In [1]:
```
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
```

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

In [3]:
```
style.use('seaborn-poster')
style.use('fivethirtyeight')
```

In [4]:
```
pd.set_option('display.max_rows',500)
pd.set_option('display.max_columns',500)
pd.set_option('display.width',1000)
pd.set_option('display.expand_frame_repr',False)
```

In [5]:
```
applicationDF=pd.read_csv(r"D:\Full Stack Data Science AI & ML\ClassNotes\1.NOV\Nov 29\28th_Resume project\application_data.csv
applicationDF.head()
```

Out[5]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CR
0	100002	1	Cash loans	M	N	Y	0	202500.0	4065
1	100003	0	Cash loans	F	N	N	0	270000.0	12935
2	100004	0	Revolving loans	M	Y	Y	0	67500.0	1350
3	100006	0	Cash loans	F	N	Y	0	135000.0	3126
4	100007	0	Cash loans	M	N	Y	0	121500.0	5130

In [6]:
```
previousDF=pd.read_csv(r"D:\Full Stack Data Science AI & ML\ClassNotes\1.NOV\Nov 29\28th_Resume project\previous_application.csv
previousDF
```

Out[6]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE
0	2030495	271877	Consumer loans	1730.430	17145.0	17145.0	0.0	17145.0
1	2802425	108129	Cash loans	25188.615	607500.0	679671.0	NaN	607500.0
2	2523466	122040	Cash loans	15060.735	112500.0	136444.5	NaN	112500.0
3	2819243	176158	Cash loans	47041.335	450000.0	470790.0	NaN	450000.0
4	1784265	202054	Cash loans	31924.395	337500.0	404055.0	NaN	337500.0
...	...	...	...	...	...	...	...	...
1670209	2300464	352015	Consumer loans	14704.290	267295.5	311400.0	0.0	267295.5
1670210	2357031	334635	Consumer loans	6622.020	87750.0	64291.5	29250.0	87750.0
1670211	2659632	249544	Consumer loans	11520.855	105237.0	102523.5	10525.5	105237.0
1670212	2785582	400317	Cash loans	18821.520	180000.0	191880.0	NaN	180000.0
1670213	2418762	261212	Cash loans	16431.300	360000.0	360000.0	NaN	360000.0

1670214 rows × 37 columns

In [7]:
```
previousDF.head()
```

Out[7]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	WEEI
0	2030495	271877	Consumer loans	1730.430	17145.0	17145.0	0.0	17145.0	
1	2802425	108129	Cash loans	25188.615	607500.0	679671.0	NaN	607500.0	
2	2523466	122040	Cash loans	15060.735	112500.0	136444.5	NaN	112500.0	
3	2819243	176158	Cash loans	47041.335	450000.0	470790.0	NaN	450000.0	
4	1784265	202054	Cash loans	31924.395	337500.0	404055.0	NaN	337500.0	

In [8]:
```
#data shape
print("applicationDF dimension :",applicationDF.shape)
print("previousDF dimension :",previousDF.shape)

#data set size
print('database size-applicationDF :',applicationDF.size)
print('database size-previousDF :',previousDF.size)
```

```
applicationDF dimension : (307511, 122)
previousDF dimension : (1670214, 37)
database size-applicationDF : 37516342
database size-previousDF : 61797918
```

In [9]:
```
applicationDF.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
```

In [10]:
```
previousDF.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
```

In [11]:
```
applicationDF.describe()
```

Out[11]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_RELAT
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307499.000000	3.072330e+05	307511.000
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.573909	5.383962e+05	0.020
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.737315	3.694465e+05	0.013
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	0.000
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.000000	2.385000e+05	0.010
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.000000	4.500000e+05	0.018
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.000000	6.795000e+05	0.028
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	0.072

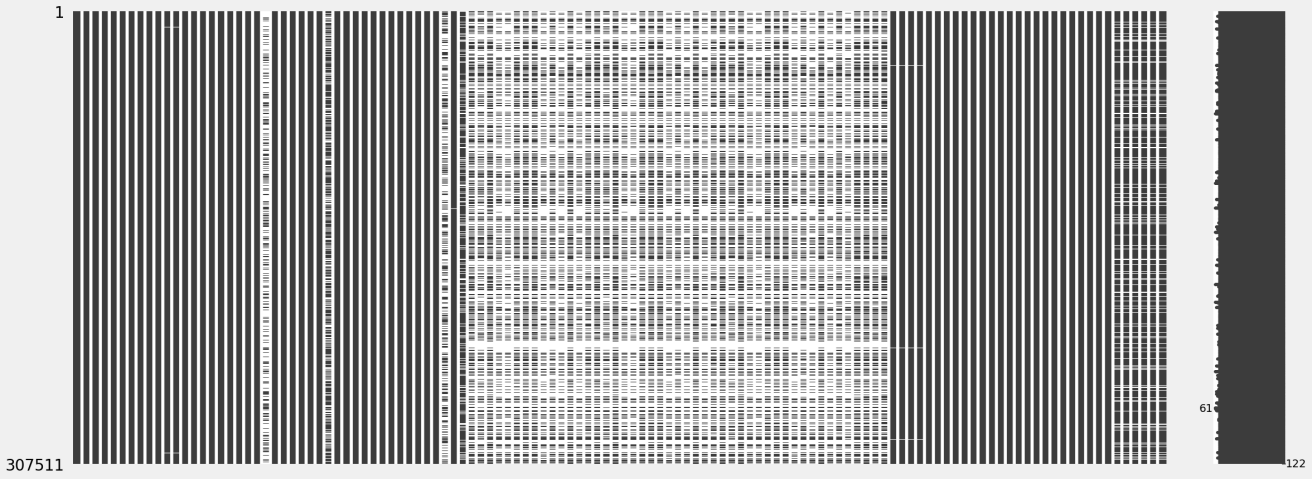
In [12]:
```
previousDF.describe()
```

Out[12]:

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	HOUR_APPR_PROCESS_ST
count	1.670214e+06	1.670214e+06	1.297979e+06	1.670214e+06	1.670213e+06	7.743700e+05	1.284699e+06	1.670214
mean	1.923089e+06	2.783572e+05	1.595512e+04	1.752339e+05	1.961140e+05	6.697402e+03	2.278473e+05	1.248418
std	5.325980e+05	1.028148e+05	1.478214e+04	2.927798e+05	3.185746e+05	2.092150e+04	3.153966e+05	3.334028
min	1.000001e+06	1.000010e+05	0.000000e+00	0.000000e+00	0.000000e+00	-9.000000e-01	0.000000e+00	0.000000
25%	1.461857e+06	1.893290e+05	6.321780e+03	1.872000e+04	2.416050e+04	0.000000e+00	5.084100e+04	1.000000
50%	1.923110e+06	2.787145e+05	1.125000e+04	7.104600e+04	8.054100e+04	1.638000e+03	1.123200e+05	1.200000
75%	2.384280e+06	3.675140e+05	2.065842e+04	1.803600e+05	2.164185e+05	7.740000e+03	2.340000e+05	1.500000
max	2.845382e+06	4.562550e+05	4.180581e+05	6.905160e+06	6.905160e+06	3.060045e+06	6.905160e+06	2.300000

In [13]:
```
import missingno as mn
mn.matrix(applicationDF)
```

Out[13]: <AxesSubplot:>

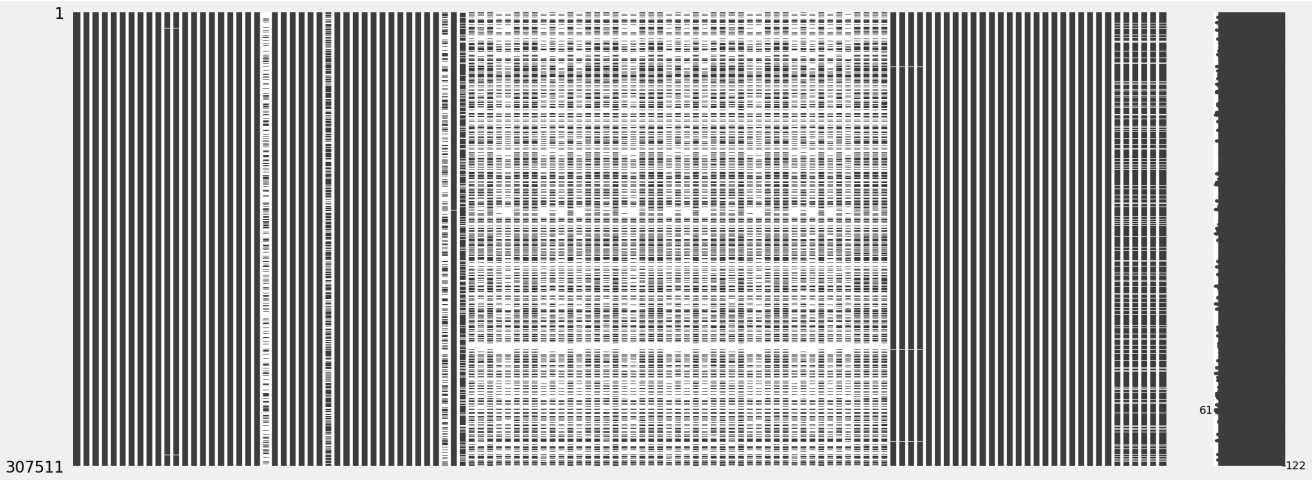


In [14]:
```
pip install missingno
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: missingno in c:\users\pavan 4288\appdata\roaming\python\python39\site-packages (0.5.2)
Requirement already satisfied: numpy in c:\users\pavan 4288\appdata\roaming\python\python39\site-packages (from missingno) (1.
24.4)
Requirement already satisfied: seaborn in c:\programdata\anaconda3\lib\site-packages (from missingno) (0.11.2)
Requirement already satisfied: matplotlib in c:\programdata\anaconda3\lib\site-packages (from missingno) (3.5.2)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-packages (from missingno) (1.9.1)
Requirement already satisfied: python-dateutil>=2.7 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno)
(2.8.2)
Requirement already satisfied: packaging>=20.0 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno) (21.
3)
Requirement already satisfied: fonttools>=4.22.0 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno)
(4.25.0)
Requirement already satisfied: pillow>=6.2.0 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno) (9.2.
0)
Requirement already satisfied: pyparsing>=2.2.1 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno) (3.
0.9)
Requirement already satisfied: cycler>=0.10 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno) (0.11.
0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\programdata\anaconda3\lib\site-packages (from matplotlib->missingno)
(1.4.2)
Requirement already satisfied: pandas>=0.23 in c:\programdata\anaconda3\lib\site-packages (from seaborn->missingno) (1.4.4)
Requirement already satisfied: pytz>=2020.1 in c:\programdata\anaconda3\lib\site-packages (from pandas>=0.23->seaborn->missing
no) (2022.1)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib->
missingno) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [15]:
```
import missingno as mn
mn.matrix(applicationDF)
```

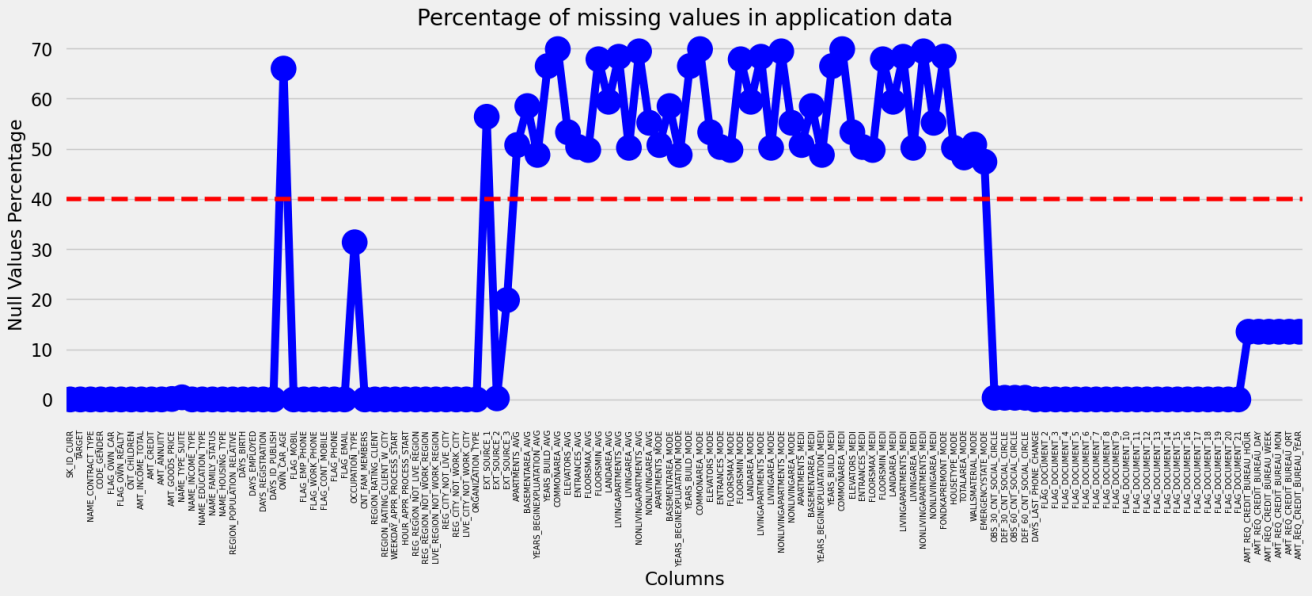
Out[15]: <AxesSubplot:>



In [16]:
```
round(applicationDF.isnull().sum()/applicationDF.shape[0]*100.00,2)
```

Out[16]:
```
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
```

In [17]:
```
null_applicationDF=pd.DataFrame((applicationDF.isnull().sum())*100/applicationDF.shape[0]).reset_index()
null_applicationDF.columns=['Column Name','Null Values Percentage']
figure =plt.figure(figsize=(18,6))
ax=sns.pointplot(x='Column Name',y='Null Values Percentage',data=null_applicationDF,color='blue')
plt.xticks(rotation=90,fontsize=7)
ax.axhline(40,ls='--',color='red')
plt.title('Percentage of missing values in application data')
plt.ylabel('Null Values Percentage')
plt.xlabel('Columns')
plt.show()
```



In [18]:
```
nullcol_40_application=null_applicationDF[null_applicationDF['Null Values Percentage']>=40]
nullcol_40_application
```

Out[18]:

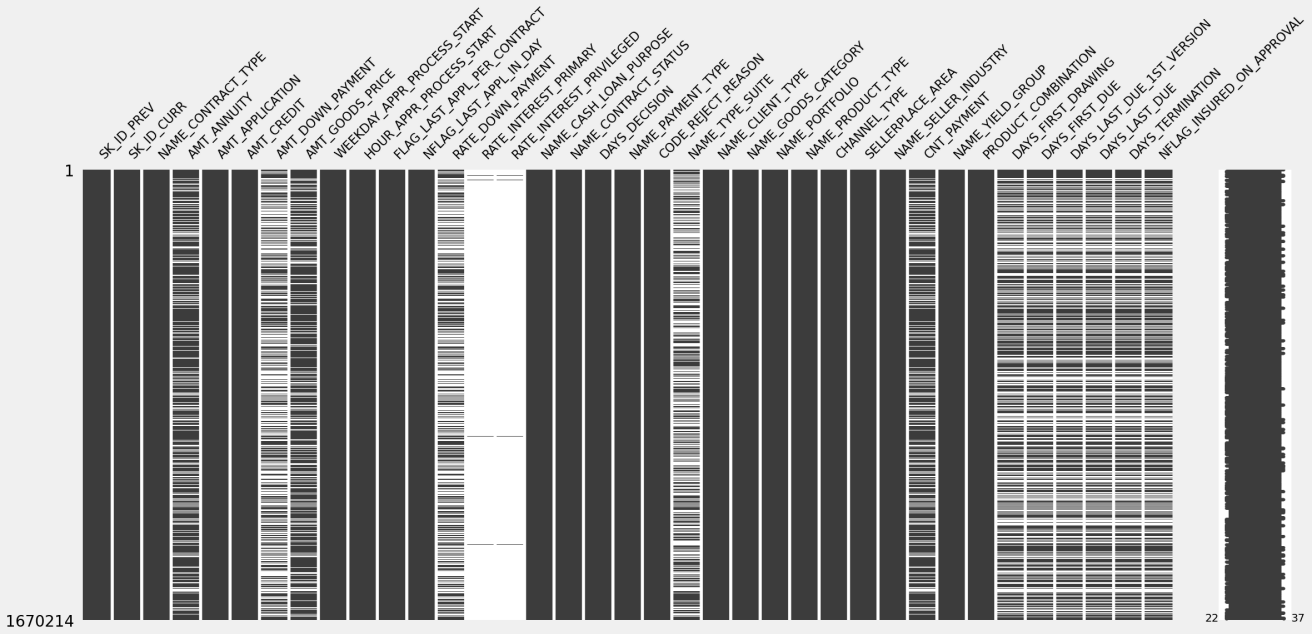
	Column Name	Null Values Percentage
21	OWN_CAR_AGE	65.990810
41	EXT_SOURCE_1	56.381073
44	APARTMENTS_AVG	50.749729
45	BASEMENTAREA_AVG	58.515956
46	YEARS_BEGINEXPLUATATION_AVG	48.781019
47	YEARS_BUILD_AVG	66.497784
48	COMMONAREA_AVG	69.872297
49	ELEVATORS_AVG	53.295980
50	ENTRANCES_AVG	50.348768
51	FLOORSMAX_AVG	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

In [19]:
```
len(nullcol_40_application)
```

Out[19]: 49

In [20]:
```
mn.matrix(previousDF)
```

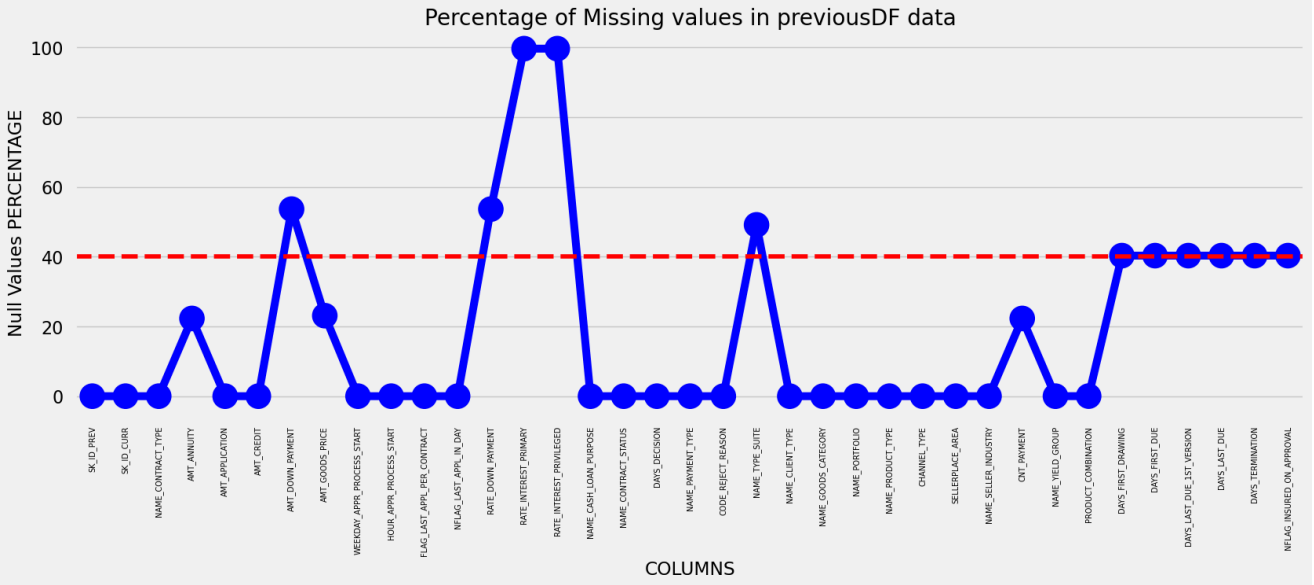
Out[20]: <AxesSubplot:>



In [21]:
```
round(previousDF.isnull().sum()/previousDF.shape[0]*100.00,2)
```

Out[21]:
```
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
```

In [22]:
```
null_previousDF=pd.DataFrame((previousDF.isnull().sum())*100/previousDF.shape[0]).reset_index()
null_previousDF.columns=['Column Name','Null Values Percentage']
fig=plt.figure(figsize=(18,6))
ax=sns.pointplot(x='Column Name',y='Null Values Percentage',data=null_previousDF,color='blue')
plt.xticks(rotation=90,fontsize=7)
ax.axhline(40,ls='--',color='red')
plt.title('Percentage of Missing values in previousDF data')
plt.ylabel('Null Values PERCENTAGE')
plt.xlabel('COLUMNS')
plt.show()
```



In [23]:
```
nullcol_40_previous = null_previousDF[null_previousDF['Null Values Percentage']>=40]
nullcol_40_previous
```

Out[23]:

	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

In [24]:
```
len(nullcol_40_previous)
```

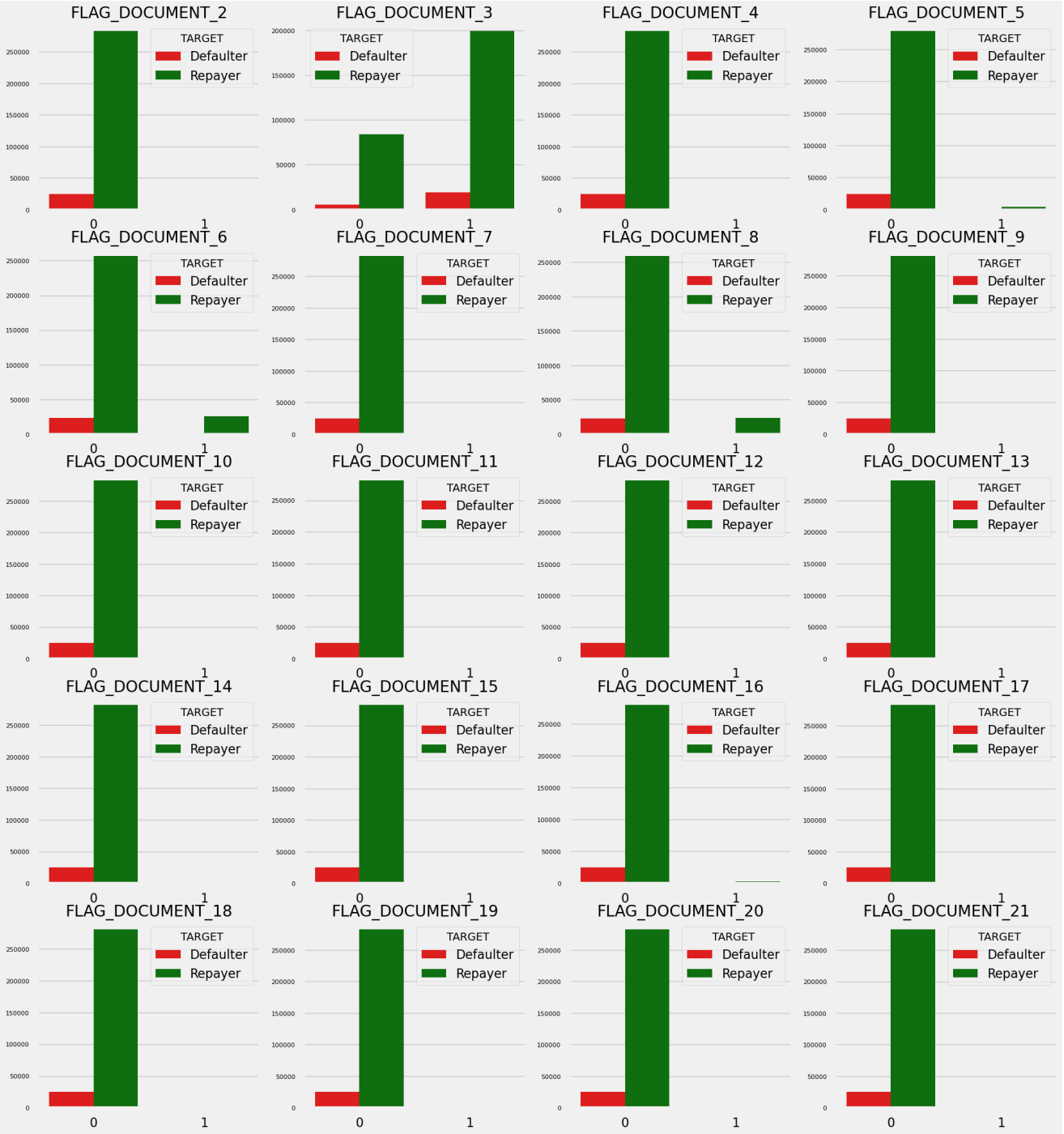
Out[24]: 11

In [25]:
```
Source = applicationDF[['EXT_SOURCE_1','EXT_SOURCE_2','EXT_SOURCE_3','TARGET']]
source_corr=Source.corr()
ax=sns.heatmap(source_corr,xticklabels=source_corr.columns,yticklabels=source_corr.columns,annot=True,cmap='RdYlGn')
```

In [26]:
```
Unwanted_application=nullcol_40_application['Column Name'].tolist()+['EXT_SOURCE_2','EXT_SOURCE_3']
len(Unwanted_application)
```

Out[26]: 51

In [27]:
```
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 = applicationDF[col_Doc+["TARGET"]]

length = len(col_Doc)

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

fig = plt.figure(figsize=(21,24))

for i,j in itertools.zip_longest(col_Doc,range(length)):
    plt.subplot(5,4,j+1)
    ax = sns.countplot(df_flag[i],hue=df_flag["TARGET"],palette=["r","g"])
    plt.yticks(fontsize=8)
    plt.xlabel("")
    plt.ylabel("")
    plt.title(i)
```



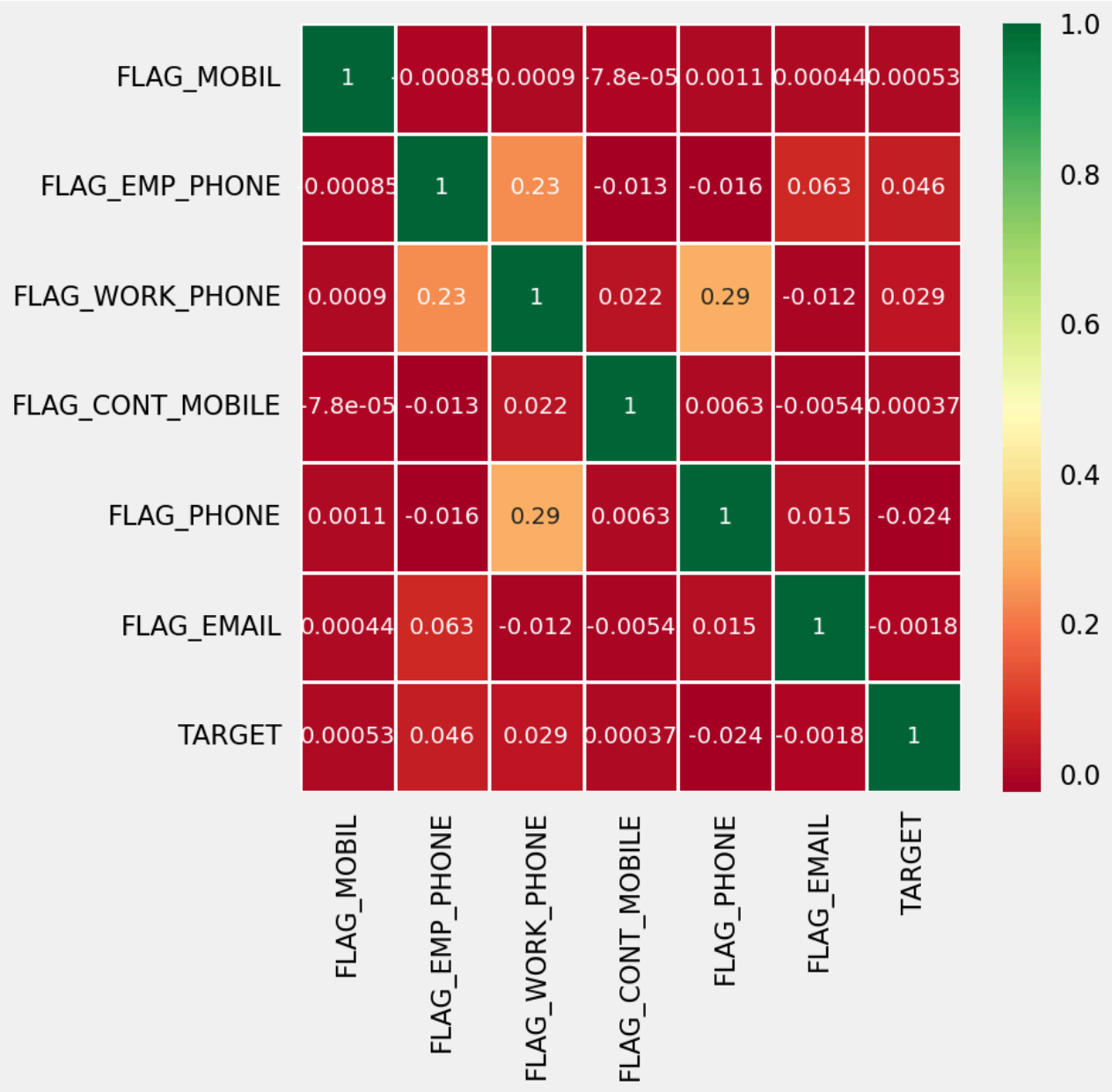
In [28]:
```
Unwnated_application = nullcol_40_application["Column Name"].tolist()+['EXT_SOURCE_2','EXT_SOURCE_3']
len(Unwanted_application)
```

Out[28]: 51

In [29]:
```
col_Doc.remove('FLAG_DOCUMENT_3')
Unwanted_application = Unwanted_application + col_Doc
len(Unwanted_application)
```

Out[29]: 70

In [30]:
```
contact_col=['FLAG_MOBIL','FLAG_EMP_PHONE','FLAG_WORK_PHONE','FLAG_CONT_MOBILE','FLAG_PHONE','FLAG_EMAIL','TARGET']
Contact_corr=applicationDF[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='RdYlGn',linewidtl
```



In [31]:
```
contact_col.remove('TARGET')
Unwanted_application = Unwanted_application+contact_col
len(Unwanted_application)
```

Out[31]: 76

In [32]:
```
applicationDF.drop(labels=Unwanted_application,axis=1,inplace=True)
```

In [33]:
```
applicationDF.shape
```

Out[33]:
```
(307511, 46)
```

In [34]:
```
applicationDF.info()
```

```
<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
```

In [35]:
```
Unwanted_previous = nullcol_40_previous['Column Name'].tolist()
Unwanted_previous
```

Out[35]:
```
['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']
```

In [36]:
```
Unnecessary_previous = ['WEEKDAY_APPR_PROCESS_START','HOUR_APPR_PROCESS_START','FLAG_LAST_APPL_PER_CONTRACT','NFLAG_LAST_APPL_I
```

In [37]:
```
Unwanted_previous=Unwanted_previous+Unnecessary_previous
len(Unwanted_previous)
```

Out[37]:
```
15
```

In [38]:
```
previousDF.drop(labels=Unwanted_previous,axis=1,inplace=True)
previousDF.shape
```

Out[38]:
```
(1670214, 22)
```

In [39]:
```
previousDF.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
```

In [40]:
```
date_col = ['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH']
for col in date_col:
    applicationDF[col]=abs(applicationDF[col])
```

In [41]:
```
applicationDF['AMT_INCOME_TOTAL']=applicationDF['AMT_INCOME_TOTAL']/100000

bins = [0,1,2,3,4,5,6,7,8,9,10,11]
slot = ['0-100K','100K-200K', '200k-300k','300k-400k','400k-500k','500k-600k','600k-700k','700k-800k','800k-900k','900k-1M', '1

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

In [42]:
```
applicationDF['AMT_INCOME_RANGE'].value_counts(normalize=True)*100
```

Out[42]:
```
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: AMT_INCOME_RANGE, dtype: float64
```

In [43]:
```
applicationDF['AMT_CREDIT']=applicationDF['AMT_CREDIT']/100000

bins = [0,1,2,3,4,5,6,7,8,9,10,100]
slots = ['0-100K','100K-200K', '200k-300k','300k-400k','400k-500k','500k-600k','600k-700k','700k-800k',
       '800k-900k','900k-1M', '1M Above']

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

In [44]:
```
applicationDF['AMT_CREDIT_RANGE'].value_counts(normalize=True)*100
```

Out[44]:
```
200k-300k    17.824728
1M Above     16.254703
500k-600k    11.131960
400k-500k    10.418489
100K-200K     9.801275
300k-400k     8.564897
600k-700k     7.820533
800k-900k     7.086576
700k-800k     6.241403
900k-1M       2.902986
0-100K        1.952450
Name: AMT_CREDIT_RANGE, dtype: float64
```

In [45]:
```
applicationDF['AGE']=applicationDF['DAYS_BIRTH']//365
bins=[0,20,30,40,50,100]
slots=['0-20','20-30','30-40','40-50','50 above']
applicationDF['AGE_GROUP']=pd.cut(applicationDF['AGE'],bins=bins,labels=slots)
```

In [46]:
```
applicationDF['AGE_GROUP'].value_counts(normalize=True)*100
```

Out[46]:
```
50 above    31.604398
30-40       27.028952
40-50       24.194582
20-30       17.171743
0-20         0.000325
Name: AGE_GROUP, dtype: float64
```

In [47]:
```
applicationDF['YEARS_EMPLOYED']=applicationDF['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']
applicationDF['EMPLOYMENT_YEAR']=pd.cut(applicationDF['YEARS_EMPLOYED'],bins=bins,labels=slots)
```

In [48]:
```
applicationDF['EMPLOYMENT_YEAR'].value_counts(normalize=True)*100
```

Out[48]:
```
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: EMPLOYMENT_YEAR, dtype: float64
```

In [49]:
```
applicationDF.nunique().sort_values()
```

Out[49]:
```
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
EMPLOYMENT_YEAR                     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
AMT_CREDIT_RANGE                   11
AMT_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
```

In [50]:
```
applicationDF.info()
```

```
<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  AMT_INCOME_RANGE             307279 non-null  category
 47  AMT_CREDIT_RANGE             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  EMPLOYMENT_YEAR              224233 non-null  category
dtypes: category(4), float64(18), int64(18), object(12)
memory usage: 113.8+ MB
```

In [51]:
```
categorical_columns = ['NAME_CONTRACT_TYPE','CODE_GENDER','NAME_TYPE_SUITE','NAME_INCOME_TYPE','NAME_EDUCATION_TYPE',
                       'NAME_FAMILY_STATUS','NAME_HOUSING_TYPE','OCCUPATION_TYPE','WEEKDAY_APPR_PROCESS_START',
                       'ORGANIZATION_TYPE','FLAG_OWN_CAR','FLAG_OWN_REALTY','LIVE_CITY_NOT_WORK_CITY',
                       'REG_CITY_NOT_LIVE_CITY','REG_CITY_NOT_WORK_CITY','REG_REGION_NOT_WORK_REGION',
                       'LIVE_REGION_NOT_WORK_REGION','REGION_RATING_CLIENT','WEEKDAY_APPR_PROCESS_START',
                       'REGION_RATING_CLIENT_W_CITY'
                      ]
for col in categorical_columns:
    applicationDF[col]=pd.Categorical(applicationDF[col])
```

In [52]:
```
applicationDF.info()
```

```
<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  AMT_INCOME_RANGE             307279 non-null  category
 47  AMT_CREDIT_RANGE             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  EMPLOYMENT_YEAR              224233 non-null  category
dtypes: category(23), float64(18), int64(11)
memory usage: 74.8 MB
```

In [53]:
```
previousDF.nunique().sort_values()
```

Out[53]:
```
NAME_PRODUCT_TYPE               3
NAME_PAYMENT_TYPE               4
NAME_CONTRACT_TYPE              4
NAME_CLIENT_TYPE                4
NAME_CONTRACT_STATUS            4
NAME_PORTFOLIO                  5
NAME_YIELD_GROUP                5
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
```

In [54]:
```
previousDF.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
```

In [55]:
```
previousDF['DAYS_DECISION']=abs(previousDF['DAYS_DECISION'])
```

In [56]:
```
previousDF['DAYS_DECISION_GROUP'] = (previousDF['DAYS_DECISION']-(previousDF['DAYS_DECISION'] % 400)).astype(str)+'-'+ ((previo
```

In [57]:
```
previousDF['DAYS_DECISION_GROUP'].value_counts(normalize=True)*100
```

Out[57]:
```
0-400        37.490525
400-800      22.944724
800-1200     12.444753
1200-1600     7.904556
2400-2800     6.297456
1600-2000     5.795784
2000-2400     5.684960
2800-3200     1.437241
Name: DAYS_DECISION_GROUP, dtype: float64
```

In [58]:
```
Catgorical_col_p = ['NAME_CASH_LOAN_PURPOSE','NAME_CONTRACT_STATUS','NAME_PAYMENT_TYPE',
                    'CODE_REJECT_REASON','NAME_CLIENT_TYPE','NAME_GOODS_CATEGORY','NAME_PORTFOLIO',
                   'NAME_PRODUCT_TYPE','CHANNEL_TYPE','NAME_SELLER_INDUSTRY','NAME_YIELD_GROUP','PRODUCT_COMBINATION',
                    'NAME_CONTRACT_TYPE','DAYS_DECISION_GROUP']
for col in Catgorical_col_p:
    previousDF[col] =pd.Categorical(previousDF[col])
```

In [59]:
```
previousDF.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
```

In [60]:
```
round(applicationDF.isnull().sum()/applicationDF.shape[0]*100.00,2)
```

Out[60]:
```
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
AMT_INCOME_RANGE               0.08
AMT_CREDIT_RANGE               0.00
AGE                            0.00
AGE_GROUP                      0.00
YEARS_EMPLOYED                 0.00
EMPLOYMENT_YEAR               27.08
dtype: float64
```

In [61]:
```
applicationDF['NAME_TYPE_SUITE'].describe()
```

Out[61]:
```
count            306219
unique                7
top       Unaccompanied
freq             248526
Name: NAME_TYPE_SUITE, dtype: object
```

In [62]:
```
applicationDF['NAME_TYPE_SUITE'].fillna((applicationDF['NAME_TYPE_SUITE'].mode()[0]),inplace=True)
```

In [63]:
```
applicationDF['OCCUPATION_TYPE']=applicationDF['OCCUPATION_TYPE'].cat.add_categories('UNKNOWN')
applicationDF['OCCUPATION_TYPE'].fillna('UNKNOWN',inplace=True)
```

In [64]:
```
applicationDF[['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']].describe()
```

Out[64]:

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ
count	265992.000000	265992.000000	265992.000000	265992.000000	
mean	0.006402	0.007000	0.034362	0.267395	
std	0.083849	0.110757	0.204685	0.916002	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	0.000000	0.000000	0.000000	0.000000	
max	4.000000	9.000000	8.000000	27.000000	

In [65]:
```
amount=['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']
for col in amount:
    applicationDF[col].fillna(applicationDF[col].median(),inplace=True)
```

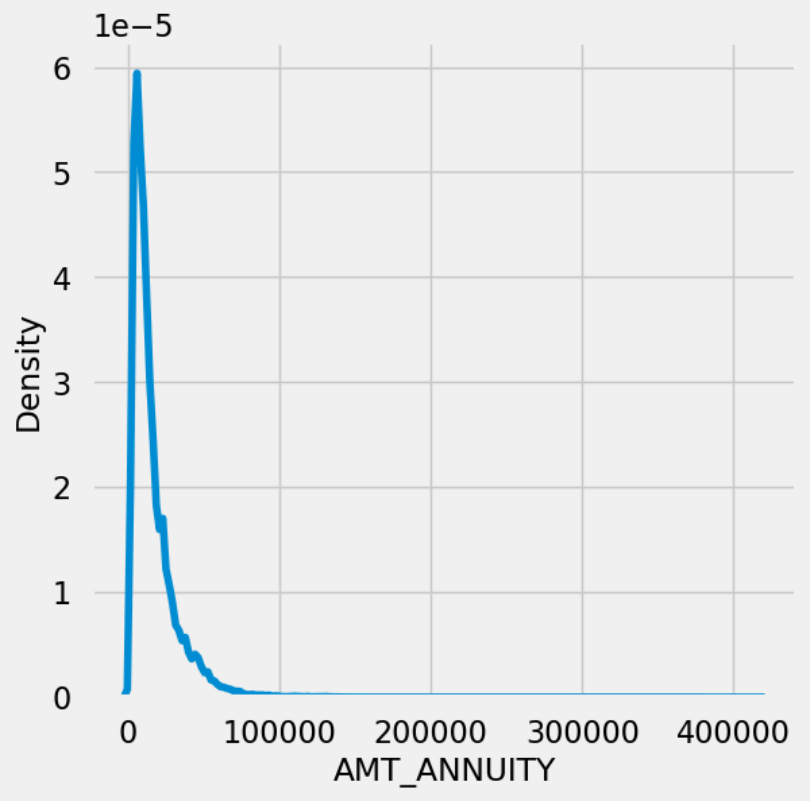
In [66]:
```
round(applicationDF.isnull().sum()/previousDF.shape[0]*100.00,2)
```

Out[66]:
```
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                0.02
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       0.06
DEF_30_CNT_SOCIAL_CIRCLE       0.06
OBS_60_CNT_SOCIAL_CIRCLE       0.06
DEF_60_CNT_SOCIAL_CIRCLE       0.06
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
AMT_INCOME_RANGE               0.01
AMT_CREDIT_RANGE               0.00
AGE                            0.00
AGE_GROUP                      0.00
YEARS_EMPLOYED                 0.00
EMPLOYMENT_YEAR                4.99
dtype: float64
```

In [67]:
```
round(previousDF.isnull().sum()/previousDF.shape[0]*100.00,2)
```

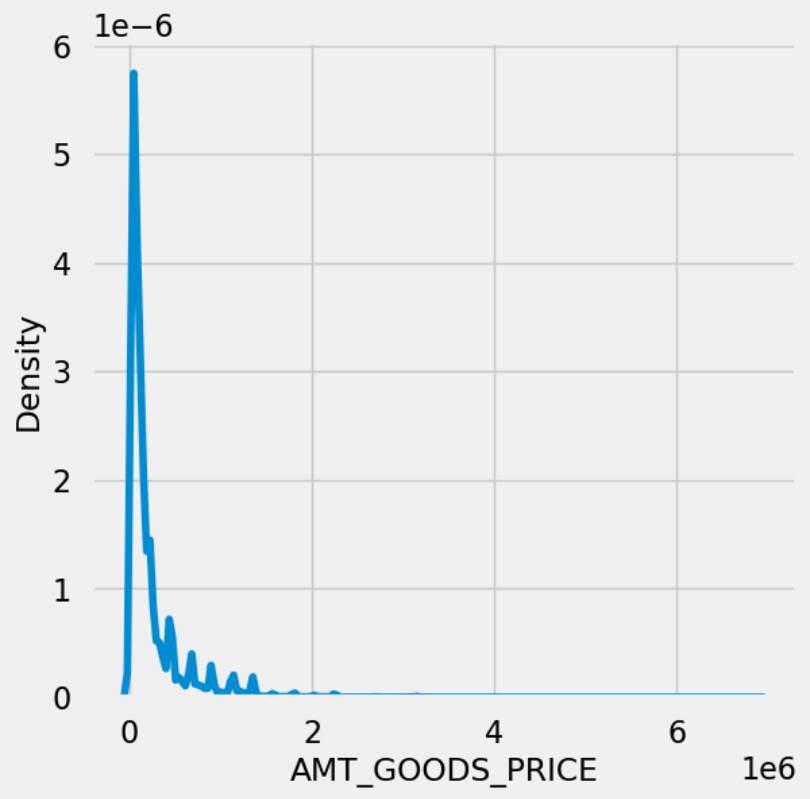
Out[67]:
```
SK_ID_PREV                 0.00
SK_ID_CURR                 0.00
NAME_CONTRACT_TYPE         0.00
AMT_ANNUITY               22.29
AMT_APPLICATION            0.00
AMT_CREDIT                 0.00
AMT_GOODS_PRICE           23.08
NAME_CASH_LOAN_PURPOSE     0.00
NAME_CONTRACT_STATUS       0.00
DAYS_DECISION              0.00
NAME_PAYMENT_TYPE          0.00
CODE_REJECT_REASON         0.00
NAME_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_DECISION_GROUP        0.00
dtype: float64
```

In [68]:
```
plt.figure(figsize=(6,6))
sns.kdeplot(previousDF['AMT_ANNUITY'])
plt.show()
```

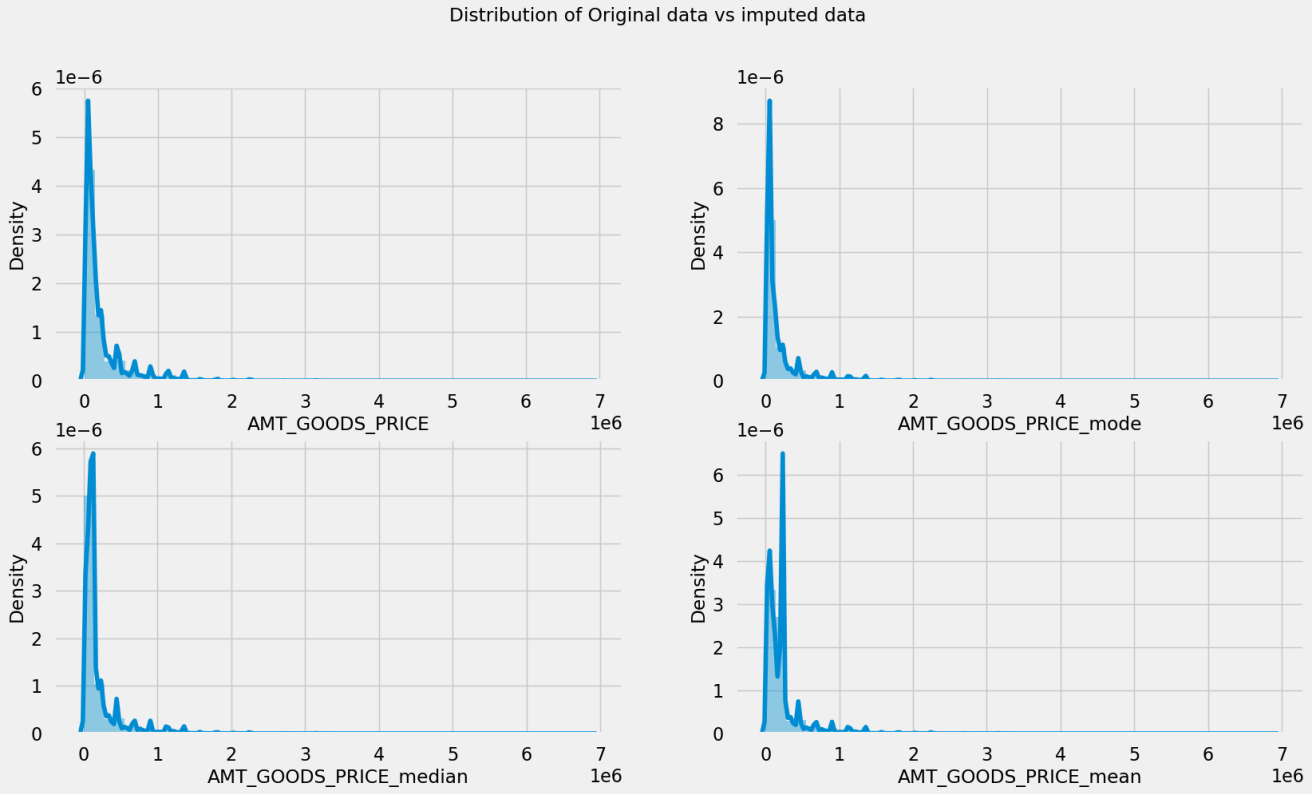


In [69]:
```
previousDF['AMT_ANNUITY'].fillna(previousDF['AMT_ANNUITY'].median(),inplace=True)
```

In [70]:
```
plt.figure(figsize=(6,6))
sns.kdeplot(previousDF['AMT_GOODS_PRICE'][pd.notnull(previousDF['AMT_GOODS_PRICE'])])
plt.show()
```



In [71]:
```
statsDF = pd.DataFrame()
statsDF['AMT_GOODS_PRICE_mode'] = previousDF['AMT_GOODS_PRICE'].fillna(previousDF['AMT_GOODS_PRICE'].mode()[0])
statsDF['AMT_GOODS_PRICE_median'] = previousDF['AMT_GOODS_PRICE'].fillna(previousDF['AMT_GOODS_PRICE'].median())
statsDF['AMT_GOODS_PRICE_mean'] = previousDF['AMT_GOODS_PRICE'].fillna(previousDF['AMT_GOODS_PRICE'].mean())

cols = ['AMT_GOODS_PRICE_mode', 'AMT_GOODS_PRICE_median','AMT_GOODS_PRICE_mean']

plt.figure(figsize=(18,10))
plt.suptitle('Distribution of Original data vs imputed data')
plt.subplot(221)
sns.distplot(previousDF['AMT_GOODS_PRICE'][pd.notnull(previousDF['AMT_GOODS_PRICE'])]);
for i in enumerate(cols):
    plt.subplot(2,2,i[0]+2)
    sns.distplot(statsDF[i[1]])
```



In [72]:
```
previousDF['AMT_GOODS_PRICE'].fillna(previousDF['AMT_GOODS_PRICE'].mode()[0],inplace=True)
```

In [73]:
```
previousDF.loc[previousDF['CNT_PAYMENT'].isnull(),'NAME_CONTRACT_STATUS'].value_counts()
```

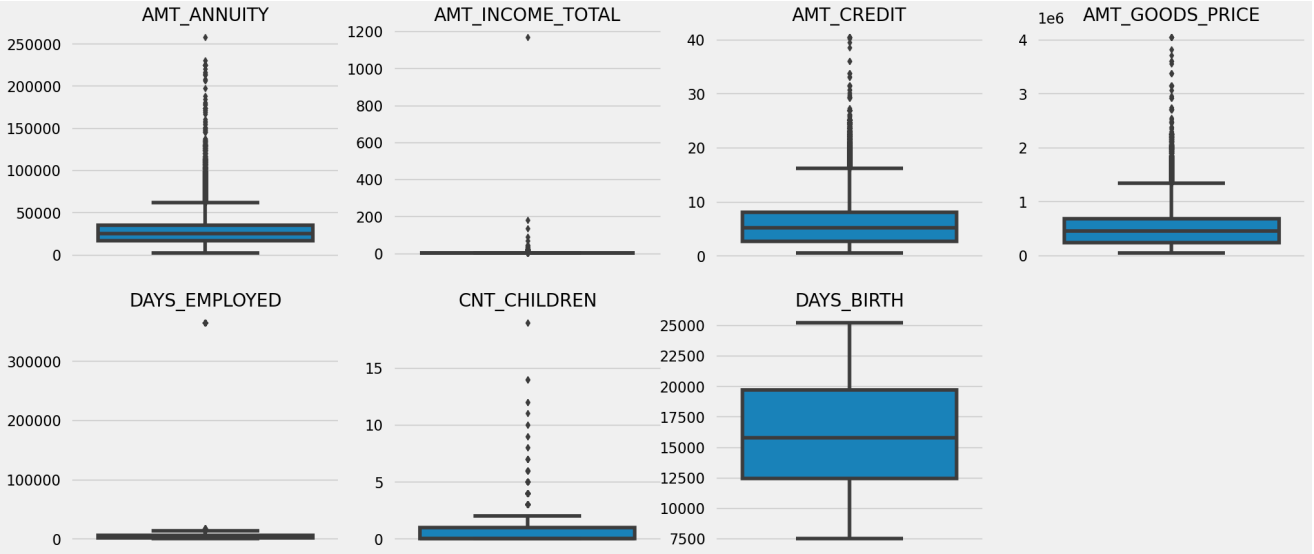
Out[73]:
```
Canceled        305805
Refused          40897
Unused offer     25524
Approved             4
Name: NAME_CONTRACT_STATUS, dtype: int64
```

In [74]:
```
previousDF['CNT_PAYMENT'].fillna(0,inplace=True)
```

In [75]:
```
round(previousDF.isnull().sum()/previousDF.shape[0]*100.00,2)
```

Out[75]:
```
SK_ID_PREV                0.00
SK_ID_CURR                0.00
NAME_CONTRACT_TYPE        0.00
AMT_ANNUITY               0.00
AMT_APPLICATION           0.00
AMT_CREDIT                0.00
AMT_GOODS_PRICE           0.00
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_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               0.00
NAME_YIELD_GROUP          0.00
PRODUCT_COMBINATION       0.02
DAYS_DECISION_GROUP       0.00
dtype: float64
```

In [76]:
```
plt.figure(figsize=(22,10))

app_outlier_col_1=['AMT_ANNUITY','AMT_INCOME_TOTAL','AMT_CREDIT','AMT_GOODS_PRICE','DAYS_EMPLOYED']
app_outlier_col_2=['CNT_CHILDREN','DAYS_BIRTH']
for i in enumerate(app_outlier_col_1):
    plt.subplot(2,4,i[0]+1)
    sns.boxplot(y=applicationDF[i[1]])
    plt.title(i[1])
    plt.ylabel("")

for i in enumerate(app_outlier_col_2):
    plt.subplot(2,4,i[0]+6)
    sns.boxplot(y=applicationDF[i[1]])
    plt.title(i[1])
    plt.ylabel("")
```

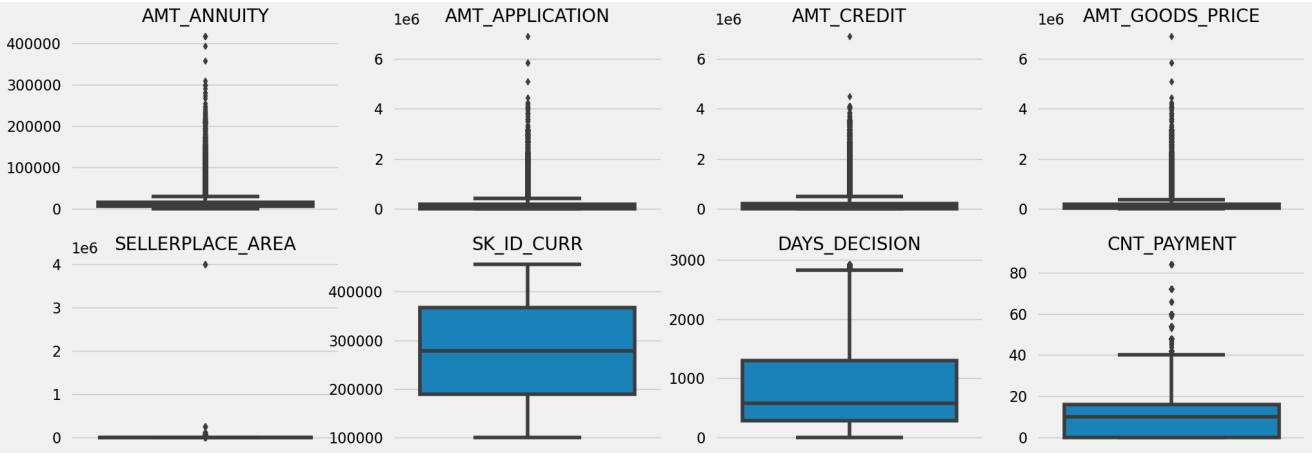


In [77]:
```
nDF[['AMT_ANNUITY', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_GOODS_PRICE', 'DAYS_BIRTH','CNT_CHILDREN','DAYS_EMPLOYED']].describe(
```

Out[77]:

	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

In [78]:
```
plt.figure(figsize=(22,8))

prev_outlier_col_1 = ['AMT_ANNUITY','AMT_APPLICATION','AMT_CREDIT','AMT_GOODS_PRICE','SELLERPLACE_AREA']
prev_outlier_col_2 = ['SK_ID_CURR','DAYS_DECISION','CNT_PAYMENT']
for i in enumerate(prev_outlier_col_1):
    plt.subplot(2,4,i[0]+1)
    sns.boxplot(y=previousDF[i[1]])
    plt.title(i[1])
    plt.ylabel("")

for i in enumerate(prev_outlier_col_2):
    plt.subplot(2,4,i[0]+6)
    sns.boxplot(y=previousDF[i[1]])
    plt.title(i[1])
    plt.ylabel("")
```

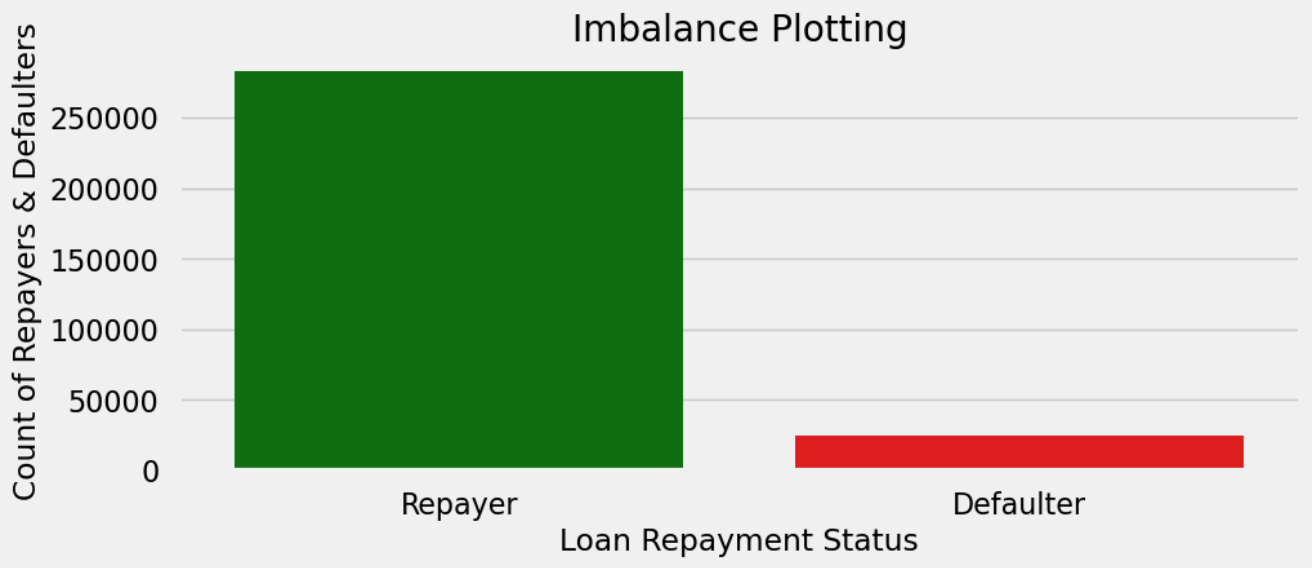


In [79]:
```
previousDF[['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_GOODS_PRICE', 'SELLERPLACE_AREA','CNT_PAYMENT','DAYS_DECISION'
```

Out[79]:

	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

In [80]:
```
Imbalance = applicationDF["TARGET"].value_counts().reset_index()

plt.figure(figsize=(10,4))
x= ['Repayer','Defaulter']
sns.barplot(x,"TARGET",data = Imbalance,palette= ['g','r'])
plt.xlabel("Loan Repayment Status")
plt.ylabel("Count of Repayers & Defaulters")
plt.title("Imbalance Plotting")
plt.show()
```



In [81]:
```
count_0 = Imbalance.iloc[0]["TARGET"]
count_1 = Imbalance.iloc[1]["TARGET"]
count_0_perc = round(count_0/(count_0+count_1)*100,2)
count_1_perc = round(count_1/(count_0+count_1)*100,2)

print('Ratios of imbalance in percentage with respect to Repayer and Defaulter datas are: %.2f and %.2f'%(count_0_perc,count_1_
print('Ratios of imbalance in relative with respect to Repayer and Defaulter datas is %.2f : 1 (approx)'%(count_0/count_1))
```

```
Ratios of imbalance in percentage with respect to Repayer and Defaulter datas are: 91.93 and 8.07
Ratios of imbalance in relative with respect to Repayer and Defaulter datas is 11.39 : 1 (approx)
```

In [82]:
```
def univariate_categorical(feature,ylog=False,label_rotation=False,horizontal_layout=True):
    temp = applicationDF[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 = applicationDF[[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=applicationDF,
                      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();
```

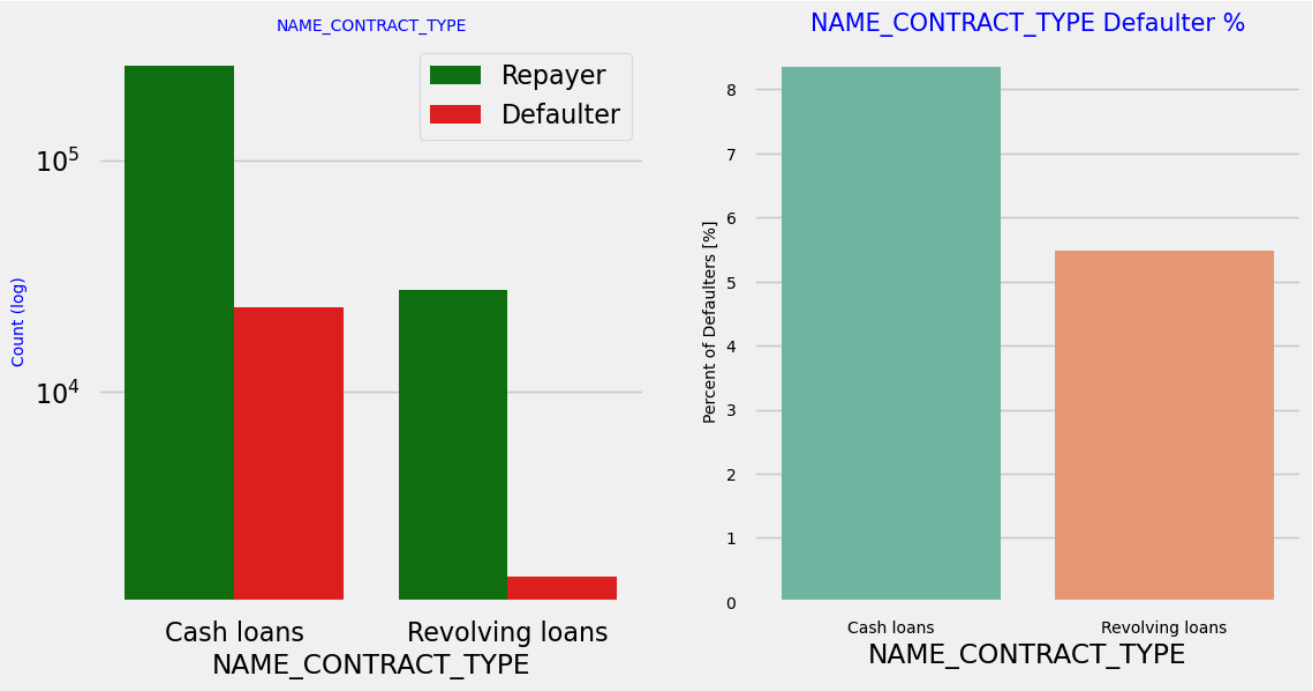
In [83]:
```
def bivariate_bar(x,y,df,hue,figsize):

    plt.figure(figsize=figsize)
    sns.barplot(x=x,
                y=y,
                data=df,
                hue=hue,
                palette =['g','r'])

    # Defining aesthetics of Labels and Title of the plot using style dictionaries
    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()
```

In [84]:
```
def bivariate_rel(x,y,data, hue, kind, palette, legend,figsize):

    plt.figure(figsize=figsize)
    sns.relplot(x=x,
                y=y,
                data=applicationDF,
                hue="TARGET",
                kind=kind,
                palette = ['g','r'],
                legend = False)
    plt.legend(['Repayer','Defaulter'])
    plt.xticks(rotation=90, ha='right')
    plt.show()
```

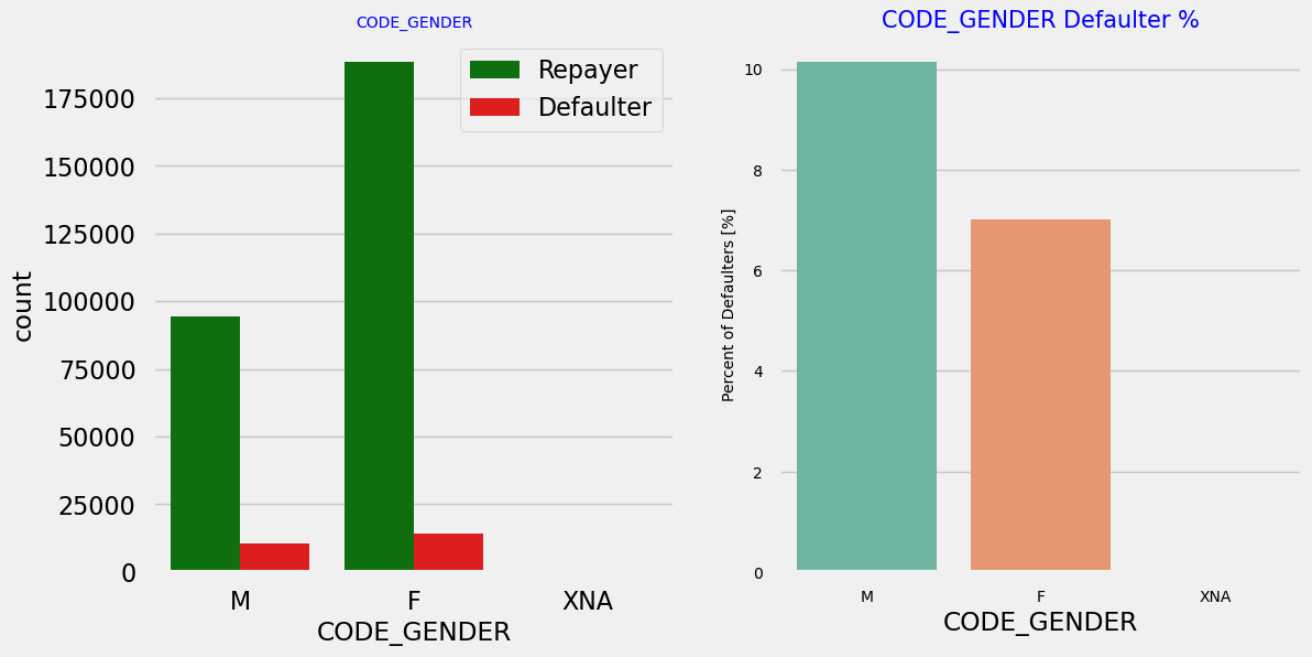
In [85]:
```
def univariate_merged(col,df,hue,palette,ylog,figsize):
    plt.figure(figsize=figsize)
    ax=sns.countplot(x=col,
                  data=df,
                  hue= hue,
                  palette= palette,
                  order=df[col].value_counts().index)


    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()
```

In [86]:
```
def merged_pointplot(x,y):
    plt.figure(figsize=(8,4))
    sns.pointplot(x=x,
                  y=y,
                  hue="TARGET",
                  data=loan_process_df,
                  palette =['g','r'])
```

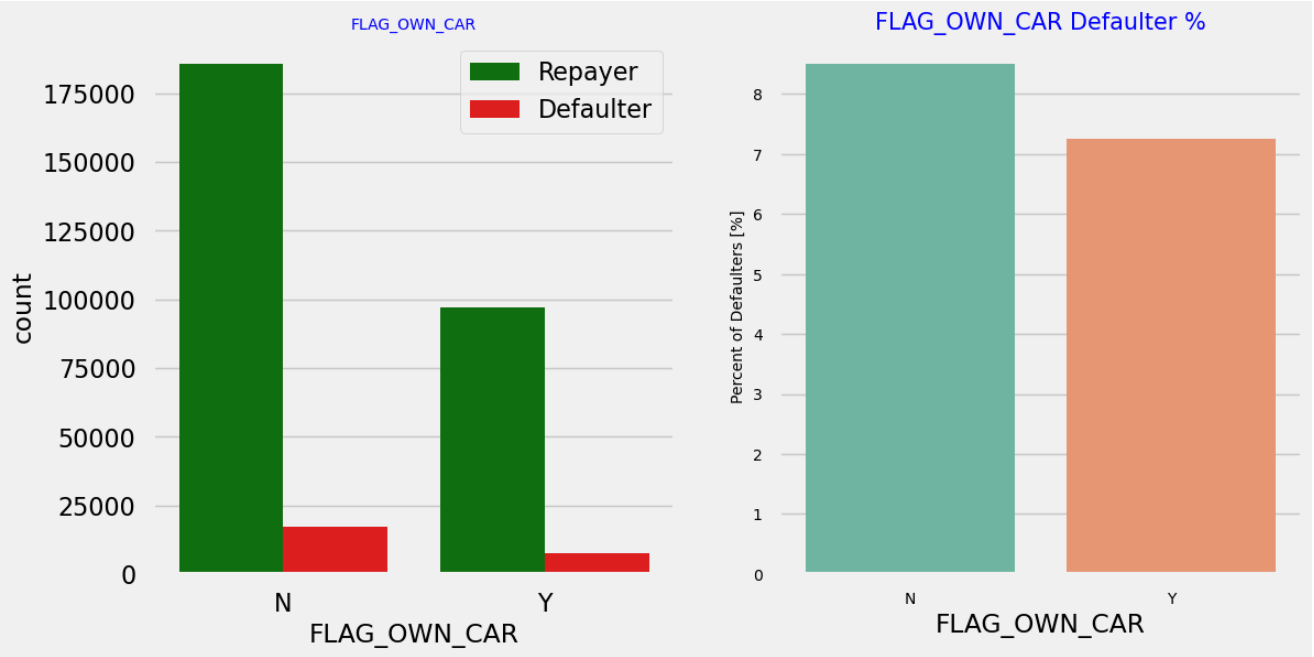
In [87]:
```
univariate_categorical('NAME_CONTRACT_TYPE',True)
```



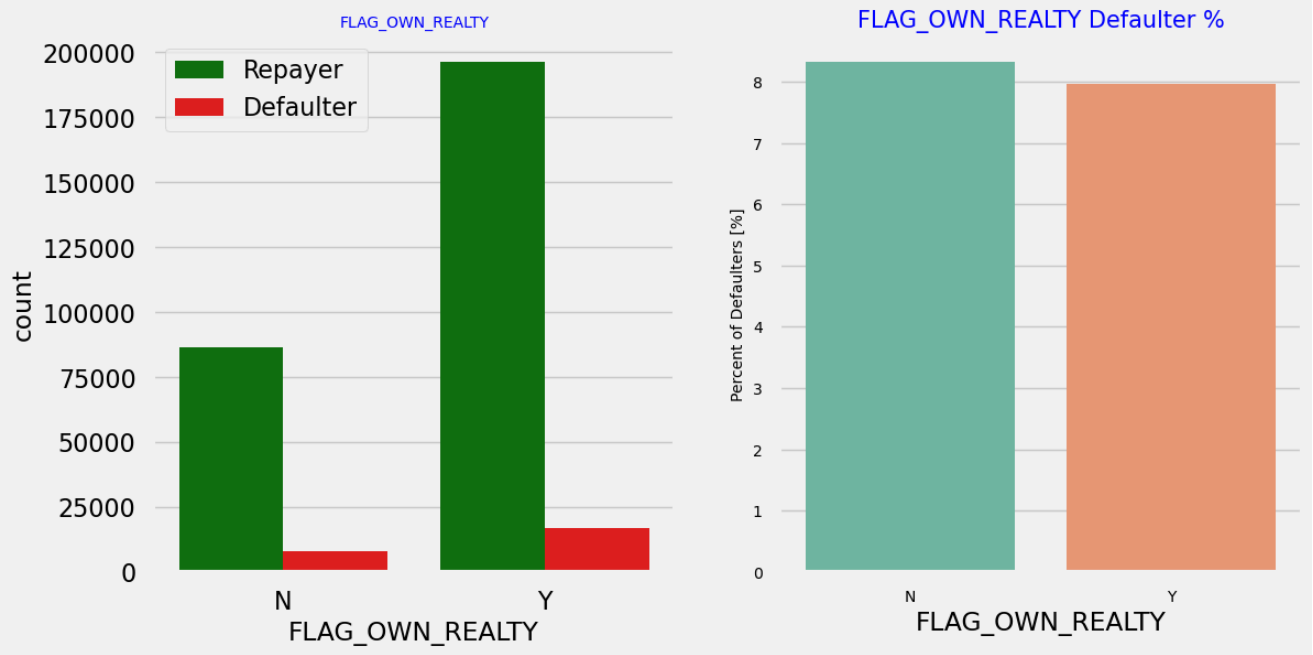
In [88]:
```
univariate_categorical('CODE_GENDER')
```



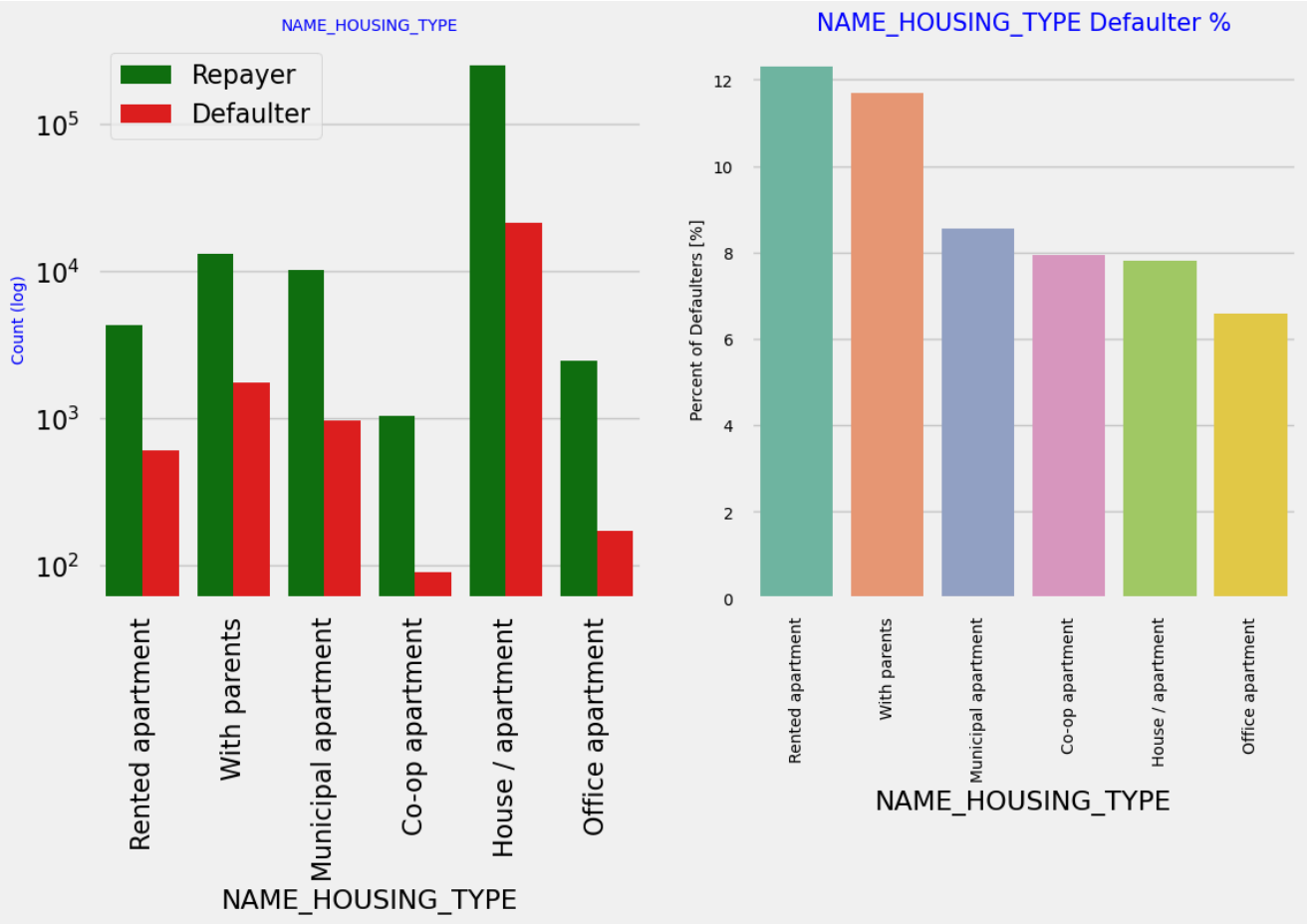
In [89]:
```
univariate_categorical('FLAG_OWN_CAR')
```



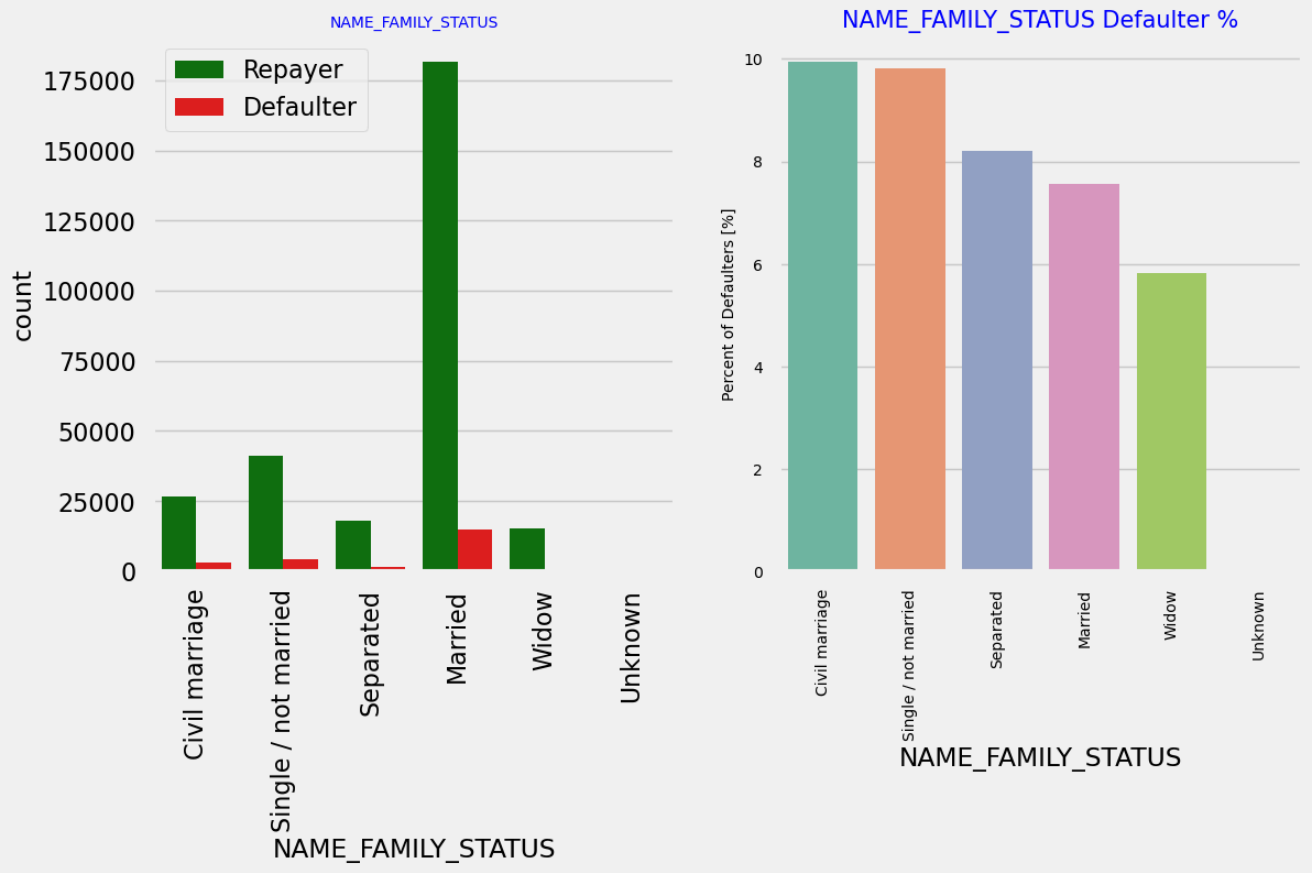
In [90]:
```
univariate_categorical('FLAG_OWN_REALTY')
```



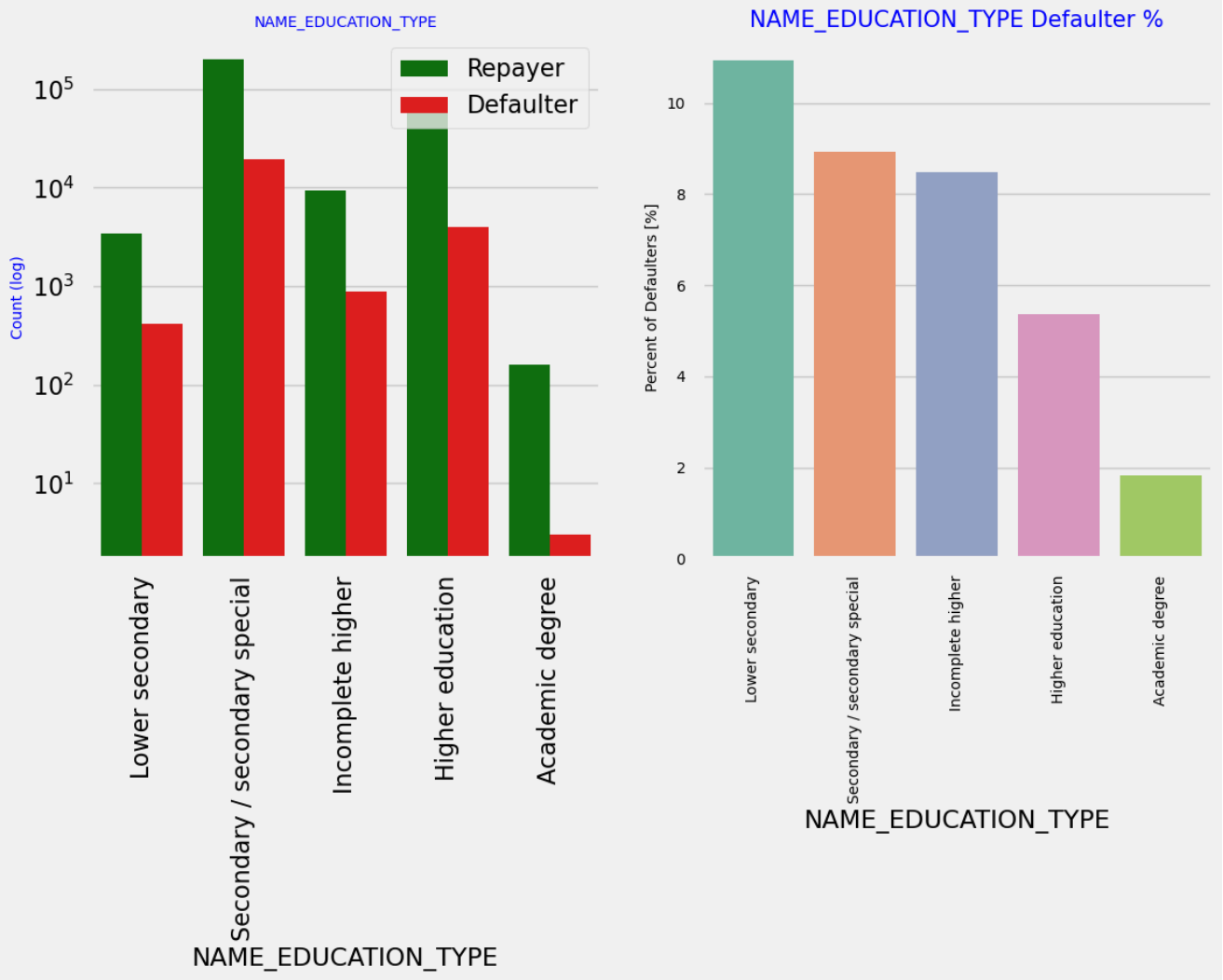
In [91]:
```
univariate_categorical("NAME_HOUSING_TYPE",True,True,True)
```



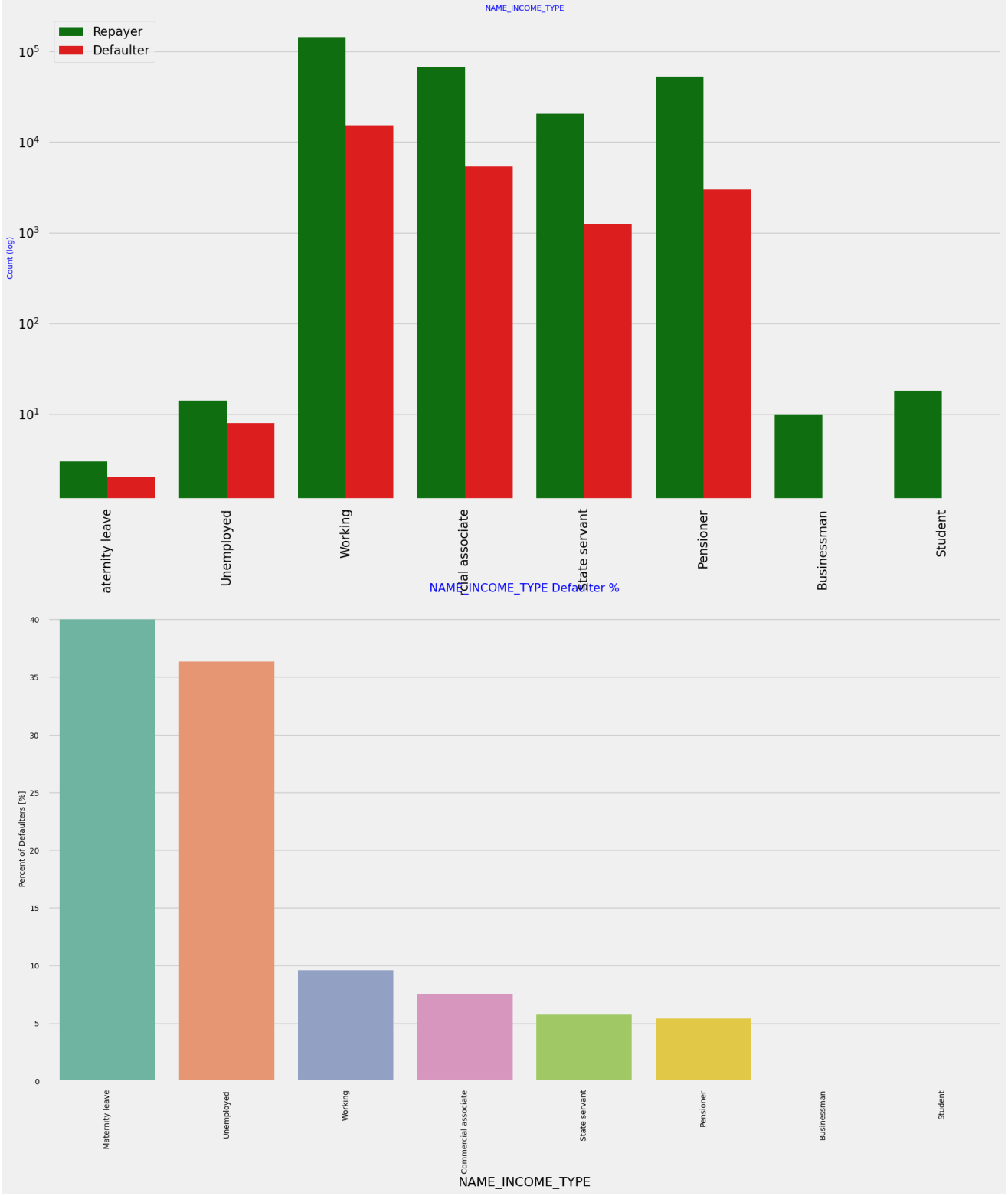
In [92]:
```
univariate_categorical("NAME_FAMILY_STATUS",False,True,True)
```



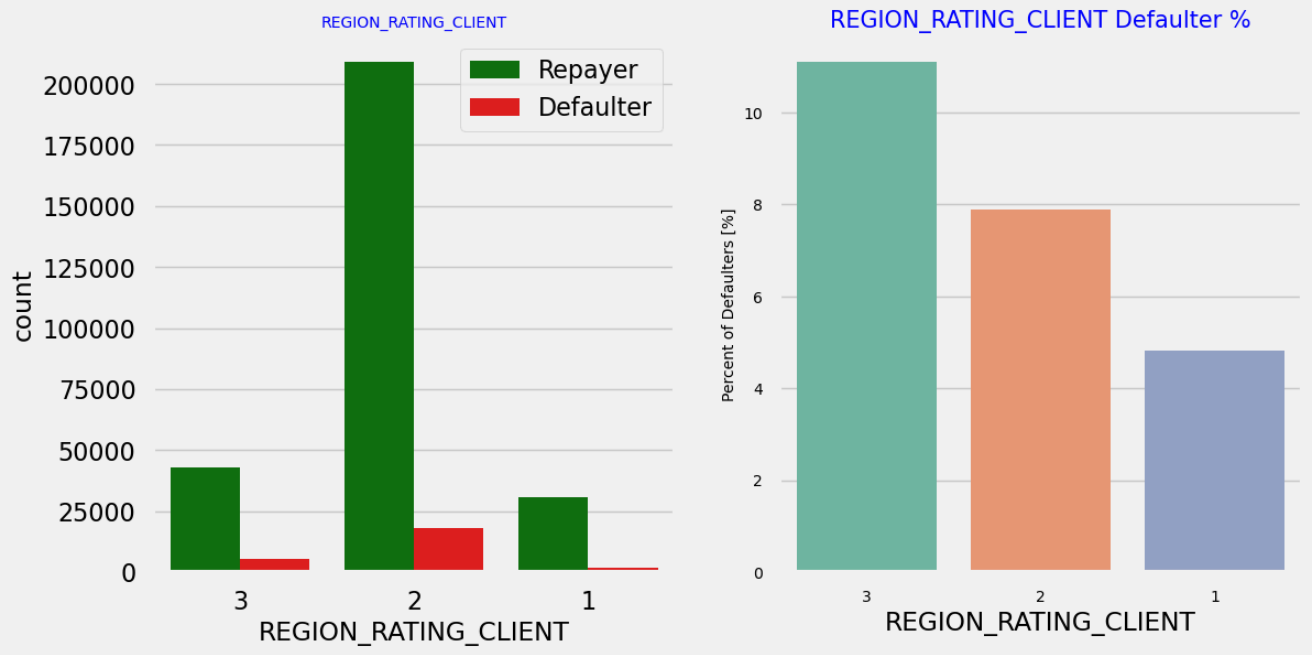
In [93]:
```
univariate_categorical("NAME_EDUCATION_TYPE",True,True,True)
```



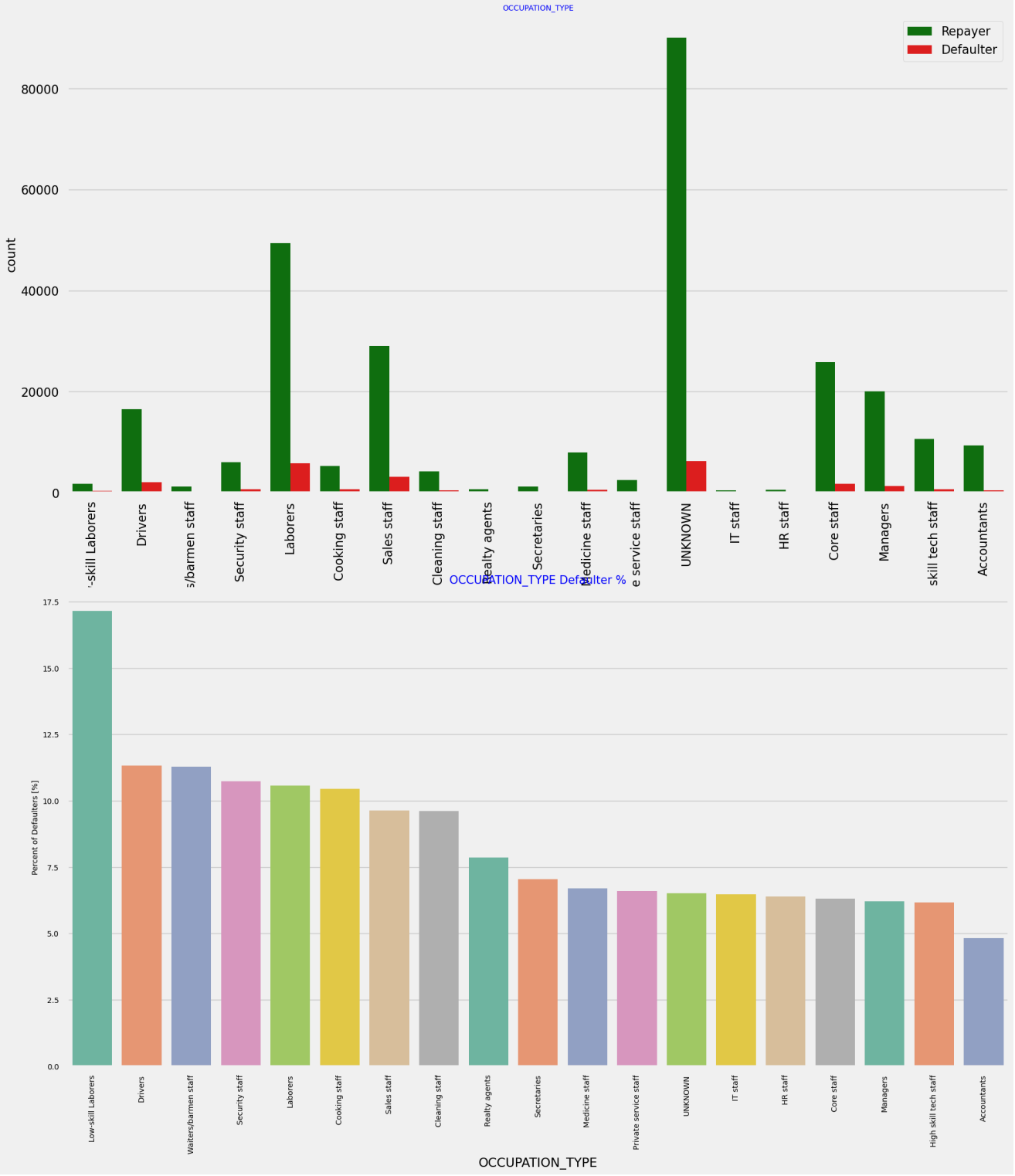
In [94]:
```
univariate_categorical("NAME_INCOME_TYPE",True,True,False)
```



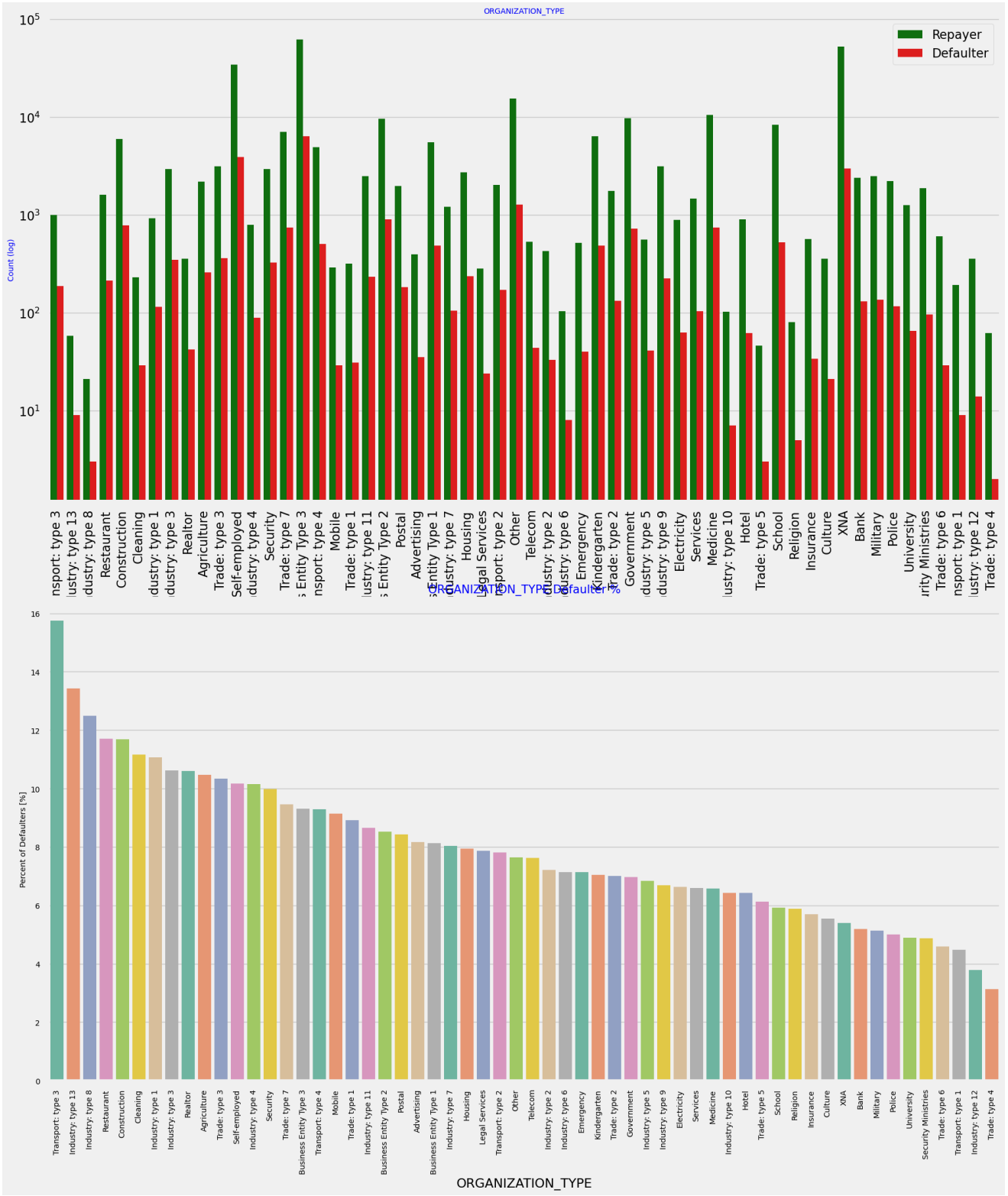
In [95]:
```
univariate_categorical("REGION_RATING_CLIENT",False,False,True)
```



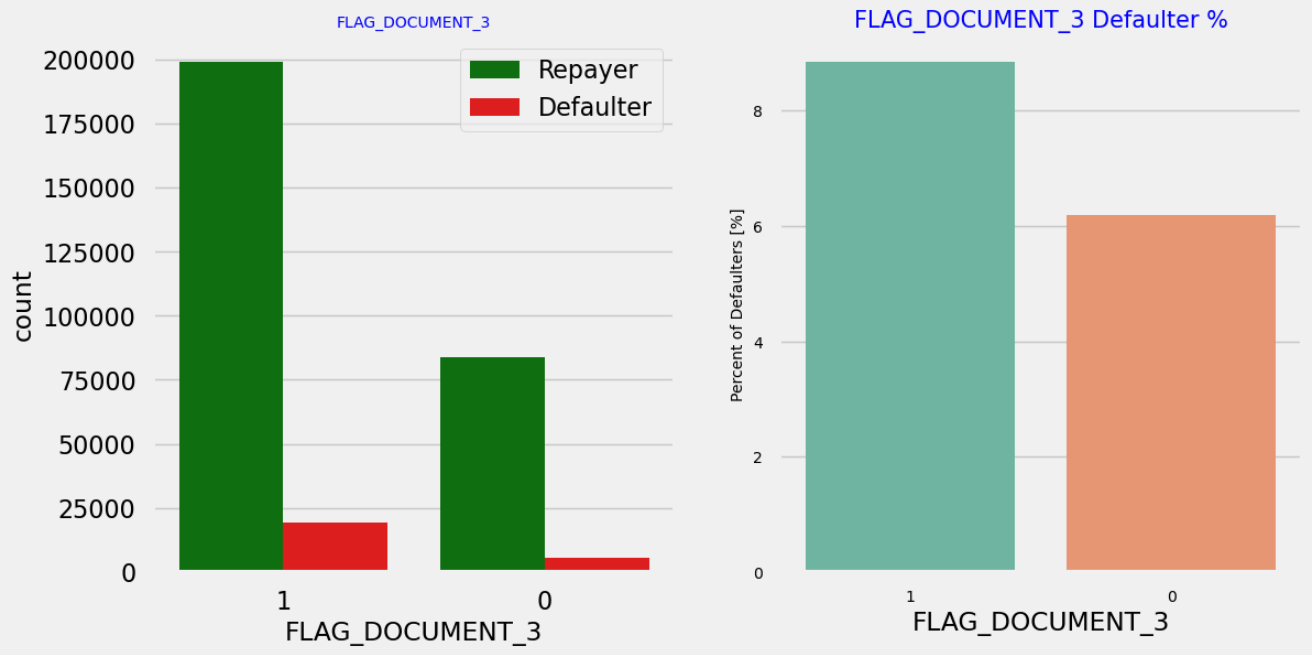
In [96]:
```
univariate_categorical("OCCUPATION_TYPE",False,True,False)
```



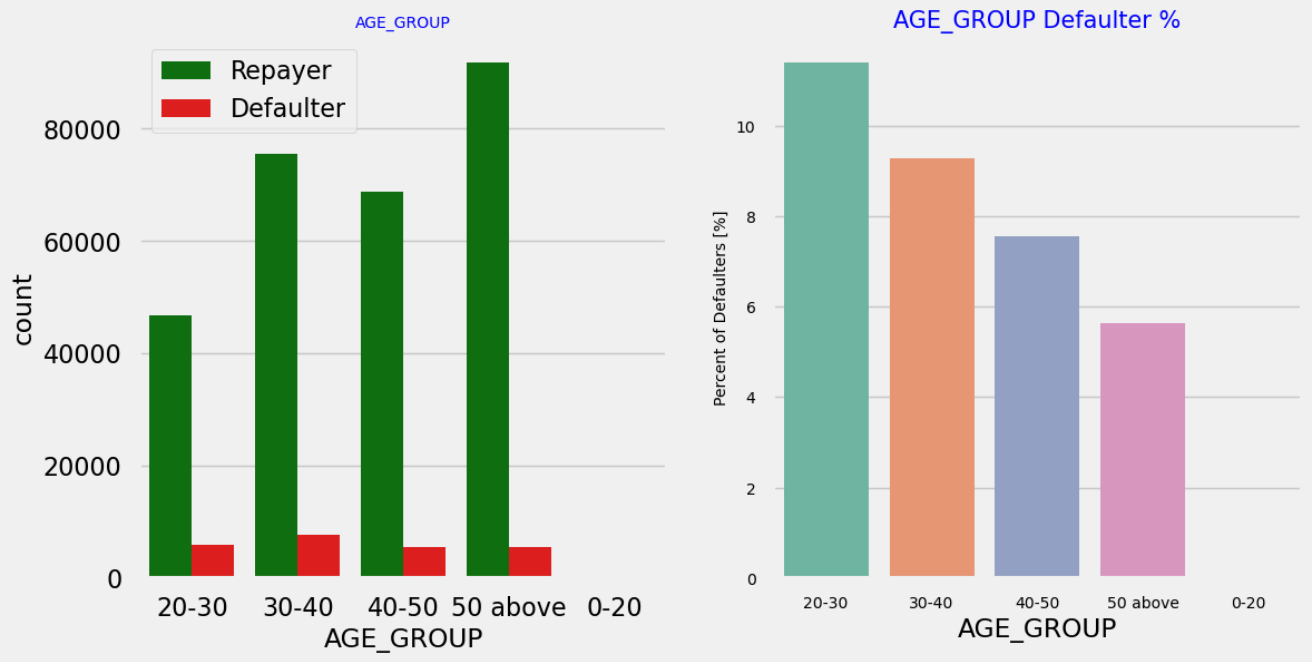
In [97]:
```
univariate_categorical("ORGANIZATION_TYPE",True,True,False)
```



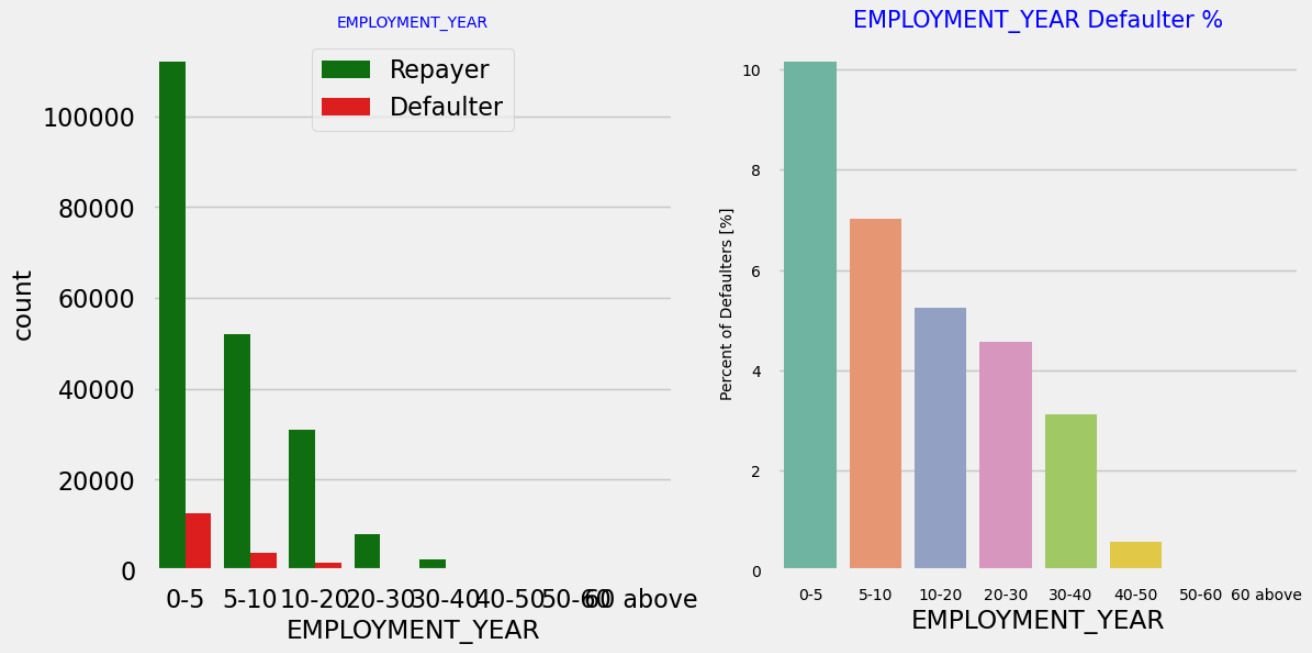
In [98]:
```
univariate_categorical("FLAG_DOCUMENT_3",False,False,True)
```



In [99]:
```
univariate_categorical("AGE_GROUP",False,False,True)
```

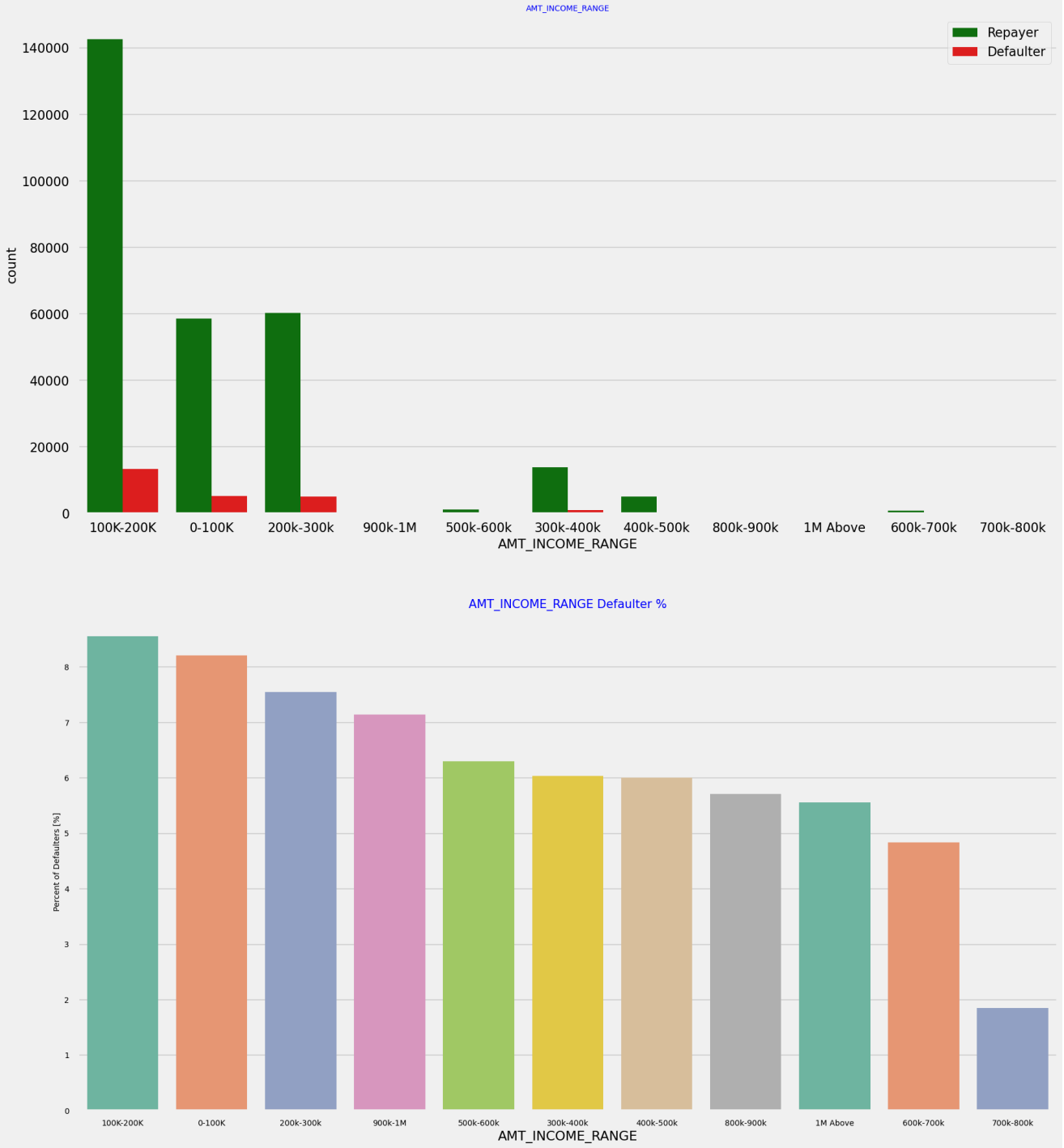


In [100]:
```
univariate_categorical("EMPLOYMENT_YEAR",False,False,True)
```

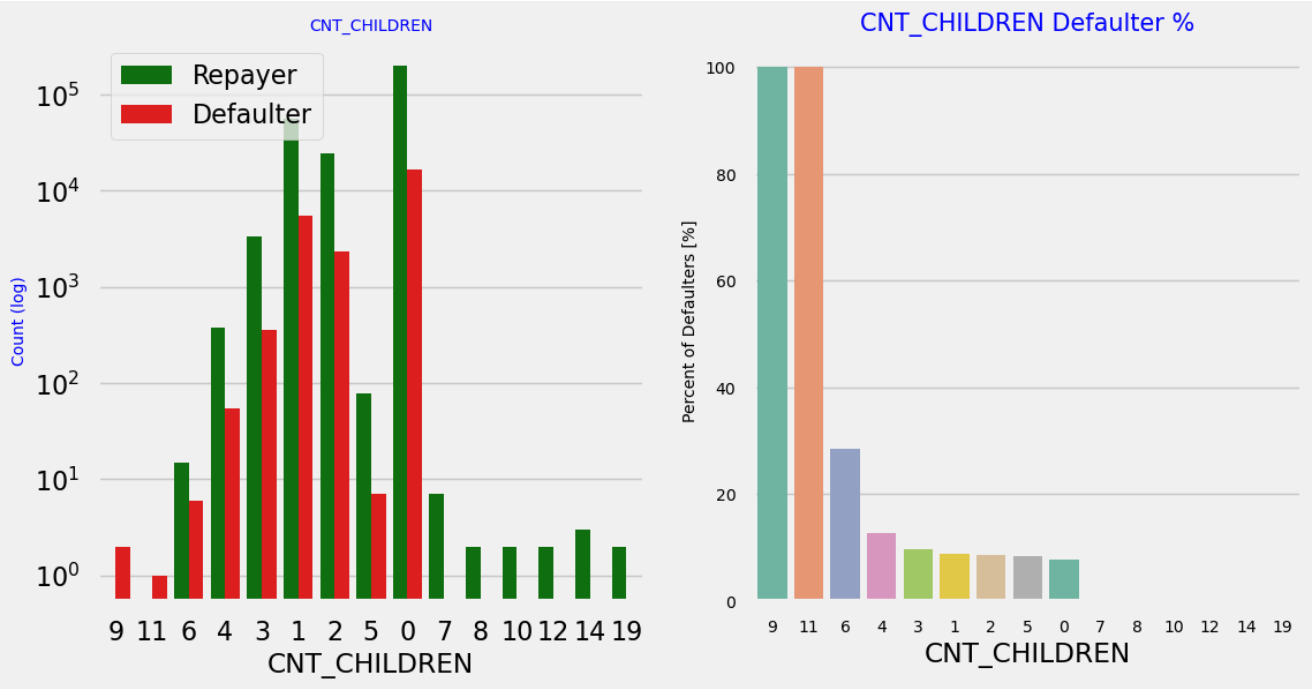


In [101]:
```
univariate_categorical("AMT_CREDIT_RANGE",False,False,False)
```

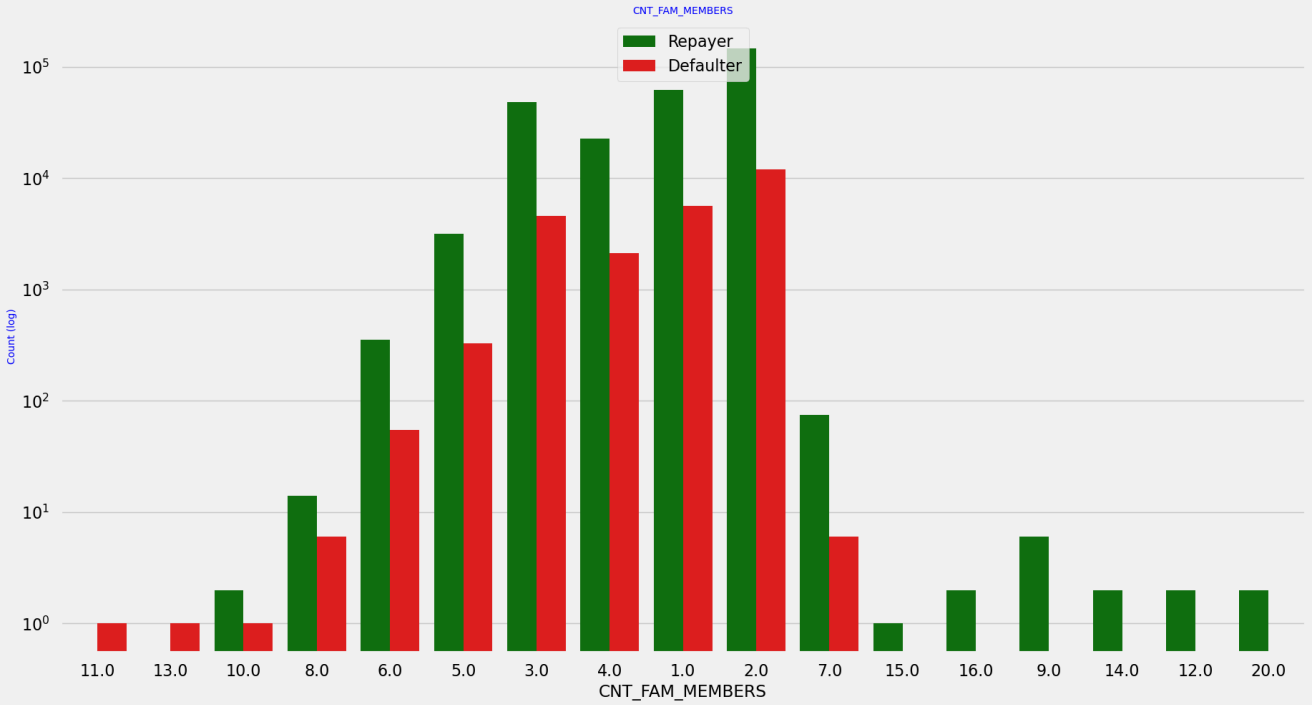
In [102]:
```
univariate_categorical("AMT_INCOME_RANGE",False,False,False)
```

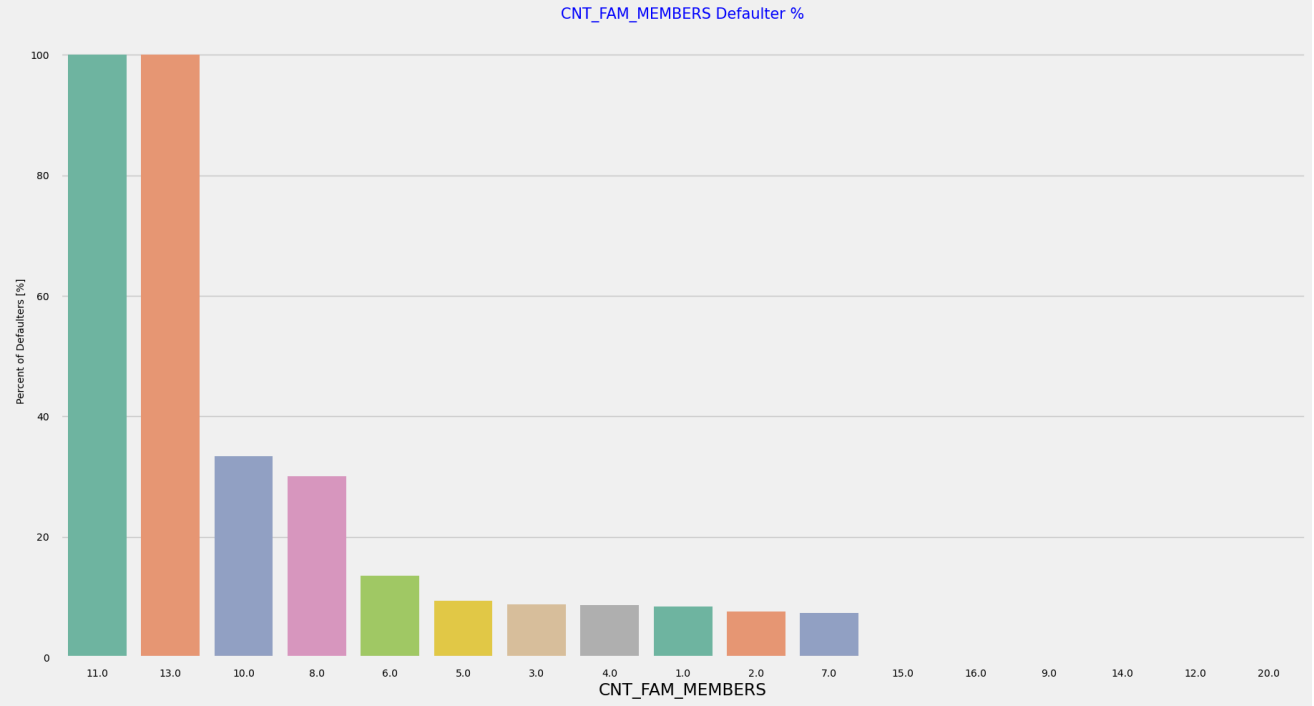


In [103]:
```
univariate_categorical("CNT_CHILDREN",True)
```



In [104]:
```
univariate_categorical("CNT_FAM_MEMBERS",True, False, False)
```



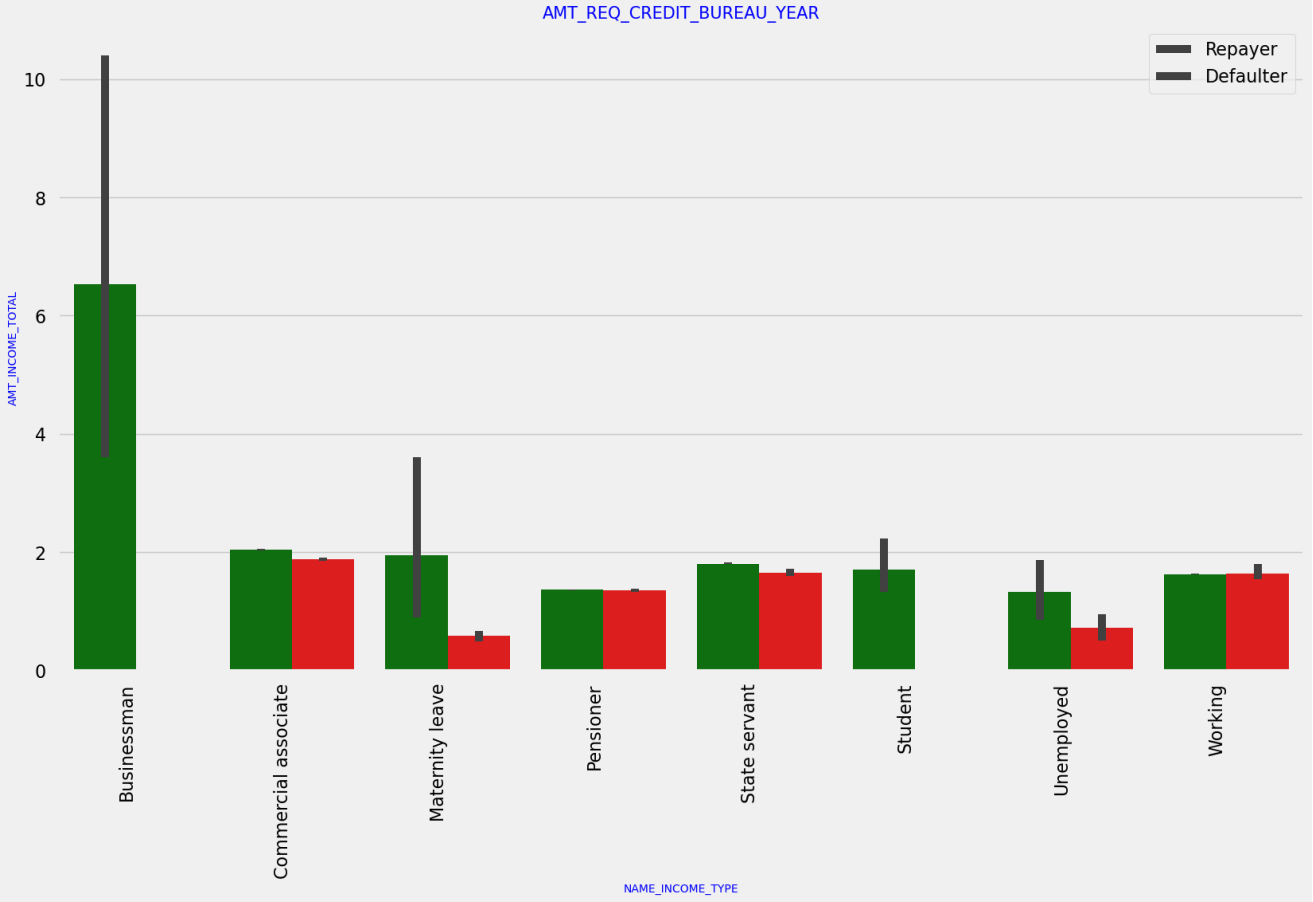


In [105]:
```
applicationDF.groupby('NAME_INCOME_TYPE')['AMT_INCOME_TOTAL'].describe()
```

Out[105]:

NAME_INCOME_TYPE	count	mean	std	min	25%	50%	75%	max
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

In [106]:
```
bivariate_bar("NAME_INCOME_TYPE","AMT_INCOME_TOTAL",applicationDF,"TARGET",(18,10))
```



In [107]:
```
applicationDF.columns
```

Out[107]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_IN
COME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NA
ME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAY
S_ID_PUBLISH', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROC
ESS_START', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGIO
N', 'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'OBS_30_CNT_SOCIAL_CIR
CLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCU
MENT_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', 'AMT_INCOME_RANGE', 'AMT_CREDIT
_RANGE', 'AGE', 'AGE_GROUP', 'YEARS_EMPLOYED', 'EMPLOYMENT_YEAR'],
      dtype='object')
```

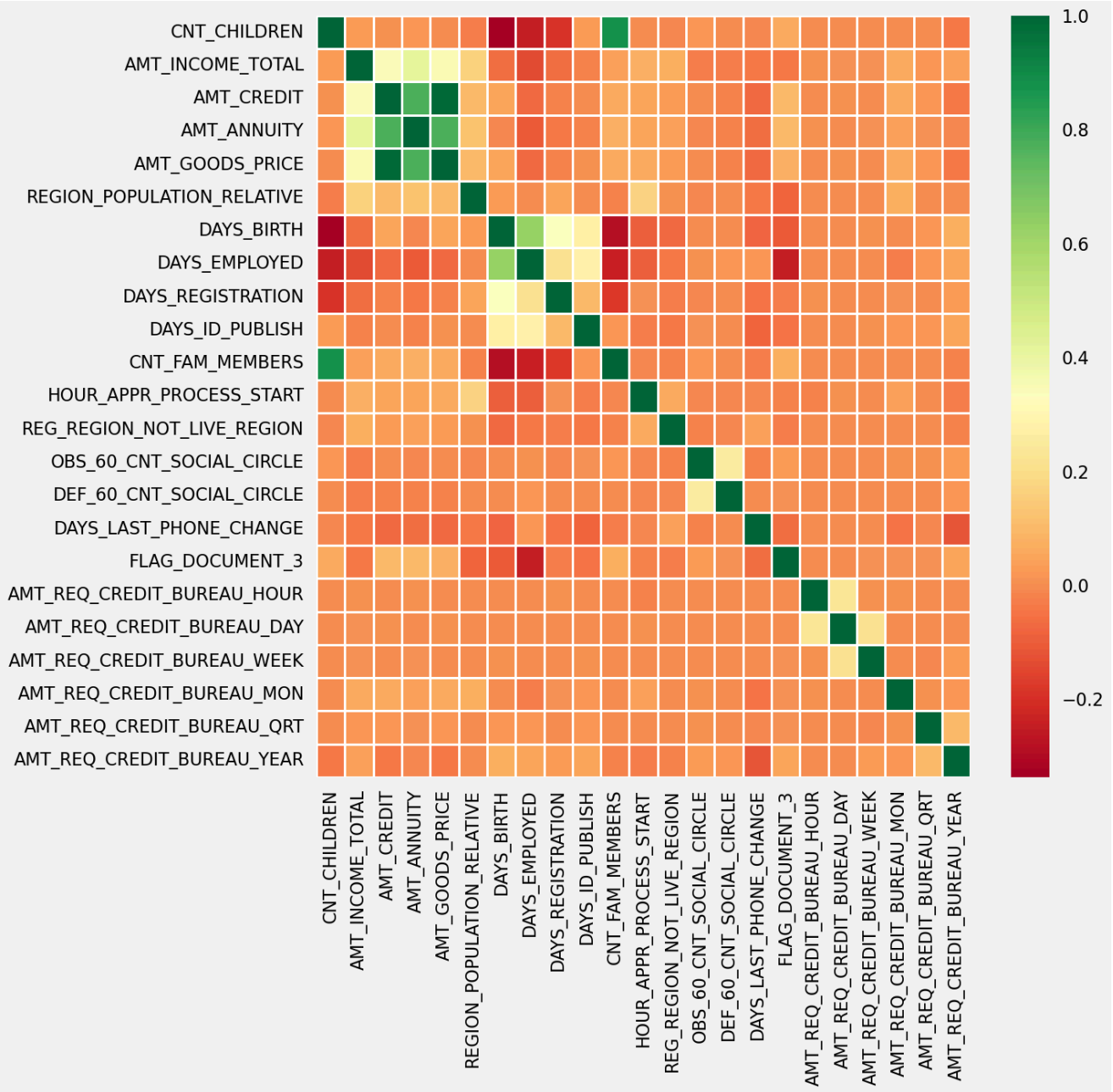
In [108]:
```
cols_for_correlation = ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY',
                        'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
                        'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', '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_df = applicationDF.loc[applicationDF['TARGET']==0, cols_for_correlation] # Repayers
Defaulter_df = applicationDF.loc[applicationDF['TARGET']==1, cols_for_correlation] # Defaulters
```

In [111]:
```
# Getting the top 10 correlation for the Repayers data
corr_repayer = Repayer_df.corr()
corr_repayer = corr_repayer.where(np.triu(np.ones(corr_repayer.shape),k=1).astype(bool))
corr_df_repayer = corr_repayer.unstack().reset_index()
corr_df_repayer.columns =['VAR1','VAR2','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)
```

Out[111]:

	VAR1	VAR2	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

In [112]:
```
fig = plt.figure(figsize=(12,12))
ax = sns.heatmap(Repayer_df.corr(), cmap="RdYlGn",annot=False,linewidth =1)
```

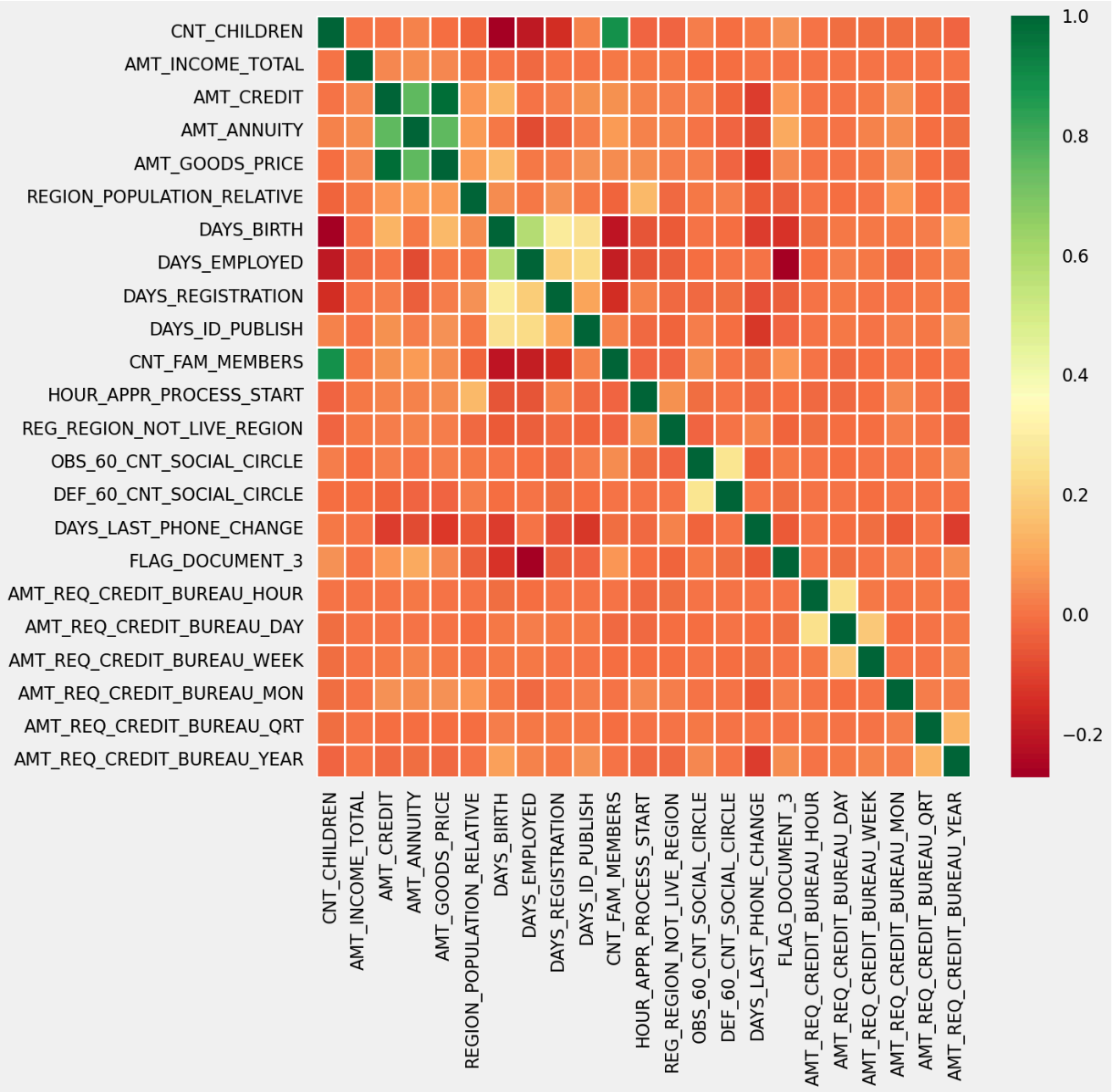


In [114]:
```
# Getting the top 10 correlation for the Defaulter data
corr_Defaulter = Defaulter_df.corr()
corr_Defaulter = corr_Defaulter.where(np.triu(np.ones(corr_Defaulter.shape),k=1).astype(bool))
corr_df_Defaulter = corr_Defaulter.unstack().reset_index()
corr_df_Defaulter.columns =['VAR1','VAR2','Correlation']
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)
```

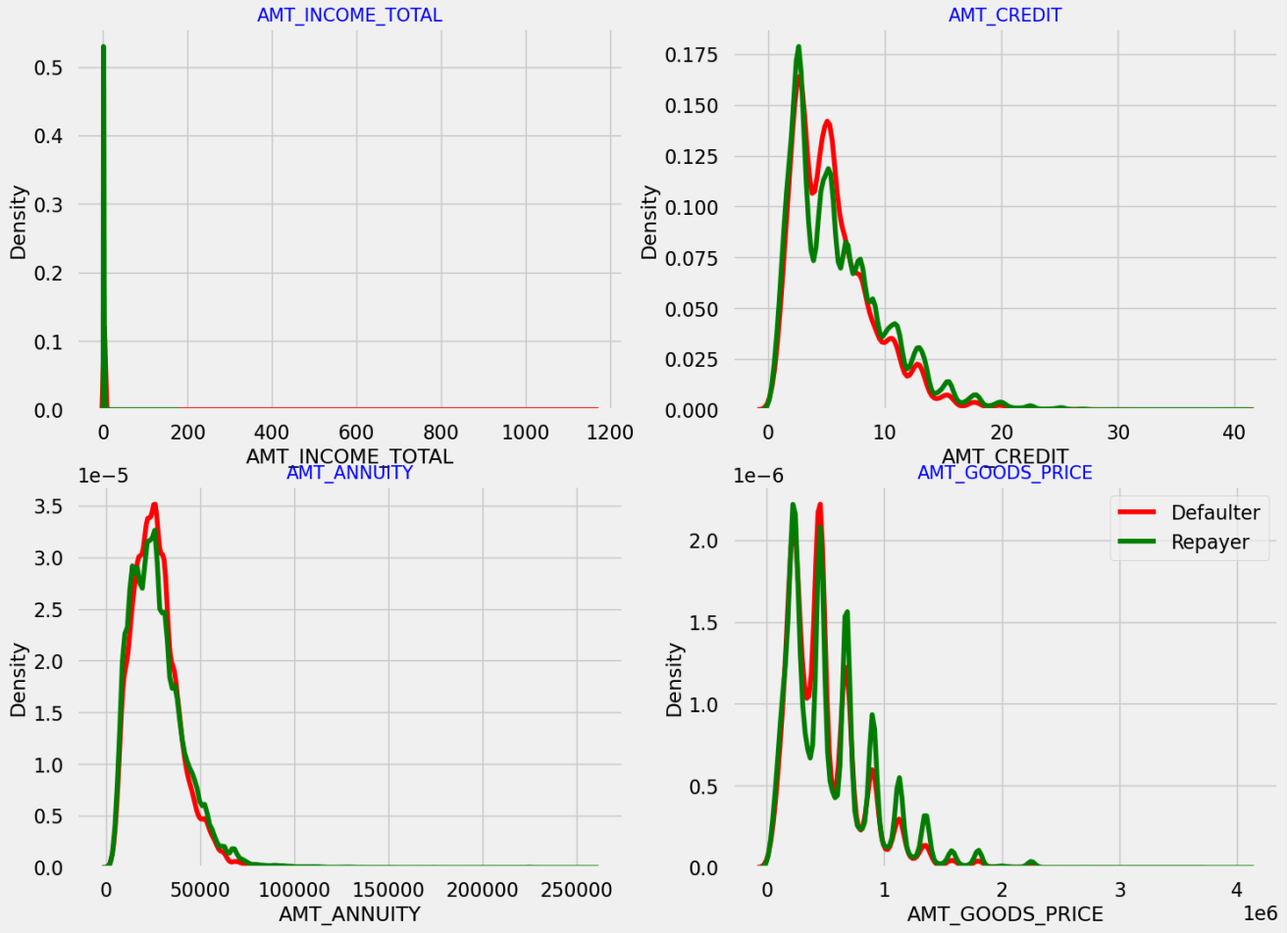
Out[114]:

	VAR1	VAR2	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

In [115]:
```
fig = plt.figure(figsize=(12,12))
ax = sns.heatmap(Defaulter_df.corr(), cmap="RdYlGn",annot=False,linewidth =1)
```

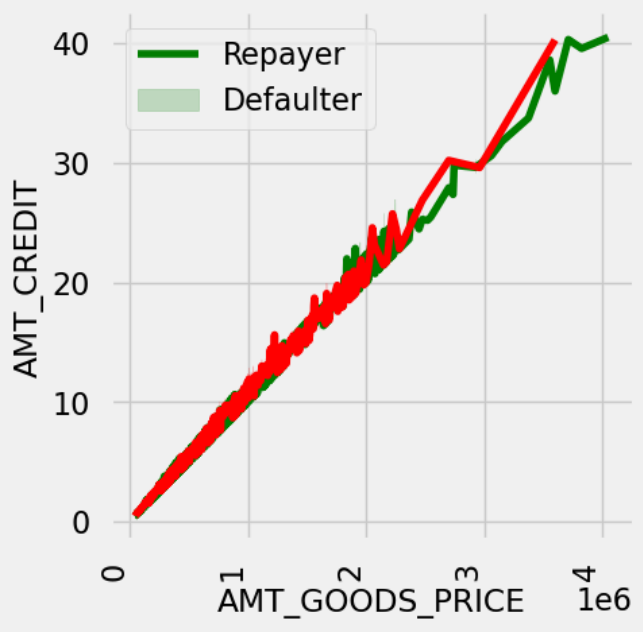


In [116]:
```
# Plotting the numerical columns related to amount as distribution plot to see density
amount = applicationDF[[ 'AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY', 'AMT_GOODS_PRICE']]

fig = plt.figure(figsize=(16,12))

for i in enumerate(amount):
    plt.subplot(2,2,i[0]+1)
    sns.distplot(Defaulter_df[i[1]], hist=False, color='r',label ="Defaulter")
    sns.distplot(Repayer_df[i[1]], hist=False, color='g', label ="Repayer")
    plt.title(i[1], fontdict={'fontsize' : 15, 'fontweight' : 5, 'color' : 'Blue'})

plt.legend()

plt.show()
```

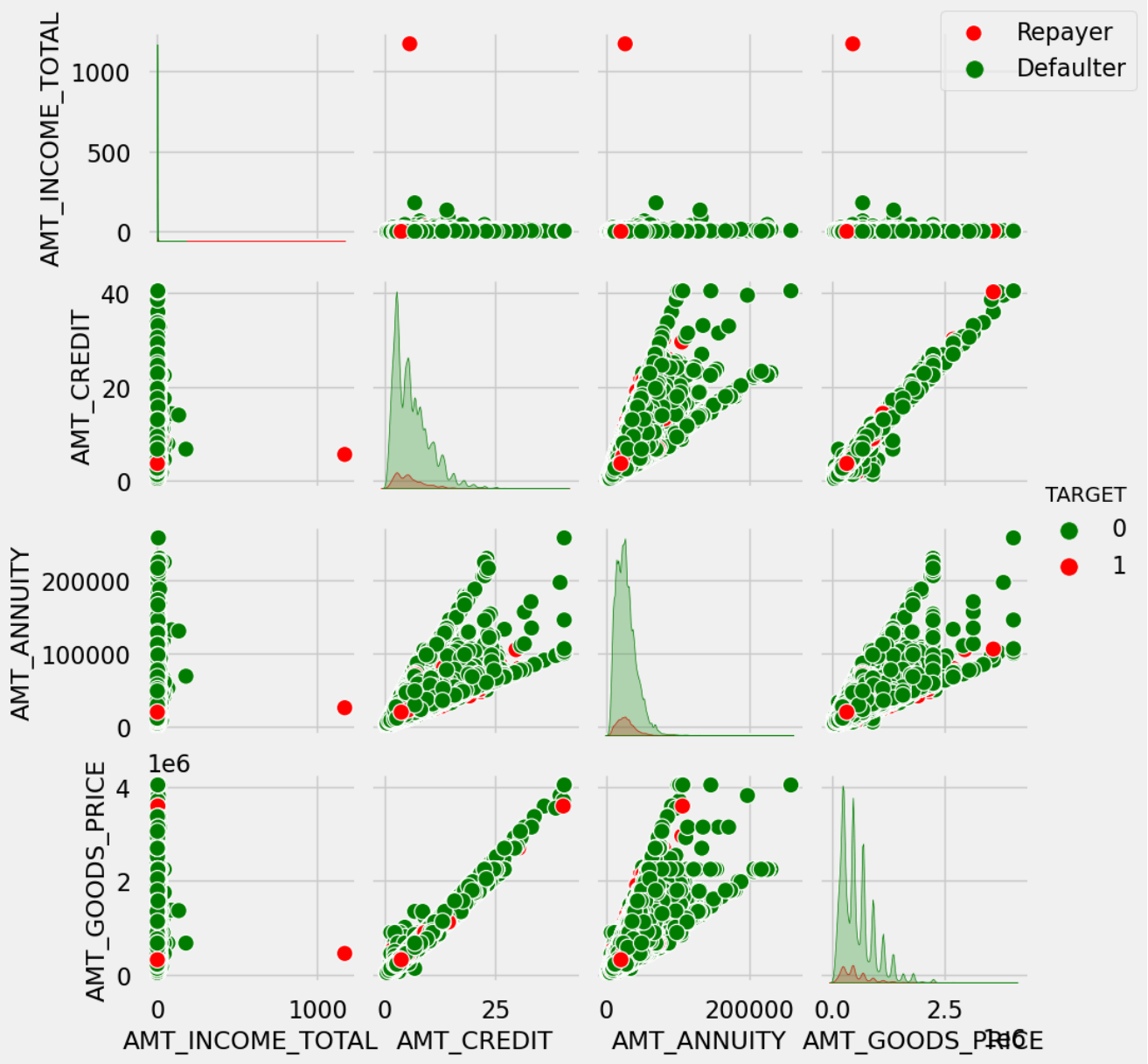


In [117]:
```
bivariate_rel('AMT_GOODS_PRICE','AMT_CREDIT',applicationDF,"TARGET", "line", ['g','r'], False,(15,6))
```

```
<Figure size 1500x600 with 0 Axes>
```



In [118]:
```
# Plotting pairplot between amount variable to draw reference against loan repayment status
amount = applicationDF[[ '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()
```



In [119]:
```
#merge both the dataframe on SK_ID_CURR with Inner Joins
loan_process_df = pd.merge(applicationDF, previousDF, how='inner', on='SK_ID_CURR')
loan_process_df.head()
```

Out[119]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE_x	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_C
0	100002	1	Cash loans	M	N	Y	0	2.025	
1	100003	0	Cash loans	F	N	N	0	2.700	
2	100003	0	Cash loans	F	N	N	0	2.700	
3	100003	0	Cash loans	F	N	N	0	2.700	
4	100004	0	Revolving loans	M	Y	Y	0	0.675	

In [120]:
```
#Checking the details of the merged dataframe
loan_process_df.shape
```

Out[120]: (1413701, 74)

In [121]:
```
# Checking the element count of the dataframe
loan_process_df.size
```

Out[121]: 104613874

In [122]:
```
# checking the columns and column types of the dataframe
loan_process_df.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  AMT_INCOME_RANGE             1413024 non-null  category
 47  AMT_CREDIT_RANGE             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  EMPLOYMENT_YEAR              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
```

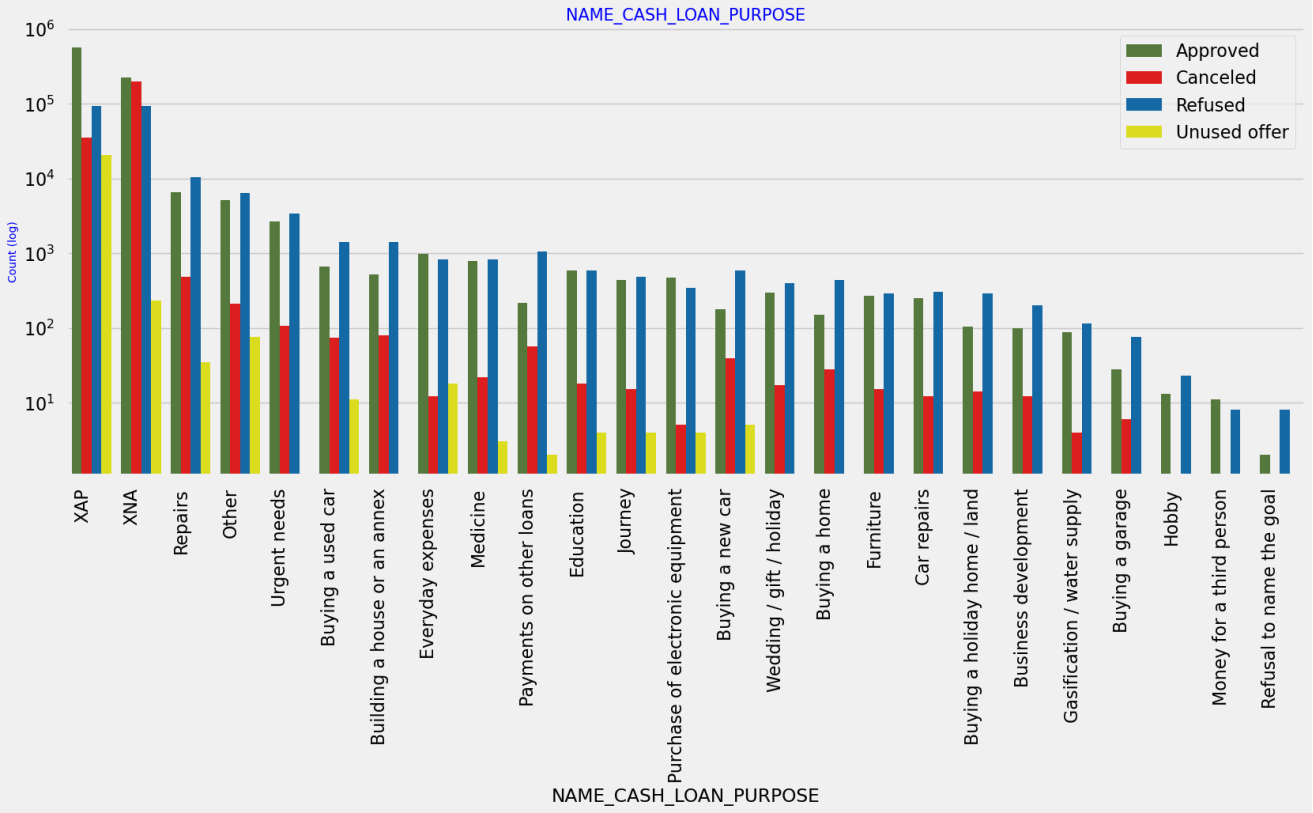
In [123]:
```
# Checking merged dataframe numerical columns statistics
loan_process_df.describe()
```

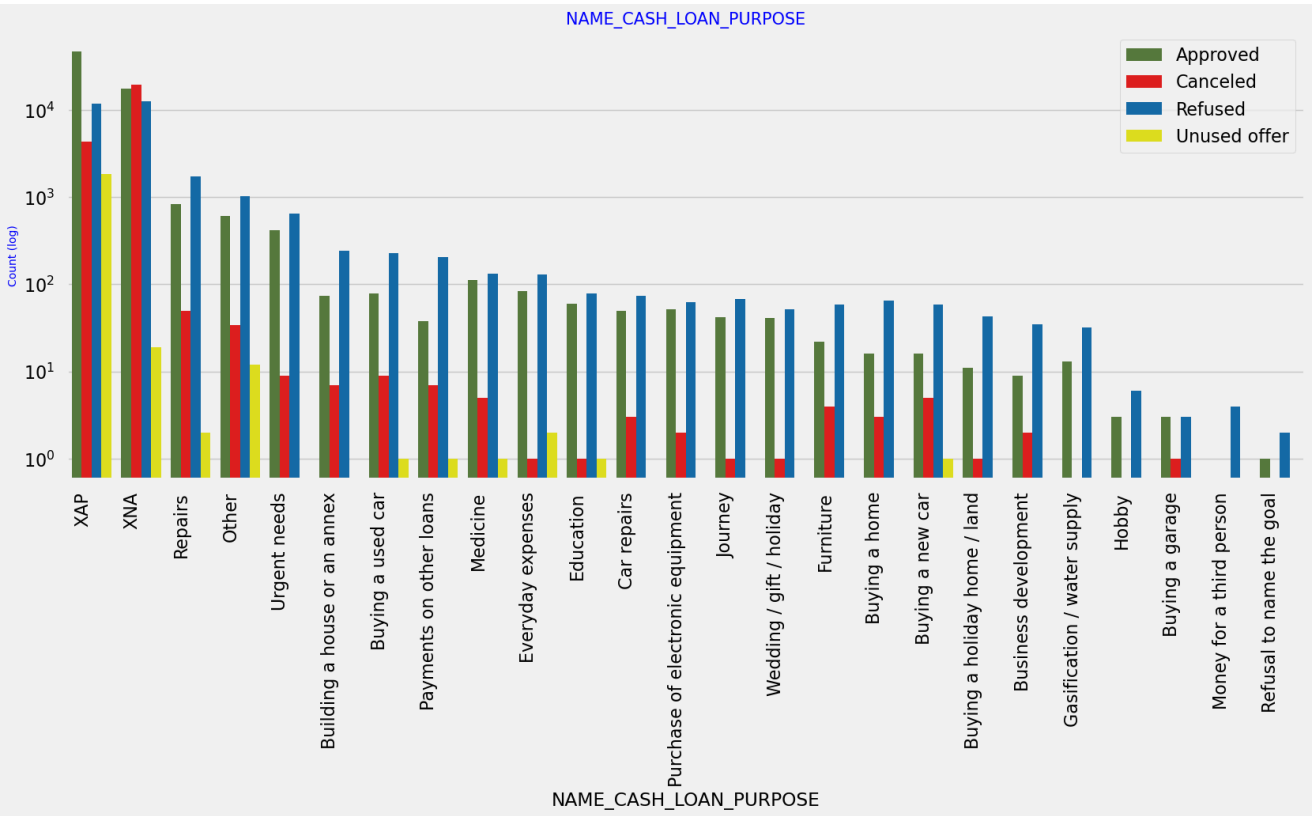
Out[123]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT_x	AMT_ANNUITY_x	AMT_GOODS_PRICE_x	REGION_POPULATION_R
count	1.413701e+06	1.413701e+06	1.413701e+06	1.413701e+06	1.413701e+06	1.413608e+06	1.412493e+06	1.413
mean	2.784813e+05	8.655296e-02	4.048933e-01	1.733160e+00	5.875537e+00	2.701702e+04	5.277186e+05	2.07
std	1.028118e+05	2.811789e-01	7.173454e-01	1.985734e+00	3.849173e+00	1.395116e+04	3.532465e+05	1.33
min	1.000020e+05	0.000000e+00	0.000000e+00	2.565000e-01	4.500000e-01	1.615500e+03	4.050000e+04	2.90
25%	1.893640e+05	0.000000e+00	0.000000e+00	1.125000e+00	2.700000e+00	1.682100e+04	2.385000e+05	1.00
50%	2.789920e+05	0.000000e+00	0.000000e+00	1.575000e+00	5.084955e+00	2.492550e+04	4.500000e+05	1.88
75%	3.675560e+05	0.000000e+00	1.000000e+00	2.070000e+00	8.079840e+00	3.454200e+04	6.795000e+05	2.86
max	4.562550e+05	1.000000e+00	1.900000e+01	1.170000e+03	4.050000e+01	2.250000e+05	4.050000e+06	7.25

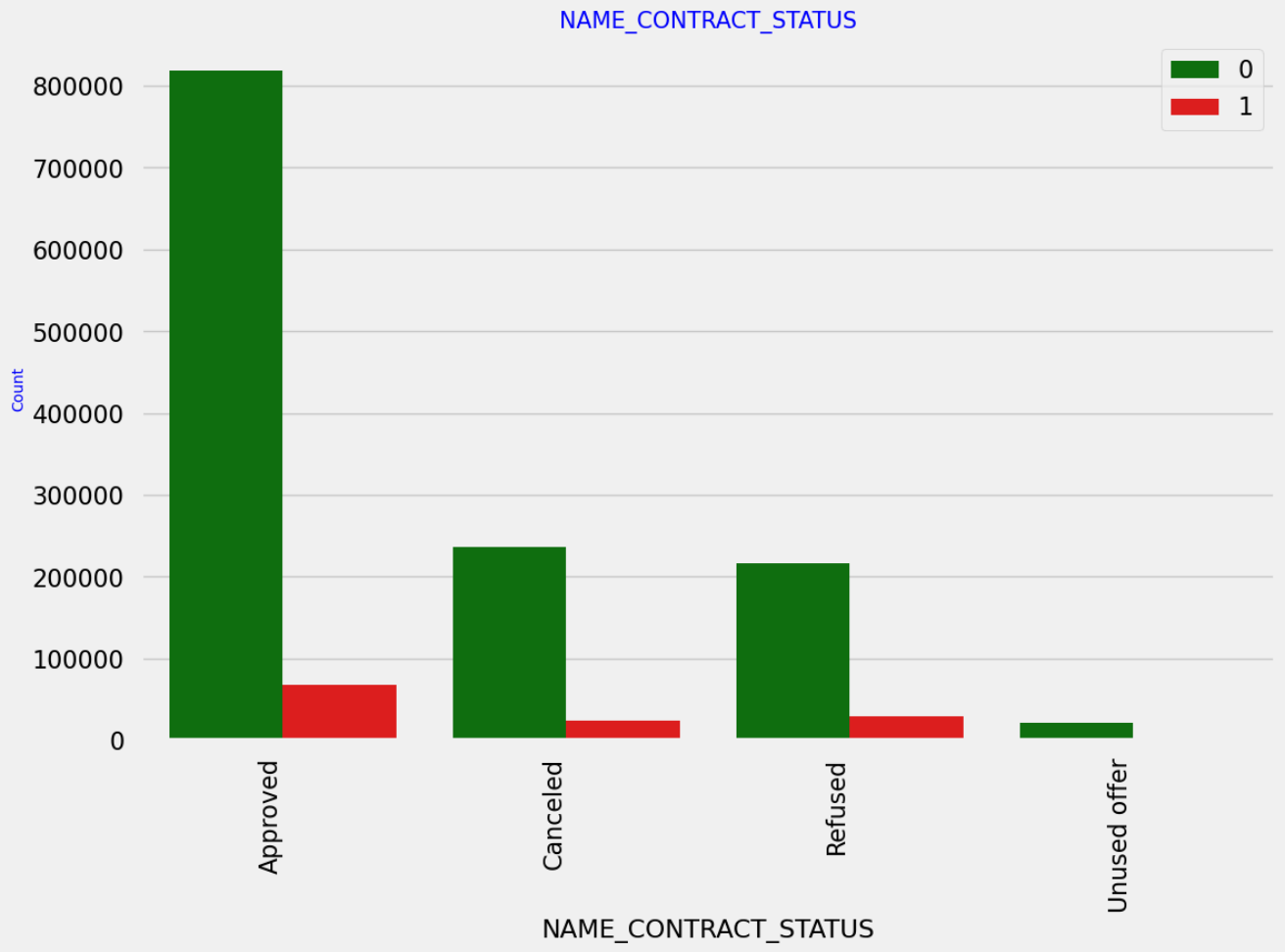
In [124]:
```
# Bifurcating the applicationDF dataframe based on Target value 0 and 1 for correlation and other analysis

L0 = loan_process_df[loan_process_df['TARGET']==0] # Repayers
L1 = loan_process_df[loan_process_df['TARGET']==1] # Defaulters
```

In [125]:
```
#Plotting Contract Status vs purpose of the loan:

univariate_merged("NAME_CASH_LOAN_PURPOSE",L0,"NAME_CONTRACT_STATUS",["#548235","#FF0000","#0070C0","#FFFF00"],True,(18,7))

univariate_merged("NAME_CASH_LOAN_PURPOSE",L1,"NAME_CONTRACT_STATUS",["#548235","#FF0000","#0070C0","#FFFF00"],True,(18,7))
```



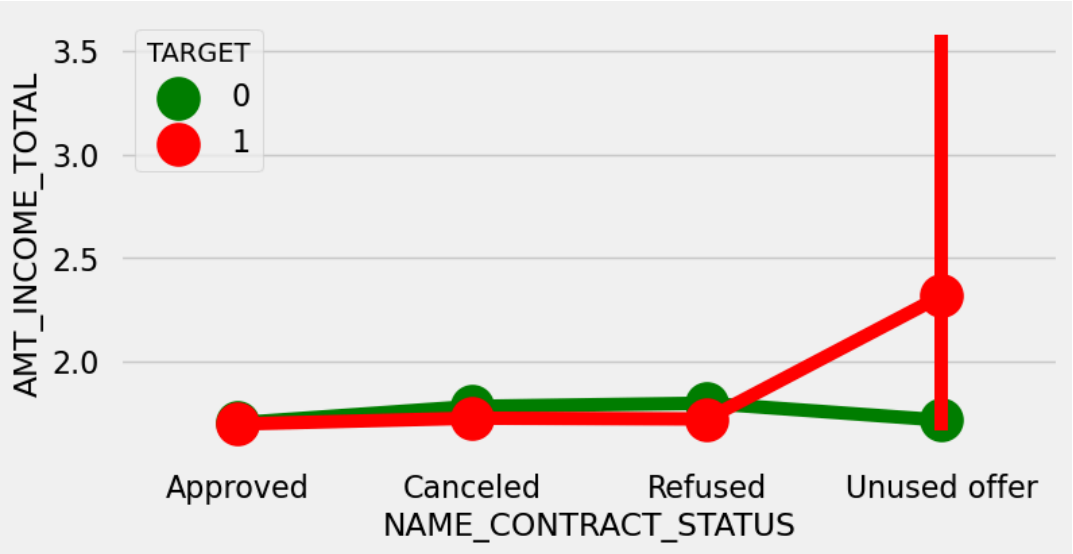


In [126]:
```
# Checking the Contract Status based on loan repayment status and whether there is any business loss or financial loss
univariate_merged("NAME_CONTRACT_STATUS",loan_process_df,"TARGET",['g','r'],False,(12,8))
g = loan_process_df.groupby("NAME_CONTRACT_STATUS")["TARGET"]
df1 = pd.concat([g.value_counts(),round(g.value_counts(normalize=True).mul(100),2)],axis=1, keys=('Counts','Percentage'))
df1['Percentage'] = df1['Percentage'].astype(str) +"%" # adding percentage symbol in the results for understanding
print (df1)
```

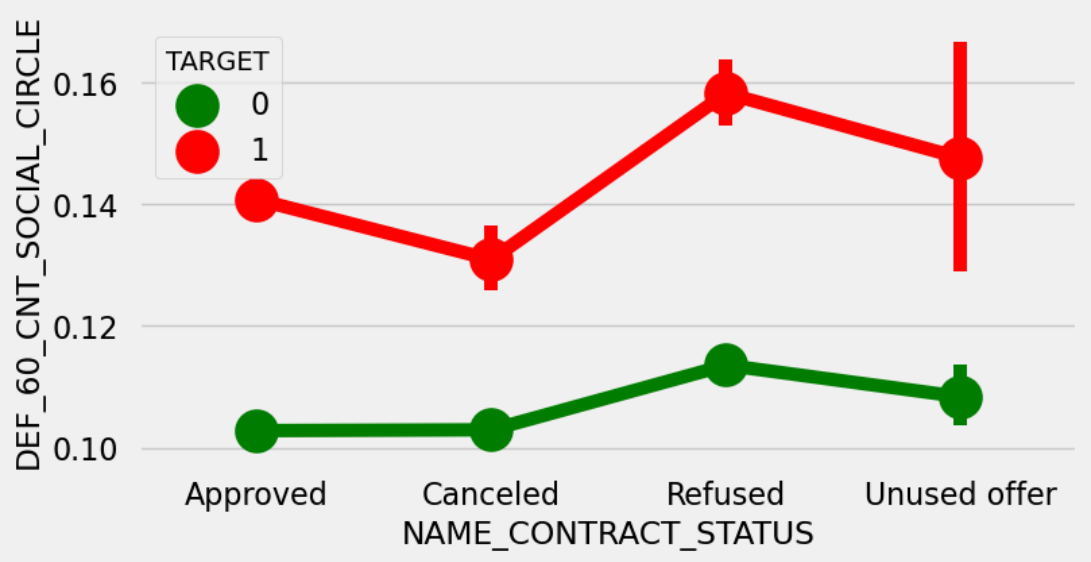


NAME_CONTRACT_STATUS	TARGET	Counts	Percentage
Approved	0	818856	92.41%
	1	67243	7.59%
Canceled	0	235641	90.83%
	1	23800	9.17%
Refused	0	215952	88.0%
	1	29438	12.0%
Unused offer	0	20892	91.75%
	1	1879	8.25%

In [127]:
```
# plotting the relationship between income total and contact status
merged_pointplot("NAME_CONTRACT_STATUS",'AMT_INCOME_TOTAL')
```



In [128]:
```
# plotting the relationship between people who defaulted in last 60 days being in client's social circle and contact status
merged_pointplot("NAME_CONTRACT_STATUS",'DEF_60_CNT_SOCIAL_CIRCLE')
```



7. Conclusions

After analysing the datasets, there are few attributes of a client with which the bank would be able to identify if they will repay the loan or not. The analysis is consised as below with the contributing factors and categorization:

1.Decisive Factor whether an applicant will be Repayer:

2.NAME_EDUCATION_TYPE: Academic degree has less defaults.
3.NAME_INCOME_TYPE: Student and Businessmen have no defaults.
4.REGION_RATING_CLIENT: RATING 1 is safer.
5.ORGANIZATION_TYPE: Clients with Trade Type 4 and 5 and Industry type 8 have defaulted less than 3%
6.DAYS_BIRTH: People above age of 50 have low probability of defaulting
7.DAYS_EMPLOYED: Clients with 40+ year experience having less than 1% default rate
8.AMT_INCOME_TOTAL:Applicant with Income more than 700,000 are less likely to default
9.NAME_CASH_LOAN_PURPOSE: Loans bought for Hobby, Buying garage are being repayed mostly.
10.CNT_CHILDREN: People with zero to two children tend to repay the loans.

Decisive Factor whether an applicant will be Defaulter:

1.CODE_GENDER: Men are at relatively higher default rate
2.NAME_FAMILY_STATUS : People who have civil marriage or who are single default a lot.
3.NAME_EDUCATION_TYPE: People with Lower Secondary & Secondary education
4.NAME_INCOME_TYPE: Clients who are either at Maternity leave OR Unemployed default a lot.
5.REGION_RATING_CLIENT: People who live in Rating 3 has highest defaults.

6.OCCUPATION_TYPE: Avoid Low-skill Laborers, Drivers and Waiters/barmen staff, Security staff, Laborers and Cooking staff as the default rate is huge.

7ORGANIZATION_TYPE: Organizations with highest percent of loans not repaid are Transport: type 3 (16%), Industry: type 13 (13.5%), Industry: type 8 (12.5%) and Restaurant (less than 12%). Self-employed people have relative high defaulting rate, and thus should be avoided to be approved for loan or provide loan with higher interest rate to mitigate the risk of defaulting.

8.DAYS_BIRTH: Avoid young people who are in age group of 20-40 as they have higher probability of defaulting

9.DAYS_EMPLOYED: People who have less than 5 years of employment have high default rate.

10.CNT_CHILDREN & CNT_FAM_MEMBERS: Client who have children equal to or more than 9 default 100% and hence their applications are to be rejected.

11.AMT_GOODS_PRICE: When the credit amount goes beyond 3M, there is an increase in defaulters.

In [ ]:

The following attributes indicate that people from these category tend to default but then due to the number of people and the amount of loan, the bank could provide loan with higher interest to mitigate any default risk thus preventing business loss:

1.NAME_HOUSING_TYPE: High number of loan applications are from the category of people who live in Rented apartments & living with parents and hence offering the loan would mitigate the loss if any of those default.

2.AMT_CREDIT: People who get loan for 300-600k tend to default more than others and hence having higher interest specifically for this credit range would be ideal.

3.AMT_INCOME: Since 90% of the applications have Income total less than 300,000 and they have high probability of defaulting, they could be offered loan with higher interest compared to other income category.

4.CNT_CHILDREN & CNT_FAM_MEMBERS: Clients who have 4 to 8 children has a very high default rate and hence higher interest should be imposed on their loans.

5.NAME_CASH_LOAN_PURPOSE: Loan taken for the purpose of Repairs seems to have highest default rate. A very high number applications have been rejected by bank or refused by client in previous applications as well which has purpose as repair or other. This shows that purpose repair is taken as high risk by bank and either they are rejected, or bank offers very high loan interest rate which is not feasible by the clients, thus they refuse the loan. The same approach could be followed in future as well.

Other suggestions:

1.90% of the previously cancelled client have actually repayed the loan. Record the reason for cancellation which might help the bank to determine and negotiate terms with these repaying customers in future for increase business opportunity.

2.88% of the clients who were refused by bank for loan earlier have now turned into a repaying client. Hence documenting the reason for rejection could mitigate the business loss and these clients could be contacted for further loans.