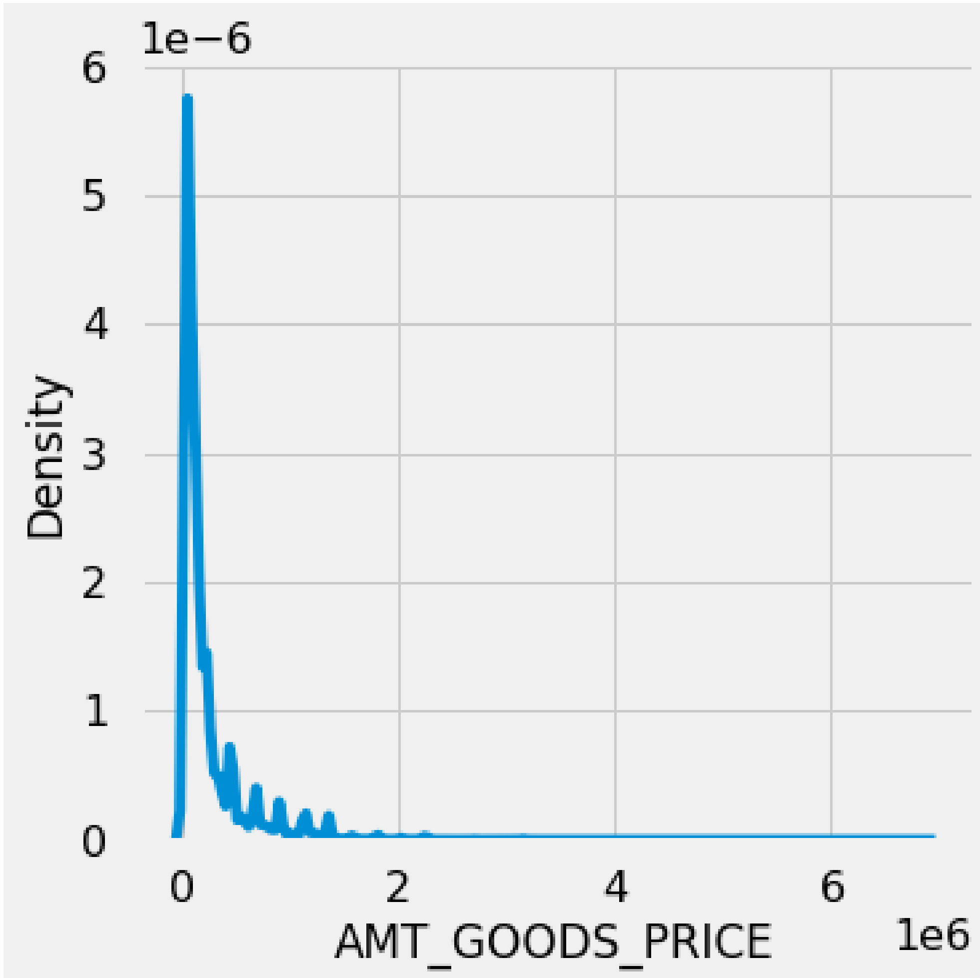
```
dtype: float64
```

[77]:
```
#plotting the distribution of columns
plt.figure(figsize=(5,5))
ax=sns.kdeplot(previous['AMT_ANNUITY'])
```



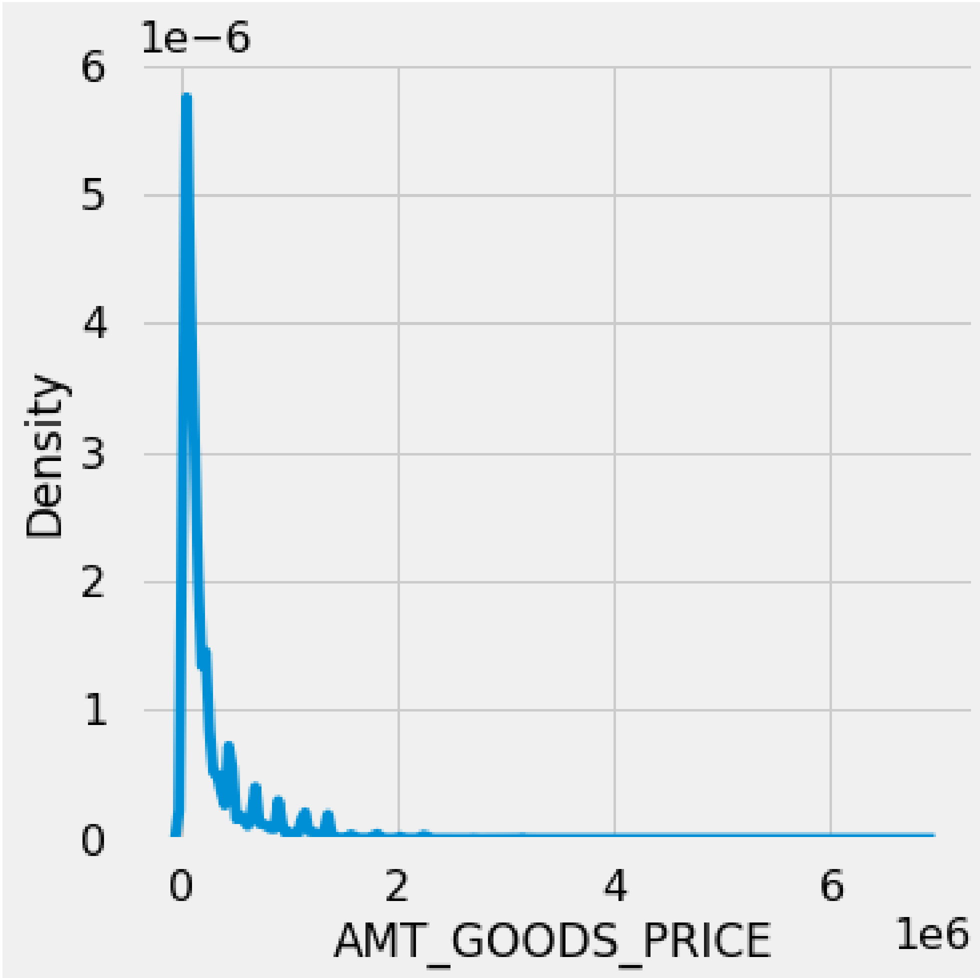
[78]:
```
#imputing with median as there is an outlier and would impact the mean
previous['AMT_ANNUITY'].fillna(previous['AMT_ANNUITY'].median(),inplace=True)
```

[79]:
```
#plotting the distribution of columns
plt.figure(figsize=(5,5))
bx=sns.kdeplot(previous['AMT_GOODS_PRICE'])
```



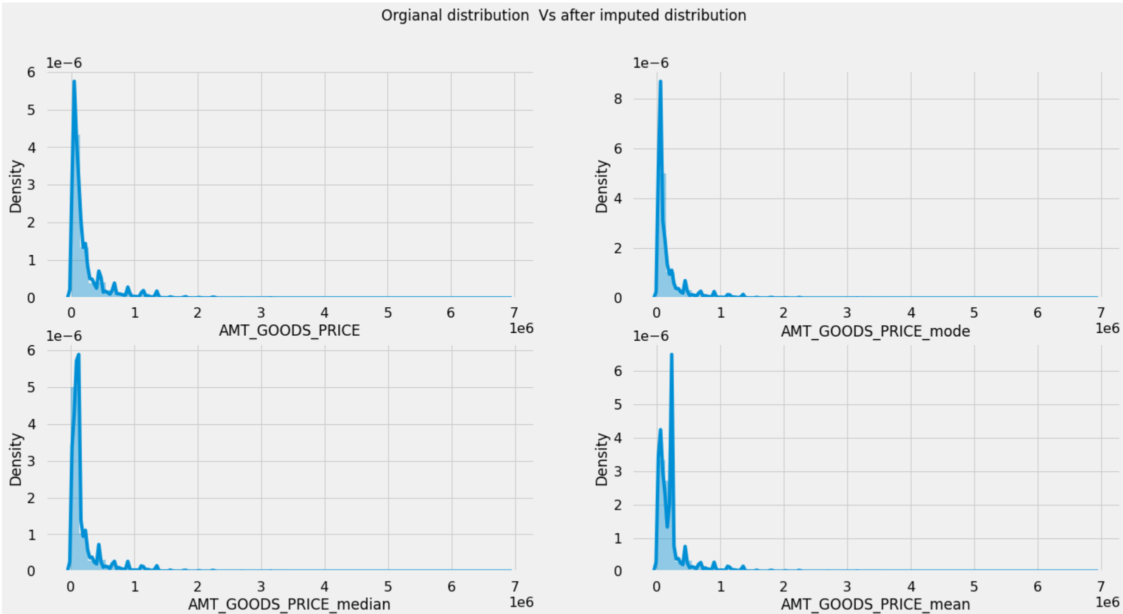
[80]:
```
plt.figure(figsize=(5,5))
sns.kdeplot(previous['AMT_GOODS_PRICE'][pd.
↪notnull(previous['AMT_GOODS_PRICE'])])
```

[80]: <AxesSubplot:xlabel='AMT_GOODS_PRICE', ylabel='Density'>



[81]:
```
#checking which method to impute as there are several peaks in the distribution
stats=pd.DataFrame()
stats['AMT_GOODS_PRICE_mode']=previous['AMT_GOODS_PRICE'].
 ↪fillna(previous['AMT_GOODS_PRICE'].mode()[0])
stats['AMT_GOODS_PRICE_median']=previous['AMT_GOODS_PRICE'].
 ↪fillna(previous['AMT_GOODS_PRICE'].median())
stats['AMT_GOODS_PRICE_mean']=previous['AMT_GOODS_PRICE'].
 ↪fillna(previous['AMT_GOODS_PRICE'].mean())
cols=['AMT_GOODS_PRICE_mode','AMT_GOODS_PRICE_median','AMT_GOODS_PRICE_mean']
plt.figure(figsize=(20,10))
plt.suptitle('Orgianal distribution  Vs after imputed distribution')
plt.subplot(221)
sns.distplot(previous['AMT_GOODS_PRICE'][pd.
 ↪notnull(previous['AMT_GOODS_PRICE'])]);
for i in enumerate(cols):
    plt.subplot(2,2,i[0]+2)
```

```
    sns.distplot(stats[i[1]])
```



[82]:
```
#imputing by mode as the orginal distribution is closer the imputed distribution
previous['AMT_GOODS_PRICE'].fillna(previous['AMT_GOODS_PRICE'].
 ↪mode()[0],inplace=True)
```

[83]:
```
#checking the relation for null values in CNT_PAYMENT with contract status
previous.loc[previous['CNT_PAYMENT'].isnull(),'NAME_CONTRACT_STATUS'].
 ↪value_counts()
```

[83]:
```
Canceled        305805
Refused          40897
Unused offer     25524
Approved             4
Name: NAME_CONTRACT_STATUS, dtype: int64
```

[84]:
```
#imputing by relevant information
previous['CNT_PAYMENT'].fillna(0,inplace=True)
```

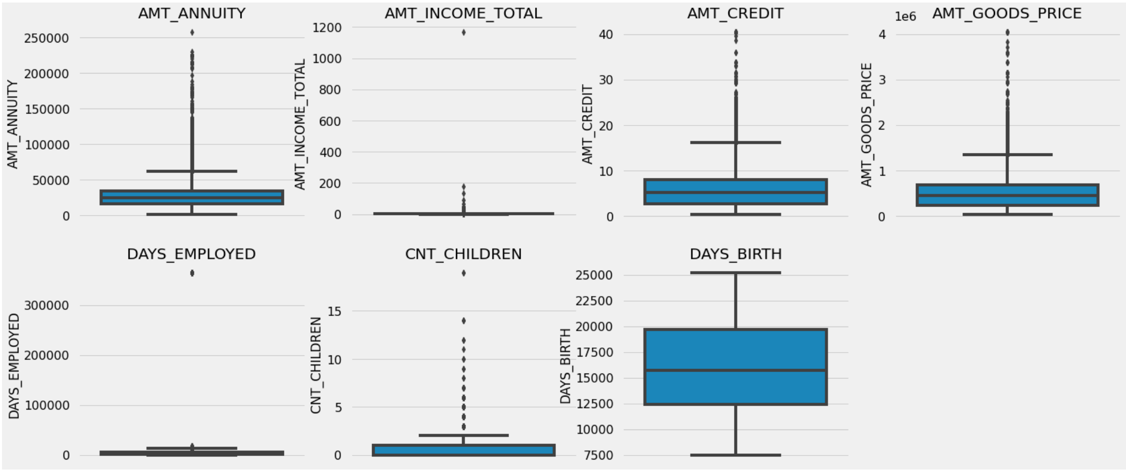
[85]:
```
#checking the percentage of null values
round(previous.isnull().sum()/previous.shape[0]*100.0,3)
```

[85]:
```
SK_ID_PREV                 0.000
SK_ID_CURR                 0.000
NAME_CONTRACT_TYPE         0.000
AMT_ANNUITY                0.000
AMT_APPLICATION            0.000
```

```
AMT_CREDIT                0.000
AMT_GOODS_PRICE           0.000
NAME_CASH_LOAN_PURPOSE    0.000
NAME_CONTRACT_STATUS      0.000
DAYS_DECISION             0.000
NAME_PAYMENT_TYPE         0.000
CODE_REJECT_REASON        0.000
NAME_CLIENT_TYPE          0.000
NAME_GOODS_CATEGORY       0.000
NAME_PORTFOLIO            0.000
NAME_PRODUCT_TYPE         0.000
CHANNEL_TYPE              0.000
SELLERPLACE_AREA          0.000
NAME_SELLER_INDUSTRY      0.000
CNT_PAYMENT               0.000
NAME_YIELD_GROUP          0.000
PRODUCT_COMBINATION       0.021
DAYS_DECISION_GROUP       0.000
dtype: float64
```

[86]:

```
#checking for outliers
plt.figure(figsize=(22,10))
application_outliers=['AMT_ANNUITY','AMT_INCOME_TOTAL','AMT_CREDIT','AMT_GOODS_PRICE','DAYS_EM
for i in enumerate(application_outliers):
    plt.subplot(2,4,i[0]+1)
    sns.boxplot(y=application[i[1]])
    plt.title(i[1])
```

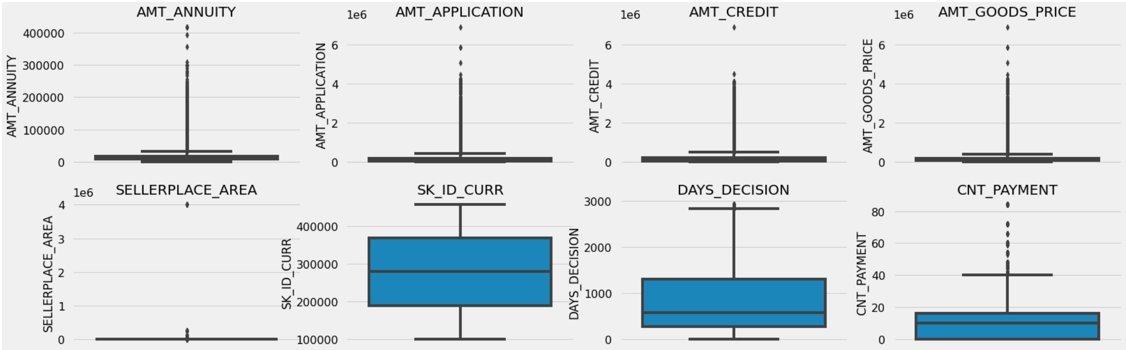


[87]:

```
application[['AMT_ANNUITY', 'AMT_INCOME_TOTAL', 'AMT_CREDIT',␣
↪'AMT_GOODS_PRICE', 'DAYS_BIRTH','CNT_CHILDREN','DAYS_EMPLOYED']].describe()
```

[87]:
```
          AMT_ANNUITY  AMT_INCOME_TOTAL     AMT_CREDIT  AMT_GOODS_PRICE
DAYS_BIRTH   CNT_CHILDREN  DAYS_EMPLOYED
count  307499.000000     307511.000000  307511.000000     3.072330e+05
307511.000000  307511.000000  307511.000000
mean    27108.573909          1.687979       5.990260     5.383962e+05
16036.995067       0.417052   67724.742149
std     14493.737315          2.371231       4.024908     3.694465e+05
4363.988632       0.722121  139443.751806
min      1615.500000          0.256500       0.450000     4.050000e+04
7489.000000       0.000000       0.000000
25%     16524.000000          1.125000       2.700000     2.385000e+05
12413.000000       0.000000     933.000000
50%     24903.000000          1.471500       5.135310     4.500000e+05
15750.000000       0.000000    2219.000000
75%     34596.000000          2.025000       8.086500     6.795000e+05
19682.000000       1.000000    5707.000000
max    258025.500000       1170.000000      40.500000     4.050000e+06
25229.000000      19.000000  365243.000000
```

[88]:
```python
#to identify outliers in previous data set
plt.figure(figsize=(24,8))
from matplotlib import pyplot, pylab
import matplotlib.pyplot as plt
previous_outliers=['AMT_ANNUITY','AMT_APPLICATION','AMT_CREDIT','AMT_GOODS_PRICE','SELLERPLACE
for i in enumerate(previous_outliers):
    plt.subplot(2,4,i[0]+1)
    sns.boxplot(y=previous[i[1]])
    pylab.title(i[1])
```



[89]:
```python
previous[['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_GOODS_PRICE',␣
↪'SELLERPLACE_AREA','CNT_PAYMENT','DAYS_DECISION']].describe()
```

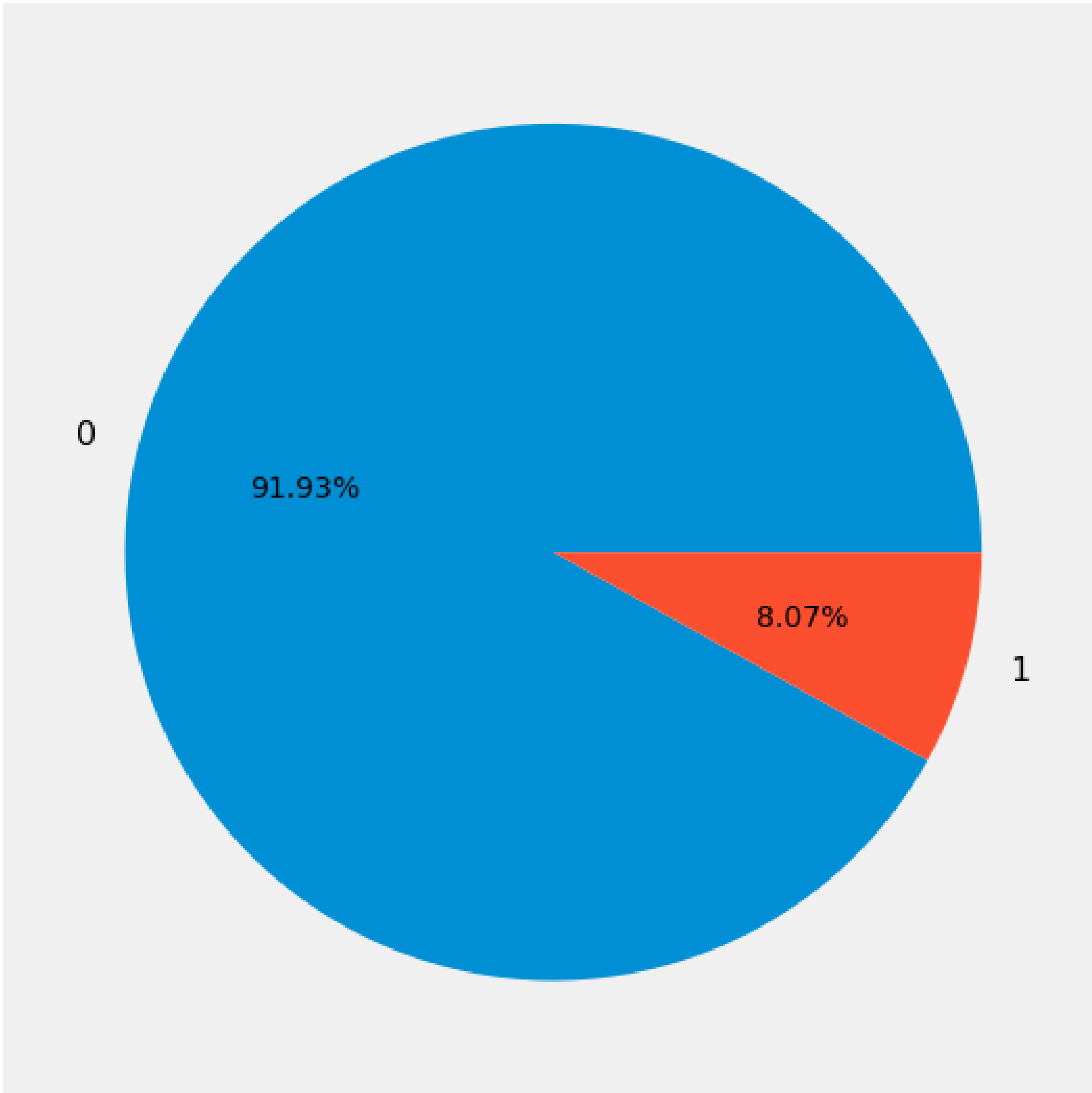
[89]:
```
         AMT_ANNUITY  AMT_APPLICATION    AMT_CREDIT  AMT_GOODS_PRICE
SELLERPLACE_AREA   CNT_PAYMENT  DAYS_DECISION
```

```
count  1.670214e+06     1.670214e+06  1.670213e+06     1.670214e+06
1.670214e+06  1.670214e+06   1.670214e+06
mean   1.490651e+04     1.752339e+05  1.961140e+05     1.856429e+05
3.139511e+02  1.247621e+01   8.806797e+02
std    1.317751e+04     2.927798e+05  3.185746e+05     2.871413e+05
7.127443e+03  1.447588e+01   7.790997e+02
min    0.000000e+00     0.000000e+00  0.000000e+00     0.000000e+00
-1.000000e+00  0.000000e+00   1.000000e+00
25%    7.547096e+03     1.872000e+04  2.416050e+04     4.500000e+04
-1.000000e+00  0.000000e+00   2.800000e+02
50%    1.125000e+04     7.104600e+04  8.054100e+04     7.105050e+04
3.000000e+00  1.000000e+01   5.810000e+02
75%    1.682403e+04     1.803600e+05  2.164185e+05     1.804050e+05
8.200000e+01  1.600000e+01   1.300000e+03
max    4.180581e+05     6.905160e+06  6.905160e+06     6.905160e+06
4.000000e+06  8.400000e+01   2.922000e+03
```

[90]:
```
loan_repay_status=application["TARGET"].value_counts().reset_index()
```

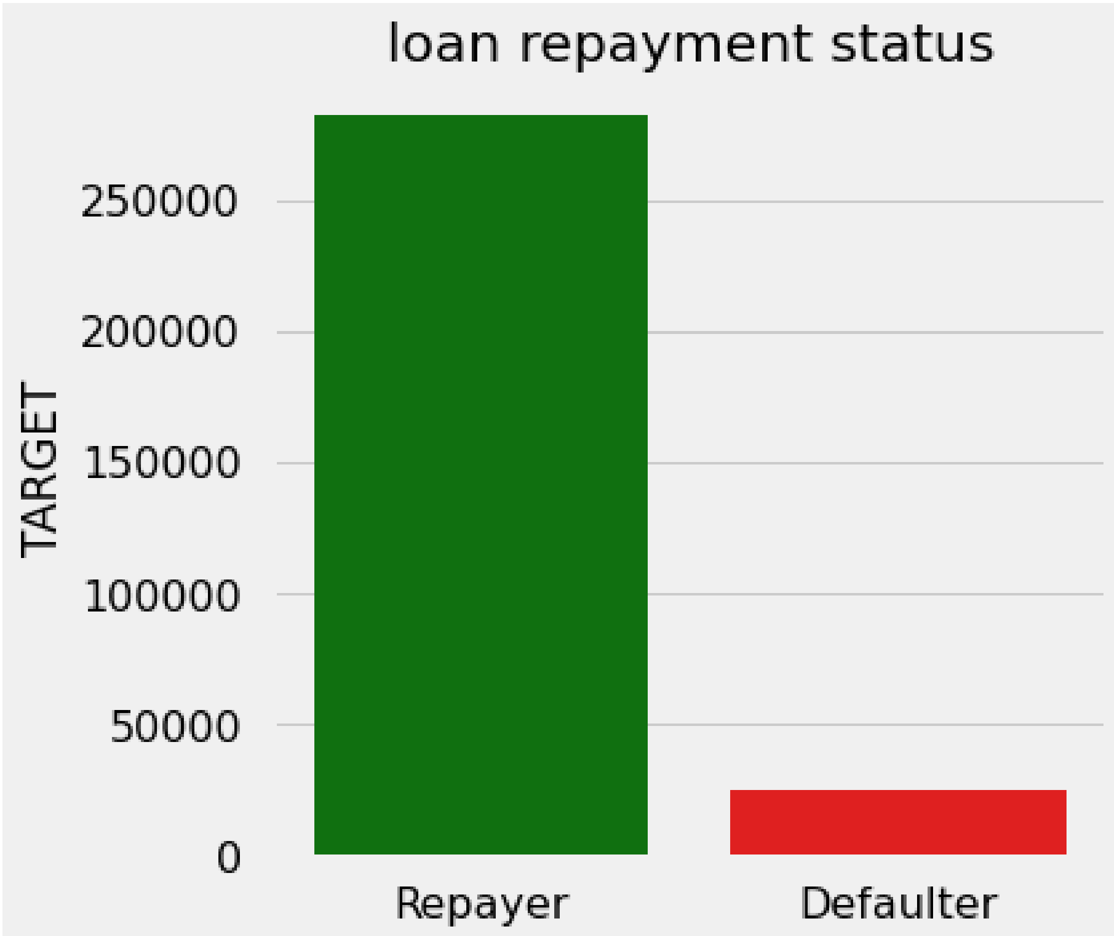
[91]:
```
freq_repay_status=loan_repay_status
freq_repay_status["index"] = freq_repay_status["index"].replace({1:
 ↪"Defaulter",0:"Repayer"})

plt.pie(freq_repay_status.TARGET,labels=freq_repay_status.index,autopct='%.
 ↪2f%%')
```

[91]:
```
([<matplotlib.patches.Wedge at 0x20826fae8b0>,
  <matplotlib.patches.Wedge at 0x20826fb0100>],
 [Text(-1.0648123216659293, 0.27599768047650985, '0'),
  Text(1.0648123152057372, -0.27599770540024077, '1')],
 [Text(-0.5808067209086887, 0.15054418935082356, '91.93%'),
  Text(0.5808067173849475, -0.15054420294558588, '8.07%')])
```



[92]:
```
plt.figure(figsize=(5,5))
a=['Repayer','Defaulter']
sns.barplot(a,'TARGET',data=loan_repay_status,palette=['g','r'])
plt.title('loan repayment status')
```

[92]: Text(0.5, 1.0, 'loan repayment status')



[93]:
```
countof_0=loan_repay_status.iloc[0]['TARGET']
countof_1=loan_repay_status.iloc[1]['TARGET']
count_per_0=round(countof_0/(countof_0+countof_1)*100.00,2)
count_per_1=round(countof_1/(countof_0+countof_1)*100.00,2)
print('percentage of repayers and defaulters are: %.2f and %.
 ↪2f'%(count_per_0,count_per_1))
print('ratios of repay stats with respective to repayer to defaulters is %.2f:
 ↪1'%(countof_0/countof_1))
```

```
percentage of repayers and defaulters are: 91.93 and 8.07
ratios of repay stats with respective to repayer to defaulters is 11.39:1
```

[94]:
```
# function for plotting countplots in univariate categorical analysis on␣
 ↪application
# This function will create two subplots:
# 1. Count plot of categorical column w.r.t TARGET;
# 2. Percentage of defaulters within column
#feature- attribute
```

```
#ylog- to set the scale of y axis to log (Set the y-axis scale)
#label_rotation- to rotate the label of x axis to 90 degrees
#horizontal_layout- to get plots in two rows or columns
def␣
↪univariate_categorical(feature,ylog=False,label_rotation=False,horizontal_layout=True):
↪
    temp = application[feature].value_counts()
    df1 = pd.DataFrame({feature: temp.index,'Number of contracts': temp.values})

  # Calculate the percentage of target=1 per category value
    cat_perc = application[[feature, 'TARGET']].
↪groupby([feature],as_index=False).mean()
    cat_perc["TARGET"] = cat_perc["TARGET"]*100
    cat_perc.sort_values(by='TARGET', ascending=False, inplace=True)

    if(horizontal_layout):
        fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12,6))
    else:
        fig, (ax1, ax2) = plt.subplots(nrows=2, figsize=(20,24))

    # 1. Subplot 1: Count plot of categorical column
    # sns.set_palette("Set2")
    s = sns.countplot(ax=ax1, x = feature, data=application,hue␣
↪="TARGET",order=cat_perc[feature],palette=['g','r'])

    # Define common styling
    ax1.set_title(feature, fontdict={'fontsize' : 10, 'fontweight' : 3, 'color'␣
↪: 'Blue'})
    ax1.legend(['Repayer','Defaulter'])

    # If the plot is not readable, use the log scale.
    if ylog:
        ax1.set_yscale('log')
        ax1.set_ylabel("Count (log)",fontdict={'fontsize' : 10, 'fontweight' :␣
↪3, 'color' : 'Blue'})


    if(label_rotation):
        s.set_xticklabels(s.get_xticklabels(),rotation=90)

    # 2. Subplot 2: Percentage of defaulters within the categorical column
    s = sns.barplot(ax=ax2, x = feature, y='TARGET', order=cat_perc[feature],␣
↪data=cat_perc,palette='Set2')

    if(label_rotation):
        s.set_xticklabels(s.get_xticklabels(),rotation=90)
```

```
    plt.ylabel('Percent of Defaulters [%]', fontsize=10)
    plt.tick_params(axis='both', which='major', labelsize=10)
    ax2.set_title(feature + " Defaulter %", fontdict={'fontsize' : 15,␣
↪'fontweight' : 5, 'color' : 'Blue'})

    plt.show();
```

[95]:
```
# function for plotting repetitive barplots in bivariate categorical analysis
def bivariate_bar(x,y,df,hue,figsize):
    plt.figure(figsize=figsize)
    sns.barplot(x=x,y=y,data=df, hue=hue, palette =['g','r'])
    plt.xlabel(x,fontdict={'fontsize' : 10, 'fontweight' : 3, 'color' : 'Blue'})
    plt.ylabel(y,fontdict={'fontsize' : 10, 'fontweight' : 3, 'color' : 'Blue'})
    plt.title(col, fontdict={'fontsize' : 15, 'fontweight' : 5, 'color' :␣
↪'Blue'})
    plt.xticks(rotation=90, ha='right')
    plt.legend(labels = ['Repayer','Defaulter'])
    plt.show()
```

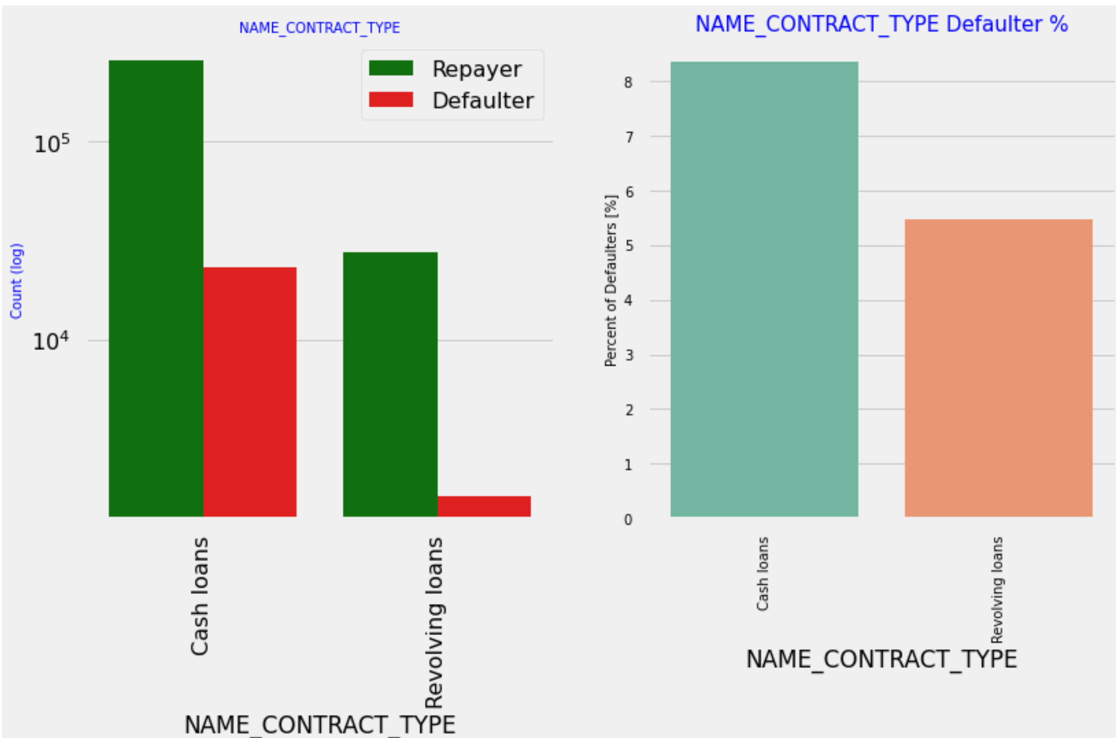
[96]:
```
# function for plotting repetitive rel plots in bivaritae numerical analysis on␣
↪application
#.relplot() shows the relationships between two variables
def bivariate_rel(x,y,data, hue, kind, palette, legend,figsize):
    plt.figure(figsize=figsize)
    sns.relplot(x=x, y=y, data=application, hue="TARGET",kind=kind,palette =␣
↪['g','r'],legend = False)
    plt.legend(['Repayer','Defaulter'])
    plt.xticks(rotation=90, ha='right')
    plt.show()
```

[97]:
```
#function for plotting repetitive countplots in univariate categorical analysis␣
↪on the merged
def univariate_merged(col,df,hue,palette,ylog,figsize):
    plt.figure(figsize=figsize)
    ax=sns.countplot(x=col, data=df,hue= hue,palette= palette,order=df[col].
↪value_counts().index)
    if ylog:
        plt.yscale('log')
        plt.ylabel("Count (log)",fontdict={'fontsize' : 10, 'fontweight' : 3,␣
↪'color' : 'Blue'})
    else:
        plt.ylabel("Count",fontdict={'fontsize' : 10, 'fontweight' : 3, 'color'␣
↪: 'Blue'})
    plt.title(col , fontdict={'fontsize' : 15, 'fontweight' : 5, 'color' :␣
↪'Blue'})
    plt.legend(loc = "upper right")
```

```
    plt.xticks(rotation=90, ha='right')

    plt.show()
```

[98]:
```
# Function to plot point plots on merged dataframe
#Show point estimates and confidence intervals using scatter plot glyphs.
def merged_pointplot(x,y):
    plt.figure(figsize=(8,4))
    sns.pointplot(x=x,y=y, hue="TARGET", data=loan_application, palette␣
 ↪=['g','r'])
```

[99]:
```
# Checking the contract type based on loan repayment status
univariate_categorical('NAME_CONTRACT_TYPE',True,True)
```



[100]:
```
cat_perc = application[['NAME_CONTRACT_TYPE', 'TARGET']].
 ↪groupby(['NAME_CONTRACT_TYPE'],as_index=False).mean()
cat_perc
```

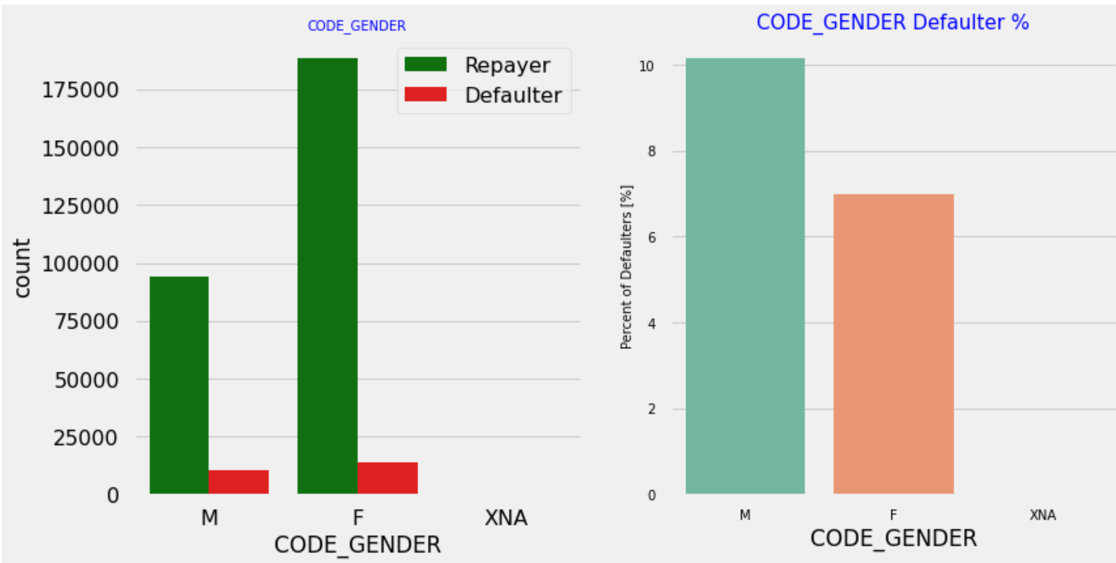
[100]:

	NAME_CONTRACT_TYPE	TARGET
0	Cash loans	0.083459
1	Revolving loans	0.054783

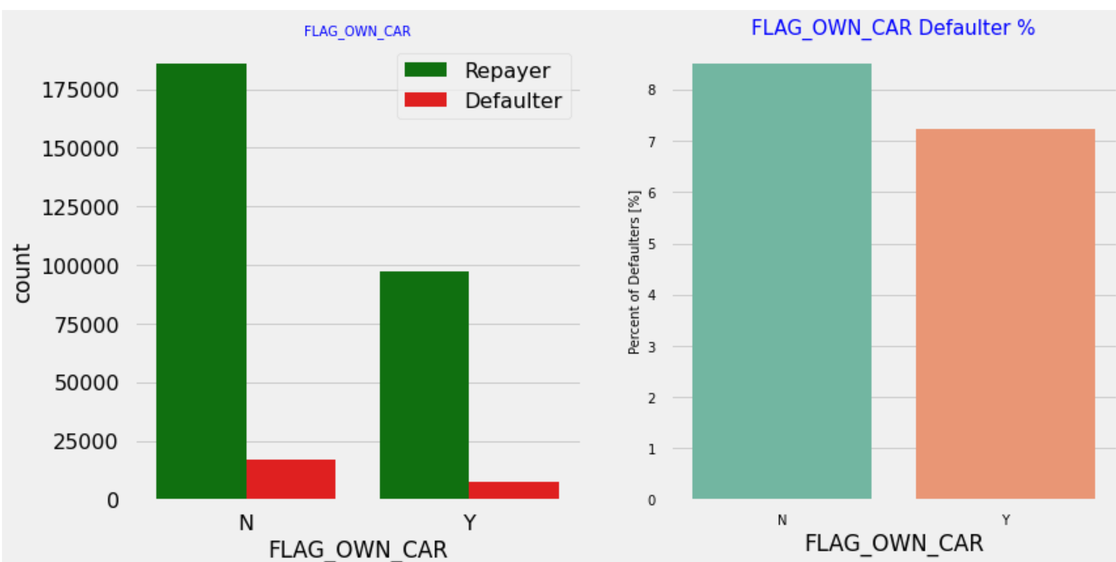
[101]:
```
cat_perc = application[['NAME_CONTRACT_TYPE', 'TARGET']].
 ↪groupby(['NAME_CONTRACT_TYPE'],as_index=False)
cat_perc
```

[101]: <pandas.core.groupby.generic.DataFrameGroupBy object at 0x0000020828C99490>

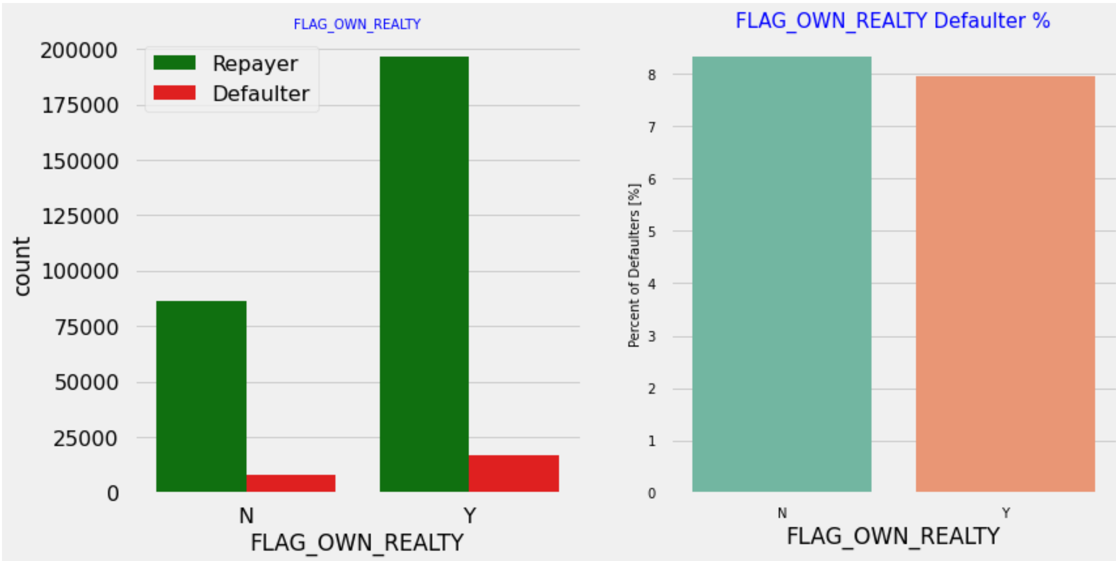
[102]:
```
#repaying status based on gender
univariate_categorical('CODE_GENDER')
```



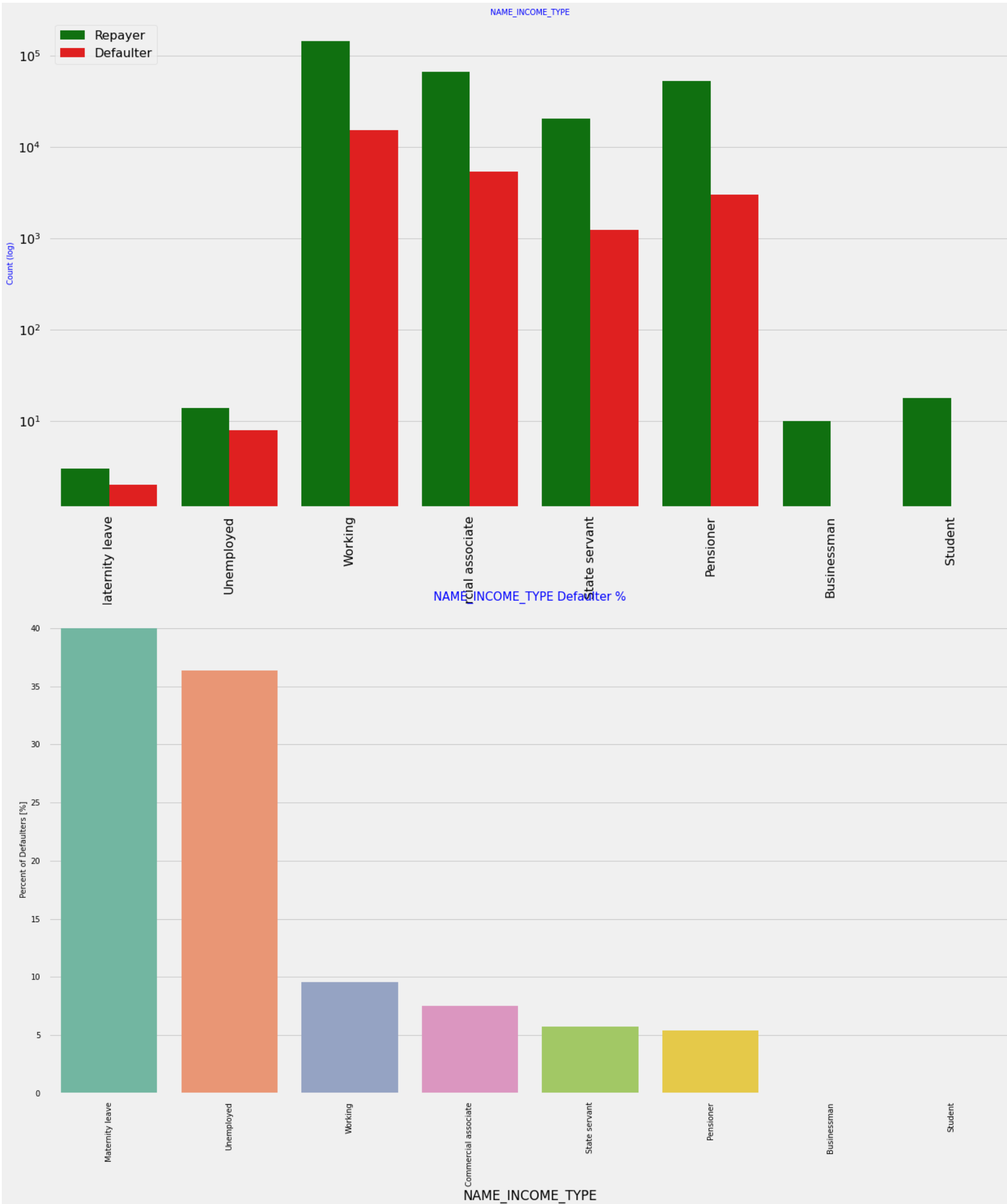
[103]:
```
#checking whether car owned is related to loan repayment status or not
univariate_categorical('FLAG_OWN_CAR')
```



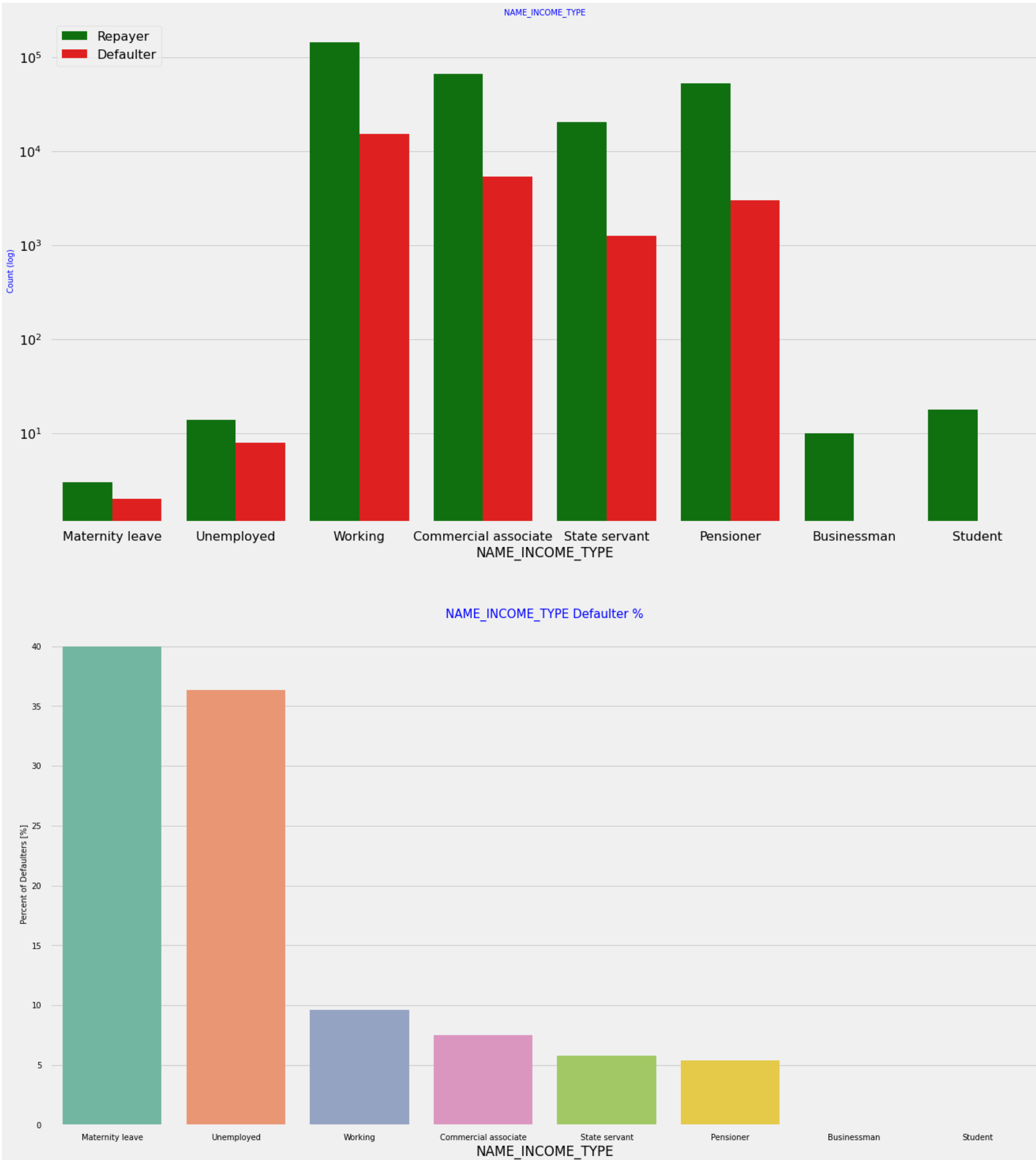
[104]:
```
#checking whether a client owns a house or flat
univariate_categorical('FLAG_OWN_REALTY')
```



[105]:
```
#analysing client income type with loan repayment status
univariate_categorical("NAME_INCOME_TYPE",True,True,False)
```

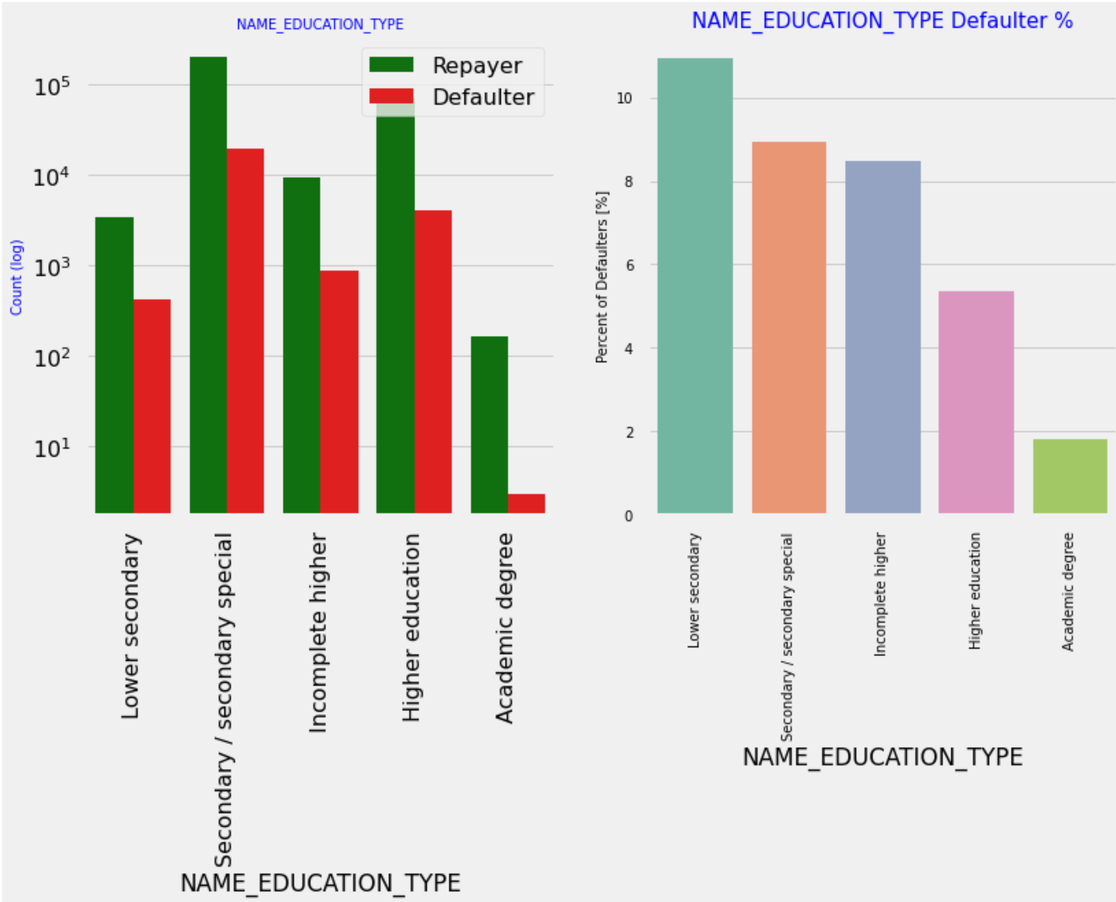


[106]:
```
univariate_categorical("NAME_INCOME_TYPE",True,False,False)
```

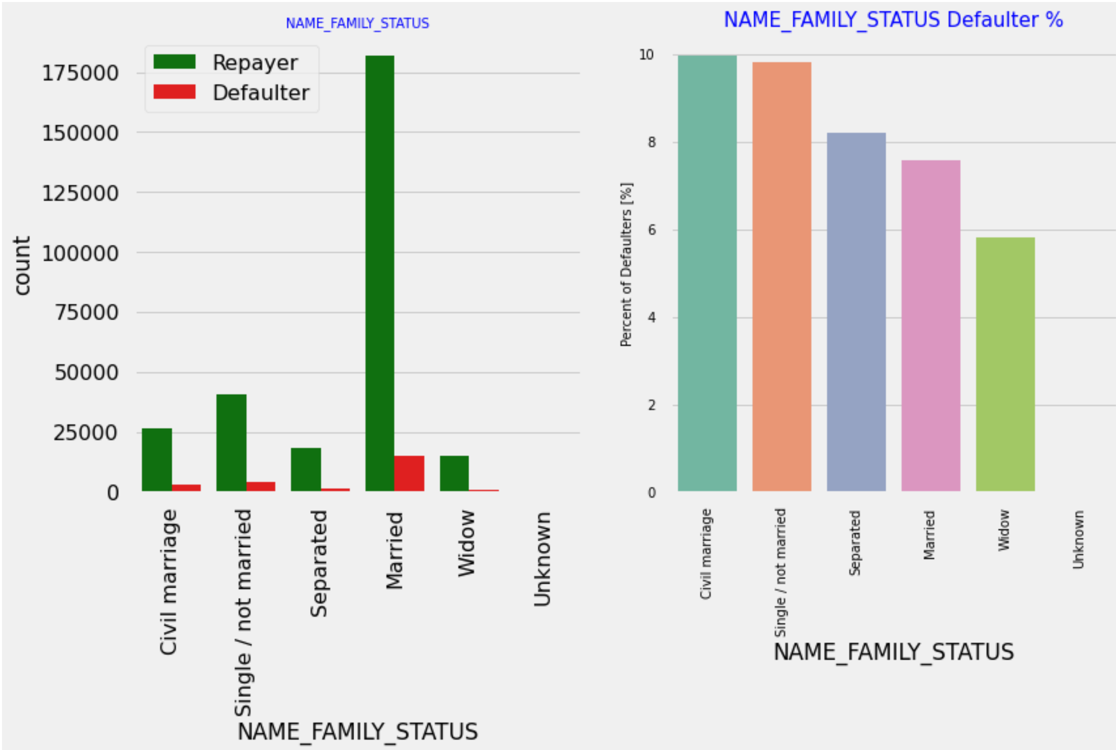


[107]:

```
#analysing client education to loan repayment status
univariate_categorical("NAME_EDUCATION_TYPE",True,True,True)
```

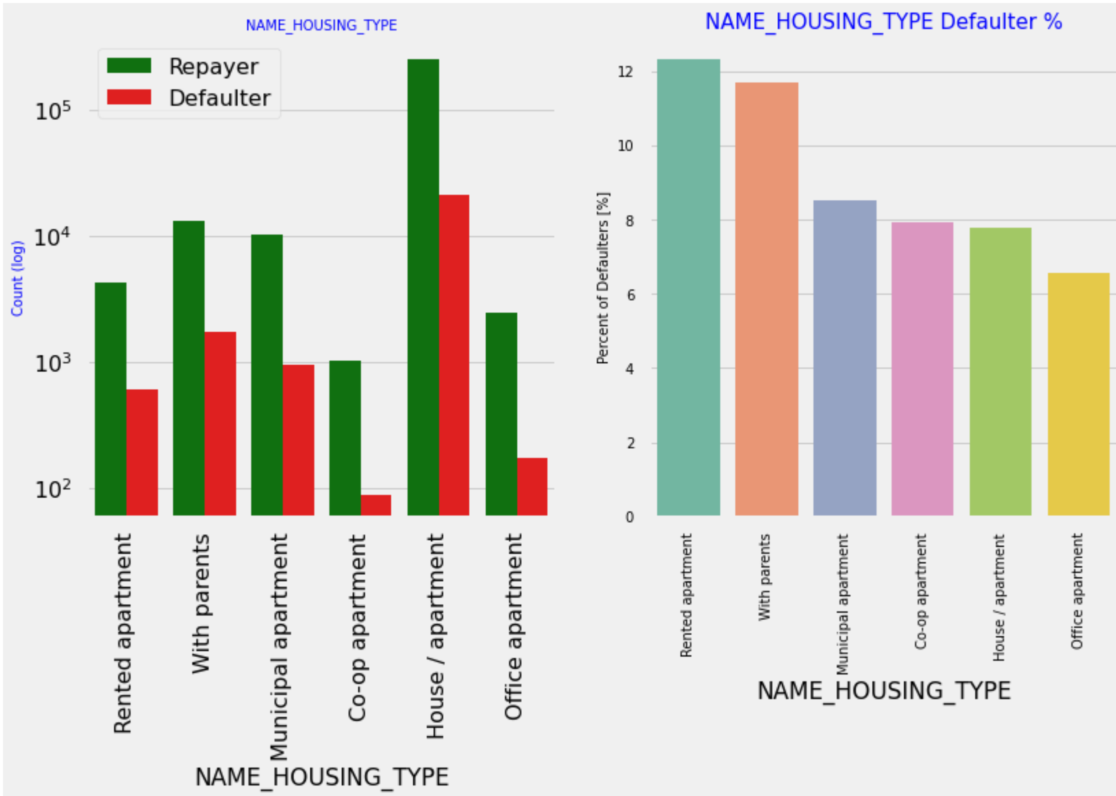


[108]:
```
#analysing family status based on loan replyment status
univariate_categorical("NAME_FAMILY_STATUS",False,True,True)
```

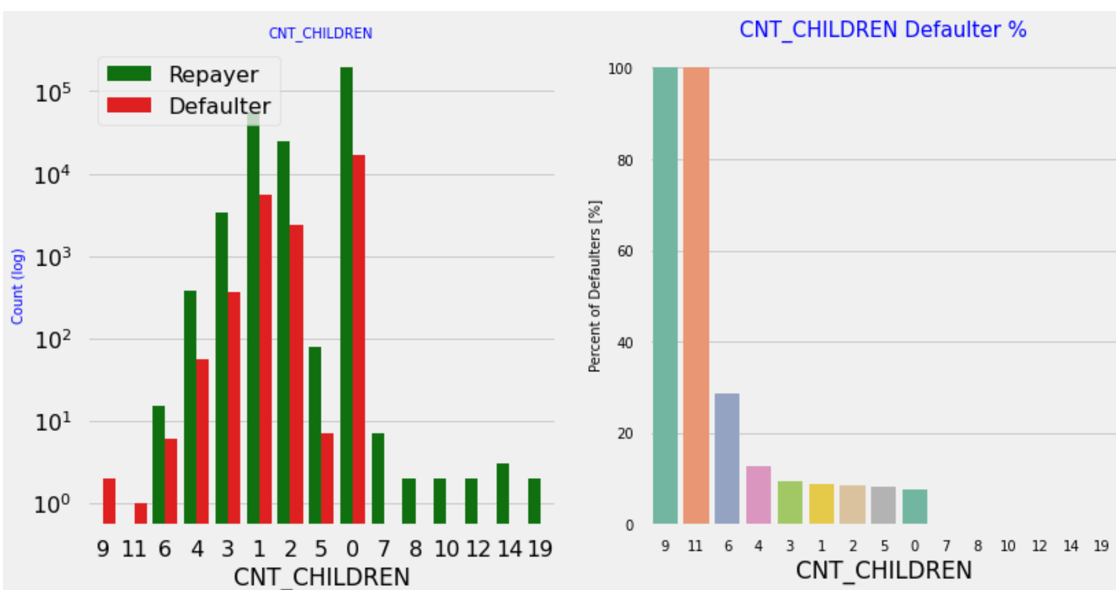


[109]:

```
#analysing the housing situation of the client(renting,living with parents...)␣
↪with the loan repayment status
univariate_categorical("NAME_HOUSING_TYPE",True,True,True)
```

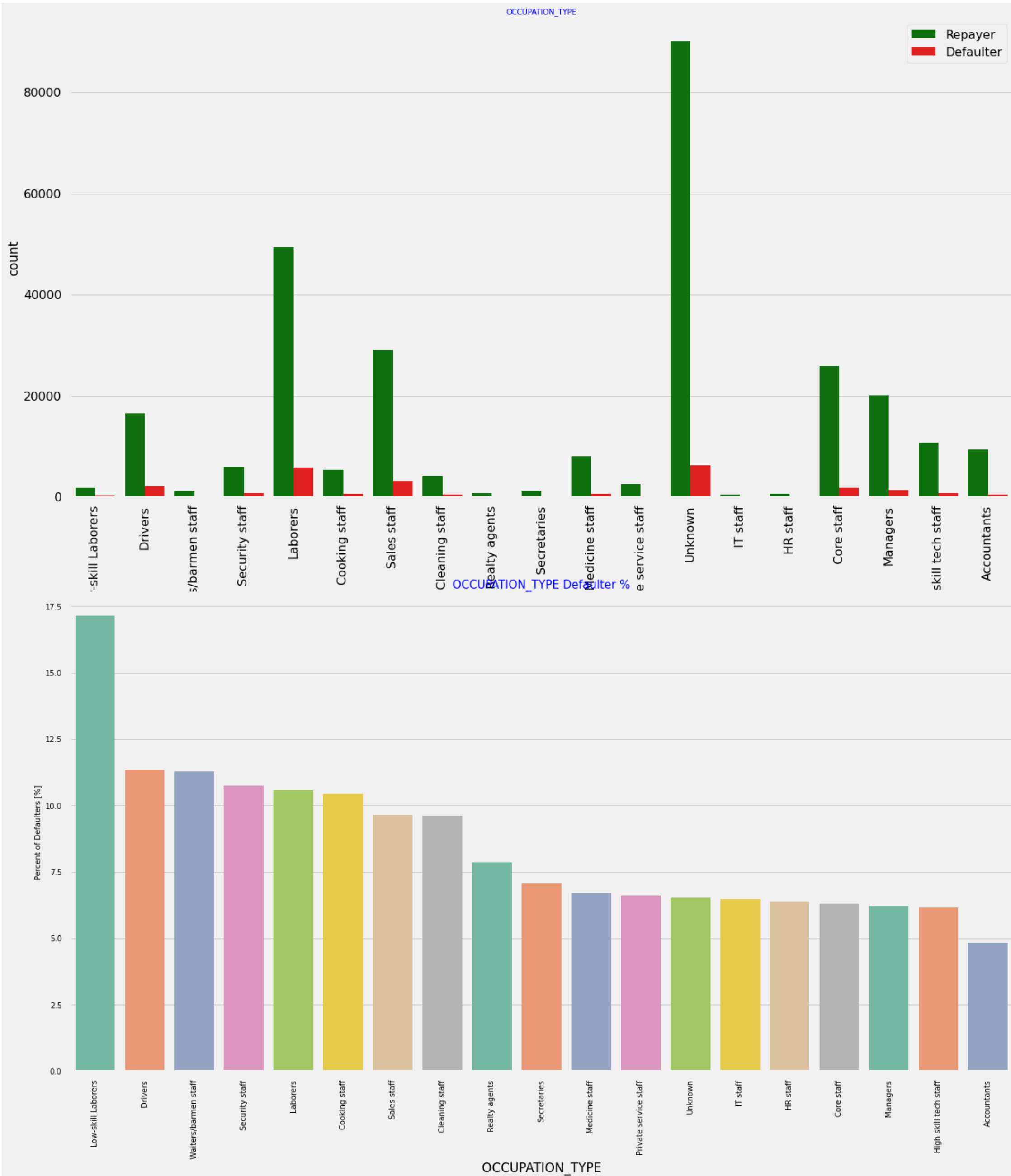


[110]:
```
# Analyzing Number of children based on loan repayment status
univariate_categorical("CNT_CHILDREN",True)
```

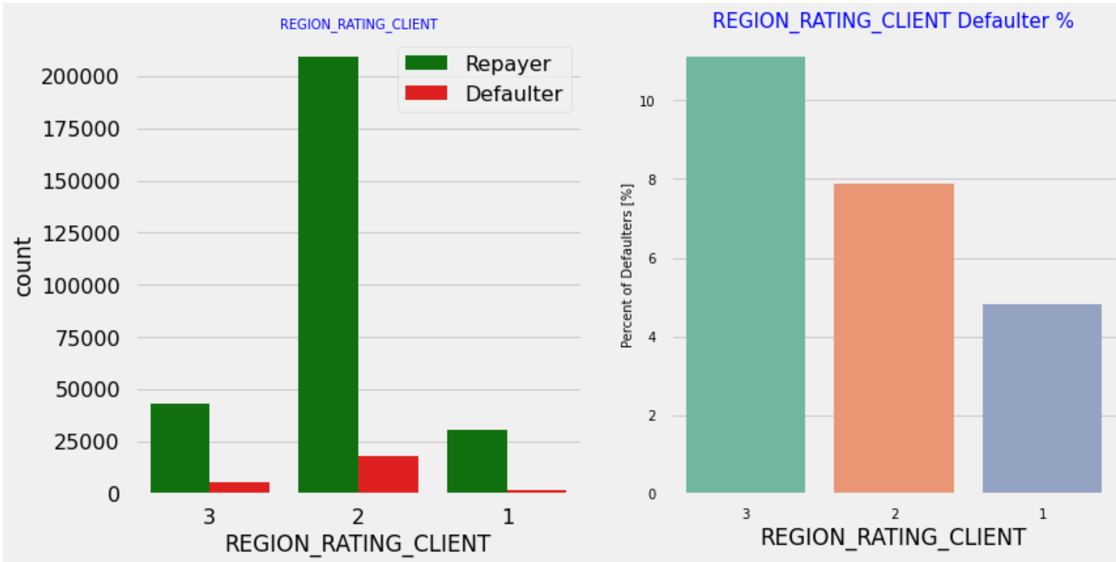


[111]:
```
#analysing with the credit amount of loan to repayment status
univariate_categorical('LOAN_AMT',False,False,False)
```

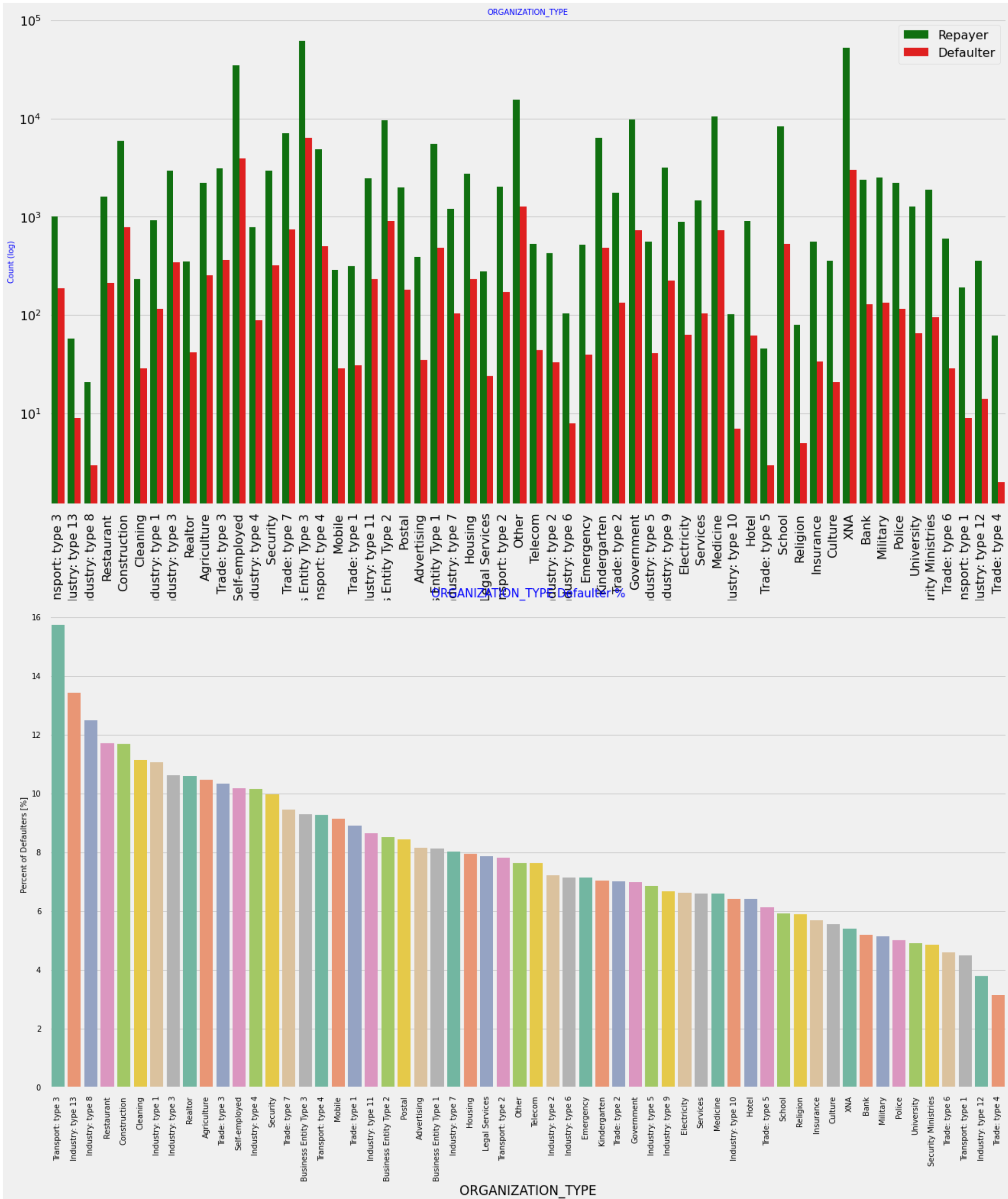
[112]:
```
#analysing occupation type and loan repaymet status
univariate_categorical("OCCUPATION_TYPE",False,True,False)
```



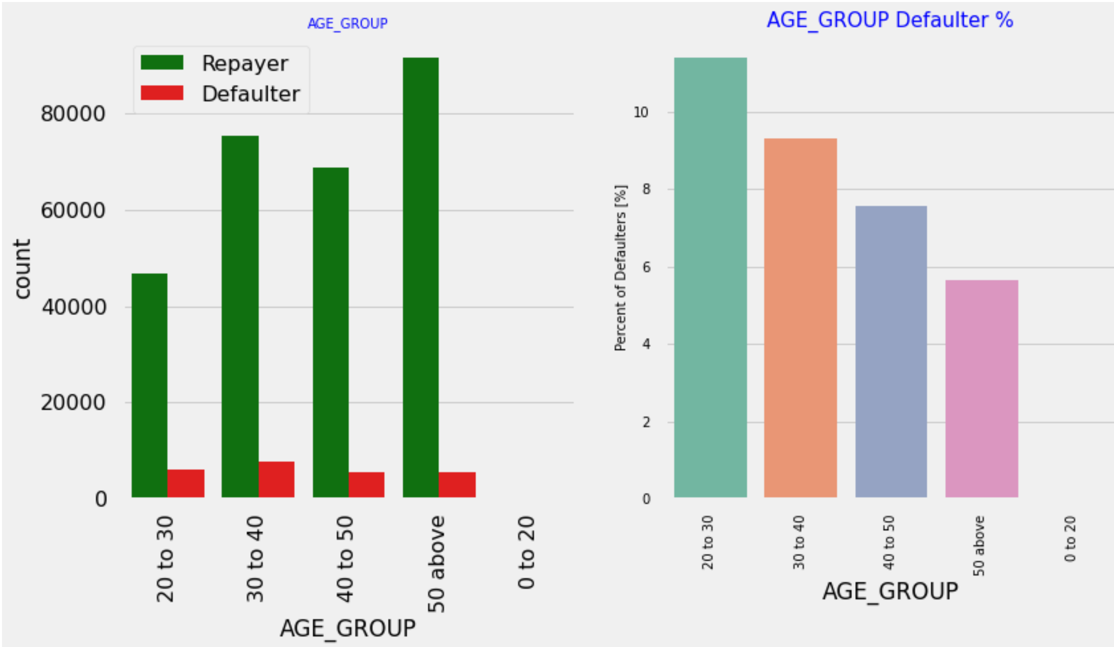
[113]:
```
#analysing loan repayment status based on client living locality rating
univariate_categorical("REGION_RATING_CLIENT",False,False,True)
```



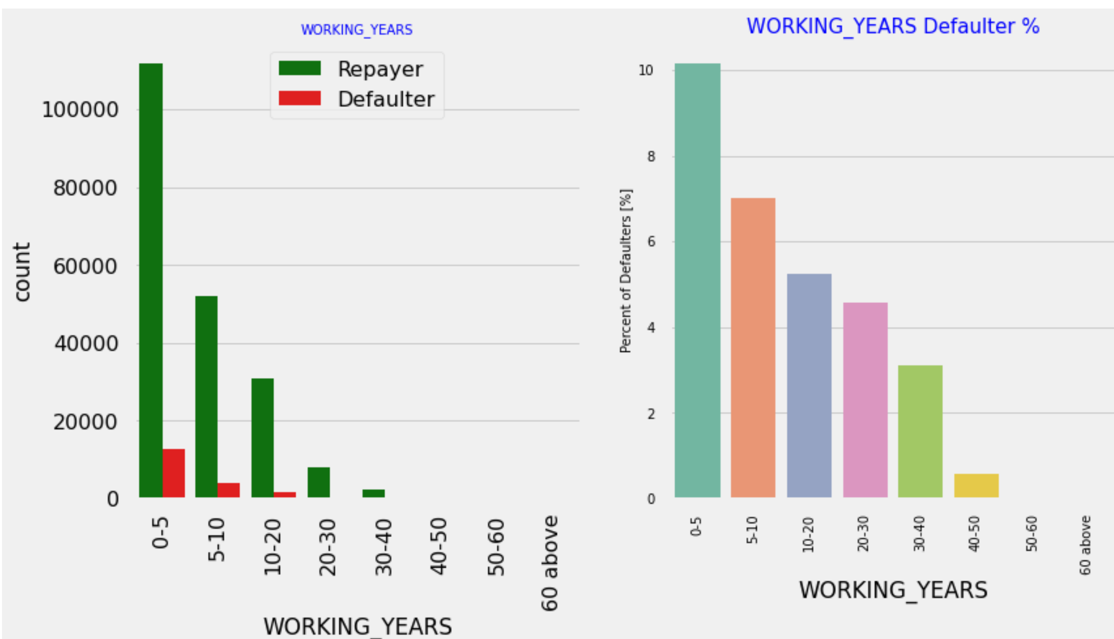
[114]:
```
#analysing the loan repayment status bases on type of organisation the client␣
↪works
univariate_categorical("ORGANIZATION_TYPE",True,True,False)
```



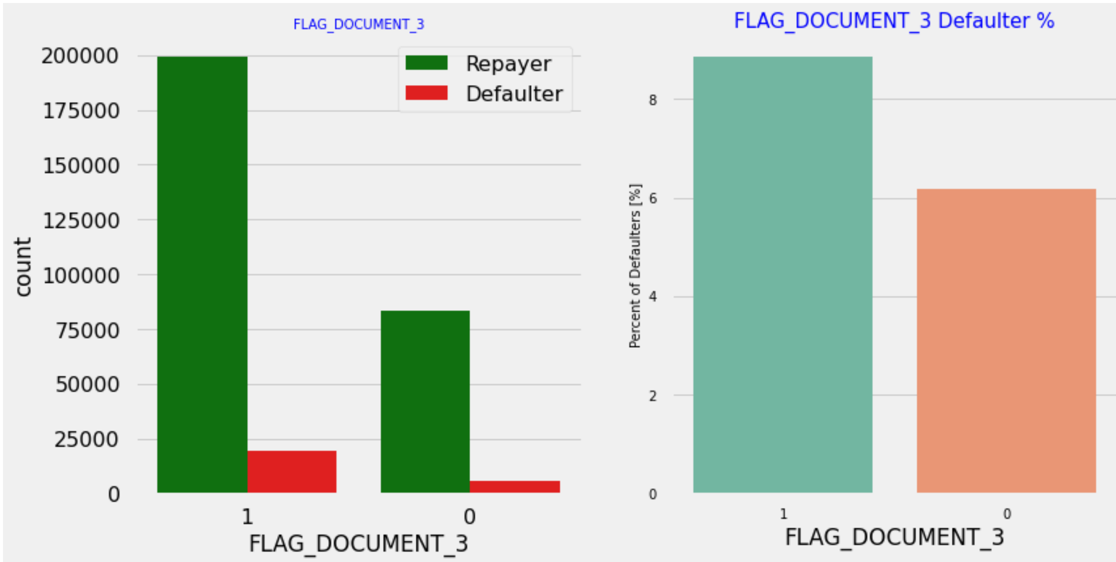
[115]:
```
#analysing by age
univariate_categorical("AGE_GROUP",False,True,True)
```



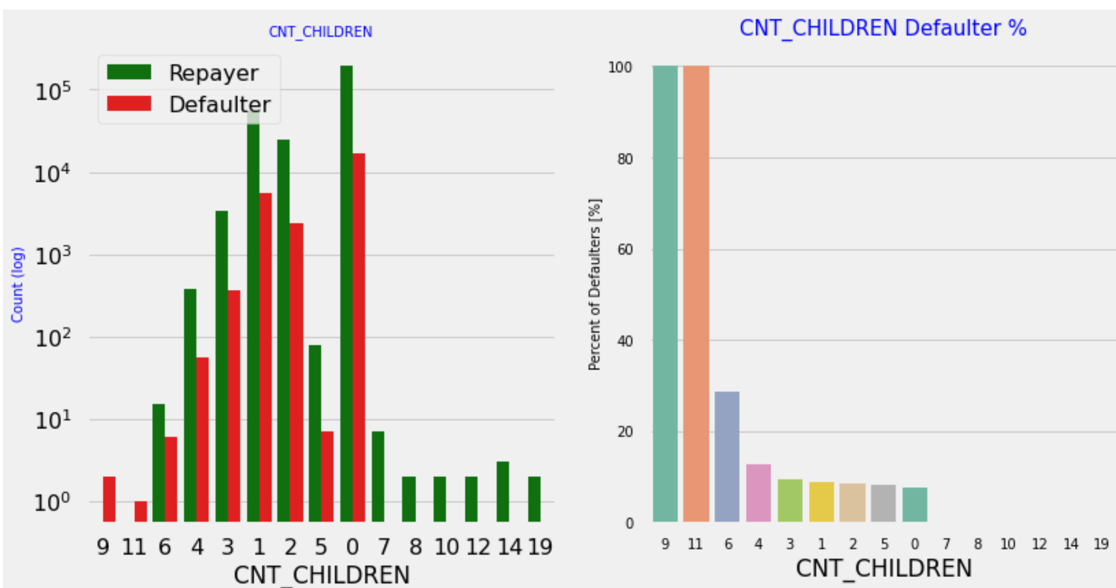
[116]:
```
#analysing the employment years of the applicant to repayment status
univariate_categorical("WORKING_YEARS",False,True,True)
```



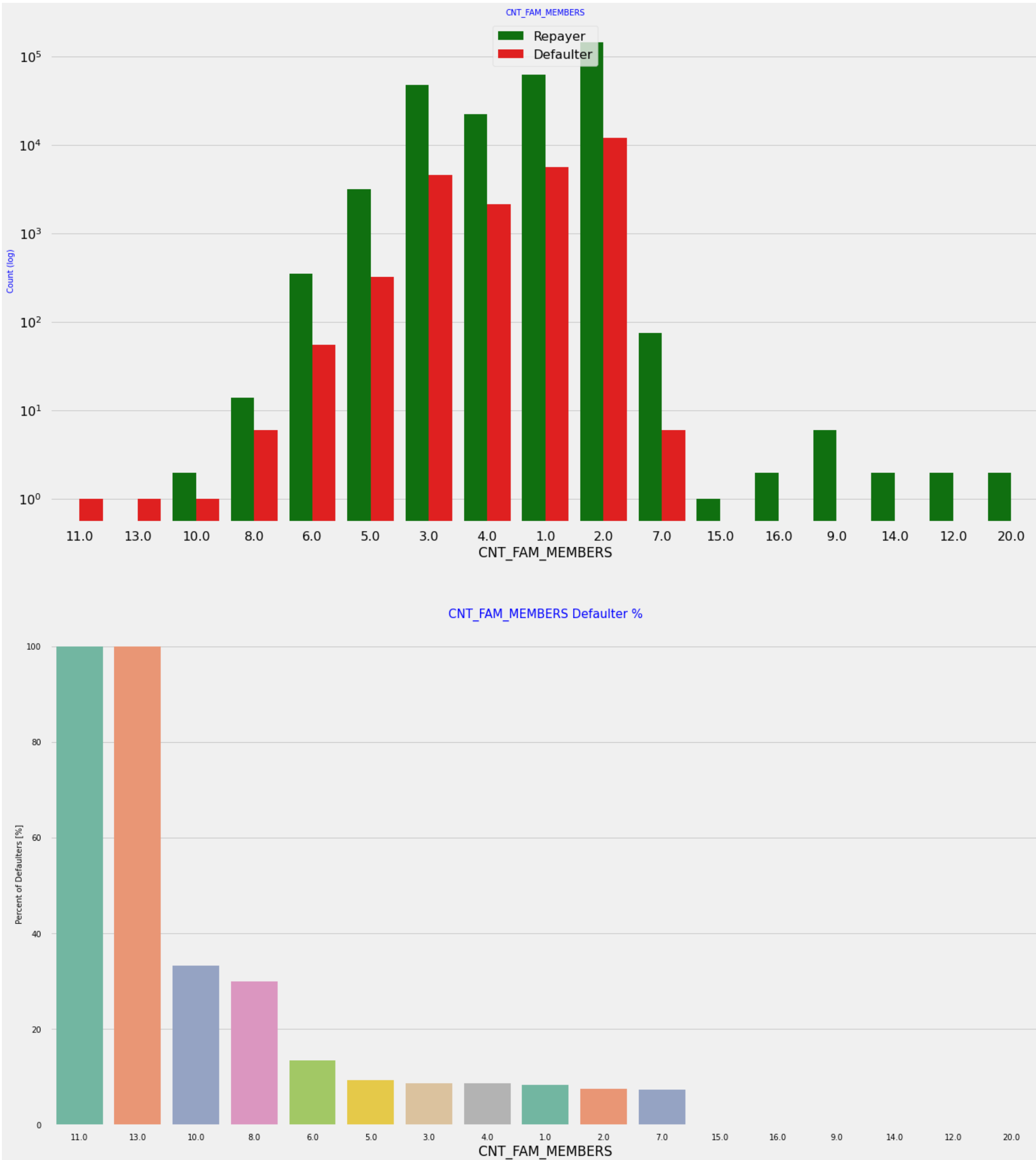
[117]:
```
# Analyzing Flag_Doc_3 submission status based on loan repayment status
univariate_categorical("FLAG_DOCUMENT_3",False,False,True)
```



[118]:
```python
# Analyzing Number of children based on loan repayment status
univariate_categorical("CNT_CHILDREN",True)
```



[119]:
```python
# Analyzing Number of family members of client based on loan repayment status
univariate_categorical("CNT_FAM_MEMBERS",True, False, False)
```



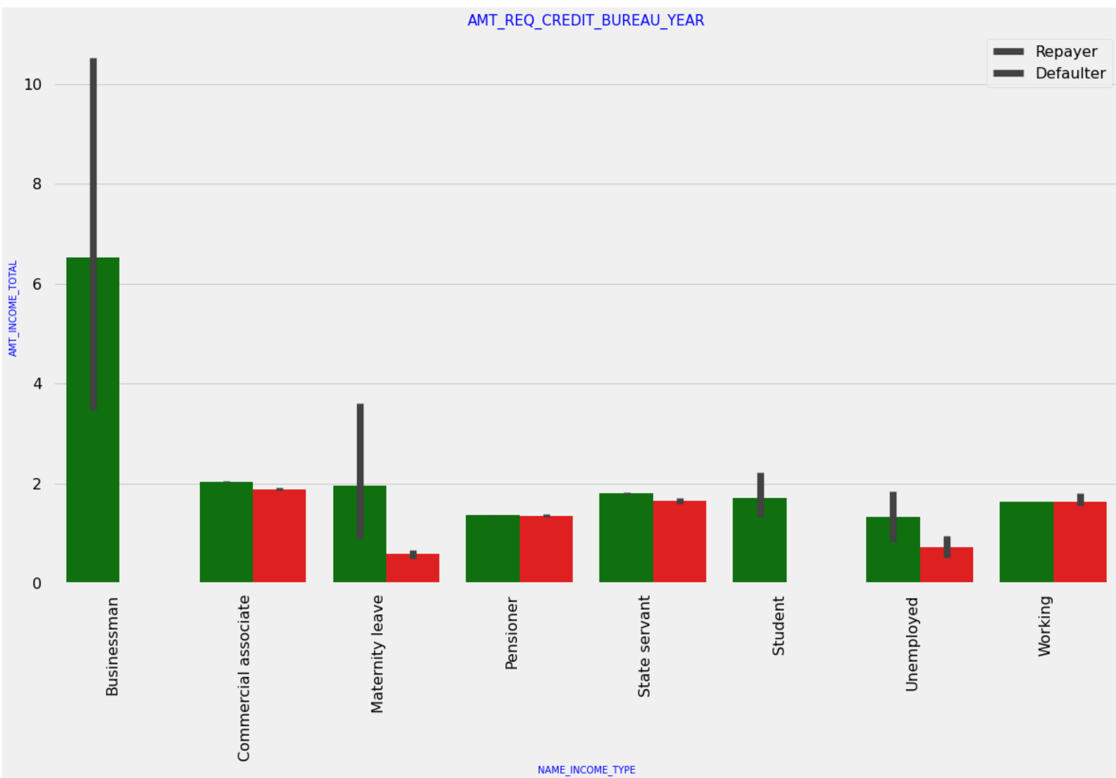
[120]:
```
application.groupby('NAME_INCOME_TYPE')['AMT_INCOME_TOTAL'].describe()
```

[120]:
```
                         count      mean       std     min    25%     50%
75%        max
NAME_INCOME_TYPE
Businessman               10.0  6.525000  6.272260  1.8000  2.250  4.9500
8.43750    22.5000
Commercial associate   71617.0  2.029553  1.479742  0.2655  1.350  1.8000
2.25000   180.0009
```

```
Maternity leave            5.0  1.404000  1.268569  0.4950  0.675  0.9000
1.35000     3.6000
Pensioner              55362.0  1.364013  0.766503  0.2565  0.900  1.1700
1.66500    22.5000
State servant          21703.0  1.797380  1.008806  0.2700  1.125  1.5750
2.25000    31.5000
Student                   18.0  1.705000  1.066447  0.8100  1.125  1.5750
1.78875     5.6250
Unemployed                22.0  1.105364  0.880551  0.2655  0.540  0.7875
1.35000     3.3750
Working               158774.0  1.631699  3.075777  0.2565  1.125  1.3500
2.02500  1170.0000
```

[ ]:

[121]:
```
#Income type vs Income Amount Range
bivariate_bar("NAME_INCOME_TYPE","AMT_INCOME_TOTAL",application,"TARGET",(18,10))
```



[122]:
```
application.columns
```

[122]:
```
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', 'OCCUPATION_TYPE',
'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',
'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3', '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', 'INCOME_RANGE', 'LOAN_AMT', 'AGE', 'AGE_GROUP',
'YEARS_EMPLOYED', 'WORKING_YEARS'],
      dtype='object')
```

[123]:
```
corr_of_colms =['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',␣
 ↪'OCCUPATION_TYPE', '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',
                            'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',␣
 ↪'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3',
                            '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']
repayer=application.loc[application['TARGET']==0, corr_of_colms]
defaulter=application.loc[application['TARGET']==1,corr_of_colms]
```

[124]:
```
#top 10 correlation for the Repayers data
corr_repayer = repayer.corr()
```

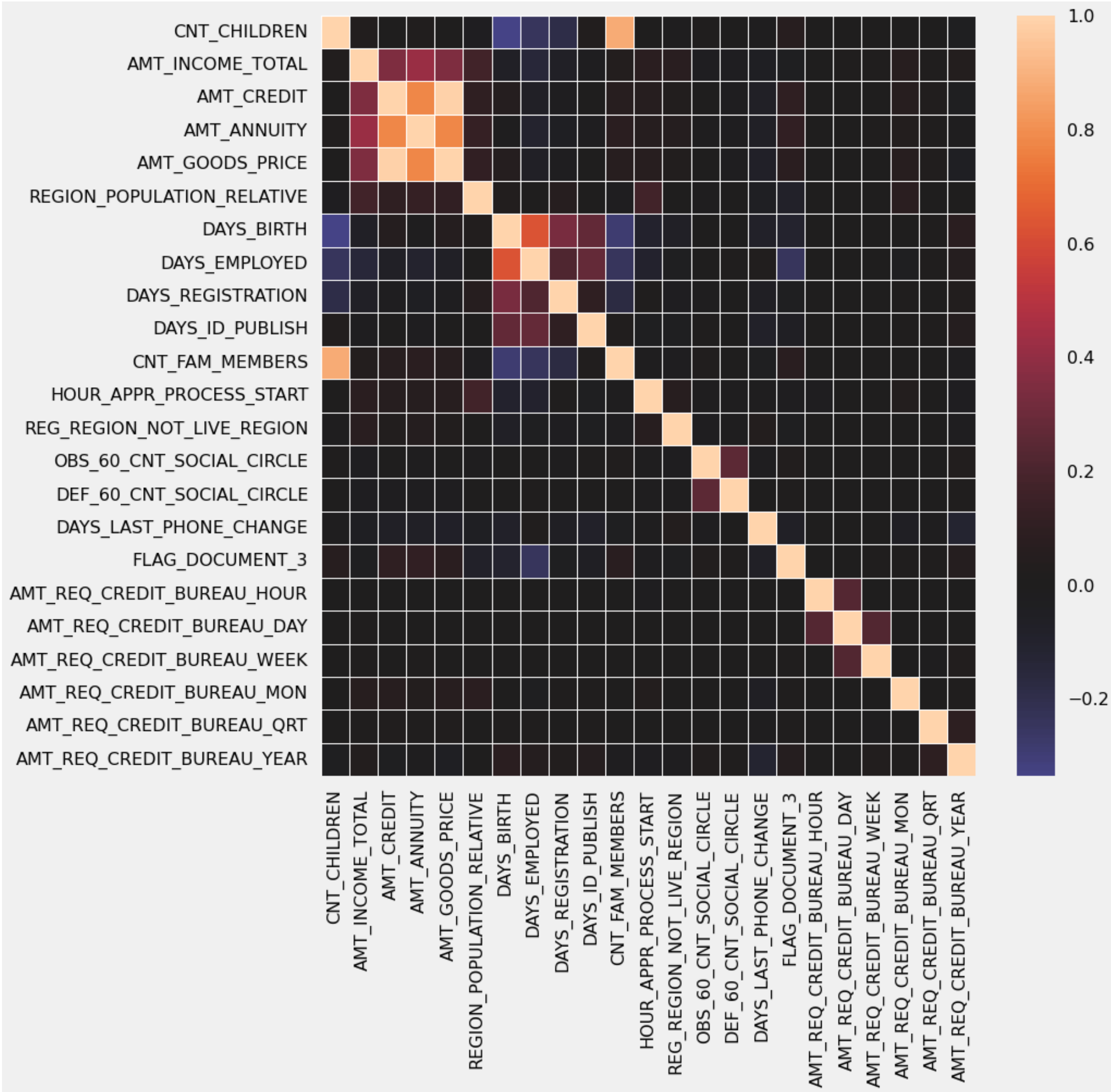
```
corr_repayer = corr_repayer.where(np.triu(np.ones(corr_repayer.shape),k=1).
 ↪astype(np.bool))
corr_df_repayer = corr_repayer.unstack().reset_index()
corr_df_repayer.columns =['atribute1','atribute2','Correlation']
corr_df_repayer.dropna(subset = ["Correlation"], inplace = True)
corr_df_repayer["Correlation"]=corr_df_repayer["Correlation"].abs()
corr_df_repayer.sort_values(by='Correlation', ascending=False, inplace=True)
corr_df_repayer.head(10)
```

[124]:

	atribute1	atribute2	Correlation
94	AMT_GOODS_PRICE	AMT_CREDIT	0.987250
230	CNT_FAM_MEMBERS	CNT_CHILDREN	0.878571
95	AMT_GOODS_PRICE	AMT_ANNUITY	0.776686
71	AMT_ANNUITY	AMT_CREDIT	0.771309
167	DAYS_EMPLOYED	DAYS_BIRTH	0.626114
70	AMT_ANNUITY	AMT_INCOME_TOTAL	0.418953
93	AMT_GOODS_PRICE	AMT_INCOME_TOTAL	0.349462
47	AMT_CREDIT	AMT_INCOME_TOTAL	0.342799
138	DAYS_BIRTH	CNT_CHILDREN	0.336966
190	DAYS_REGISTRATION	DAYS_BIRTH	0.333151

[125]:

```
fig = plt.figure(figsize=(12,12))
ax = sns.heatmap(repayer.corr(), center=0,annot=False,linewidth =1)
```



[126]:

```
corr_Defaulter = defaulter.corr()
corr_Defaulter = corr_Defaulter.where(np.triu(np.ones(corr_Defaulter.
↪shape),k=1).astype(np.bool))
corr_df_Defaulter = corr_Defaulter.unstack().reset_index()
corr_df_Defaulter.columns =['atribute1','atribute2','Correlation']
corr_df_Defaulter.dropna(subset = ["Correlation"], inplace = True)
corr_df_Defaulter["Correlation"]=corr_df_Defaulter["Correlation"].abs()
corr_df_Defaulter.sort_values(by='Correlation', ascending=False, inplace=True)
corr_df_Defaulter.head(10)
```

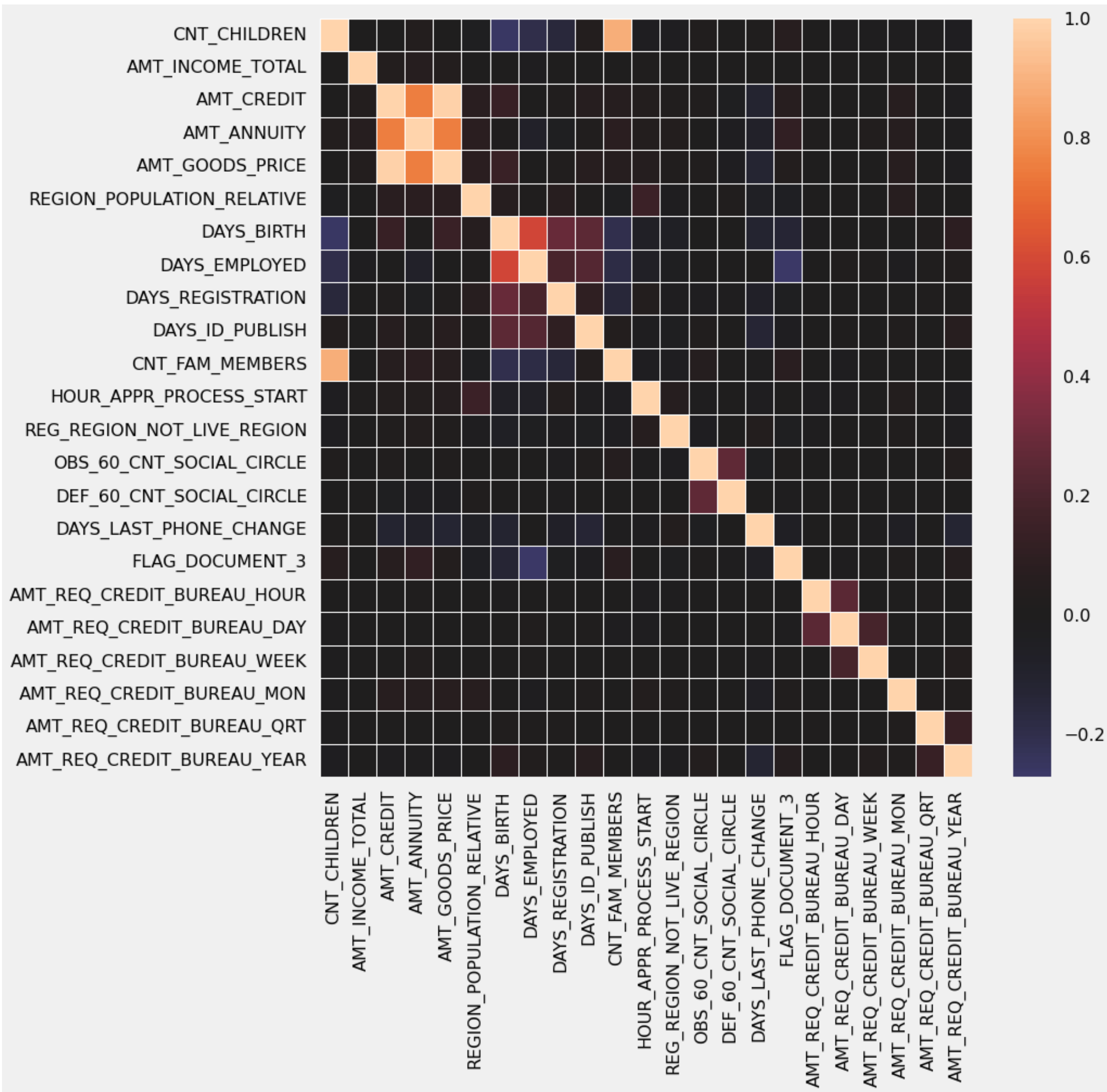
[126]:

	atribute1	atribute2	Correlation
94	AMT_GOODS_PRICE	AMT_CREDIT	0.983103
230	CNT_FAM_MEMBERS	CNT_CHILDREN	0.885484

```
95              AMT_GOODS_PRICE                 AMT_ANNUITY     0.752699
71                  AMT_ANNUITY                  AMT_CREDIT     0.752195
167               DAYS_EMPLOYED                  DAYS_BIRTH     0.582185
190           DAYS_REGISTRATION                  DAYS_BIRTH     0.289114
375             FLAG_DOCUMENT_3               DAYS_EMPLOYED     0.272169
335  DEF_60_CNT_SOCIAL_CIRCLE  OBS_60_CNT_SOCIAL_CIRCLE     0.264159
138                  DAYS_BIRTH                CNT_CHILDREN     0.259109
213              DAYS_ID_PUBLISH                  DAYS_BIRTH     0.252863
```

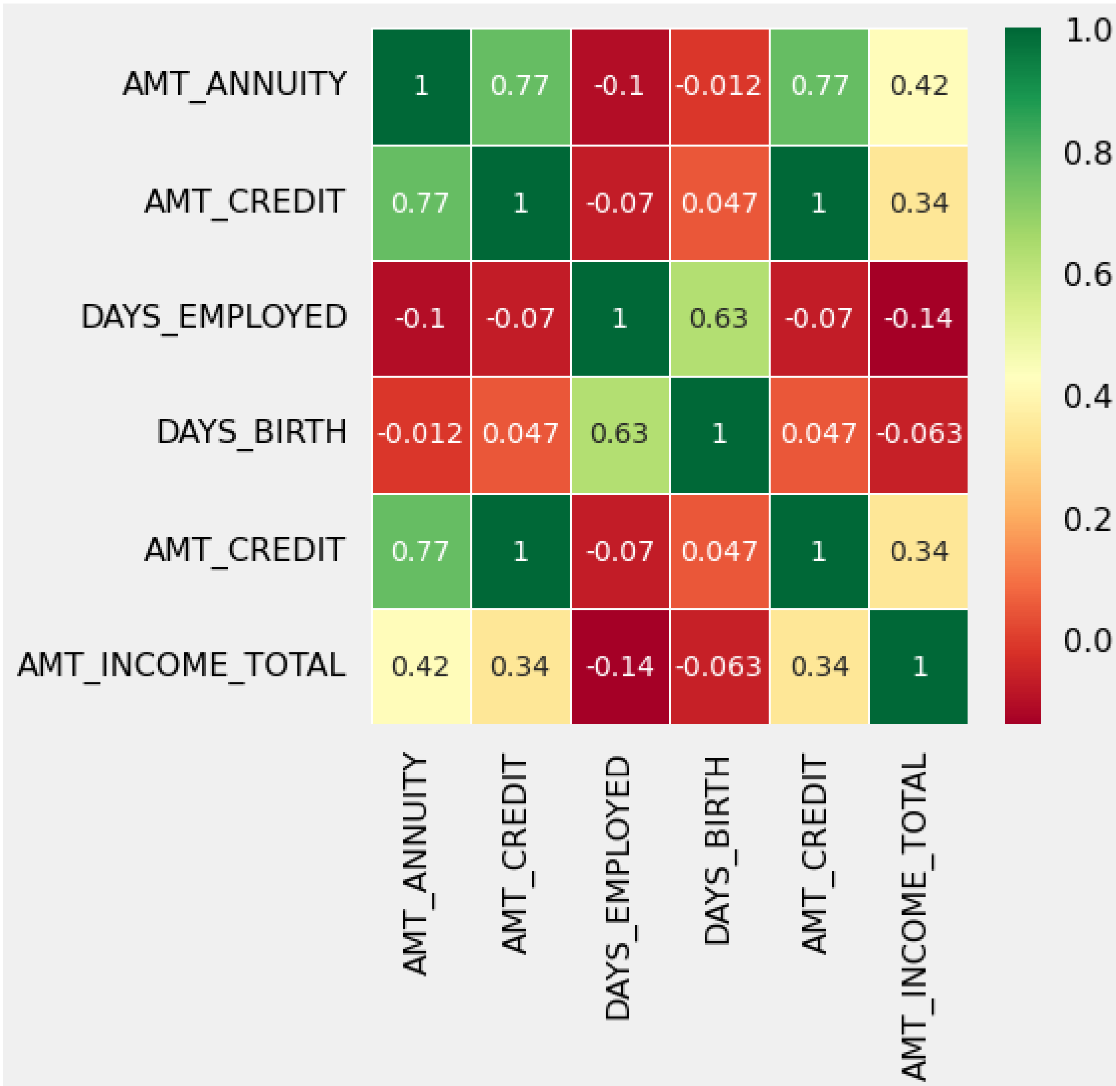
[127]:

```
fig = plt.figure(figsize=(12,12))
ax = sns.heatmap(defaulter.corr(), center=0,annot=False,linewidth =1)
```

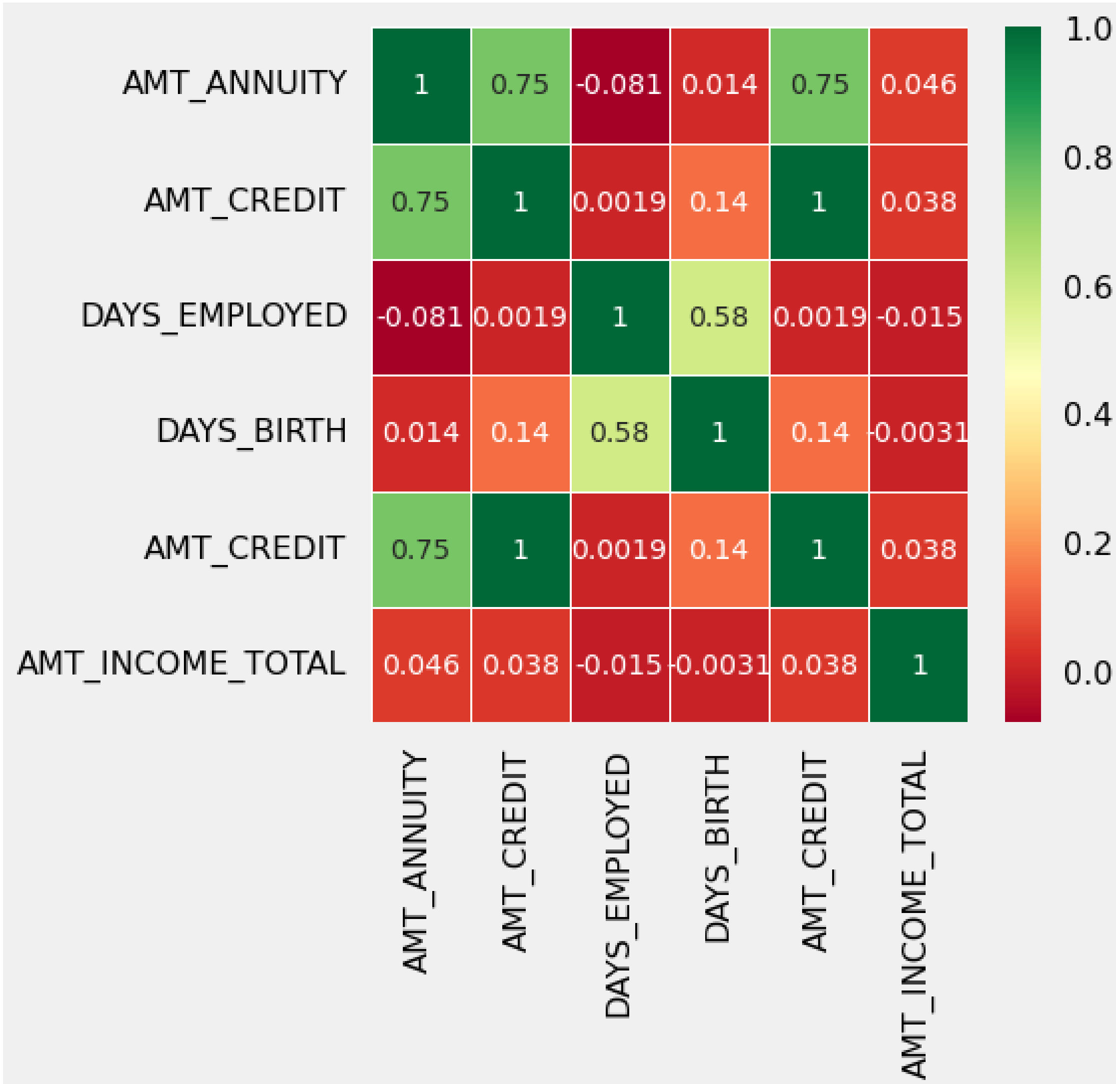


[128]:
```
final_corr=['AMT_ANNUITY','AMT_CREDIT','DAYS_EMPLOYED','DAYS_BIRTH','AMT_CREDIT','AMT_INCOME_T
repayer_final=application.loc[application['TARGET']==0,final_corr]
defaulter_final=application.loc[application['TARGET']==1,final_corr]
```

[129]:
```
fig = plt.figure(figsize=(6,6))
ax = sns.heatmap(repayer_final.corr(), cmap="RdYlGn",annot=True,linewidth =1)
```

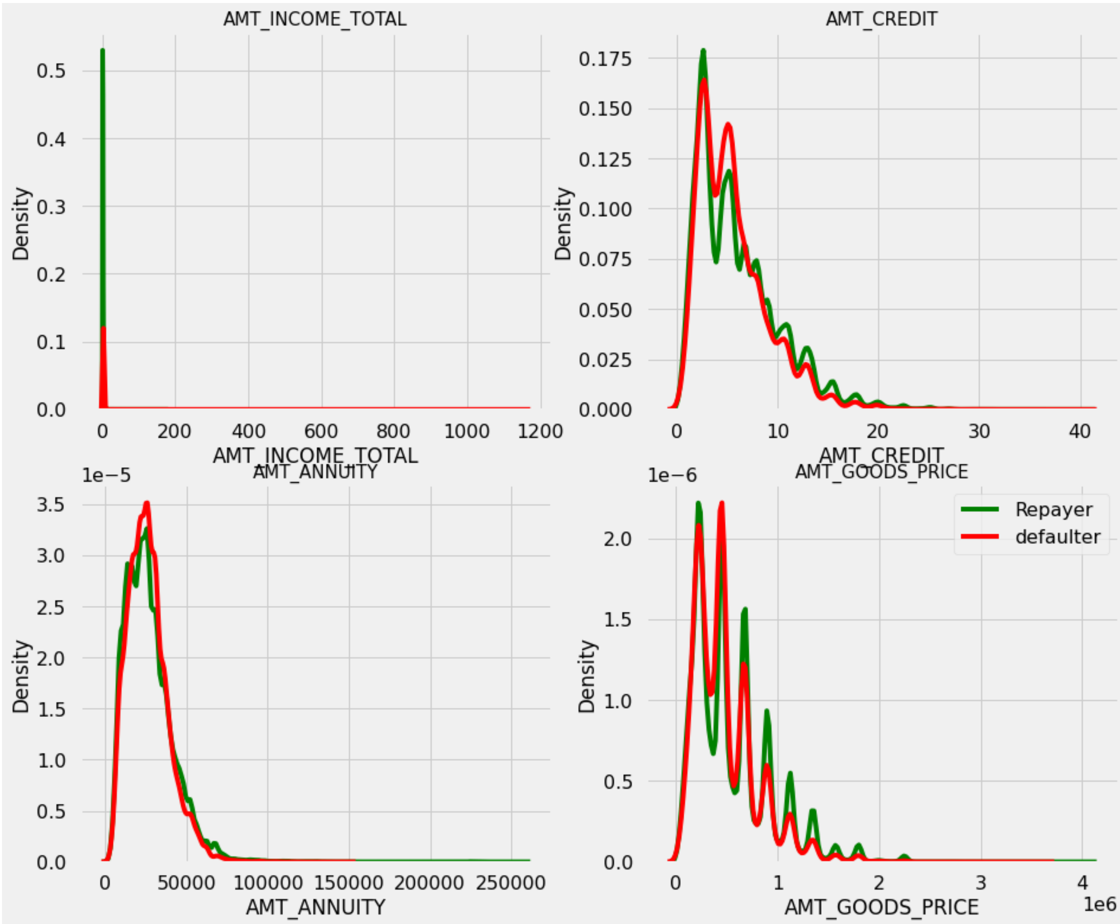


[130]:
```
plt.figure(figsize=(6,6))
ax=sns.heatmap(defaulter_final.corr(),annot=True,cmap="RdYlGn",linewidth=1)
```



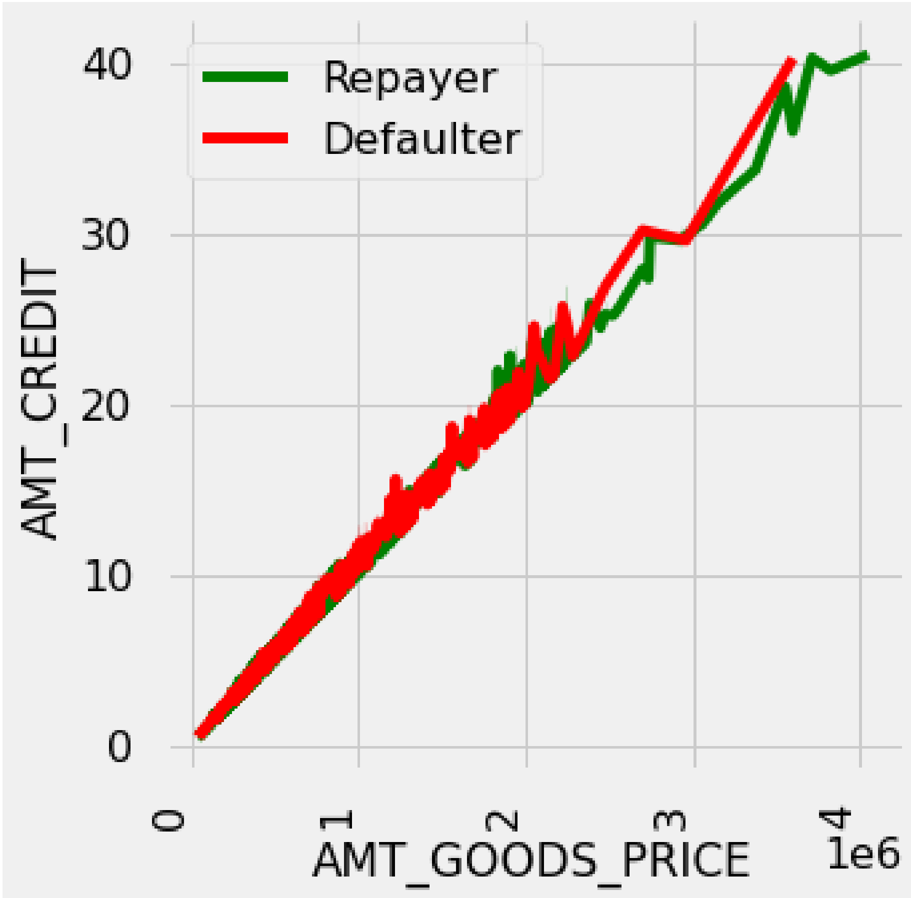
[131]:

```
fig=plt.figure(figsize=(14,12))
amount=application[['AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY',␣
 ↪'AMT_GOODS_PRICE']]
for i in enumerate(amount):
    plt.subplot(2,2,i[0]+1)
    sns.distplot(repayer[i[1]],hist=False,color='g',label='Repayer')
    sns.distplot(defaulter[i[1]],hist=False,color='r',label='defaulter')
    plt.title(i[1],fontdict={'fontsize' : 15, 'fontweight' : 5})
plt.legend()
plt.show()
```

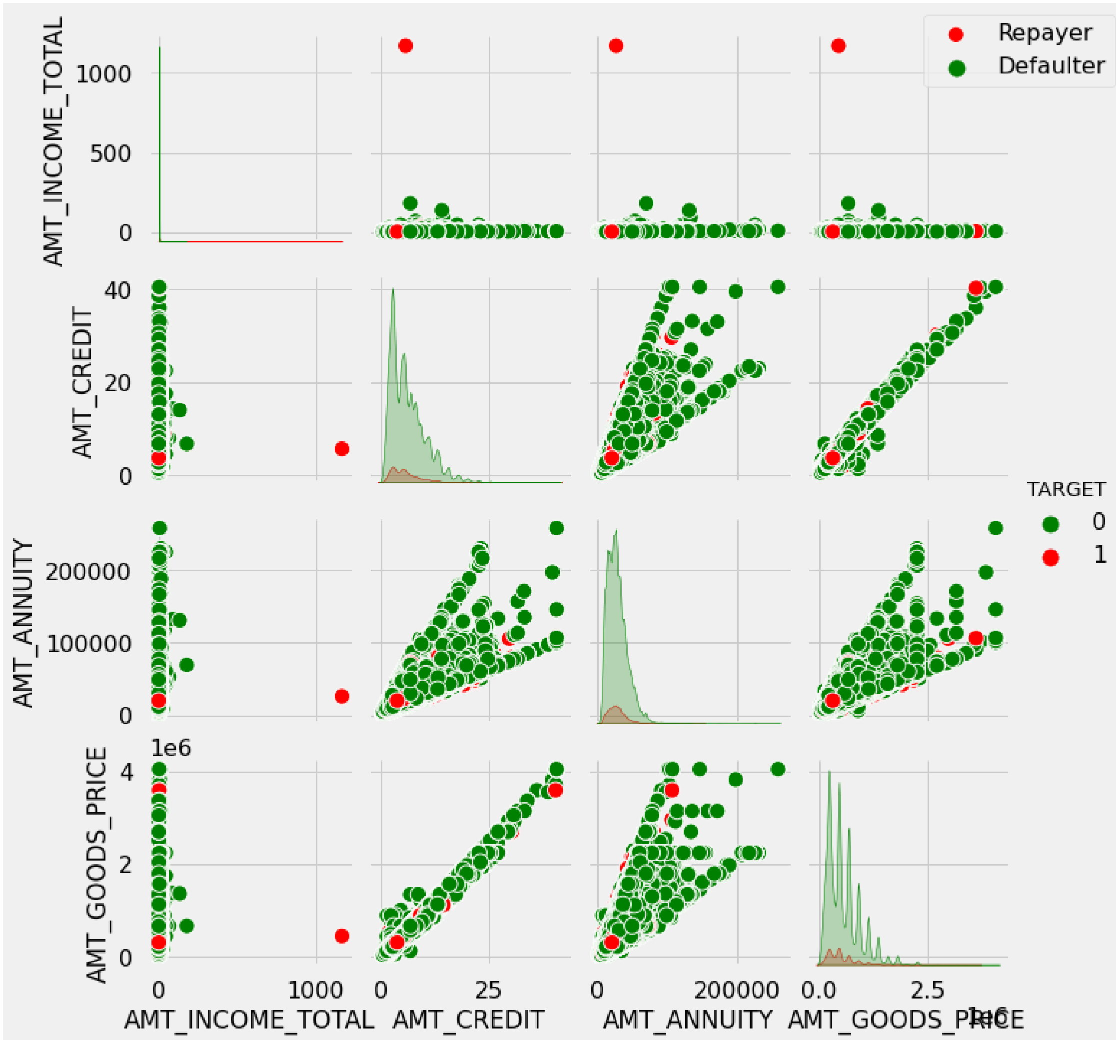


[132]:
```
bivariate_rel('AMT_GOODS_PRICE','AMT_CREDIT',application,"TARGET", "line",␣
↪['g','r'], False,(15,6))
```

<Figure size 1080x432 with 0 Axes>

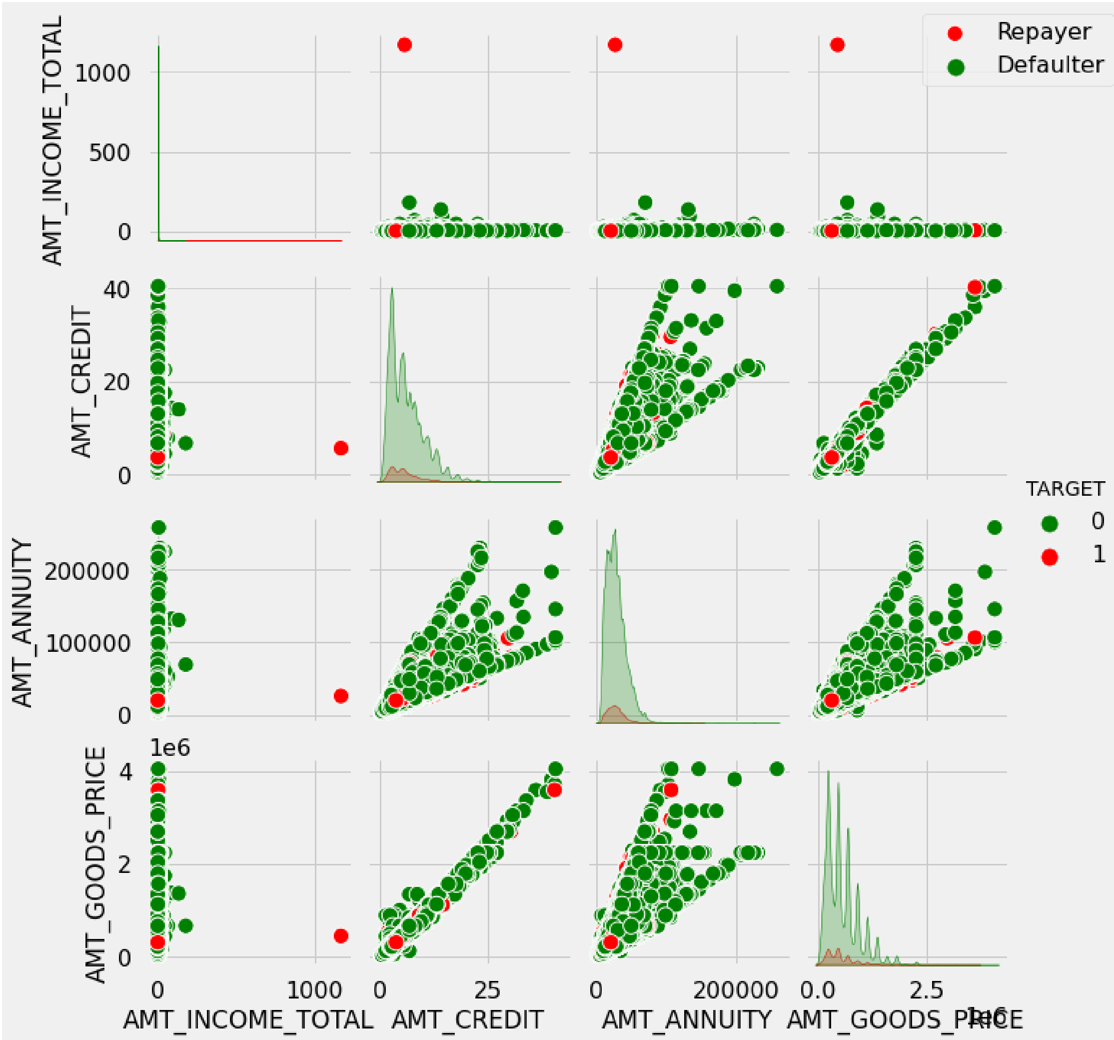


[133]:
```
amount = application[[ 'AMT_INCOME_TOTAL','AMT_CREDIT',
                        'AMT_ANNUITY', 'AMT_GOODS_PRICE','TARGET']]
amount = amount[(amount["AMT_GOODS_PRICE"].notnull()) & (amount["AMT_ANNUITY"].
 ↪notnull())]
ax= sns.pairplot(amount,hue="TARGET",palette=["g","r"])
ax.fig.legend(labels=['Repayer','Defaulter'])
plt.show()
```

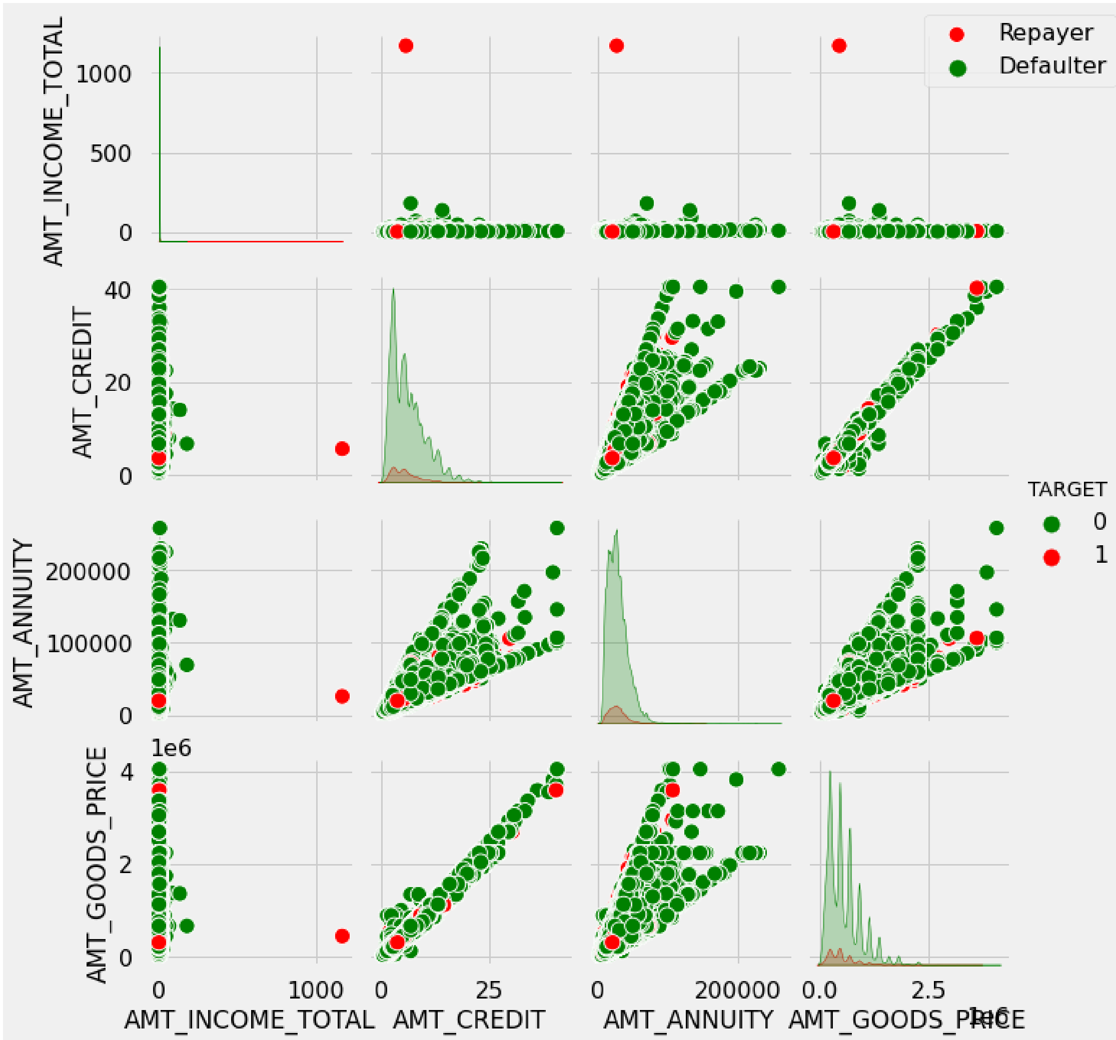


[134]:

```
amount = application[[ 'AMT_INCOME_TOTAL','AMT_CREDIT',
                             'AMT_ANNUITY', 'AMT_GOODS_PRICE','TARGET']]
amount = amount[(amount["AMT_GOODS_PRICE"].notnull()) & (amount["AMT_ANNUITY"].
 ↪notnull())]
ax= sns.pairplot(amount,hue="TARGET",palette=["g","r"])
ax.fig.legend(labels=['Repayer','Defaulter'])
plt.show()
```



[135]:
```
amount = application[[ 'AMT_INCOME_TOTAL','AMT_CREDIT',
                       'AMT_ANNUITY', 'AMT_GOODS_PRICE','TARGET']]
ax= sns.pairplot(amount,hue="TARGET",palette=["g","r"])
ax.fig.legend(labels=['Repayer','Defaulter'])
plt.show()
```



[136]:
```
loan_application = pd.merge(application, previous, how='inner', on='SK_ID_CURR')
loan_application.head()
```

[136]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE_x CODE_GENDER FLAG_OWN_CAR
FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT_x  AMT_ANNUITY_x
…  NAME_GOODS_CATEGORY NAME_PORTFOLIO NAME_PRODUCT_TYPE
CHANNEL_TYPE SELLERPLACE_AREA  NAME_SELLER_INDUSTRY  CNT_PAYMENT
NAME_YIELD_GROUP          PRODUCT_COMBINATION  DAYS_DECISION_GROUP
0       100002       1           Cash loans           M            N
Y             0             2.025       4.065975        24700.5  …
Vehicles            POS                XNA                      Stone
500        Auto technology         24.0         low_normal       POS other with
interest             (400, 800]
1       100003       0           Cash loans           F            N
N             0             2.700      12.935025        35698.5  …
```

```
XNA           Cash            x-sell  Credit and cash offices              -1
XNA         12.0        low_normal            Cash X-Sell: low           (400,
800]
2       100003       0           Cash loans           F            N
N             0             2.700     12.935025        35698.5  …
Furniture            POS                XNA                    Stone
1400             Furniture          6.0            middle   POS industry with
interest           (800, 1200]
3       100003       0           Cash loans           F            N
N             0             2.700     12.935025        35698.5  …  Consumer
Electronics            POS                XNA              Country-wide
200  Consumer electronics         12.0            middle  POS household with
interest          (2000, 2400]
4       100004       0      Revolving loans           M            Y
Y             0             0.675      1.350000         6750.0  …
Mobile             POS               XNA         Regional / Local
30          Connectivity          4.0            middle  POS mobile without
interest           (800, 1200]

[5 rows x 74 columns]
```

[137]:
```
loan_application.shape
```

[137]:
```
(1413701, 74)
```

[138]:
```
loan_application.size
```

[138]:
```
104613874
```

[139]:
```
loan_application.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1413701 entries, 0 to 1413700
Data columns (total 74 columns):
 #   Column                       Non-Null Count    Dtype
---  ------                       --------------    -----
 0   SK_ID_CURR                   1413701 non-null  int64
 1   TARGET                       1413701 non-null  int64
 2   NAME_CONTRACT_TYPE_x         1413701 non-null  category
 3   CODE_GENDER                  1413701 non-null  category
 4   FLAG_OWN_CAR                 1413701 non-null  category
 5   FLAG_OWN_REALTY              1413701 non-null  category
 6   CNT_CHILDREN                 1413701 non-null  int64
 7   AMT_INCOME_TOTAL             1413701 non-null  float64
 8   AMT_CREDIT_x                 1413701 non-null  float64
 9   AMT_ANNUITY_x                1413608 non-null  float64
 10  AMT_GOODS_PRICE_x            1412493 non-null  float64
```

```
11  NAME_TYPE_SUITE              1413701 non-null  category
12  NAME_INCOME_TYPE             1413701 non-null  category
13  NAME_EDUCATION_TYPE          1413701 non-null  category
14  NAME_FAMILY_STATUS           1413701 non-null  category
15  NAME_HOUSING_TYPE            1413701 non-null  category
16  REGION_POPULATION_RELATIVE   1413701 non-null  float64
17  DAYS_BIRTH                   1413701 non-null  int64
18  DAYS_EMPLOYED                1413701 non-null  int64
19  DAYS_REGISTRATION            1413701 non-null  float64
20  DAYS_ID_PUBLISH              1413701 non-null  int64
21  OCCUPATION_TYPE              1413701 non-null  category
22  CNT_FAM_MEMBERS              1413701 non-null  float64
23  REGION_RATING_CLIENT         1413701 non-null  category
24  REGION_RATING_CLIENT_W_CITY  1413701 non-null  category
25  WEEKDAY_APPR_PROCESS_START   1413701 non-null  category
26  HOUR_APPR_PROCESS_START      1413701 non-null  int64
27  REG_REGION_NOT_LIVE_REGION   1413701 non-null  int64
28  REG_REGION_NOT_WORK_REGION   1413701 non-null  category
29  LIVE_REGION_NOT_WORK_REGION  1413701 non-null  category
30  REG_CITY_NOT_LIVE_CITY       1413701 non-null  category
31  REG_CITY_NOT_WORK_CITY       1413701 non-null  category
32  LIVE_CITY_NOT_WORK_CITY      1413701 non-null  category
33  ORGANIZATION_TYPE            1413701 non-null  category
34  OBS_30_CNT_SOCIAL_CIRCLE     1410555 non-null  float64
35  DEF_30_CNT_SOCIAL_CIRCLE     1410555 non-null  float64
36  OBS_60_CNT_SOCIAL_CIRCLE     1410555 non-null  float64
37  DEF_60_CNT_SOCIAL_CIRCLE     1410555 non-null  float64
38  DAYS_LAST_PHONE_CHANGE       1413701 non-null  float64
39  FLAG_DOCUMENT_3              1413701 non-null  int64
40  AMT_REQ_CREDIT_BUREAU_HOUR   1413701 non-null  float64
41  AMT_REQ_CREDIT_BUREAU_DAY    1413701 non-null  float64
42  AMT_REQ_CREDIT_BUREAU_WEEK   1413701 non-null  float64
43  AMT_REQ_CREDIT_BUREAU_MON    1413701 non-null  float64
44  AMT_REQ_CREDIT_BUREAU_QRT    1413701 non-null  float64
45  AMT_REQ_CREDIT_BUREAU_YEAR   1413701 non-null  float64
46  INCOME_RANGE                 1413024 non-null  category
47  LOAN_AMT                     1413701 non-null  category
48  AGE                          1413701 non-null  int64
49  AGE_GROUP                    1413701 non-null  category
50  YEARS_EMPLOYED               1413701 non-null  int64
51  WORKING_YEARS                1032756 non-null  category
52  SK_ID_PREV                   1413701 non-null  int64
53  NAME_CONTRACT_TYPE_y         1413701 non-null  category
54  AMT_ANNUITY_y                1413701 non-null  float64
55  AMT_APPLICATION              1413701 non-null  float64
56  AMT_CREDIT_y                 1413700 non-null  float64
57  AMT_GOODS_PRICE_y            1413701 non-null  float64
58  NAME_CASH_LOAN_PURPOSE       1413701 non-null  category
```

```
 59  NAME_CONTRACT_STATUS          1413701 non-null  category
 60  DAYS_DECISION                 1413701 non-null  int64
 61  NAME_PAYMENT_TYPE             1413701 non-null  category
 62  CODE_REJECT_REASON            1413701 non-null  category
 63  NAME_CLIENT_TYPE              1413701 non-null  category
 64  NAME_GOODS_CATEGORY           1413701 non-null  category
 65  NAME_PORTFOLIO                1413701 non-null  category
 66  NAME_PRODUCT_TYPE             1413701 non-null  category
 67  CHANNEL_TYPE                  1413701 non-null  category
 68  SELLERPLACE_AREA              1413701 non-null  int64
 69  NAME_SELLER_INDUSTRY          1413701 non-null  category
 70  CNT_PAYMENT                   1413701 non-null  float64
 71  NAME_YIELD_GROUP              1413701 non-null  category
 72  PRODUCT_COMBINATION           1413388 non-null  category
 73  DAYS_DECISION_GROUP           1413701 non-null  category
dtypes: category(37), float64(23), int64(14)
memory usage: 459.8 MB
```

[140]:
```
loan_application.describe()
```

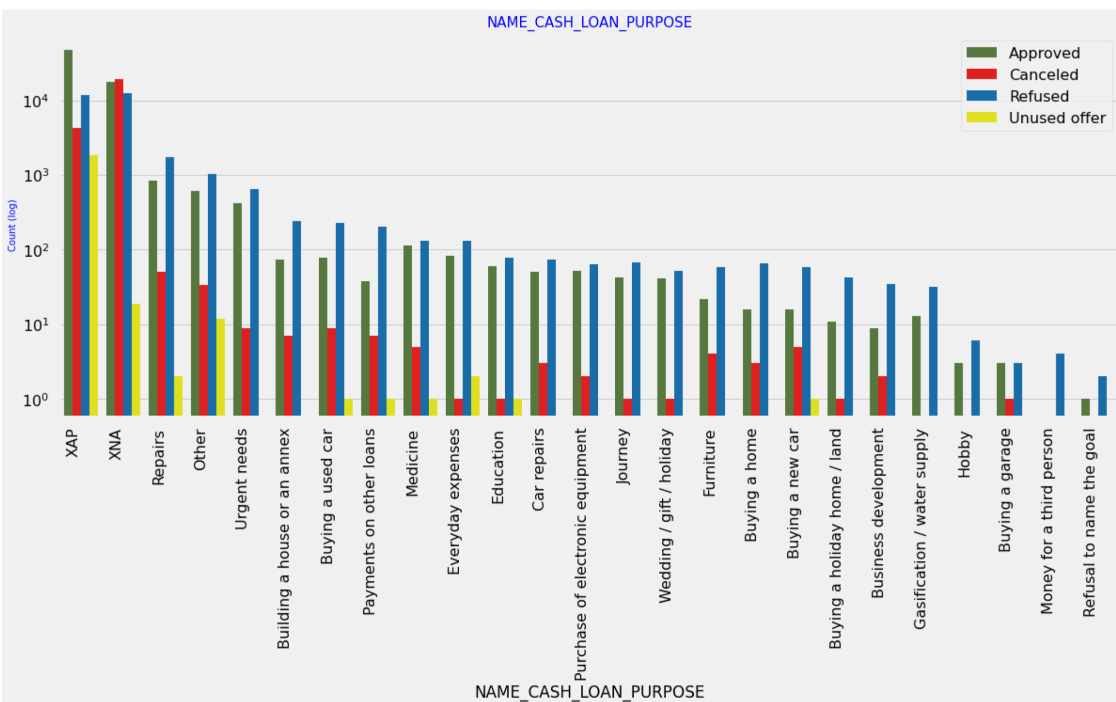
[140]:
```
         SK_ID_CURR        TARGET  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT_x
AMT_ANNUITY_x  AMT_GOODS_PRICE_x  REGION_POPULATION_RELATIVE    DAYS_BIRTH
DAYS_EMPLOYED  …           AGE  YEARS_EMPLOYED    SK_ID_PREV  AMT_ANNUITY_y
AMT_APPLICATION  AMT_CREDIT_y  AMT_GOODS_PRICE_y  DAYS_DECISION
SELLERPLACE_AREA   CNT_PAYMENT
count  1.413701e+06  1.413701e+06  1.413701e+06      1.413701e+06  1.413701e+06
1.413608e+06      1.412493e+06                1.413701e+06  1.413701e+06
1.413701e+06  …  1.413701e+06    1.413701e+06  1.413701e+06   1.413701e+06
1.413701e+06  1.413700e+06      1.413701e+06   1.413701e+06      1.413701e+06
1.413701e+06
mean   2.784813e+05  8.655296e-02  4.048933e-01      1.733160e+00  5.875537e+00
2.701702e+04      5.277186e+05                2.074985e-02  1.632105e+04
7.266347e+04  …  4.421384e+01    1.985500e+02  1.922744e+06   1.484032e+04
1.752436e+05  1.963541e+05      1.854396e+05   8.803670e+02      3.149878e+02
1.256367e+01
std    1.028118e+05  2.811789e-01  7.173454e-01      1.985734e+00  3.849173e+00
1.395116e+04      3.532465e+05                1.334702e-02  4.344557e+03
1.433374e+05  …  1.190217e+01    3.926378e+02  5.327153e+05   1.316370e+04
2.936222e+05  3.194813e+05      2.881244e+05   7.835402e+02      7.695082e+03
1.448807e+01
min    1.000020e+05  0.000000e+00  0.000000e+00      2.565000e-01  4.500000e-01
1.615500e+03      4.050000e+04                2.900000e-04  7.489000e+03
0.000000e+00  …  2.000000e+01    0.000000e+00  1.000001e+06   0.000000e+00
0.000000e+00  0.000000e+00      0.000000e+00   1.000000e+00     -1.000000e+00
0.000000e+00
25%    1.893640e+05  0.000000e+00  0.000000e+00      1.125000e+00  2.700000e+00
1.682100e+04      2.385000e+05                1.003200e-02  1.273900e+04
```

```
1.042000e+03  …  3.400000e+01    2.000000e+00  1.461346e+06   7.406055e+03
1.975050e+04  2.488050e+04       4.500000e+04   2.710000e+02      -1.000000e+00
0.000000e+00
50%     2.789920e+05  0.000000e+00  0.000000e+00      1.575000e+00  5.084955e+00
2.492550e+04       4.500000e+05                  1.885000e-02  1.604400e+04
2.401000e+03  …  4.300000e+01    6.000000e+00  1.922698e+06   1.125000e+04
7.087050e+04  8.059500e+04       7.087500e+04   5.820000e+02       4.000000e+00
1.000000e+01
75%     3.675560e+05  0.000000e+00  1.000000e+00      2.070000e+00  8.079840e+00
3.454200e+04       6.795000e+05                  2.866300e-02  1.998000e+04
6.313000e+03  …  5.400000e+01    1.700000e+01  2.384012e+06   1.674797e+04
1.800000e+05  2.156400e+05       1.800000e+05   1.313000e+03       8.500000e+01
1.800000e+01
max     4.562550e+05  1.000000e+00  1.900000e+01      1.170000e+03  4.050000e+01
2.250000e+05       4.050000e+06                  7.250800e-02  2.520100e+04
3.652430e+05  …  6.900000e+01    1.000000e+03  2.845381e+06   4.180581e+05
5.850000e+06  4.509688e+06       5.850000e+06   2.922000e+03       4.000000e+06
8.400000e+01

[8 rows x 37 columns]
```

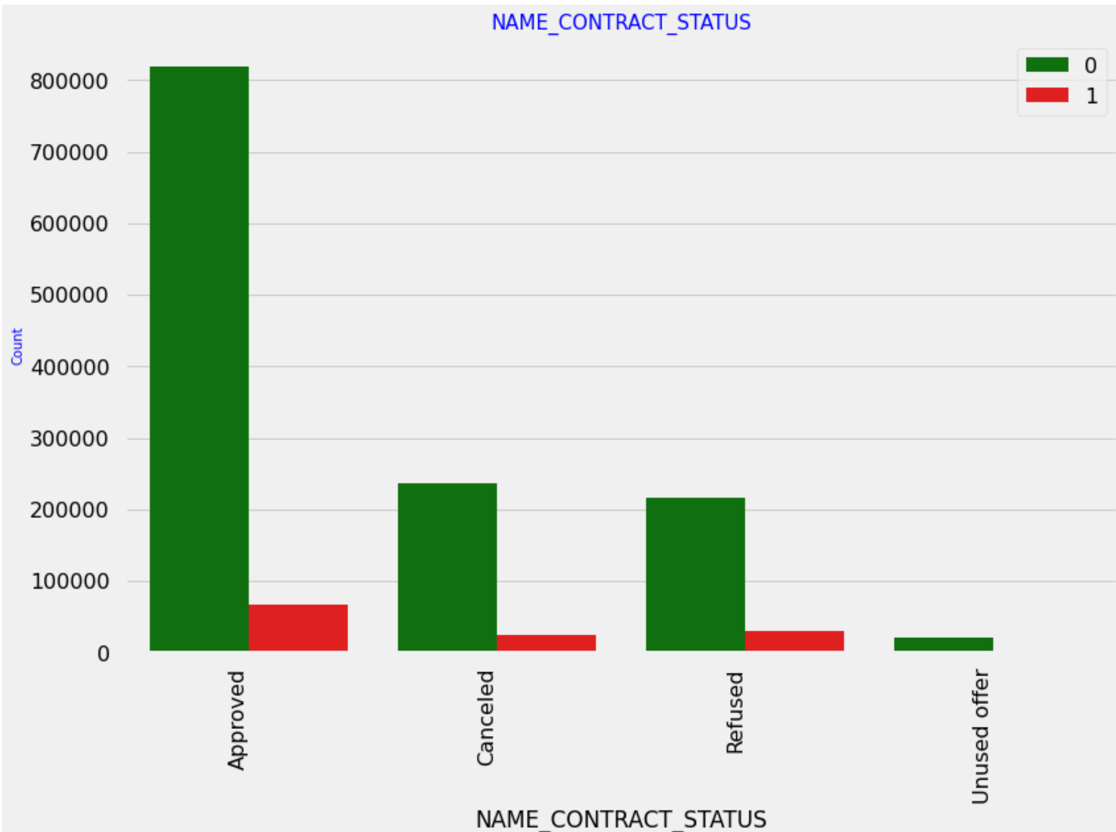
[141]:
```
Target_0=loan_application[loan_application['TARGET']==0]
```

[143]:
```
Target_1=loan_application[loan_application['TARGET']==1]
```

[144]:
```
univariate_merged("NAME_CASH_LOAN_PURPOSE",Target_1,"NAME_CONTRACT_STATUS",["#548235","#FF000C
```

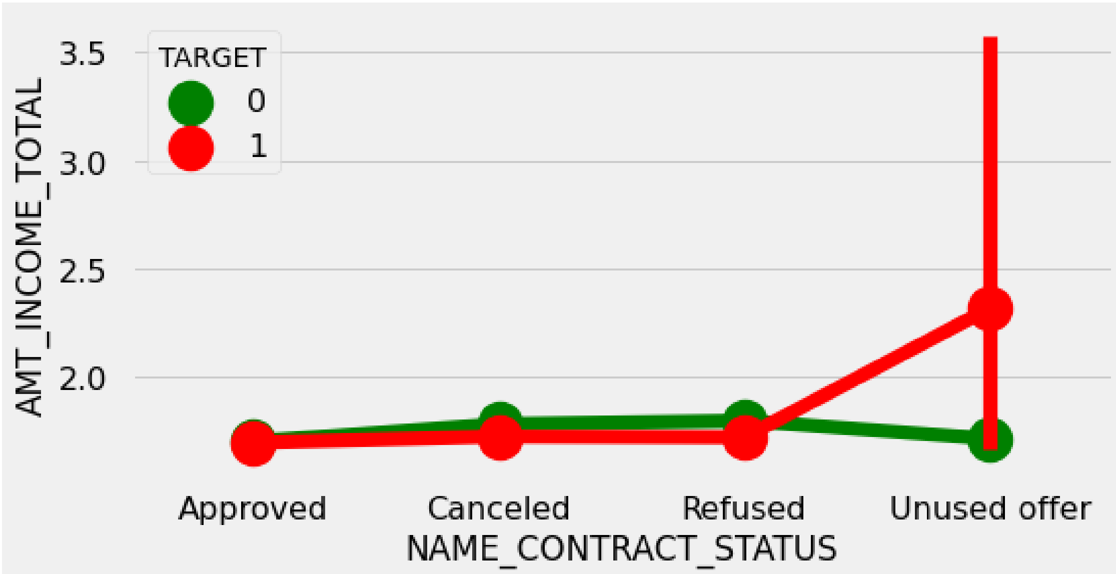


[145]:
```
univariate_merged("NAME_CONTRACT_STATUS",loan_application,"TARGET",['g','r'],False,(12,8))
g =loan_application.groupby("NAME_CONTRACT_STATUS")["TARGET"]
df1 = pd.concat([g.value_counts(),round(g.value_counts(normalize=True).
↪mul(100),2)],axis=1, keys=('Counts','Percentage'))
df1['Percentage'] = df1['Percentage'].astype(str) +"%" # adding percentage␣
↪symbol in the results for understanding
print (df1)
```

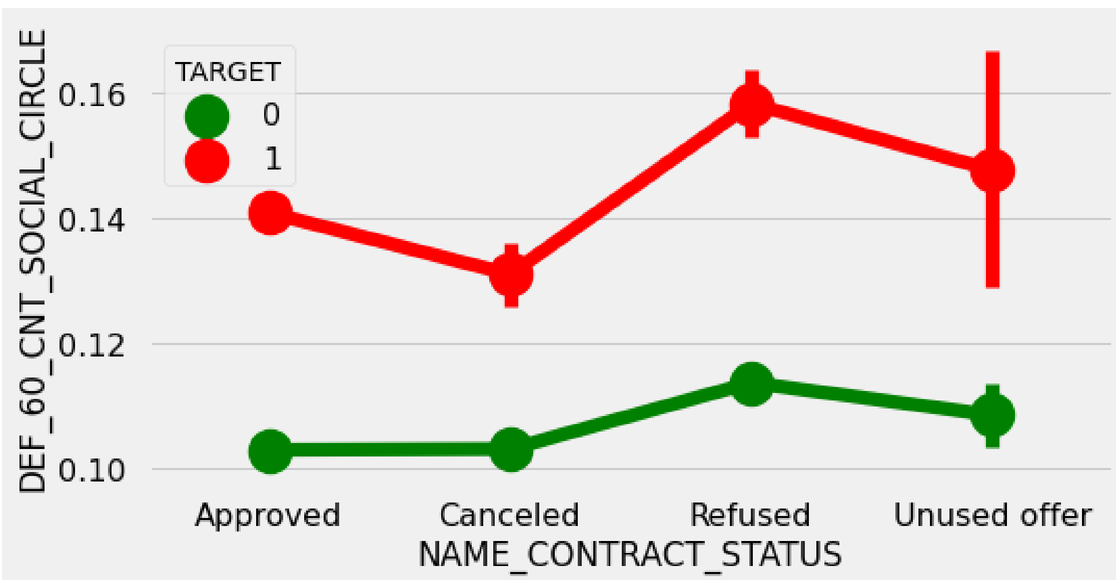



```
                             Counts Percentage
NAME_CONTRACT_STATUS TARGET
Approved             0       818856     92.41%
                     1        67243      7.59%
Canceled             0       235641     90.83%
                     1        23800      9.17%
Refused              0       215952      88.0%
                     1        29438      12.0%
Unused offer         0        20892     91.75%
                     1         1879      8.25%
```

[146]:
```
merged_pointplot("NAME_CONTRACT_STATUS",'AMT_INCOME_TOTAL')
```



[147]:
```
merged_pointplot("NAME_CONTRACT_STATUS",'DEF_60_CNT_SOCIAL_CIRCLE')
```



[ ]:
```

```