EDA : Bank Loan Default Risk Analysis

Import Python Libraries:

In [1]:
```
import numpy as np
```

In [2]:
```
import pandas as pd
```

In [3]:
```
import matplotlib.pyplot as plt
```

In [4]:
```
import matplotlib.style as style
```

In [5]:
```
import seaborn as sns
```

In [6]:
```
import itertools
```

In [7]:
```
%matplotlib inline
```

In [8]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [9]:
```
# setting up plot style

style.use('seaborn-poster')
style.use('fivethirtyeight')
```

In [10]:
```
#Adjust Jupyer Views:

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 [11]:
```
applicationdf=pd.read_csv(r'D:\16th_resume project\application_data.csv')
previousdf=pd.read_csv(r'D:\16th_resume project\previous_application.csv\previous_a
```

In [12]:
```
applicationdf
```

Out[12]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OV
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	
...	...	...	...	...	...	
307506	456251	0	Cash loans	M	N	
307507	456252	0	Cash loans	F	N	
307508	456253	0	Cash loans	F	N	
307509	456254	1	Cash loans	F	N	
307510	456255	0	Cash loans	F	N	

307511 rows × 122 columns

In [13]:
```
previousdf
```

Out[13]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	A
0	2030495	271877	Consumer loans	1730.430	17145.0	
1	2802425	108129	Cash loans	25188.615	607500.0	
2	2523466	122040	Cash loans	15060.735	112500.0	
3	2819243	176158	Cash loans	47041.335	450000.0	
4	1784265	202054	Cash loans	31924.395	337500.0	
...	...	...	...	...	...	
1670209	2300464	352015	Consumer loans	14704.290	267295.5	
1670210	2357031	334635	Consumer loans	6622.020	87750.0	
1670211	2659632	249544	Consumer loans	11520.855	105237.0	
1670212	2785582	400317	Cash loans	18821.520	180000.0	
1670213	2418762	261212	Cash loans	16431.300	360000.0	

1670214 rows × 37 columns

In [14]:
```
applicationdf.head()
```

Out[14]:

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

In [15]:
```
previousdf.head()
```

Out[15]:

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	AMT_APPLICATION	AMT_CR
0	2030495	271877	Consumer loans	1730.430	17145.0	17
1	2802425	108129	Cash loans	25188.615	607500.0	679
2	2523466	122040	Cash loans	15060.735	112500.0	136
3	2819243	176158	Cash loans	47041.335	450000.0	470
4	1784265	202054	Cash loans	31924.395	337500.0	404

In [16]:
```
# Database dimension

print("Database dimension - applicationdf :",applicationdf.shape)
print("Database dimension - prevoiusdf :",previousdf.shape)
```

```
Database dimension - applicationdf : (307511, 122)
Database dimension - prevoiusdf : (1670214, 37)
```

In [17]:
```
print("Database dimension - applicationdf :",applicationdf.size)
print("Database dimension - prevoiusdf :",previousdf.size)
```

```
Database dimension - applicationdf : 37516342
Database dimension - prevoiusdf : 61797918
```

In [18]:
```
# Database column types
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
 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
```

In [19]:
```
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 [20]:
```
applicationdf.describe()
```

Out[20]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_AI
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	30749
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	2710
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	1449
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	161
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	1652
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	2490
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	3459
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	25802

In [21]:
```
previousdf.describe()
```

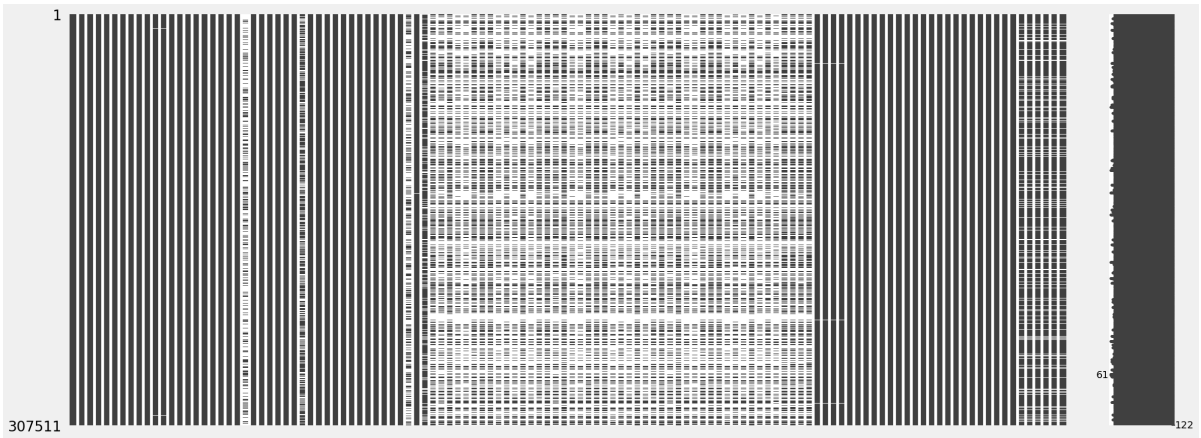
Out[21]:

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_DOWI
count	1.670214e+06	1.670214e+06	1.297979e+06	1.670214e+06	1.670213e+06	7.
mean	1.923089e+06	2.783572e+05	1.595512e+04	1.752339e+05	1.961140e+05	6.
std	5.325980e+05	1.028148e+05	1.478214e+04	2.927798e+05	3.185746e+05	2.
min	1.000001e+06	1.000010e+05	0.000000e+00	0.000000e+00	0.000000e+00	-9
25%	1.461857e+06	1.893290e+05	6.321780e+03	1.872000e+04	2.416050e+04	0.
50%	1.923110e+06	2.787145e+05	1.125000e+04	7.104600e+04	8.054100e+04	1.
75%	2.384280e+06	3.675140e+05	2.065842e+04	1.803600e+05	2.164185e+05	7.
max	2.845382e+06	4.562550e+05	4.180581e+05	6.905160e+06	6.905160e+06	3.

In [22]:
```
#! pip install missingno
```

In [23]:
```
import missingno as mn
mn.matrix(applicationdf)
```

Out[23]:
```
<Axes: >
```



Insight:

Based on the above Matrix, it is evidednt that the dataset has many missing values. Let's check for each column what is the % of missing values

In [24]:
```
# % null value in each column
round(applicationdf.isnull().sum() / applicationdf.shape[0] * 100,2)
```

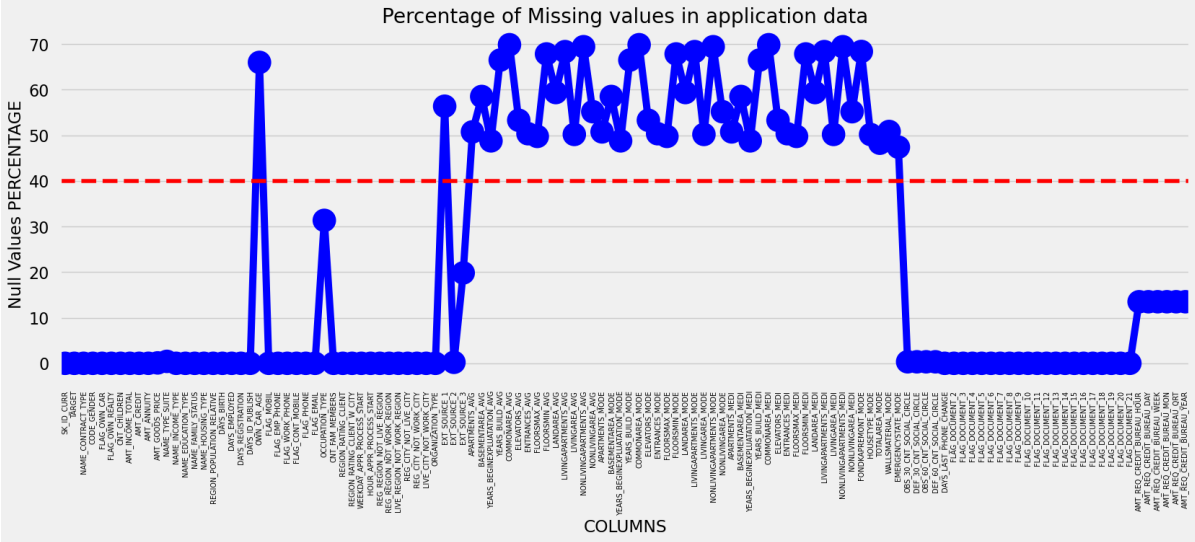
Out[24]:

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
```

Insight: There are many columns in applicationDF dataframe where missing value is more than 40%. Let's plot the columns vs missing value % with 40% being the cut-off marks

In [25]:
```
null_applicationdf = pd.DataFrame((applicationdf.isnull().sum())*100/applicationdf.
null_applicationdf.columns = ['Column Name', 'Null Values Percentage']
fig = plt.figure(figsize=(18,6))
ax = sns.pointplot(x="Column Name",y="Null Values Percentage",data=null_applicatior
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()
```



Insight: From the plot we can see the columns in which percentage of null values more than 40% are marked above the red line and the columns which have less than 40 % null values below the red line. Let's check the columns which has more than 40% missing values

In [26]:
```
# more than or equal to 40% empty rows columns
```

In [27]:
```
nullcol_40_application = null_applicationdf[null_applicationdf["Null Values Percent
nullcol_40_application
```

Out[27]:

	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

	Column Name	Null Values Percentage
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

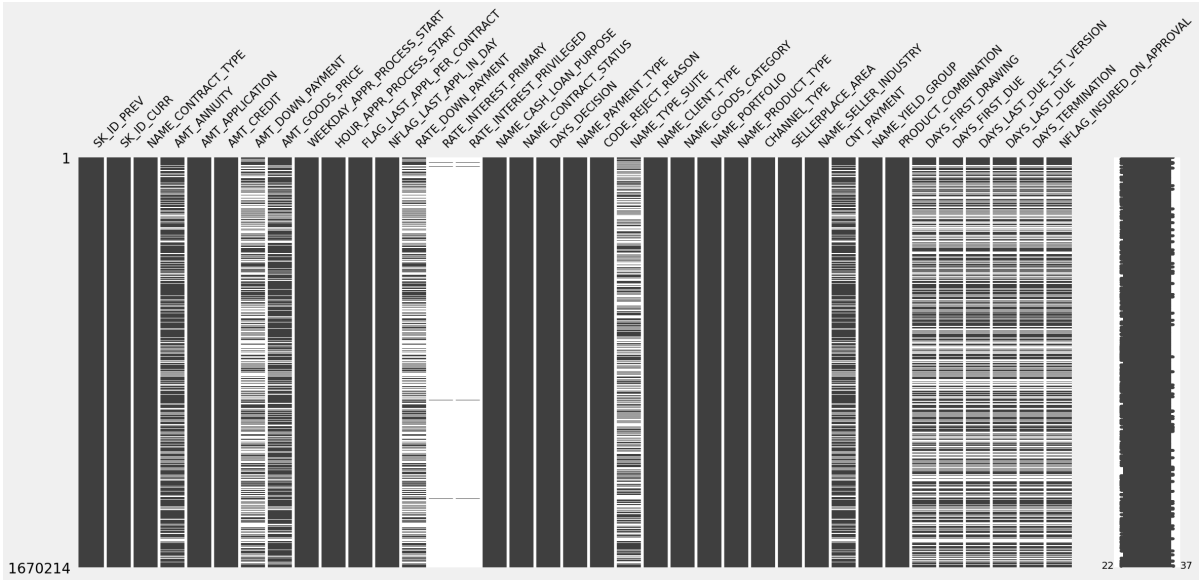
Insight:

Total of 49 columns are there which have more than 40% null values.Seems like most of the columns with high missing values are related to different area sizes on apartment owned/rented by the loan applicant

previousdf Missing Values

In [28]:
```
mn.matrix(previousdf)
```

Out[28]:
```
<Axes: >
```



checking the null value % of each column in previousdf dataframe

In [29]:
```
round(previousdf.isnull().sum() / previousdf.shape[0] * 100 ,2)
```

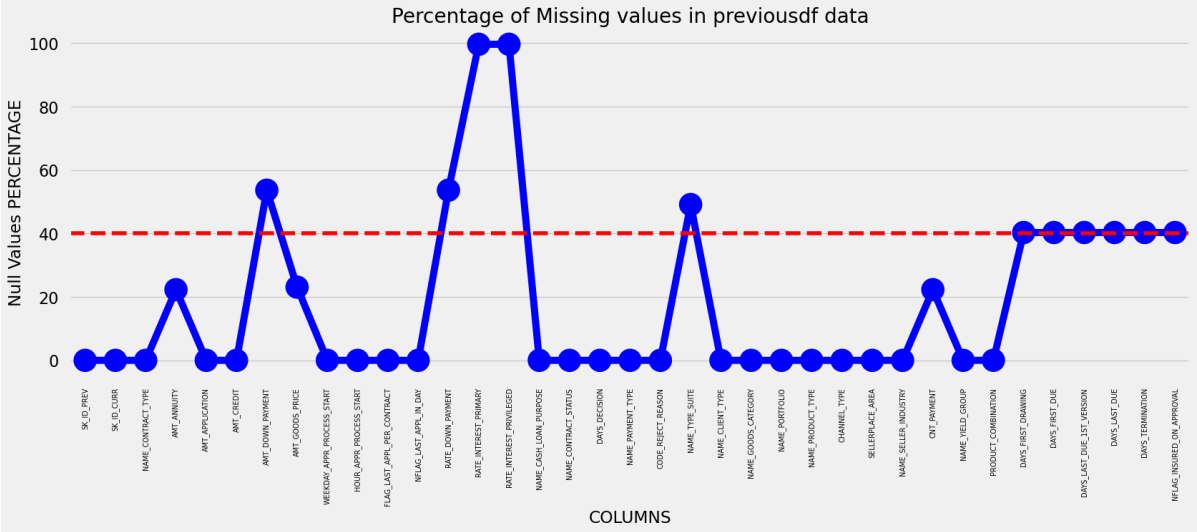
Out[29]:
```
SK_ID_PREV                    0.00
SK_ID_CURR                    0.00
NAME_CONTRACT_TYPE            0.00
AMT_ANNUITY                  22.29
AMT_APPLICATION               0.00
AMT_CREDIT                    0.00
AMT_DOWN_PAYMENT             53.64
AMT_GOODS_PRICE              23.08
WEEKDAY_APPR_PROCESS_START    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
```

Insight:

There are many columns in previousdf dataframe where missing value is more than 40%.

Let's plot the columns vs missing value % with 40% being the cut-off marks

In [30]:
```
null_previousdf = pd.DataFrame((previousdf.isnull().sum())*100/previousdf.shape[0])
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,
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 [31]:
```
# more than or equal to 40% empty rows columns
nullcol_40_previous = null_previousdf[null_previousdf["Null Values Percentage"]>=40
nullcol_40_previous
```

Out[31]:

	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 [32]:
```
# How many columns have more than or euqal to 40% null values ?
len(nullcol_40_previous)
```

Out[32]:
```
11
```

Insight:

Total of 11 columns are there which have more than 40% null values. These columns can be deleted. Before deleting these columns, let's review if there are more columns which can be dropped or not

Analyze & Delete Unnecessary Columns in applicationdf

EXT_SOURCE_X

In [33]:
```
# Checking correlation of EXT_SOURCE_X columns vs TARGET column
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")
```

Insight:

Based on the above Heatmap, we can see there is almost no correlation between EXT_SOURCE_X columns and target column, thus we can drop these columns.
EXT_SOURCE_1 has 56% null values, where as EXT_SOURCE_3 has close to 20% null values

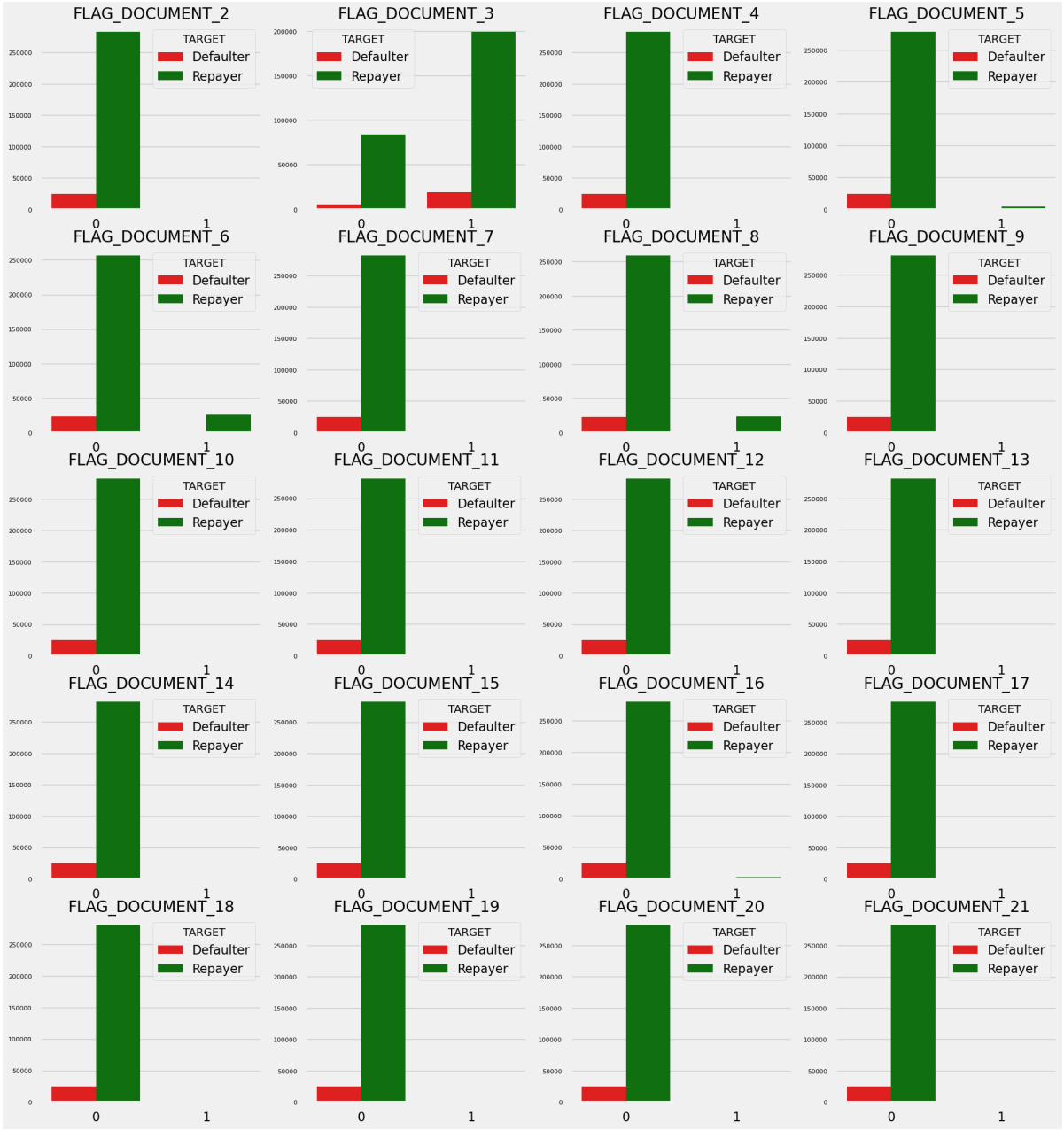
In [34]:
```
# create a list of columns that needs to be dropped including the columns with >40%

Unwanted_application = nullcol_40_application["Column Name"].tolist()+ ['EXT_SOURCE

# as EXT_SOURCE_1 column is already included in nullcol_40_application
len(Unwanted_application)
```

Out[34]:
```
51
```

Flag Document

In [35]:
```
# Checking the relevance of Flag_Document and whether it has any relation with loan
col_Doc = [ 'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3','FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_
            'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9','FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_
            'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15','FLAG_DOCUMENT_16', 'FLAG_DOCUMEN
            '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(x=df_flag[i],hue=df_flag["TARGET"],palette=["r","g"])
    plt.yticks(fontsize=8)
    plt.xlabel("")
    plt.ylabel("")
    plt.title(i)
```



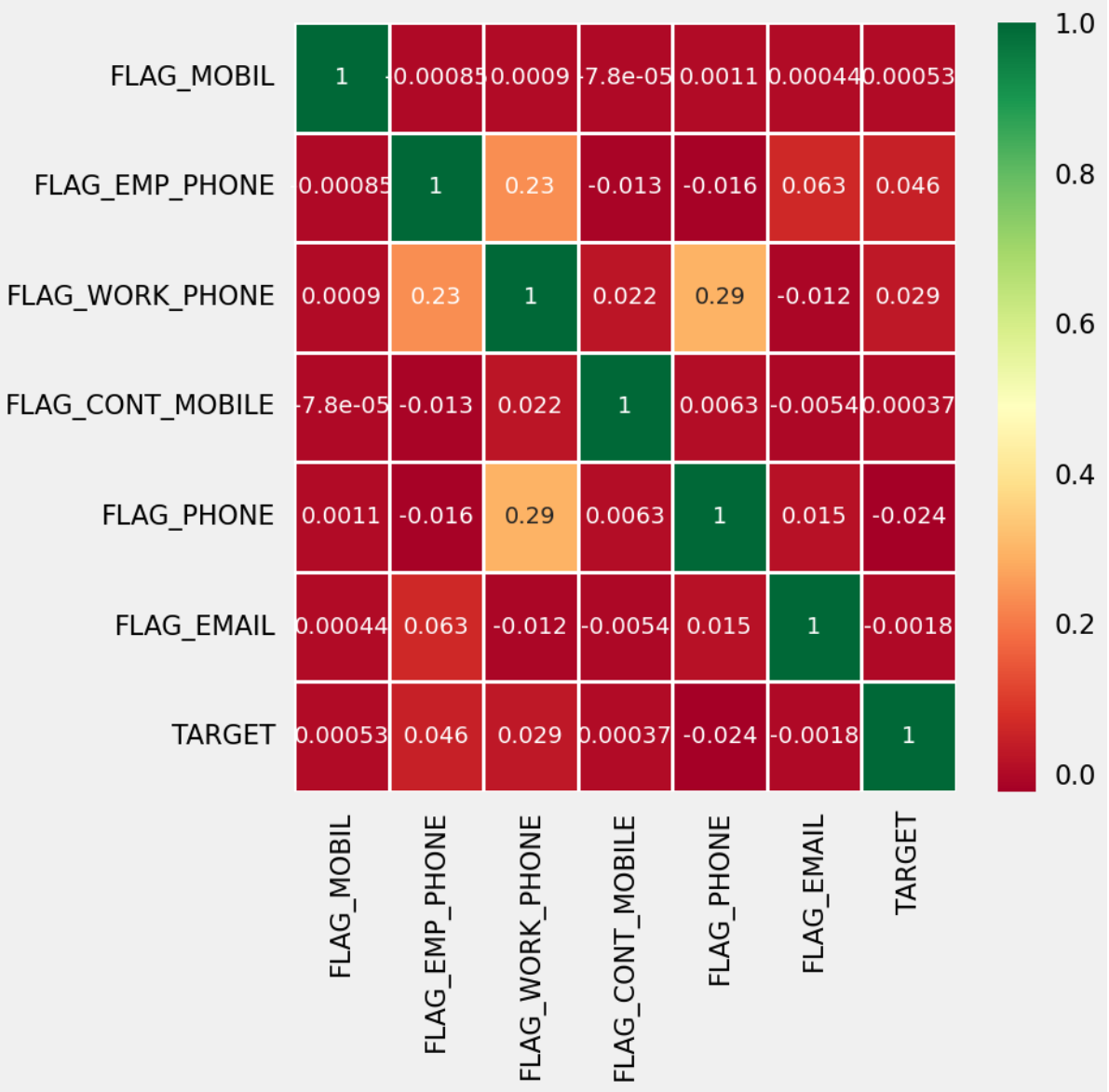
Insight:

The above graph shows that in most of the loan application cases, clients who applied for loans has not submitted FLAG_DOCUMENT_X except FLAG_DOCUMENT_3. Thus, Except for FLAG_DOCUMENT_3, we can delete rest of the columns. Data shows if borrower has submitted FLAG_DOCUMENT_3 then there is a less chance of defaulting the loan.

In [36]:
```
# Including the flag documents for dropping the Document columns
col_Doc.remove('FLAG_DOCUMENT_3')
Unwanted_application = Unwanted_application + col_Doc
len(Unwanted_application)
```

Out[36]:
```
70
```

In [37]:
```
# checking is there is any correlation between mobile phone, work phone etc, email,
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",
            linewidth=1)
```



Insight:

There is no correlation between flags of mobile phone, email etc with loan repayment; thus these columns can be deleted

In [38]:
```
# including the 6 FLAG columns to be deleted
contact_col.remove('TARGET')
Unwanted_application = Unwanted_application + contact_col
len(Unwanted_application)
```

Out[38]:
```
76
```

Insight: Total 76 columns can be deleted from applicationdf

In [39]:
```
# Dropping the unnecessary columns from applicationDF
applicationdf.drop(labels=Unwanted_application,axis=1,inplace=True)
```

In [40]:
```
# Inspecting the dataframe after removal of unnecessary columns
applicationdf.shape
```

Out[40]:
```
(307511, 46)
```

In [41]:
```
# inspecting the column types after removal of unnecessary columns
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
```

Insight:

After deleting unnecessary columns, there are 46 columns remaining in applicationdf

Analyze & Delete Unnecessary Columns in previousdf

In [42]:
```
# Getting the 11 columns which has more than 40% unknown
Unwanted_previous = nullcol_40_previous["Column Name"].tolist()
Unwanted_previous
```

Out[42]:
```
['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 [43]:
```
# Listing down columns which are not needed
Unnecessary_previous = ['WEEKDAY_APPR_PROCESS_START','HOUR_APPR_PROCESS_START',
                        'FLAG_LAST_APPL_PER_CONTRACT','NFLAG_LAST_APPL_IN_DAY']
```

In [44]:
```
Unwanted_previous = Unwanted_previous + Unnecessary_previous
len(Unwanted_previous)
```

Out[44]:
```
15
```

Insight:

Total 15 columns can be deleted from previousdf

In [45]:
```
# Dropping the unnecessary columns from previous
previousdf.drop(labels=Unwanted_previous,axis=1,inplace=True)
```

In [46]:
```
previousdf.shape
```

Out[46]:
```
(1670214, 22)
```

In [47]:
```
# inspecting the column types after after removal of unnecessary columns
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
```

Insight: After deleting unnecessary columns, there are 22 columns remaining in applicationdf

Standardize Values

Strategy for applicationdf: Convert DAYS_DECISION,DAYS_EMPLOYED, DAYS_REGISTRATION,DAYS_ID_PUBLISH from negative to positive as days cannot be negative. Convert DAYS_BIRTH from negative to positive values and calculate age and create categorical bins columns Categorize the amount variables into bins Convert region rating column and few other columns to categorical

In [48]:
```
# Converting Negative days to positive days

date_col = ['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH']

for col in date_col:
    applicationdf[col] = abs(applicationdf[col])
```

In [49]:
```
# Binning Numerical Columns to create a categorical column

# Creating bins for income amount
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

applicationdf['AMT_INCOME_RANGE']=pd.cut(applicationdf['AMT_INCOME_TOTAL'],bins,lab
```

In [50]:
```
applicationdf['AMT_INCOME_RANGE'].value_counts(normalize=True)*100
```

Out[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: AMT_INCOME_RANGE, dtype: float64
```

Insight:

More than 50% loan applicants have income amount in the range of 100K-200K. Almost 92% loan applicants have income less than 300K

In [51]:
```
# Creating bins for Credit amount
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','600
       '800k-900k','900k-1M', '1M Above']

applicationdf['AMT_CREDIT_RANGE']=pd.cut(applicationdf['AMT_CREDIT'],bins=bins,labe
```

In [52]:
```
#checking the binning of data and % of data in each category
applicationdf['AMT_CREDIT_RANGE'].value_counts(normalize=True)*100
```

Out[52]:
```
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
```

Insight:

More Than 16% loan applicants have taken loan which amounts to more than 1M.

In [53]:
```
# Creating bins for Age
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)
#checking the binning of data and % of data in each category
applicationdf['AGE_GROUP'].value_counts(normalize=True)*100
```

Out[53]:
```
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
```

Insight:

31% loan applicants have age above 50 years. More than 55% of loan applicants have age over 40 years.

In [54]:
```
# Creating bins for Employement Time
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,l
#checking the binning of data and % of data in each category
applicationdf['EMPLOYMENT_YEAR'].value_counts(normalize=True)*100
```

Out[54]:
```
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
```

Insight:

More than 55% of the loan applicants have work experience within 0-5 years and almost 80% of them have less than 10 years of work experience

In [55]:
```
#Checking the number of unique values each column possess to identify categorical c
applicationdf.nunique().sort_values()
```

Out[55]:
```
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
```

Data Type Conversion

In [56]:
```
# inspecting the column types if they are in correct data type using the above resu
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
```

Insight:

Numeric columns are already in int64 and float64 format. Hence proceeding with other columns.

In [57]:
```
#Conversion of Object and Numerical columns to Categorical Columns
categorical_columns = ['NAME_CONTRACT_TYPE','CODE_GENDER','NAME_TYPE_SUITE','NAME_I
                       'NAME_FAMILY_STATUS','NAME_HOUSING_TYPE','OCCUPATION_TYPE','
                       'ORGANIZATION_TYPE','FLAG_OWN_CAR','FLAG_OWN_REALTY','LIVE_C
                       'REG_CITY_NOT_LIVE_CITY','REG_CITY_NOT_WORK_CITY','REG_REGIC
                       'LIVE_REGION_NOT_WORK_REGION','REGION_RATING_CLIENT','WEEKDA
                       'REGION_RATING_CLIENT_W_CITY'
                      ]
for col in categorical_columns:
    applicationdf[col] =pd.Categorical(applicationdf[col])
# inspecting the column types if the above conversion is reflected
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
```

Standardize Values for previousdf

Convert DAYS_DECISION from negative to positive values and create categorical bins columns. Convert loan purpose and few other columns to categorical.

In [58]:
```
#Checking the number of unique values each column possess to identify categorical c
previousdf.nunique().sort_values()
```

Out[58]:
```
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 [59]:
```
# inspecting the column types if the above conversion is reflected
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 [60]:
```
#Converting negative days to positive days
previousdf['DAYS_DECISION'] = abs(previousdf['DAYS_DECISION'])
```

In [61]:
```
#age group calculation e.g. 388 will be grouped as 300-400
previousdf['DAYS_DECISION_GROUP'] = (previousdf['DAYS_DECISION']-(previousdf['DAYS_
```

In [62]:
```
previousdf['DAYS_DECISION_GROUP'].value_counts(normalize=True)*100
```

Out[62]:
```
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
```

Insight:

Almost 37% loan applicatants have applied for a new loan within 0-400 days of previous loan decision

In [63]:
```
#Converting Categorical columns from Object to categorical
Catgorical_col_p = ['NAME_CASH_LOAN_PURPOSE','NAME_CONTRACT_STATUS','NAME_PAYMENT_T
                    'CODE_REJECT_REASON','NAME_CLIENT_TYPE','NAME_GOODS_CATEGORY','
                   'NAME_PRODUCT_TYPE','CHANNEL_TYPE','NAME_SELLER_INDUSTRY','NAME_
                    'NAME_CONTRACT_TYPE','DAYS_DECISION_GROUP']

for col in Catgorical_col_p:
    previousdf[col] =pd.Categorical(previousdf[col])
# inspecting the column types after conversion
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
```

Null Value Data Imputation

Imputing Null Values in applicationdf

Strategy for applicationdf:

To impute null values in categorical variables which has lower null percentage, mode() is used to impute the most frequent items. To impute null values in categorical variables which has higher null percentage, a new category is created. To impute null values in numerical variables which has lower null percentage, median() is used as There are no outliers in the columns Mean returned decimal values and median returned whole numbers and the columns were number of requests

In [64]:
```
# checking the null value % of each column in applicationDF dataframe
round(applicationdf.isnull().sum() / applicationdf.shape[0] * 100.00,2)
```

Out[64]:
```
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
```

Impute categorical variable 'NAME_TYPE_SUITE' which has lower null percentage(0.42%) with the most frequent category using mode()[0]:

In [65]:
```
applicationdf['NAME_TYPE_SUITE'].describe()
```

Out[65]:
```
count             306219
unique                 7
top       Unaccompanied
freq              248526
Name: NAME_TYPE_SUITE, dtype: object
```

In [66]:
```
applicationdf['NAME_TYPE_SUITE'].fillna((applicationdf['NAME_TYPE_SUITE'].mode()[0]
```

Impute categorical variable 'OCCUPATION_TYPE' which has higher null percentage(31.35%) with a new category as assigning to any existing category might influence the analysis:

In [67]:
```
applicationdf['OCCUPATION_TYPE'] = applicationdf['OCCUPATION_TYPE'].cat.add_categor
applicationdf['OCCUPATION_TYPE'].fillna('Unknown', inplace =True)
```

Impute numerical variables with the median as there are no outliers that can be seen from results of describe() and mean() returns decimal values and these columns represent number of enquiries made which cannot be decimal:

In [68]:
```
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[68]:

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREA
count	265992.000000	265992.000000	26599
mean	0.006402	0.007000	
std	0.083849	0.110757	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	0.000000	
max	4.000000	9.000000	

Impute with median as mean has decimals and this is number of requests

amount = ['AMT_REQ_CREDIT_BUREAU_HOUR',
'AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CREDIT_BUREAU_WEEK','AMT_REQ_CREDIT_BUREA
'AMT_REQ_CREDIT_BUREAU_QRT','AMT_REQ_CREDIT_BUREAU_YEAR']

for col in amount:

```
    applicationDF[col].fillna(applicationDF[col].median(),inplace =
    True)
```

In [69]:
```
# checking the null value % of each column in previousDF dataframe
round(applicationdf.isnull().sum() / previousdf.shape[0] * 100.00,2)
```

Out[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               0.02
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    2.49
AMT_REQ_CREDIT_BUREAU_DAY     2.49
AMT_REQ_CREDIT_BUREAU_WEEK    2.49
AMT_REQ_CREDIT_BUREAU_MON     2.49
AMT_REQ_CREDIT_BUREAU_QRT     2.49
AMT_REQ_CREDIT_BUREAU_YEAR    2.49
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
```

Insight:

We still have few null values in the columns: AMT_GOODS_PRICE, OBS_30_CNT_SOCIAL_CIRCLE, DEF_30_CNT_SOCIAL_CIRCLE, OBS_60_CNT_SOCIAL_CIRCLE, DEF_60_CNT_SOCIAL_CIRCLE. We can ignore as this percentage is very less.

Imputing Null Values in previousdf

Strategy for applicationdf:

To impute null values in numerical column, we analysed the loan status and assigned values.

To impute null values in continuous variables, we plotted the distribution of the columns and used

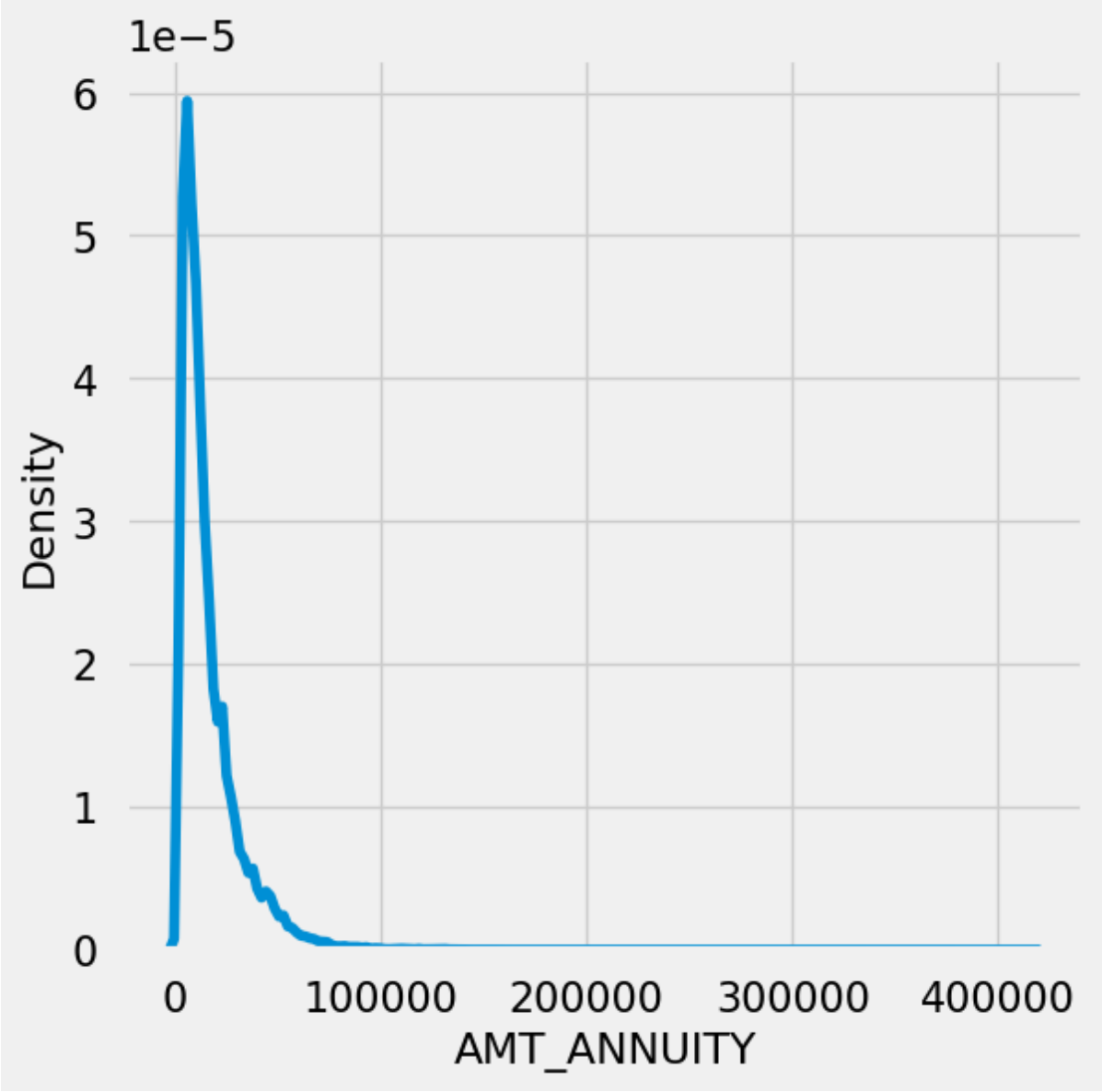
median if the distribution is skewed

mode if the distribution pattern is preserved.

In [70]:
```
# checking the null value % of each column in previousDF dataframe
round(previousdf.isnull().sum() / previousdf.shape[0] * 100.00,2)
```

Out[70]:
```
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 [71]:
```
#Impute AMT_ANNUITY with median as the distribution is greatly skewed:

plt.figure(figsize=(6,6))
sns.kdeplot(previousdf['AMT_ANNUITY'])
plt.show()
```



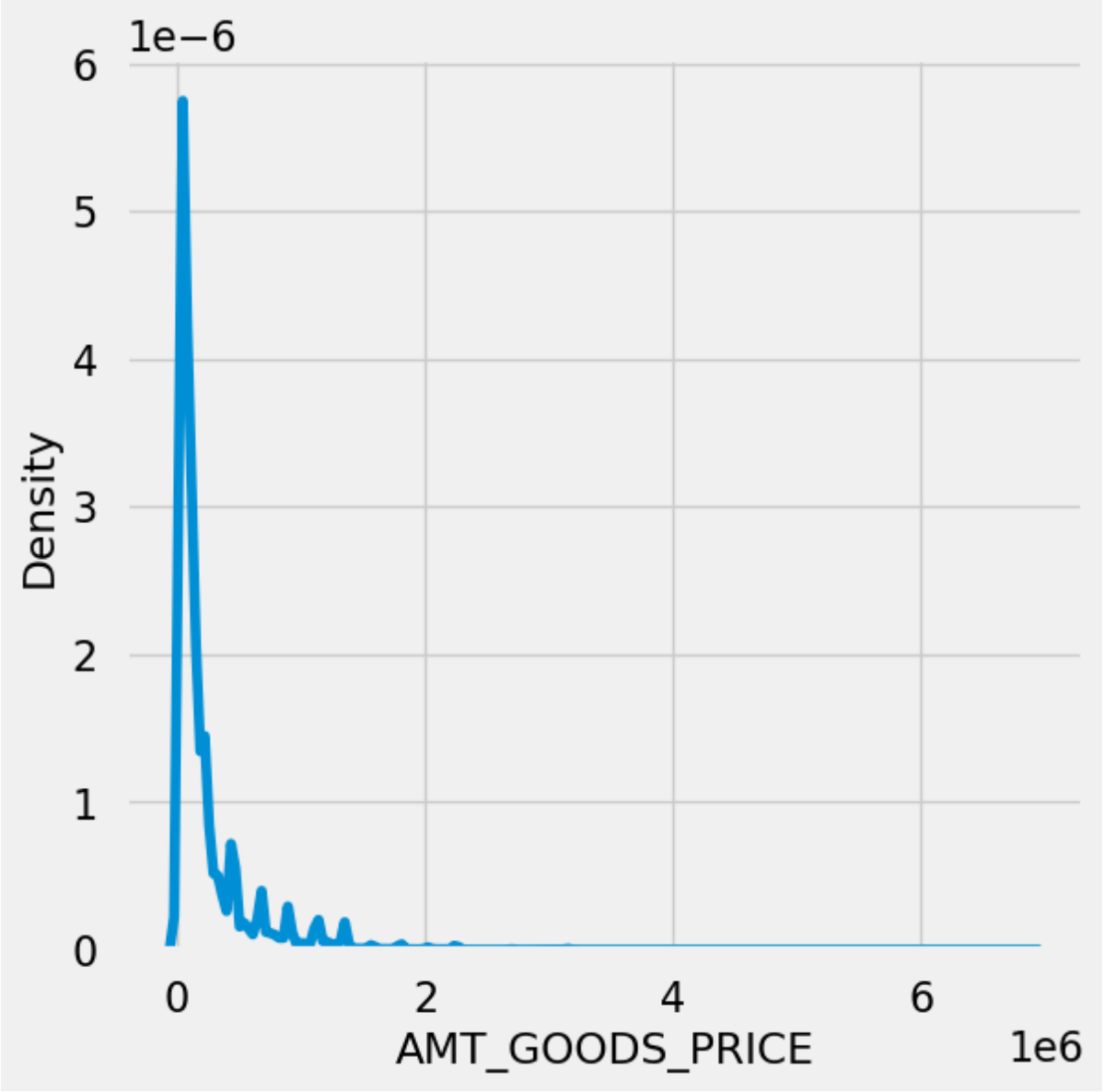
Insight:

There is a single peak at the left side of the distribution and it indicates the presence of outliers and hence imputing with mean would not be the right approach and hence imputing with median.

In [72]:
```
previousdf['AMT_ANNUITY'].fillna(previousdf['AMT_ANNUITY'].median(),inplace = True)
```

Impute AMT_GOODS_PRICE with mode as the distribution is closely similar:

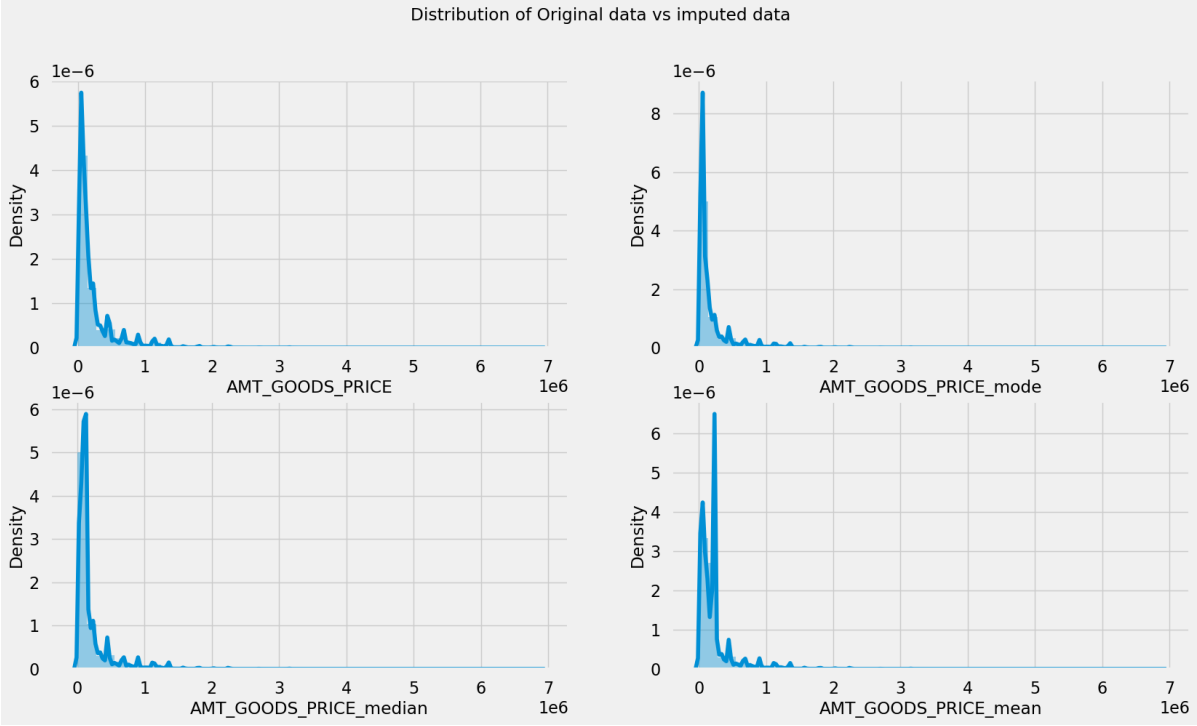
In [73]:
```
plt.figure(figsize=(6,6))
sns.kdeplot(previousdf['AMT_GOODS_PRICE'][pd.notnull(previousdf['AMT_GOODS_PRICE'])
plt.show()
```



There are several peaks along the distribution. Let's impute using the mode, mean and median and see if the distribution is still about the same.

statsDF = pd.DataFrame() # new dataframe with columns i

In [74]:
```
statsdf = pd.DataFrame() # new dataframe with columns imputed with mode, median and
statsdf['AMT_GOODS_PRICE_mode'] = previousdf['AMT_GOODS_PRICE'].fillna(previousdf['
statsdf['AMT_GOODS_PRICE_median'] = previousdf['AMT_GOODS_PRICE'].fillna(previousdf
statsdf['AMT_GOODS_PRICE_mean'] = previousdf['AMT_GOODS_PRICE'].fillna(previousdf['

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]])
```



Insight:

The original distribution is closer with the distribution of data imputed with mode in this case

In [75]:
```
previousdf['AMT_GOODS_PRICE'].fillna(previousdf['AMT_GOODS_PRICE'].mode()[0], inpla
```

Impute CNT_PAYMENT with 0 as the NAME_CONTRACT_STATUS for these indicate that most of these loans were not started:

In [76]:
```
previousdf.loc[previousdf['CNT_PAYMENT'].isnull(),'NAME_CONTRACT_STATUS'].value_cou
```

Out[76]:
```
Canceled        305805
Refused          40897
Unused offer     25524
Approved             4
Name: NAME_CONTRACT_STATUS, dtype: int64
```

In [77]:
```
previousdf['CNT_PAYMENT'].fillna(0,inplace = True)
# checking the null value % of each column in previousdf dataframe
round(previousdf.isnull().sum() / previousdf.shape[0] * 100.00,2)
```

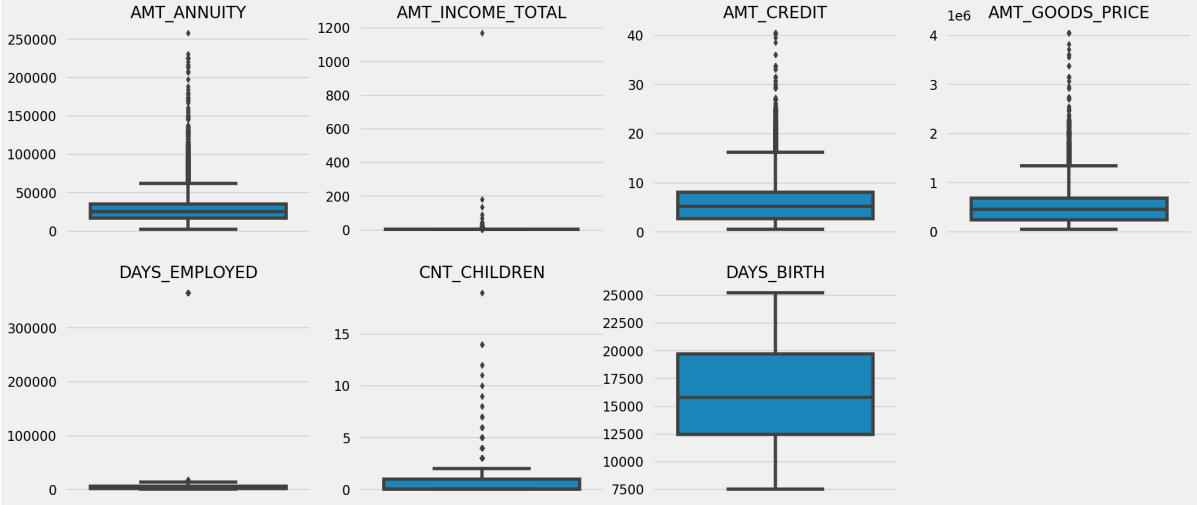
Out[77]:
```
SK_ID_PREV                0.00
SK_ID_CURR                0.00
NAME_CONTRACT_TYPE        0.00
AMT_ANNUITY               0.00
AMT_APPLICATION           0.00
AMT_CREDIT                0.00
AMT_GOODS_PRICE           0.00
NAME_CASH_LOAN_PURPOSE    0.00
NAME_CONTRACT_STATUS      0.00
DAYS_DECISION             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
```

Insight: We still have few null values in the PRODUCT_COMBINATION column. We can ignore as this percentage is very less.

Identifying the outliers

Finding outlier information in applicationdf

In [78]:
```
plt.figure(figsize=(22,10))

app_outlier_col_1 = ['AMT_ANNUITY','AMT_INCOME_TOTAL','AMT_CREDIT','AMT_GOODS_PRICE
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("")
```



Insight:

It can be seen that in current application data AMT_ANNUITY, AMT_CREDIT, AMT_GOODS_PRICE,CNT_CHILDREN have some number of outliers.

AMT_INCOME_TOTAL has huge number of outliers which indicate that few of the loan applicants have high income when compared to the others.

DAYS_BIRTH has no outliers which means the data available is reliable.

DAYS_EMPLOYED has outlier values around 350000(days) which is around 958 years which is impossible and hence this has to be incorrect entry.

In [79]:
```
#We can see the stats for these columns below as well.
```

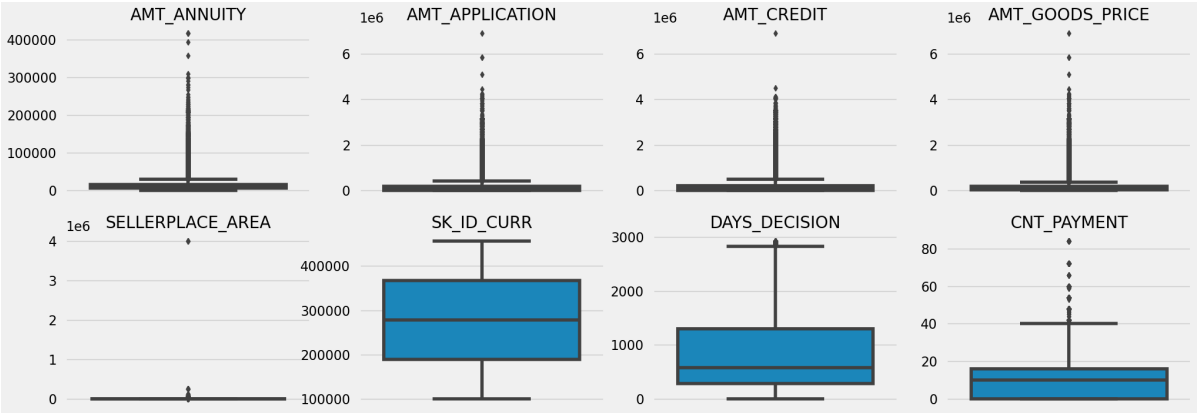
In [80]:
```
applicationdf[['AMT_ANNUITY', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_GOODS_PRICE',
```

Out[80]:

	AMT_ANNUITY	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_GOODS_PRICE	DAYS_BIRTH	C
count	307499.000000	307511.000000	307511.000000	3.072330e+05	307511.000000	
mean	27108.573909	1.687979	5.990260	5.383962e+05	16036.995067	
std	14493.737315	2.371231	4.024908	3.694465e+05	4363.988632	
min	1615.500000	0.256500	0.450000	4.050000e+04	7489.000000	
25%	16524.000000	1.125000	2.700000	2.385000e+05	12413.000000	
50%	24903.000000	1.471500	5.135310	4.500000e+05	15750.000000	
75%	34596.000000	2.025000	8.086500	6.795000e+05	19682.000000	
max	258025.500000	1170.000000	40.500000	4.050000e+06	25229.000000	

In [81]:
```
#Finding outlier information in previousdf

plt.figure(figsize=(22,8))

prev_outlier_col_1 = ['AMT_ANNUITY','AMT_APPLICATION','AMT_CREDIT','AMT_GOODS_PRICE
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("")
```



Insight: It can be seen that in previous application data.

AMT_ANNUITY, AMT_APPLICATION, AMT_CREDIT, AMT_GOODS_PRICE, SELLERPLACE_AREA have huge number of outliers. CNT_PAYMENT has few outlier values.

SK_ID_CURR is an ID column and hence no outliers.

DAYS_DECISION has little number of outliers indicating that these previous applications decisions were taken long back.

We can see the stats for these columns below as well.

In [82]:
```
previousdf[['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_GOODS_PRICE', 'SEL
```

Out[82]:

	AMT_ANNUITY	AMT_APPLICATION	AMT_CREDIT	AMT_GOODS_PRICE	SELLERPLACE_AREA
count	1.670214e+06	1.670214e+06	1.670213e+06	1.670214e+06	1.670214e+06
mean	1.490651e+04	1.752339e+05	1.961140e+05	1.856429e+05	3.139511e+02
std	1.317751e+04	2.927798e+05	3.185746e+05	2.871413e+05	7.127443e+03
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-1.000000e+00
25%	7.547096e+03	1.872000e+04	2.416050e+04	4.500000e+04	-1.000000e+00
50%	1.125000e+04	7.104600e+04	8.054100e+04	7.105050e+04	3.000000e+00
75%	1.682403e+04	1.803600e+05	2.164185e+05	1.804050e+05	8.200000e+01
max	4.180581e+05	6.905160e+06	6.905160e+06	6.905160e+06	4.000000e+06

. Data Analysis

Strategy:

The data analysis flow has been planned in following way :

Imbalance in Data.

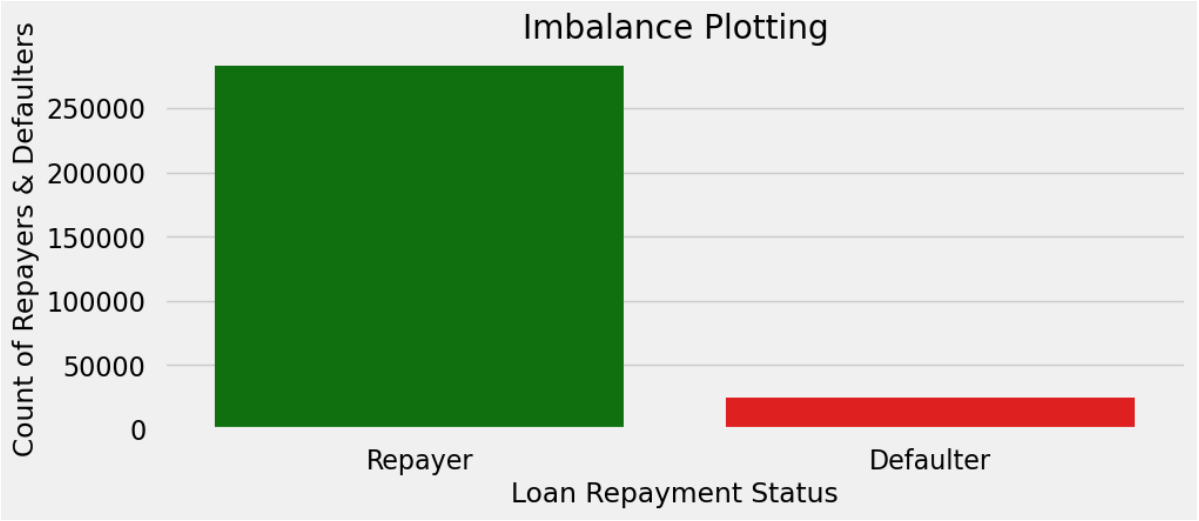
Categorical Data Analysis.

Categorical segmented Univariate Analysis.

Categorical Bi/Multivariate analysis.

Numeric Data Analysis; Bi-furcation of databased based on TARGET data. Correlation Matrix. Numerical segmented Univariate Analysis. Numerical Bi/Multivariate analysis.

In [83]:
```
#Imbalance Analysis

Imbalance = applicationdf["TARGET"].value_counts().reset_index()

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



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_perc))

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)

Plotting Functions

Following are the common functions customized to perform uniform anaysis that is called for all plots:

In [84]:
```
# function for plotting repetitive countplots in univariate categorical analysis on
# This function will create two subplots:
# 1. Count plot of categorical column w.r.t TARGET;
# 2. Percentage of defaulters within column

def univariate_categorical(feature,ylog=False,label_rotation=False,horizontal_layou
    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)
    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' : '
    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, '


    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'
```

```
    plt.show();
```

In [85]:
```
# function for plotting repetitive countplots 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'])
     # 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 [86]:
```
# function for plotting repetitive rel plots in bivaritae numerical analysis on app

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 [87]:
```
#function for plotting repetitive countplots in univariate categorical analysis on

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, 'colo
    else:
        plt.ylabel("Count",fontdict={'fontsize' : 10, 'fontweight' : 3, 'color' : '

    plt.title(col , fontdict={'fontsize' : 15, 'fontweight' : 5, 'color' : 'Blue'})
    plt.legend(loc = "upper right")
    plt.xticks(rotation=90, ha='right')

    plt.show()
```

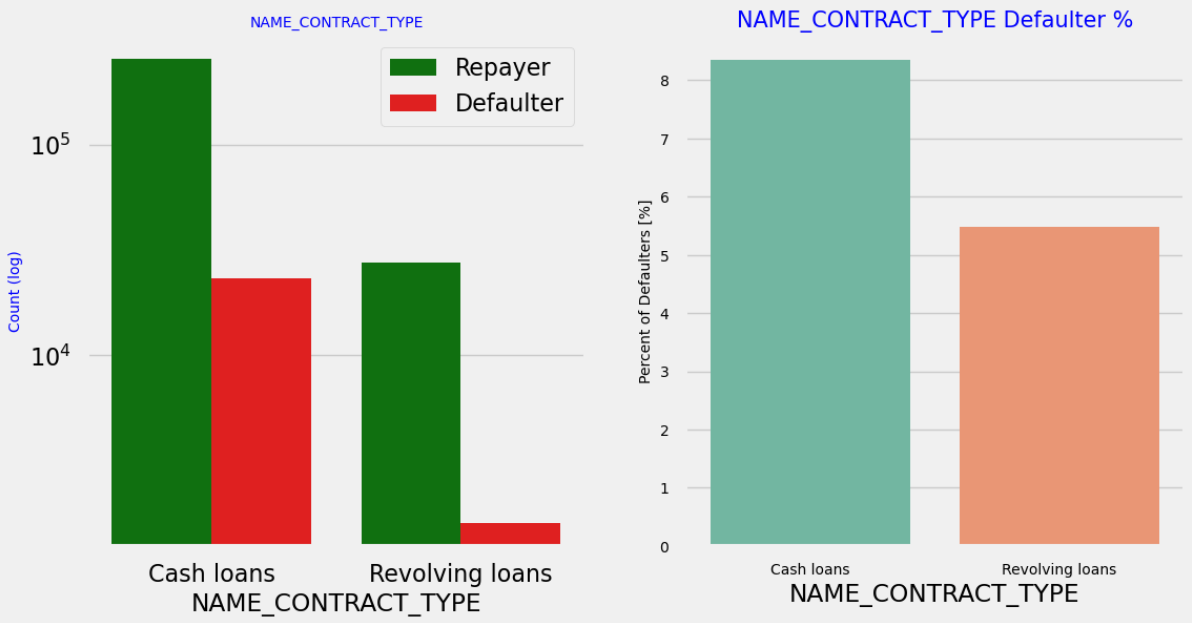
In [88]:
```
# Function to plot point plots on merged dataframe
```

```
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'])
   # plt.legend(['Repayer','Defaulter'])
```

Categorical Variables Analysis

Segmented Univariate Analysis

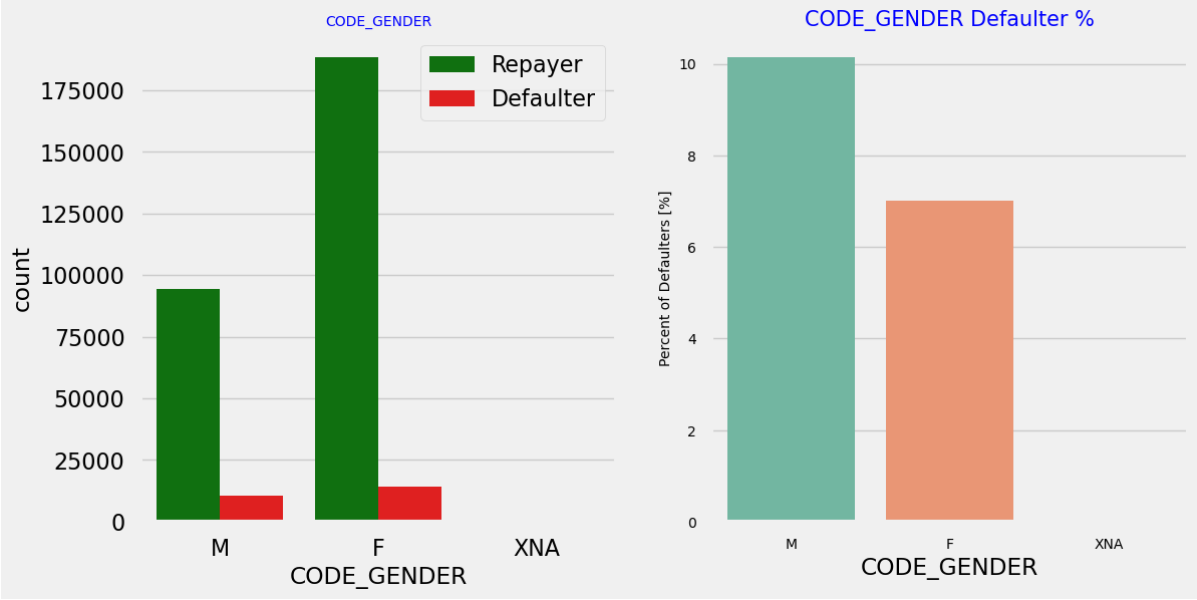
In [89]:
```
# Checking the contract type based on loan repayment status
univariate_categorical('NAME_CONTRACT_TYPE',True)
```



Inferences:

Contract type: Revolving loans are just a small fraction (10%) from the total number of loans; in the same time, a larger amount of Revolving loans, comparing with their frequency, are not repaid.

In [90]:
```
# Checking the type of Gender on loan repayment status
univariate_categorical('CODE_GENDER')
```

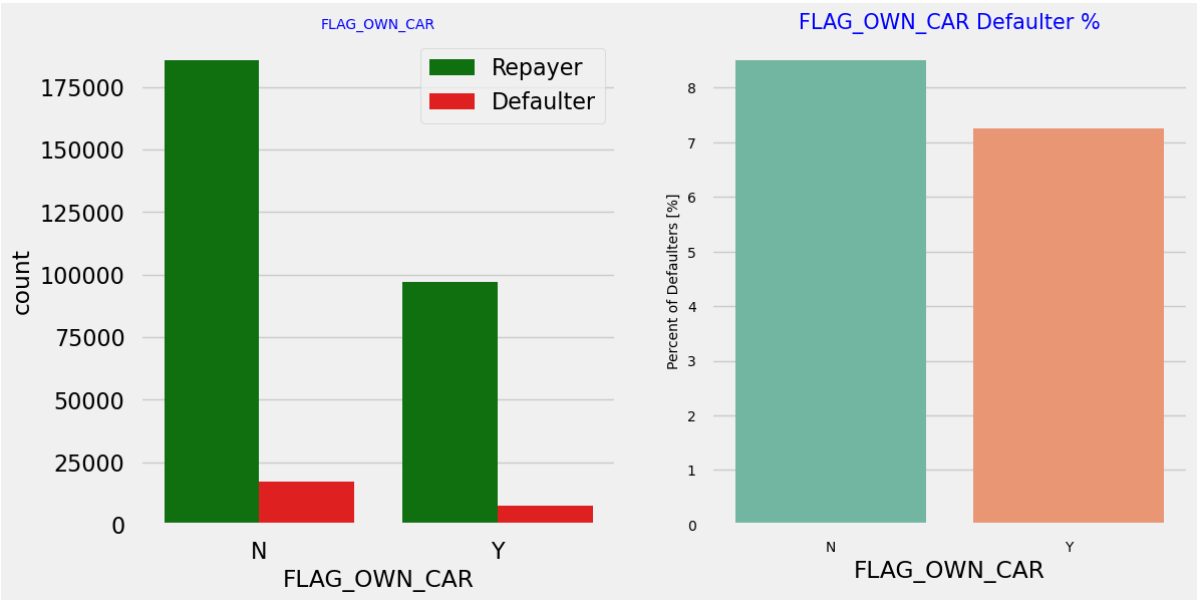


Inferences:

The number of female clients is almost double the number of male clients. Based on the percentage of defaulted credits, males have a higher chance of not returning their loans (~10%), comparing with women (~7%)

Checking if owning a car is related to loan repayment status

In [91]:
```
univariate_categorical('FLAG_OWN_CAR')
```



Inferences:

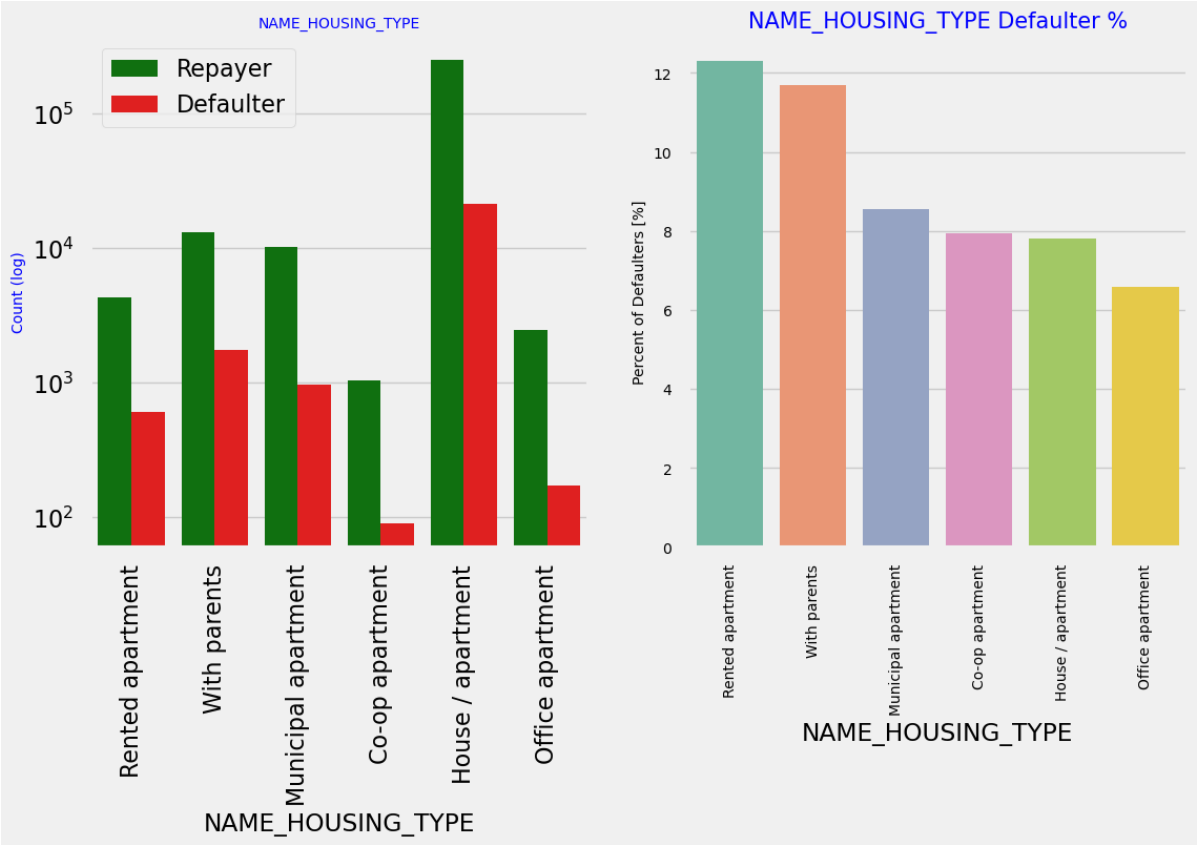
Clients who own a car are half in number of the clients who dont own a car. But based on the percentage of deault, there is no correlation between owning a car and loan repayment as in both cases the default percentage is almost same.

In [92]:
```
# Checking if owning a realty is related to loan repayment status
univariate_categorical('FLAG_OWN_REALTY')
```

Inferences:

The clients who own real estate are more than double of the ones that don't own. But the defaulting rate of both categories are around the same (~8%). Thus there is no correlation between owning a reality and defaulting the loan.

In [93]:
```
# Analyzing Housing Type based on loan repayment status
univariate_categorical("NAME_HOUSING_TYPE",True,True,True)
```



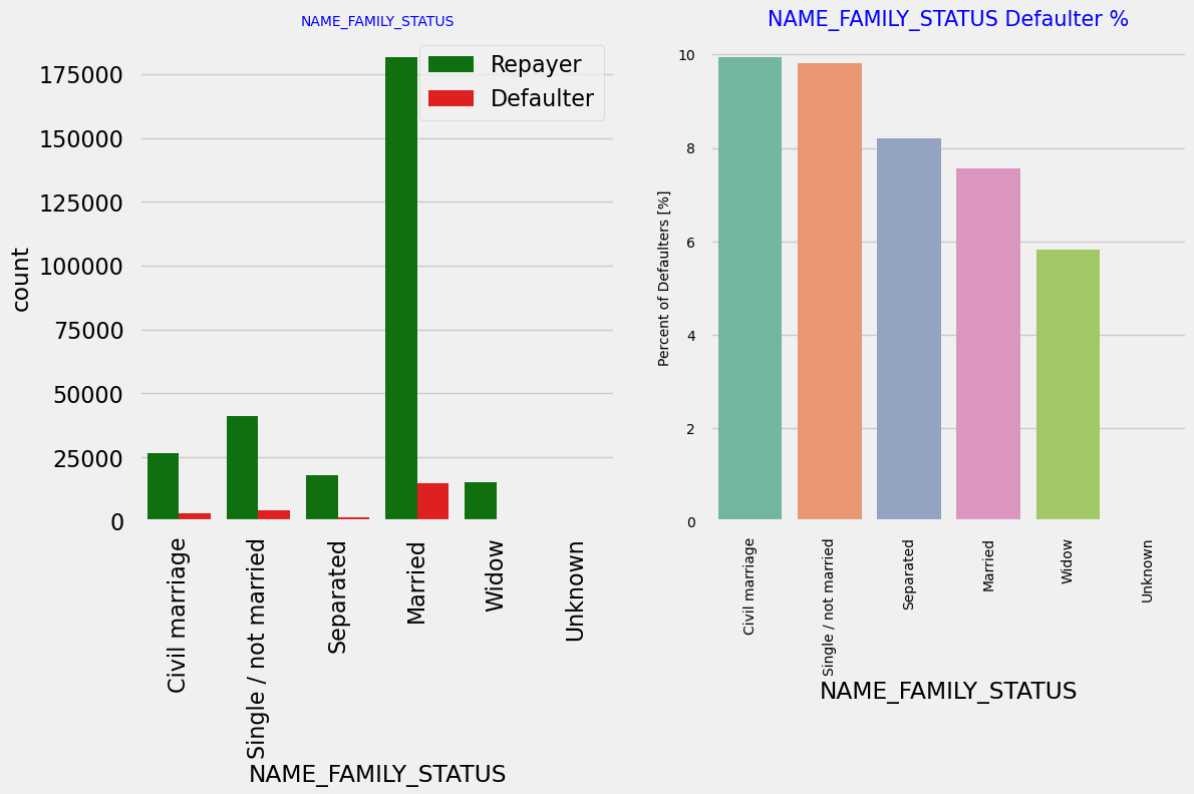
Inferences:

Majority of people live in House/apartment.

People living in office apartments have lowest default rate.

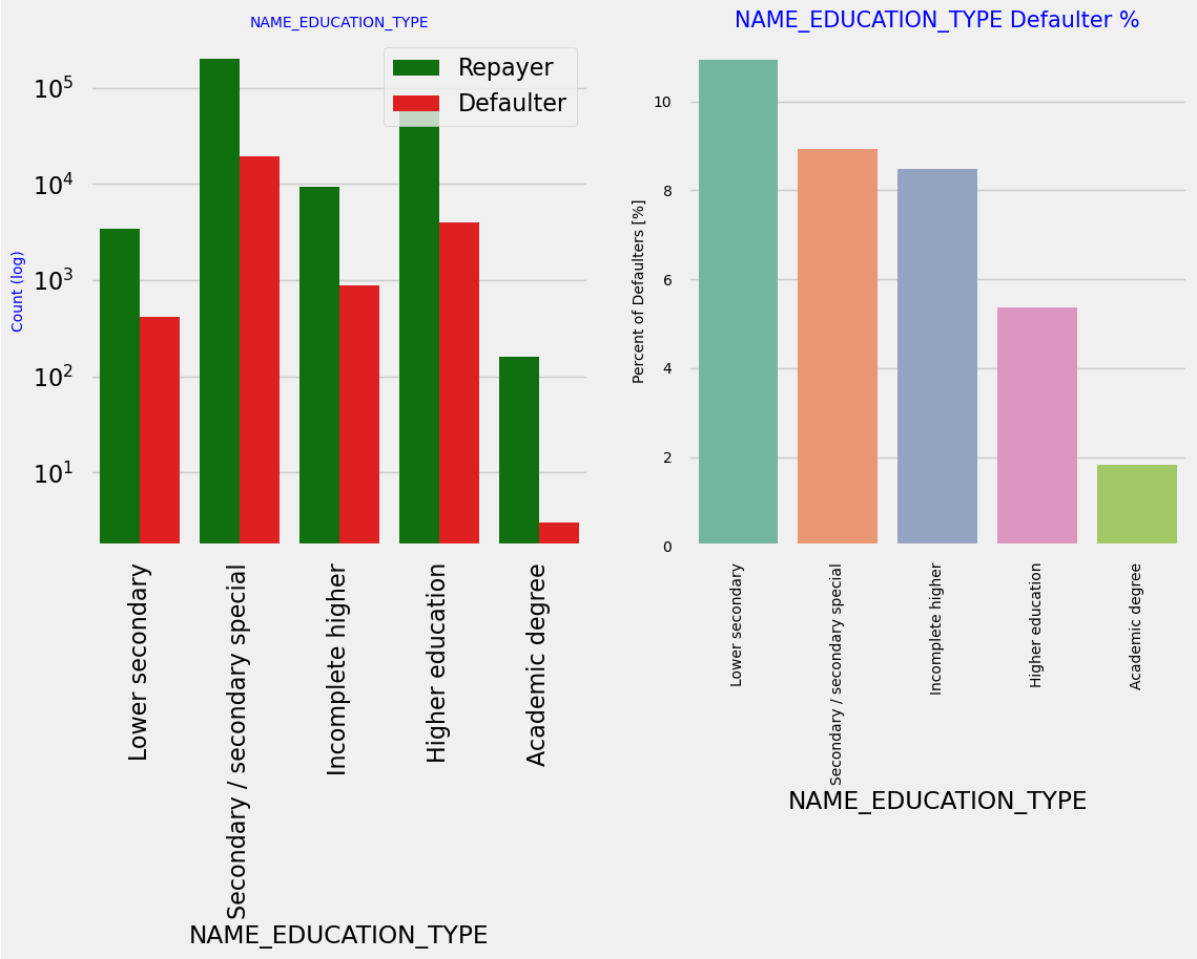
People living with parents (~11.5%) and living in rented apartments(>12%) have higher probability of defaulting.

In [94]:
```
# Analyzing Family status based on loan repayment status
univariate_categorical("NAME_FAMILY_STATUS",False,True,True)
```



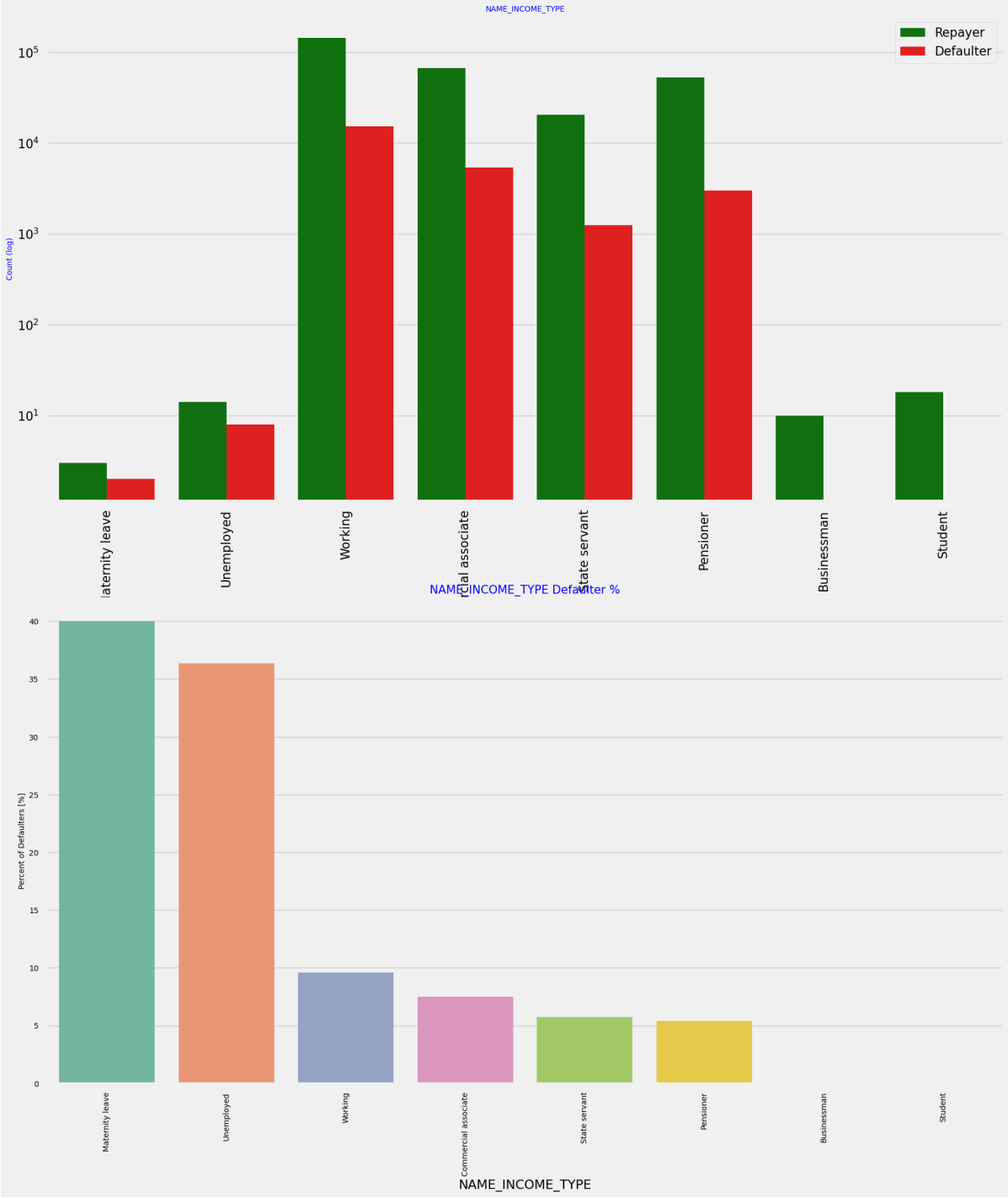
Inferences: Most of the people who have taken loan are married, followed by Single/not married and civil marriage In terms of percentage of not repayment of loan, Civil marriage has the highest percent of not repayment (10%), with Widow the lowest (exception being Unknown).

In [95]:
```
# Analyzing Education Type based on loan repayment status
univariate_categorical("NAME_EDUCATION_TYPE",True,True,True)
```



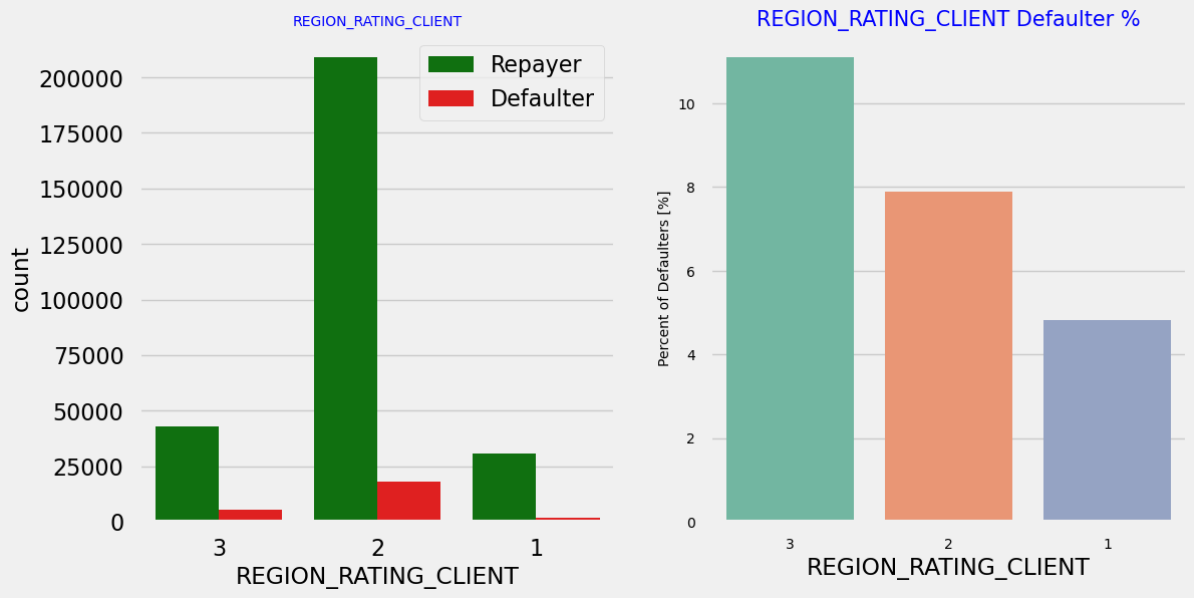
Inferences: Majority of the clients have Secondary / secondary special education, followed by clients with Higher education. Only a very small number having an academic degree. The Lower secondary category, although rare, have the largest rate of not returning the loan (11%). The people with Academic degree have less than 2% defaulting rate.

In [96]:
```
# Analyzing Income Type based on loan repayment status
univariate_categorical("NAME_INCOME_TYPE",True,True,False)
```



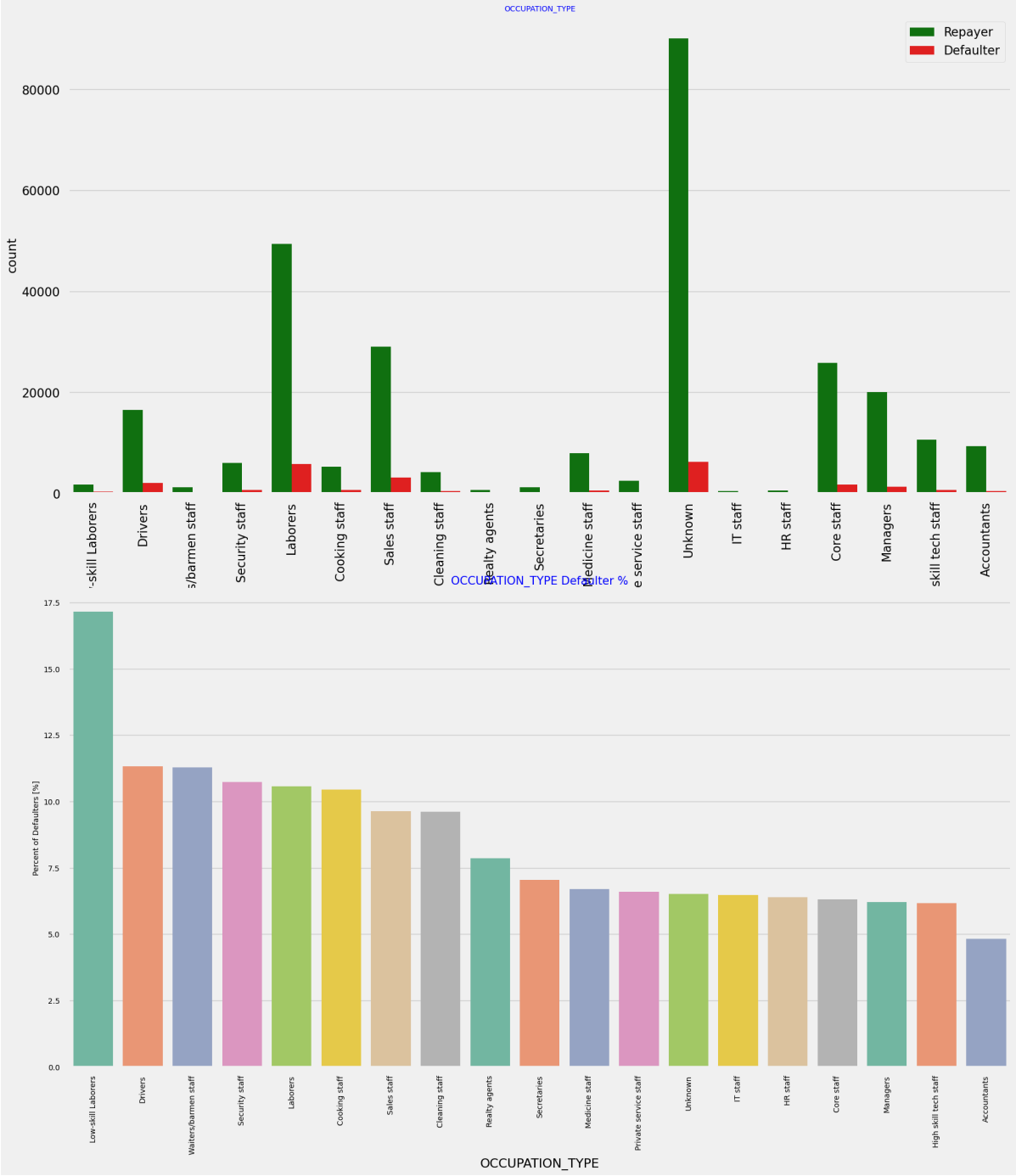
Inferences: Most of applicants for loans have income type as Working, followed by Commercial associate, Pensioner and State servant. The applicants with the type of income Maternity leave have almost 40% ratio of not returning loans, followed by Unemployed (37%). The rest of types of incomes are under the average of 10% for not returning loans. Student and Businessmen, though less in numbers do not have any default record. Thus these two category are safest for providing loan.

In [97]:
```
# Analyzing Region rating where applicant lives based on loan repayment status
univariate_categorical("REGION_RATING_CLIENT",False,False,True)
```



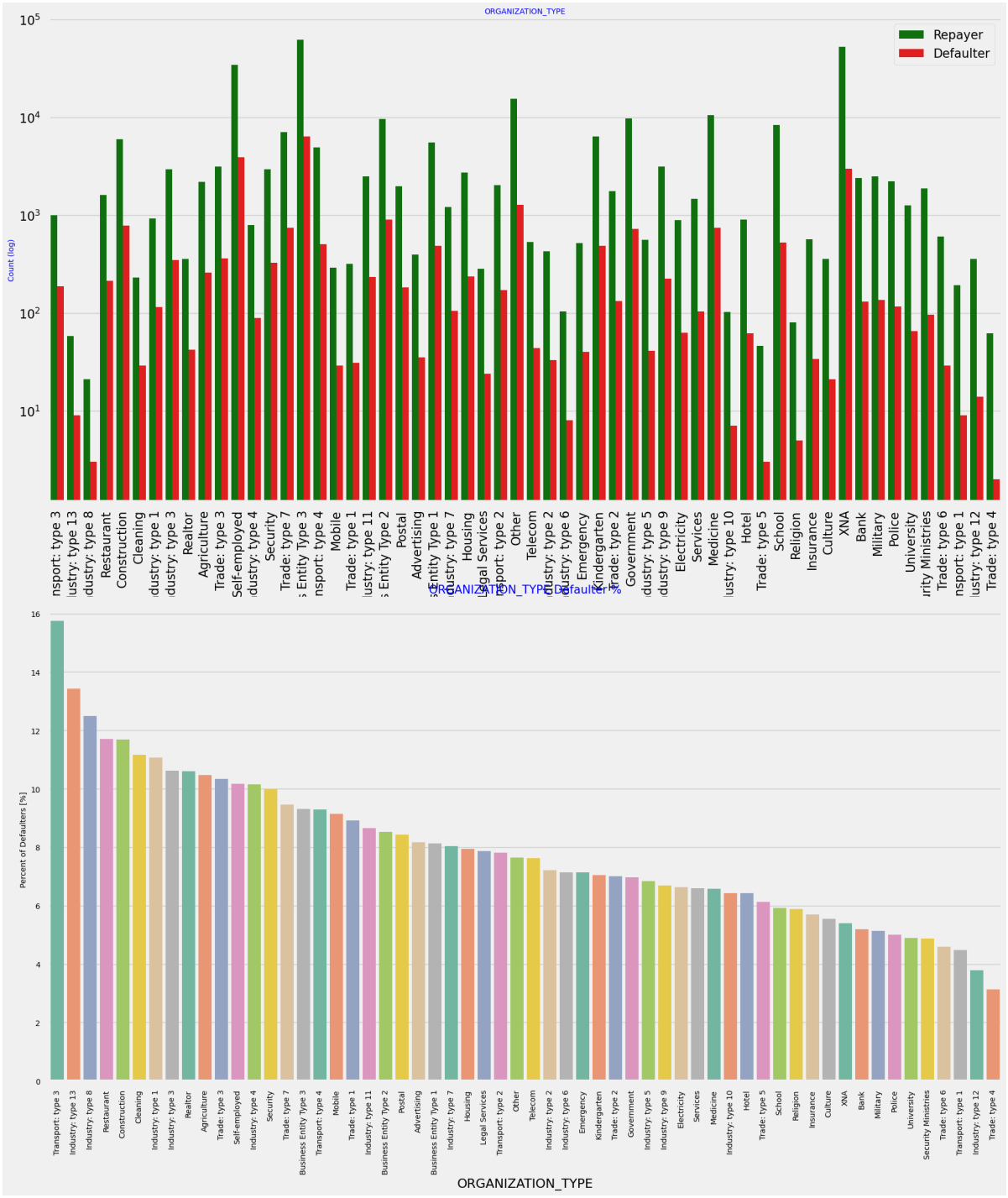
Inferences: Most of the applicants are living in Region_Rating 2 place. Region Rating 3 has the highest default rate (11%). Applicant living in Region_Rating 1 has the lowest probability of defaulting, thus safer for approving loans.

In [98]:
```
# Analyzing Occupation Type where applicant lives based on loan repayment status
univariate_categorical("OCCUPATION_TYPE",False,True,False)
```



Inferences: Most of the loans are taken by Laborers, followed by Sales staff. IT staff take the lowest amount of loans. The category with highest percent of not repaid loans are Low-skill Laborers (above 17%), followed by Drivers and Waiters/barmen staff, Security staff, Laborers and Cooking staff.

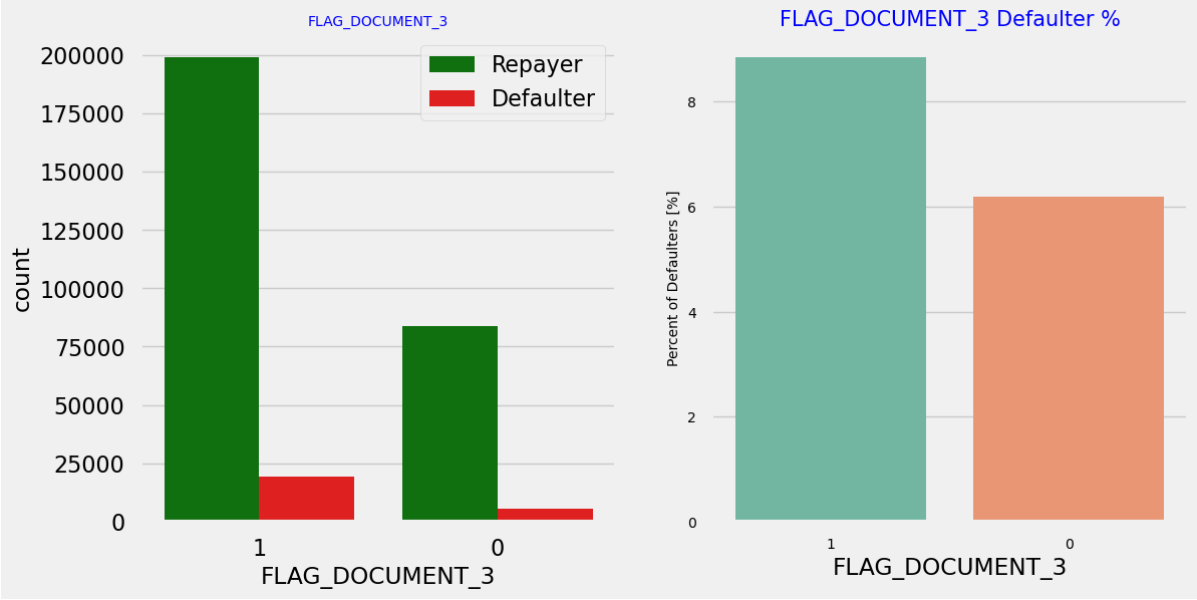
In [99]:
```
# Checking Loan repayment status based on Organization type
univariate_categorical("ORGANIZATION_TYPE",True,True,False)
```



Inferences: 1.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. 2.Most of the people application for loan are from Business Entity Type 3 3.For a very high number of applications, Organization type information is unavailable(XNA) It can be seen that following category of organization type has lesser defaulters thus safer for providing loans: Trade Type 4 and 5 Industry type 8

In [100…

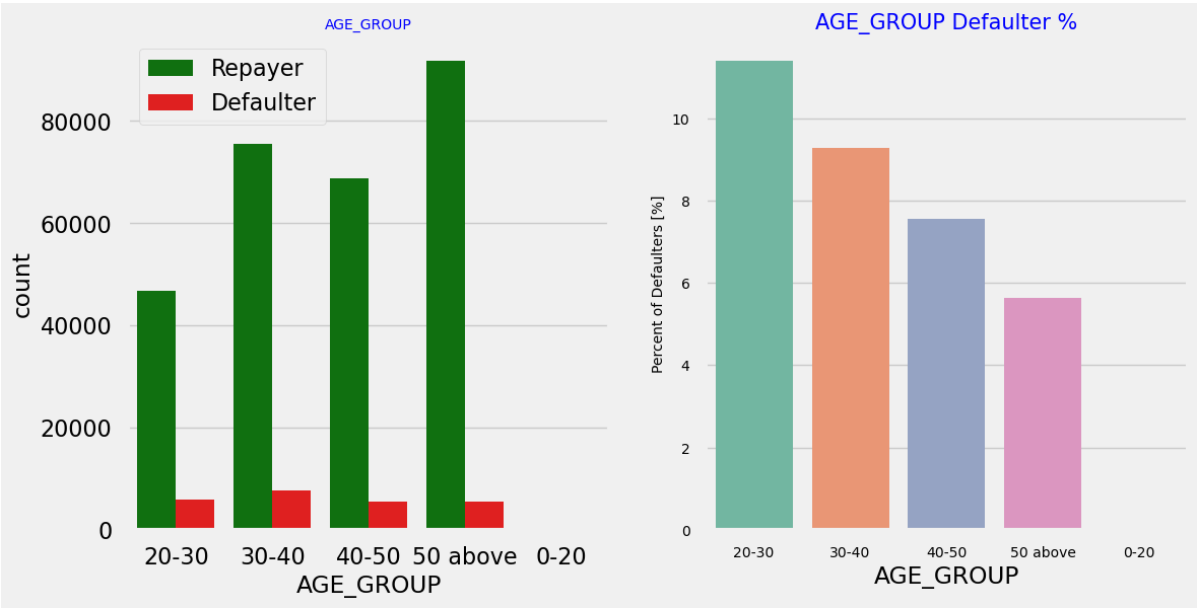
```
# Analyzing Flag_Doc_3 submission status based on loan repayment status
univariate_categorical("FLAG_DOCUMENT_3",False,False,True)
```



Inferences: There is no significant correlation between repayers and defaulters in terms of submitting document 3 as we see even if applicants have submitted the document, they have defaulted a slightly more (~9%) than who have not submitted the document (6%)

In [101…

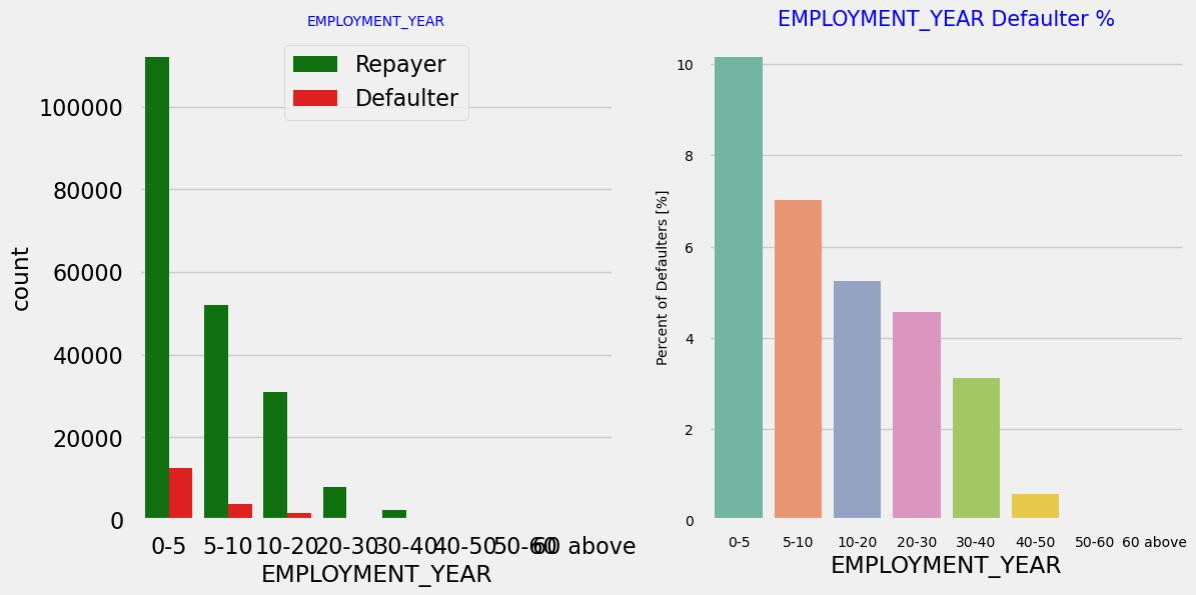
```
# Analyzing Age Group based on loan repayment status
univariate_categorical("AGE_GROUP",False,False,True)
```



Inferences: 1.People in the age group range 20-40 have higher probability of defaulting. 2.People above age of 50 have low probability of defailting.

In [102…

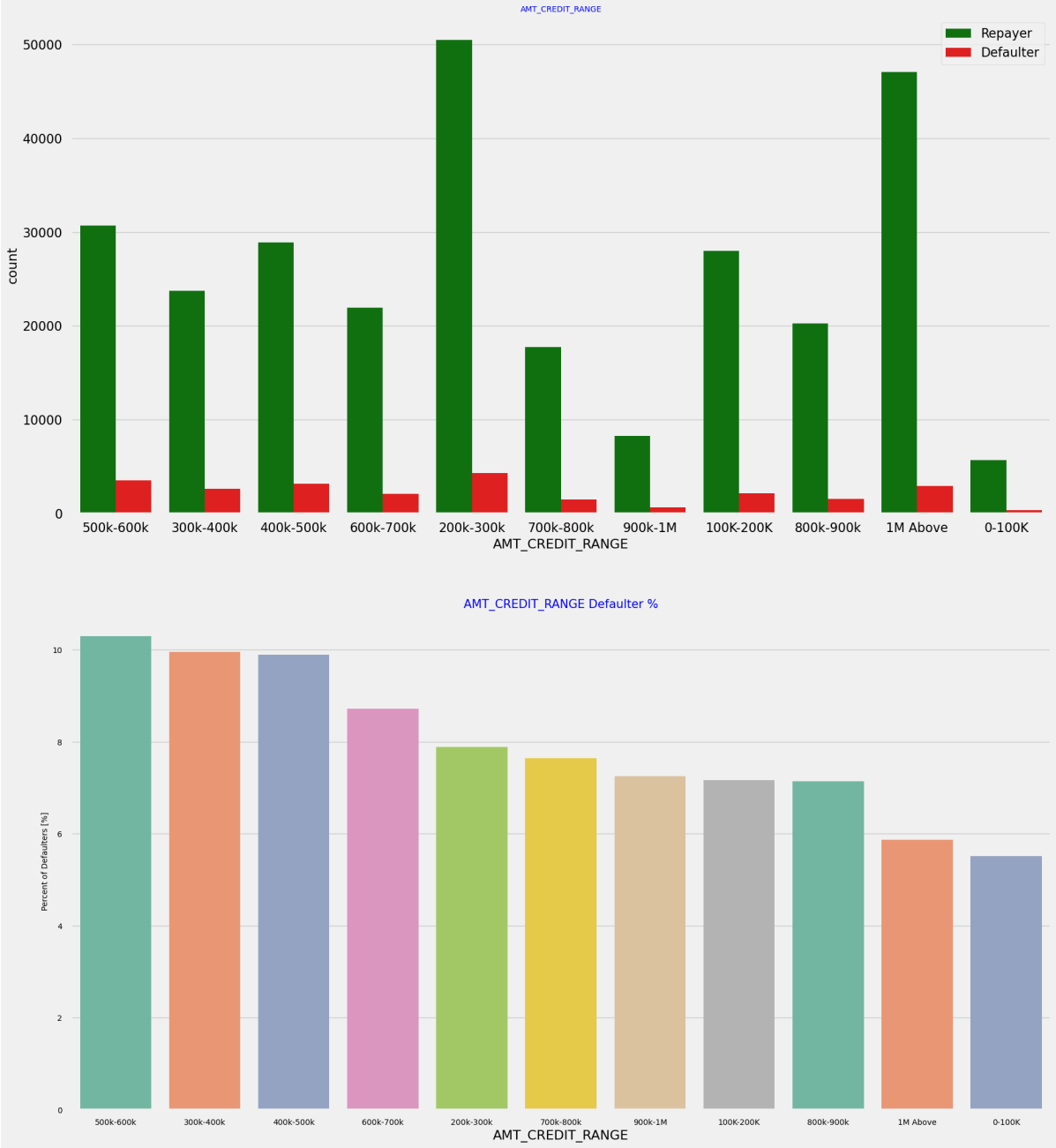
```
# Analyzing Employment_Year based on loan repayment status
univariate_categorical("EMPLOYMENT_YEAR",False,False,True)
```



Inferences: 1.Majority of the applicants have been employeed in between 0-5 years. The defaulting rating of this group is also the highest which is 10%. 2.With increase of employment year, defaulting rate is gradually decreasing with people having 40+ year experience having less than 1% default rate.

In [103…

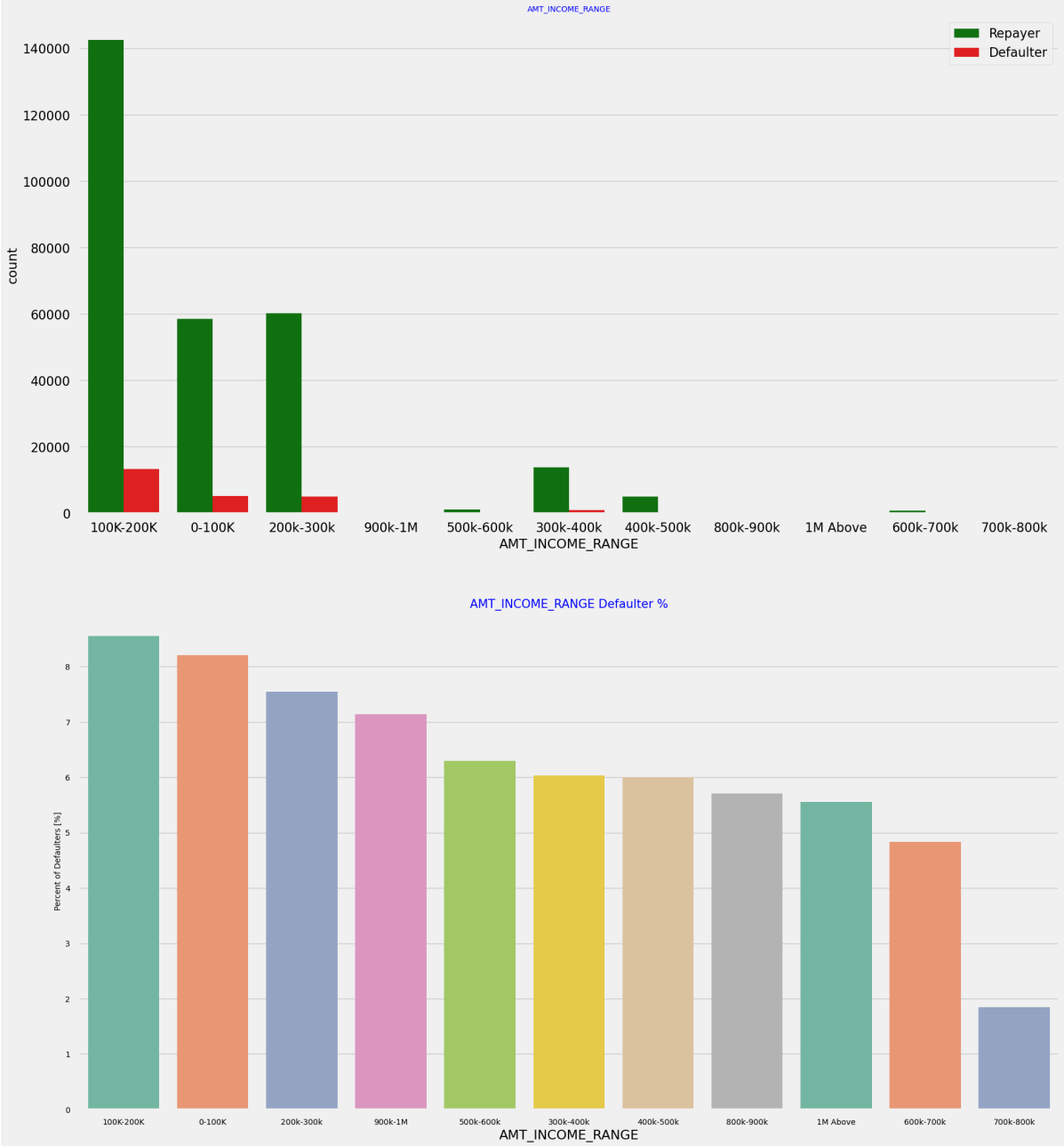
```
# Analyzing Amount_Credit based on loan repayment status
univariate_categorical("AMT_CREDIT_RANGE",False,False,False)
```



Inferences: 1.More than 80% of the loan provided are for amount less than 900,000. 2.People who get loan for 300-600k tend to default more than others.

In [104…

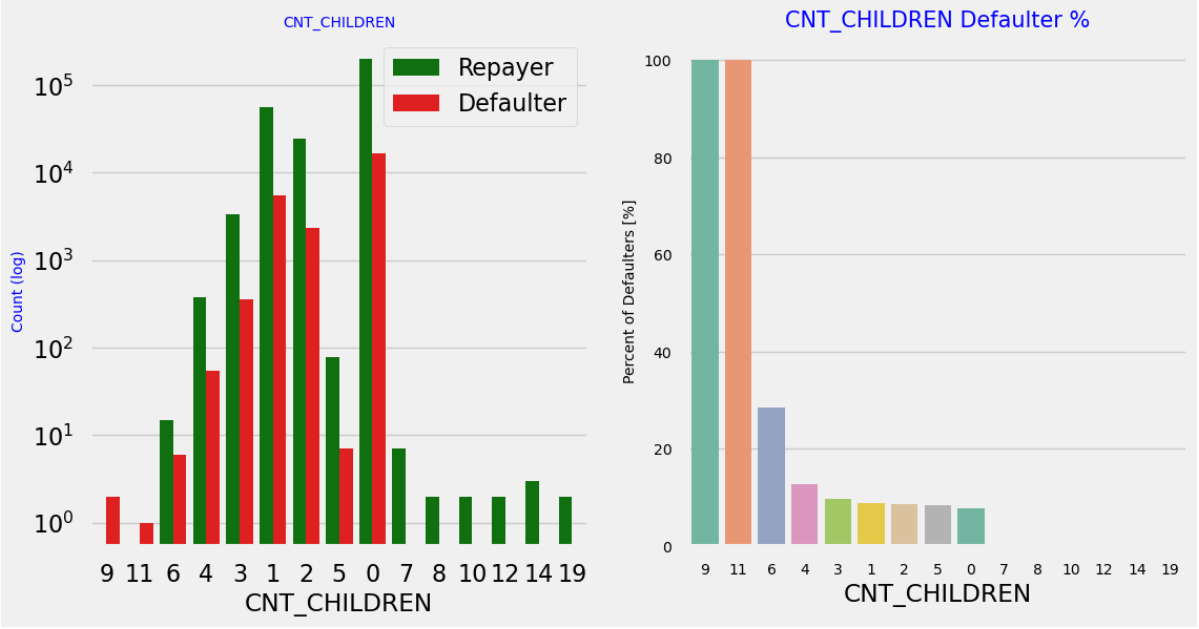
```
# Analyzing Amount_Income Range based on loan repayment status
univariate_categorical("AMT_INCOME_RANGE",False,False,False)
```



Inferences: 1.90% of the applications have Income total less than 300,000 2.Application with Income less than 300,000 has high probability of defaulting 3.Applicant with Income more than 700,000 are less likely to default

In [105…

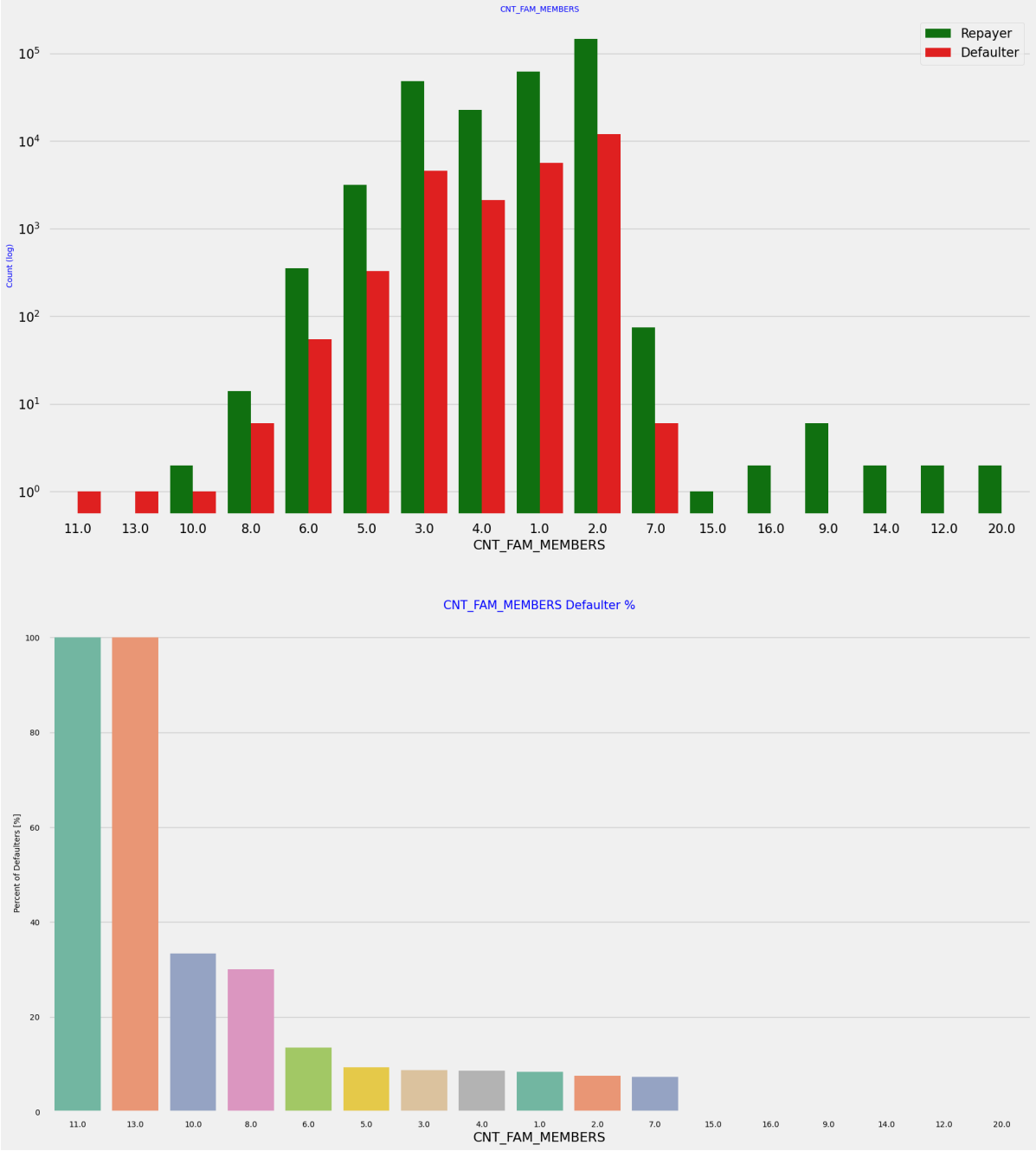
```
# Analyzing Number of children based on loan repayment status
univariate_categorical("CNT_CHILDREN",True)
```



Inferences: 1.Most of the applicants do not have children 2.Very few clients have more than 3 children. 3.Client who have more than 4 children has a very high default rate with child count 9 and 11 showing 100% default rate

In [106…

```
# Analyzing Number of family members based on loan repayment status
univariate_categorical("CNT_FAM_MEMBERS",True, False, False)
```



Inferences: Family member follows the same trend as children where having more family members increases the risk of defaulting

Categorical Bi/Multivariate Analysis

In [107…

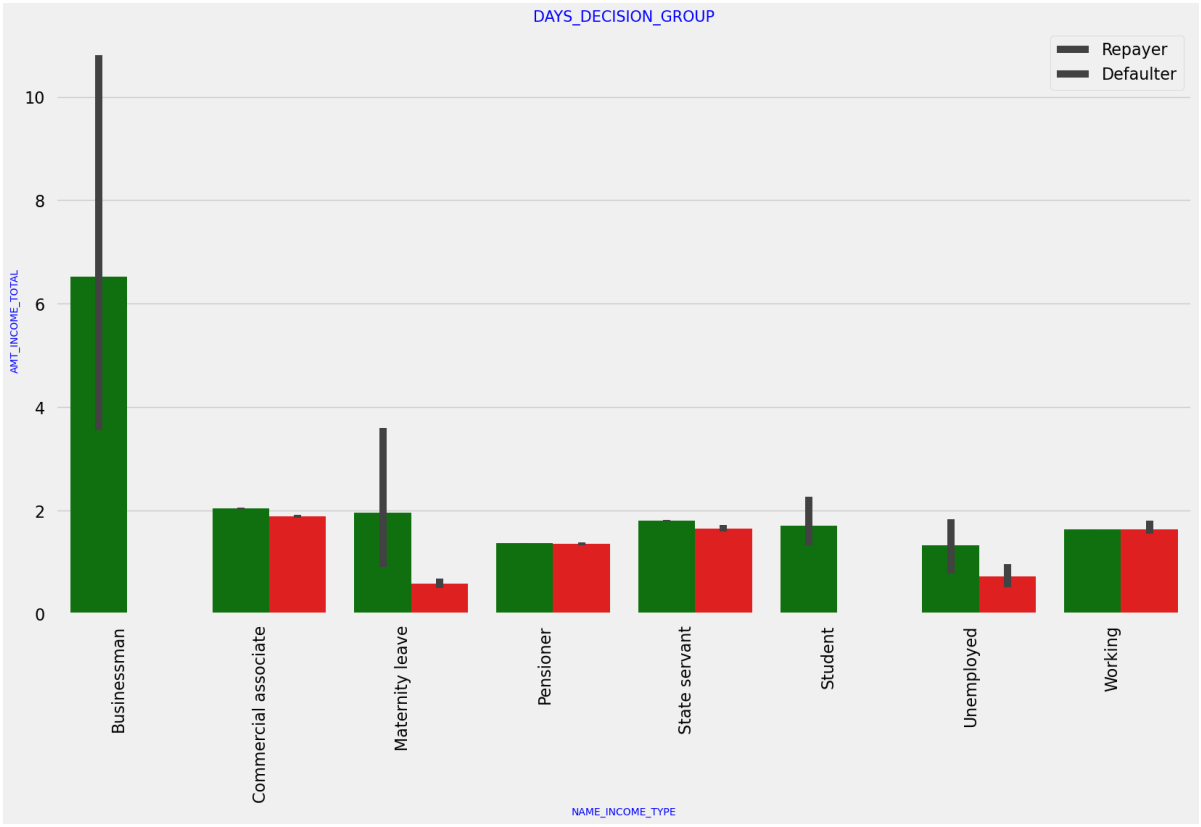
```
applicationdf.groupby('NAME_INCOME_TYPE')['AMT_INCOME_TOTAL'].describe()
```

Out[107]:

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 [108…

```
# Income type vs Income Amount Range
bivariate_bar("NAME_INCOME_TYPE","AMT_INCOME_TOTAL",applicationdf,"TARGET",(18,10))
```



Inferences: It can be seen that business man's income is the highest and the estimated range with default 95% confidence level seem to indicate that the income of a business man could be in the range of slightly close to 4 lakhs and slightly above 10 lakhs

Numeric Variables Analysis

Bifurcating the applicationdf dataframe based on Target value 0 and 1 for correlation and other analysis

In [109…

```
applicationdf.columns
```

Out[109]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CA
R', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNU
ITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TY
PE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAY
S_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OCCUPATION_TYP
E', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'WEE
KDAY_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_CI
TY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'OB
S_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_B
UREAU_YEAR', 'AMT_INCOME_RANGE', 'AMT_CREDIT_RANGE', 'AGE', 'AGE_GROUP', 'YEARS_EM
PLOYED', 'EMPLOYMENT_YEAR'],
      dtype='object')
```

In [110…
```
# Bifurcating the applicationdf dataframe based on Target value 0 and 1 for correla
cols_for_correlation = ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_
                        'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNU
                        'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE
                        'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BI
                        'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OCCUPATION_TYPE',
                        'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START'
                        'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
                        'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_C
                        'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DA
                        'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
                        'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', '


Repayer_df = applicationdf.loc[applicationdf['TARGET']==0, cols_for_correlation] #
Defaulter_df = applicationdf.loc[applicationdf['TARGET']==1, cols_for_correlation]
```

Correlation between numeric variable

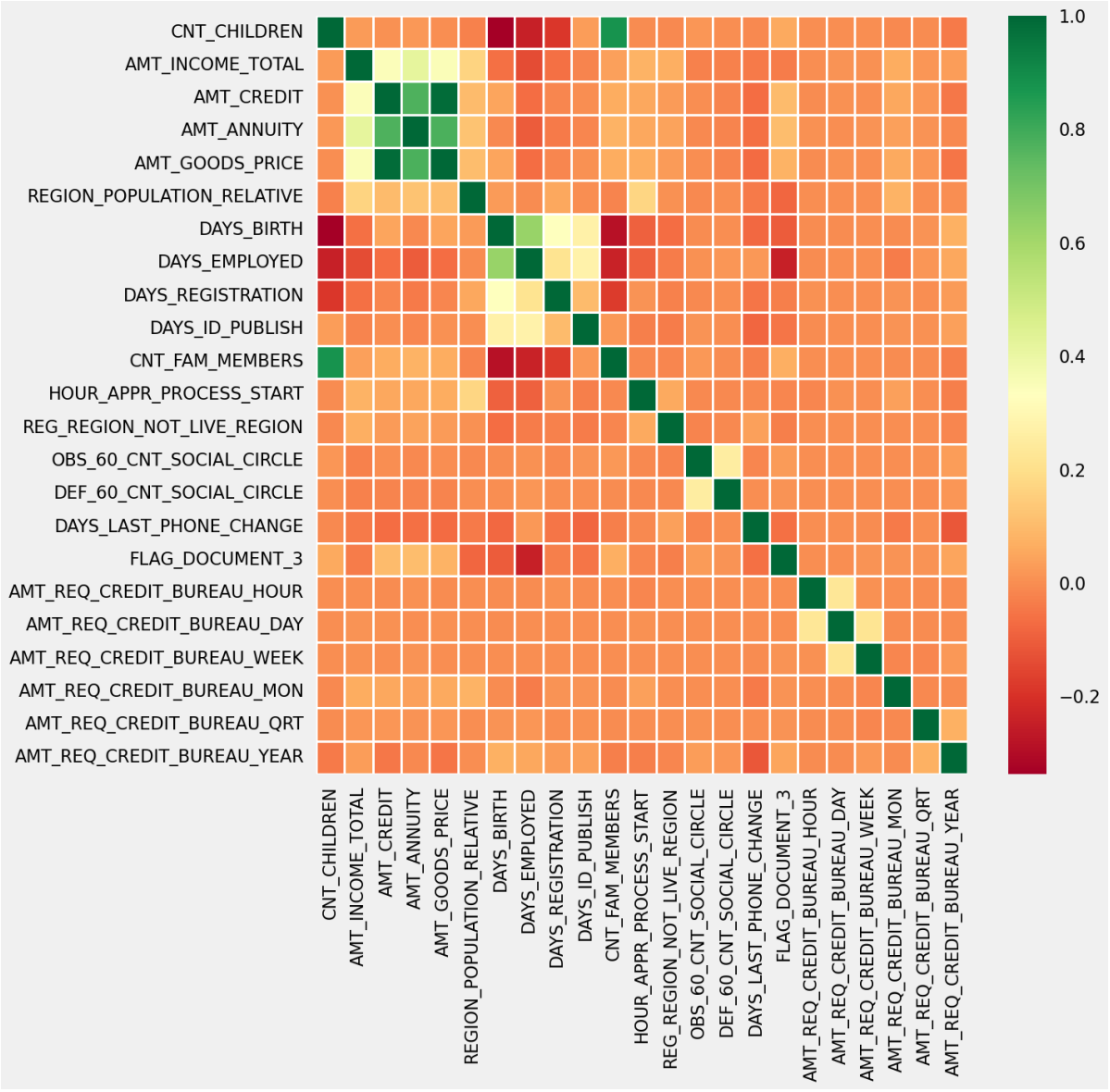
In [112…
```
# Getting the top 10 correlation for the Repayers data
corr_repayer = Repayer_df.corr()
corr_repayer = corr_repayer.where(np.triu(np.ones(corr_repayer.shape),k=1).astype('
corr_df_repayer = corr_repayer.unstack().reset_index()
corr_df_repayer.columns =['VAR1','VAR2','Correlation']
corr_df_repayer.dropna(subset = ["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[112]:

	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 [113…

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



Inferences: Correlating factors amongst repayers: Credit amount is highly correlated with .amount of goods price .loan annuity .total income We can also see that repayers have high correlation in number of days employed.

In [114…

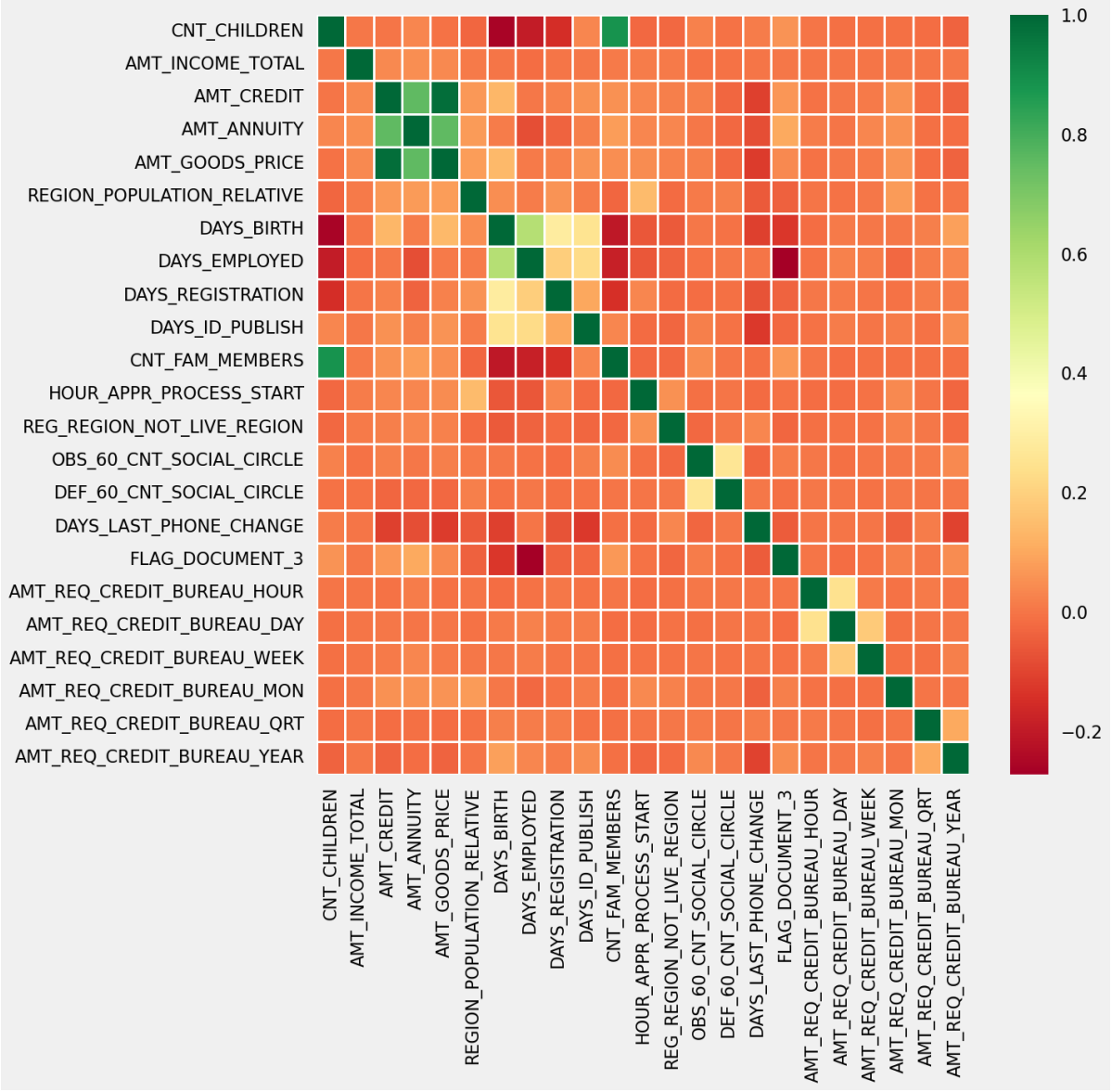
```
# Getting the top 10 correlation for the Defaulter data
corr_Defaulter = Defaulter_df.corr()
corr_Defaulter = corr_Defaulter.where(np.triu(np.ones(corr_Defaulter.shape),k=1).as
corr_df_Defaulter = corr_Defaulter.unstack().reset_index()
corr_df_Defaulter.columns =['VAR1','VAR2','Correlation']
corr_df_Defaulter.dropna(subset = ["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)
```

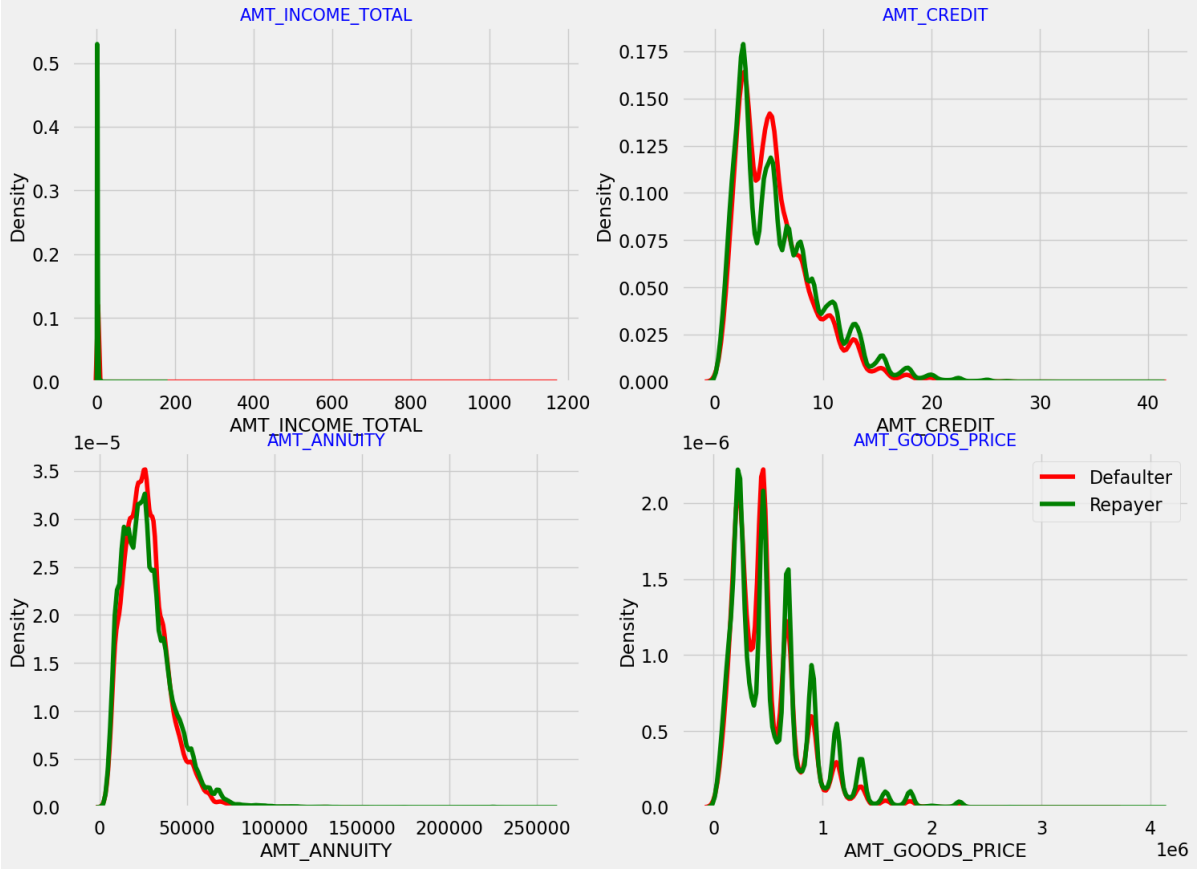


Inferences: 1.Credit amount is highly correlated with amount of goods price which is same as repayers. 2.But the loan annuity correlation with credit amount has slightly reduced in defaulters(0.75) when compared to repayers(0.77). 3.We can also see that repayers have high correlation in number of days employed(0.62) when compared to defaulters(0.58). 4.There is a severe drop in the correlation between total income of the client and the credit amount(0.038) amongst defaulters whereas it is 0.342 among repayers. 5.Days_birth and number of children correlation has reduced to 0.259 in defaulters when compared to 0.337 in repayers. 6.There is a slight increase in defaulted to observed count in social circle among defaulters(0.264) when compared to repayers(0.254).

Numerical Univariate Analysis

In [116…

```
# Plotting the numerical columns related to amount as distribution plot to see dens
amount = applicationdf[[ 'AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY', 'AMT_GOODS_

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()
```



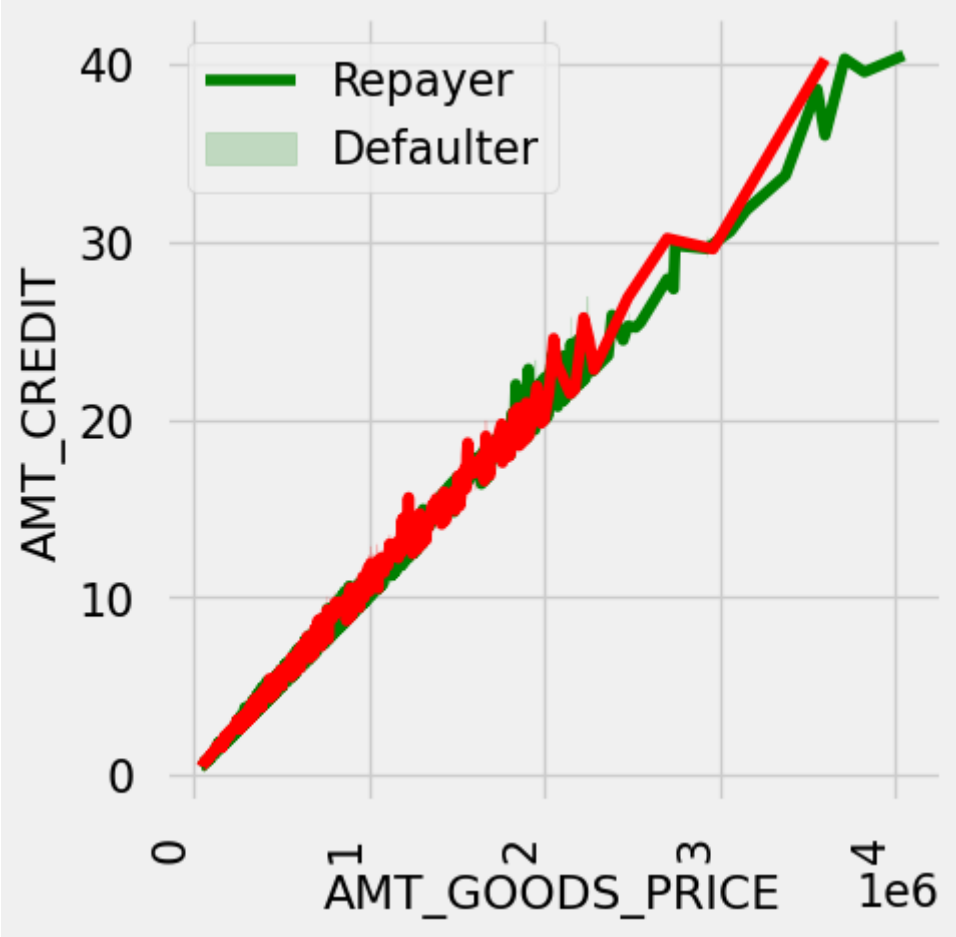
Inferences: 1.Most no of loans are given for goods price below 10 lakhs. 2.Most people pay annuity below 50000 for the credit loan. 3.Credit amount of the loan is mostly less then 10 lakhs. 4.The repayers and defaulters distribution overlap in all the plots and hence we cannot use any of these variables in isolation to make a decision.

Numerical Bivariate Analysis

In [117…

```
# Checking the relationship between Goods price and credit and comparing with loan
bivariate_rel('AMT_GOODS_PRICE','AMT_CREDIT',applicationdf,"TARGET", "line", ['g','
```

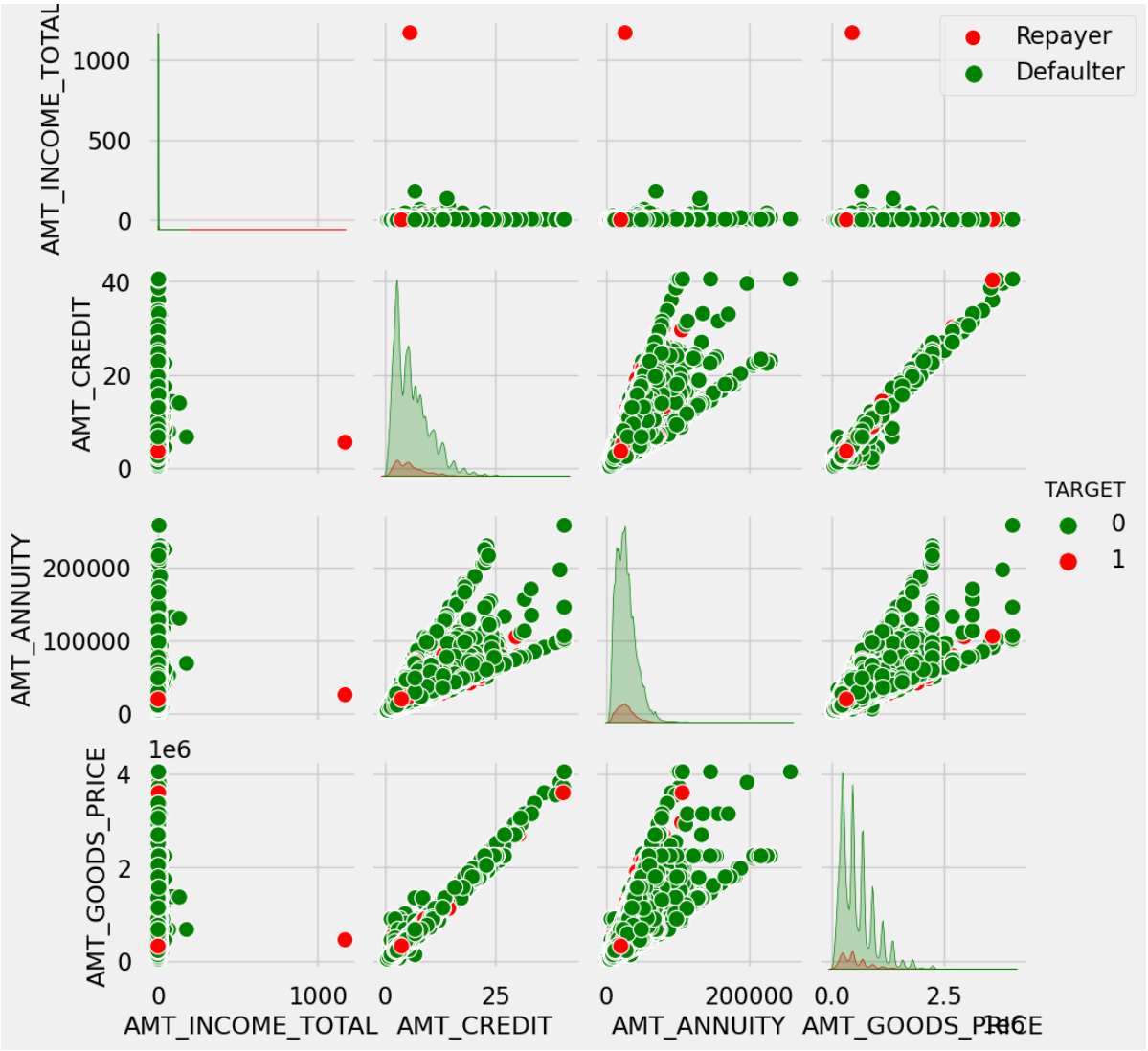
```
<Figure size 1500x600 with 0 Axes>
```



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

In [118…

```
# Plotting pairplot between amount variable to draw reference against loan repaymen
amount = applicationdf[[ 'AMT_INCOME_TOTAL','AMT_CREDIT',
                         'AMT_ANNUITY', 'AMT_GOODS_PRICE','TARGET']]
amount = amount[(amount["AMT_GOODS_PRICE"].notnull()) & (amount["AMT_ANNUITY"].notn
ax= sns.pairplot(amount,hue="TARGET",palette=["g","r"])
ax.fig.legend(labels=['Repayer','Defaulter'])
plt.show()
```



Inferences: 1.When amt_annuity >15000 amt_goods_price> 3M, there is a lesser chance of defaulters 2.AMT_CREDIT and AMT_GOODS_PRICE are highly correlated as based on the scatterplot where most of the data are consolidated in form of a line 3.There are very less defaulters for AMT_CREDIT >3M 4.Inferences related to distribution plot has been already mentioned in previous distplot graphs inferences section

Merged Dataframes Analysis

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_
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100003	0	Cash loans	F	N	
3	100003	0	Cash loans	F	N	
4	100004	0	Revolving loans	M	Y	

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    1250074 non-null  float64
 41  AMT_REQ_CREDIT_BUREAU_DAY     1250074 non-null  float64
 42  AMT_REQ_CREDIT_BUREAU_WEEK    1250074 non-null  float64
 43  AMT_REQ_CREDIT_BUREAU_MON     1250074 non-null  float64
 44  AMT_REQ_CREDIT_BUREAU_QRT     1250074 non-null  float64
 45  AMT_REQ_CREDIT_BUREAU_YEAR    1250074 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_AI
count	1.413701e+06	1.413701e+06	1.413701e+06	1.413701e+06	1.413701e+06	1.41
mean	2.784813e+05	8.655296e-02	4.048933e-01	1.733160e+00	5.875537e+00	2.70
std	1.028118e+05	2.811789e-01	7.173454e-01	1.985734e+00	3.849173e+00	1.39
min	1.000020e+05	0.000000e+00	0.000000e+00	2.565000e-01	4.500000e-01	1.61
25%	1.893640e+05	0.000000e+00	0.000000e+00	1.125000e+00	2.700000e+00	1.68
50%	2.789920e+05	0.000000e+00	0.000000e+00	1.575000e+00	5.084955e+00	2.49
75%	3.675560e+05	0.000000e+00	1.000000e+00	2.070000e+00	8.079840e+00	3.45
max	4.562550e+05	1.000000e+00	1.900000e+01	1.170000e+03	4.050000e+01	2.25

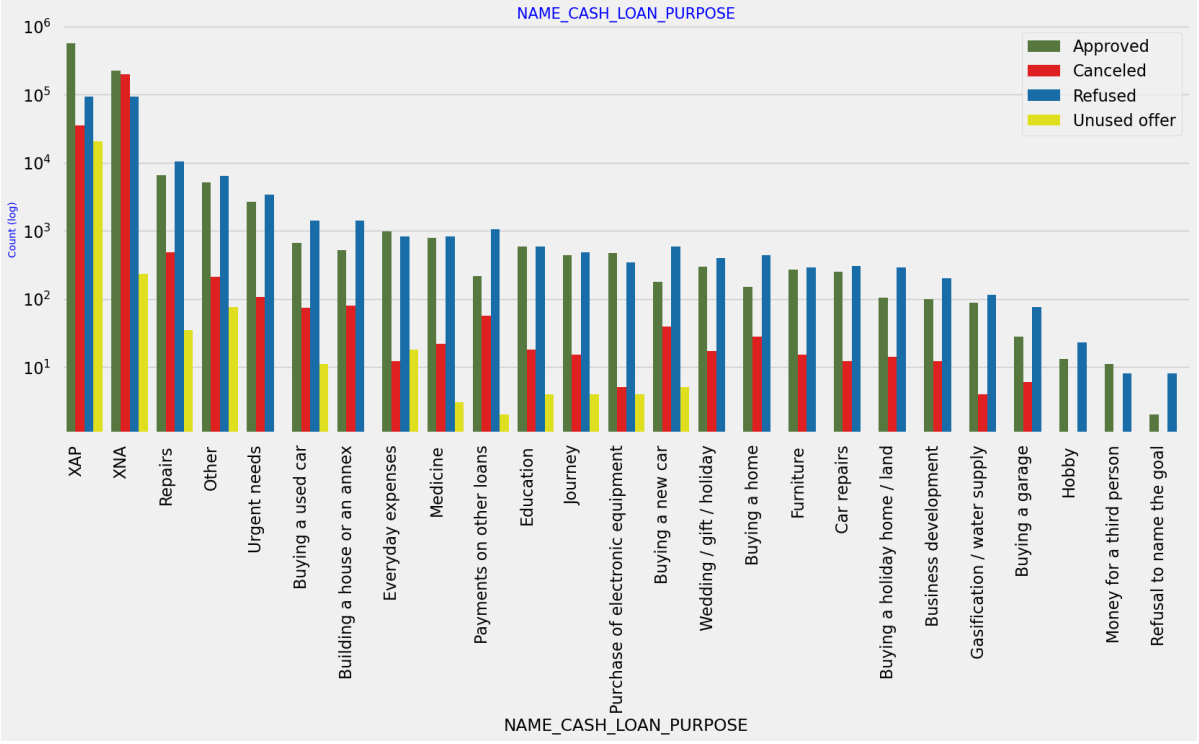
In [124…

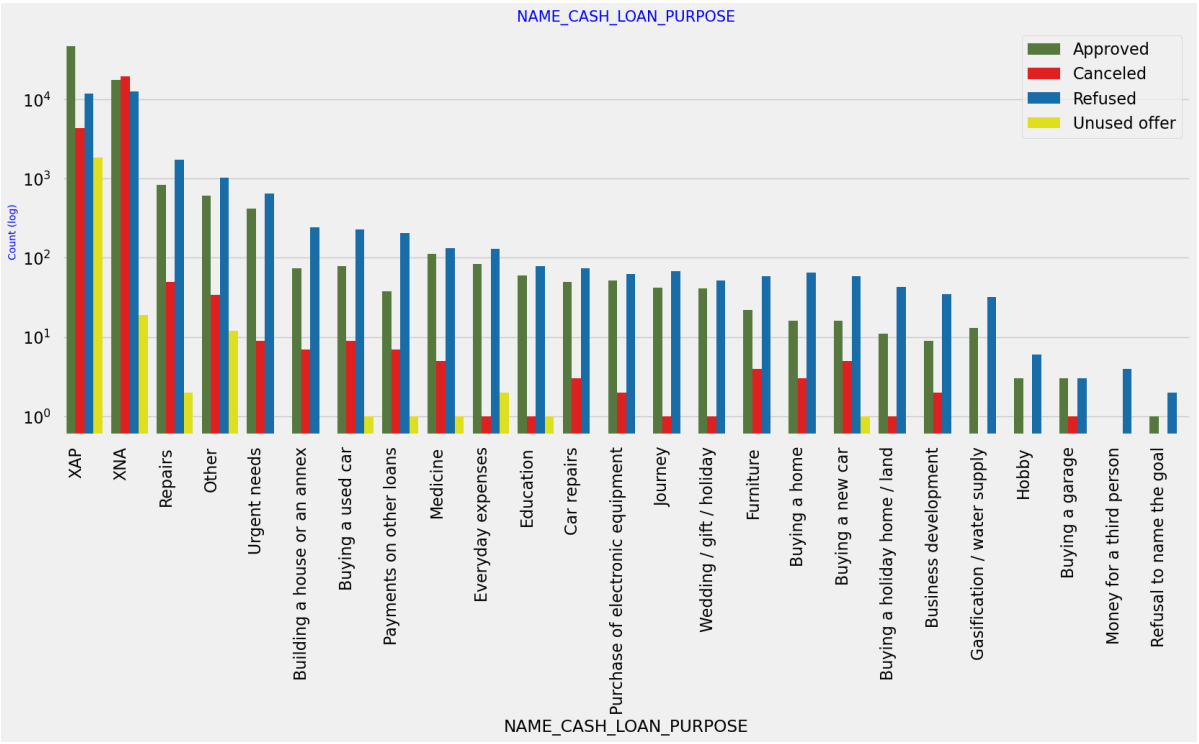
```
# Bifurcating the applicationDF dataframe based on Target value 0 and 1 for correla

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

Plotting Contract Status vs purpose of the loan:

In [125…

```
univariate_merged("NAME_CASH_LOAN_PURPOSE",L0,"NAME_CONTRACT_STATUS",["#548235","#F

univariate_merged("NAME_CASH_LOAN_PURPOSE",L1,"NAME_CONTRACT_STATUS",["#548235","#F
```

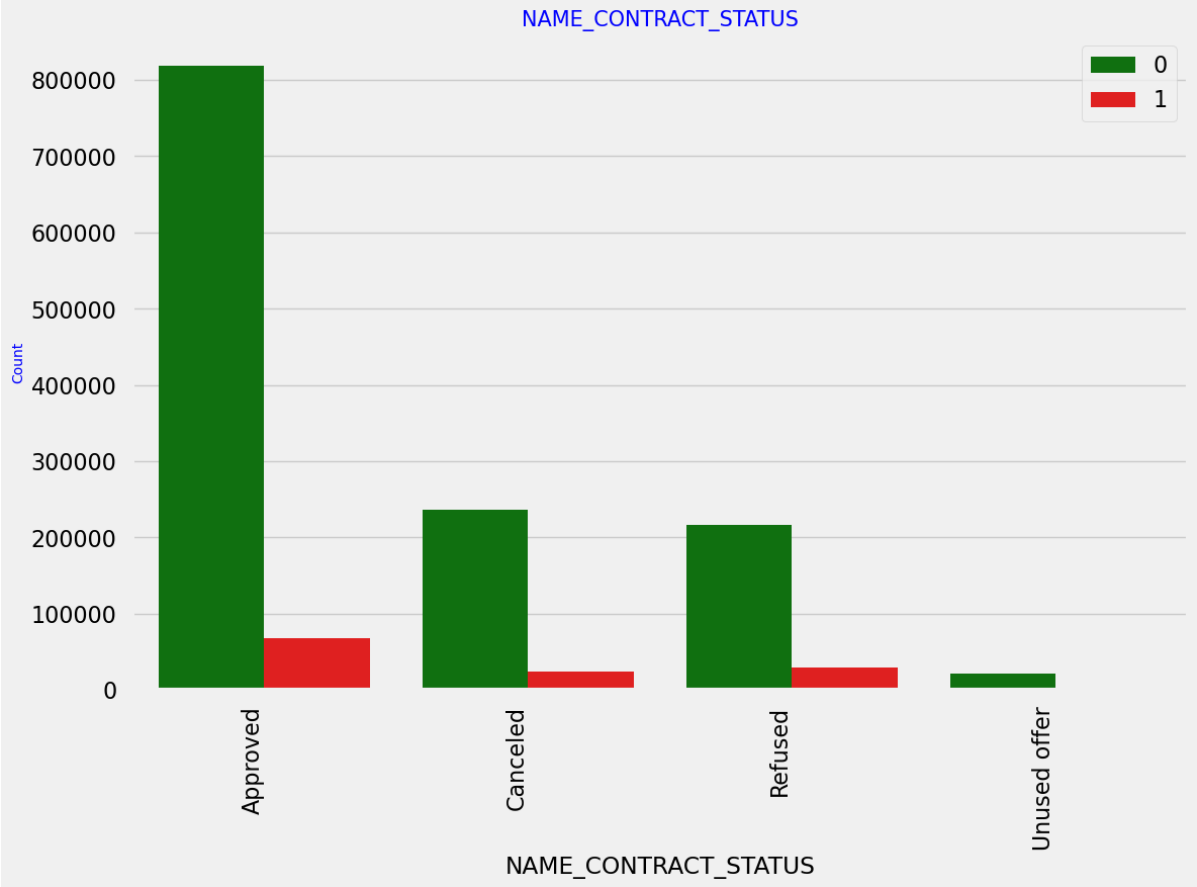




Inferences: Loan purpose has high number of unknown values (XAP, XNA) Loan taken for the purpose of Repairs seems to have highest default rate A very high number application have been rejected by bank or refused by client which has purpose as repair or other. This shows that purpose repair is taken as 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.

In [126…

```
# Checking the Contract Status based on loan repayment status and whether there is
univariate_merged("NAME_CONTRACT_STATUS",loan_process_df,"TARGET",['g','r'],False,(
g = loan_process_df.groupby("NAME_CONTRACT_STATUS")["TARGET"]
df1 = pd.concat([g.value_counts(),round(g.value_counts(normalize=True).mul(100),2)]
df1['Percentage'] = df1['Percentage'].astype(str) +"%" # adding percentage symbol i
print (df1)
```

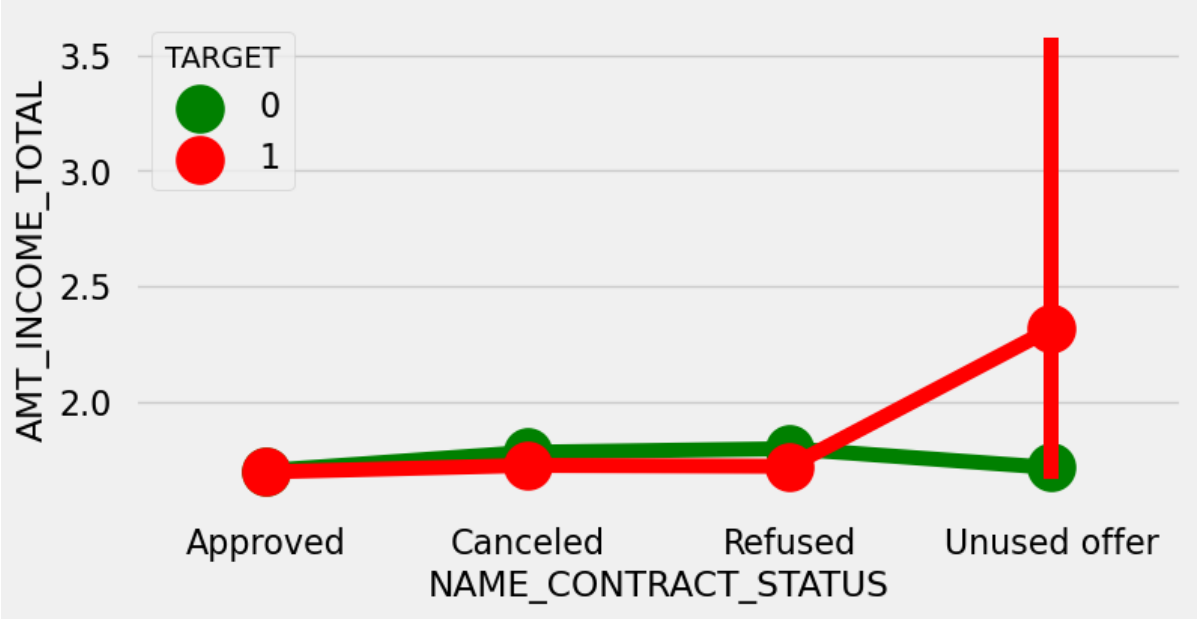


		Counts	Percentage
NAME_CONTRACT_STATUS	TARGET		
Approved	0	818856	92.41%
	1	67243	7.59%
Canceled	0	235641	90.83%
	1	23800	9.17%
Refused	0	215952	88.0%
	1	29438	12.0%
Unused offer	0	20892	91.75%
	1	1879	8.25%

Inferences: 90% of the previously cancelled client have actually repayed the loan. Revisiting the interest rates would increase business opoortunity for these clients. 88% of the clients who have been previously refused a loan has payed back the loan in current case. Refual reason should be recorded for further analysis as these clients would turn into potential repaying customer.

In [127…

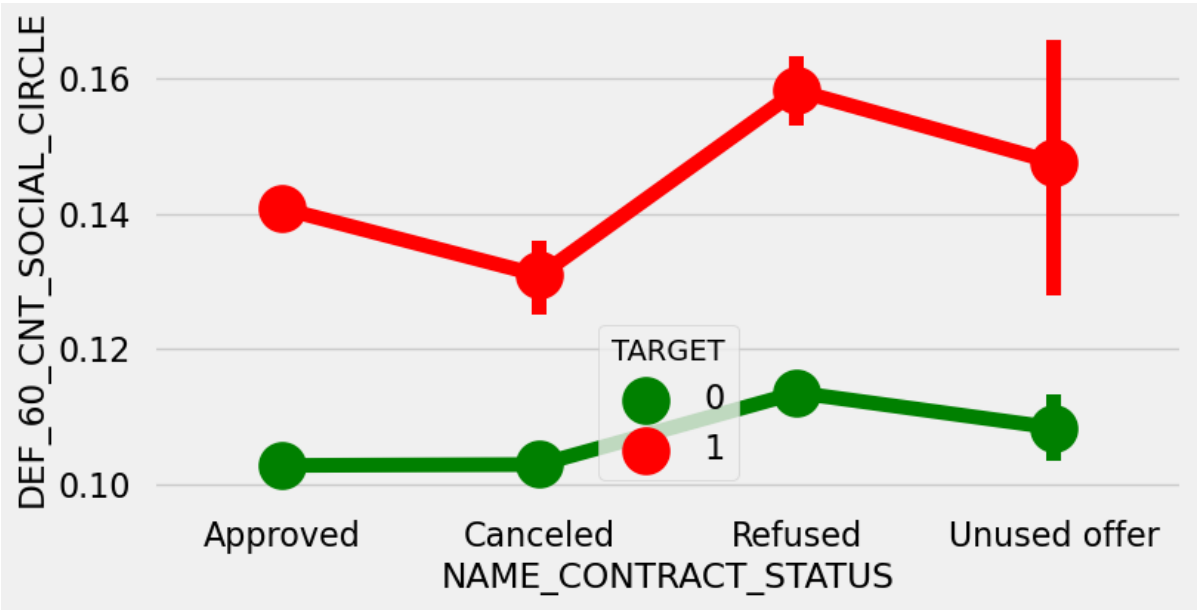
```
# plotting the relationship between income total and contact status
merged_pointplot("NAME_CONTRACT_STATUS",'AMT_INCOME_TOTAL')
```



Inferences: The point plot show that the people who have not used offer earlier have defaulted even when there average income is higher than others

In [128…

```
# plotting the relationship between people who defaulted in last 60 days being in c
merged_pointplot("NAME_CONTRACT_STATUS",'DEF_60_CNT_SOCIAL_CIRCLE')
```



Inferences: Clients who have average of 0.13 or higher DEF_60_CNT_SOCIAL_CIRCLE score tend to default more and hence client's social circle has to be analysed before providing the loan.
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:
Decisive Factor whether an applicant will be Repayer: 1.NAME_EDUCATION_TYPE: Academic degree has less defaults. 2.NAME_INCOME_TYPE: Student and Businessmen have no defaults. 3.REGION_RATING_CLIENT: RATING 1 is safer. 4.ORGANIZATION_TYPE: Clients with Trade Type 4 and 5 and Industry type 8 have defaulted less than 3% 5.DAYS_BIRTH: People above age of 50 have low probability of defaulting 6.DAYS_EMPLOYED: Clients with 40+ year experience having less than 1% default rate 7.AMT_INCOME_TOTAL:Applicant with Income more than 700,000 are less likely to default 8.NAME_CASH_LOAN_PURPOSE: Loans bought for Hobby, Buying garage are being repayed mostly. 9.CNT_CHILDREN: People with zero to two children tend to repay the loans.
Decisive Factor whether an applicant will be Defaulter: CODE_GENDER: Men are at relatively higher default rate NAME_FAMILY_STATUS : People who have civil marriage or who are single default a lot.
NAME_EDUCATION_TYPE: People with Lower Secondary & Secondary education NAME_INCOME_TYPE: Clients who are either at Maternity leave OR Unemployed default a lot. REGION_RATING_CLIENT: People who live in Rating 3 has highest defaults. OCCUPATION_TYPE: Avoid Low-skill Laborers, Drivers and Waiters/barmen staff,

Security staff, Laborers and Cooking staff as the default rate is huge. ORGANIZATION_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. DAYS_BIRTH: Avoid young people who are in age group of 20-40 as they have higher probability of defaulting. DAYS_EMPLOYED: People who have less than 5 years of employment have high default rate. 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. AMT_GOODS_PRICE: When the credit amount goes beyond 3M, there is an increase in defaulters.

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: 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. 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. 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. 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. 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.