IMPORTING ALL THE NECCESSARY MODULES

```
#importing all the important libraries like numpy. pandas, matlplolib, and warnings to keep notebook clean

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```
# to suppress warnings

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

```
#notebook setting to display all the rowns and columns to have better clearity on the data.

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)
```

Dataset 1 - "application_data.csv"

1. reading and understanding the data

1.1 Importing the dataset

```
# importing application_data.csv

appl_data = pd.read_csv("application_data.csv")
```

Understanding the dataset

```
#checking the rows and columns of the raw dataset

appl_data.shape
```

(307511, 122)

```
#Checking information of all the columns like data types
appl_data.info("all")
```

<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

- **There are 122 columns having various data types like object, int, float and 305711 rows.**

appl_data.head()

 # Checking the numeric variables of the dataframes
appl_data.describe()

INSIGHT

- **there are 122 columns and 307511 rows.**
- **there columns having negative, postive values which includes days. fixing is required**
- **there are columns with very hight values, columns related to Amount(Price). standardising is required, will perform these task later in the notebook**

2. Data Cleaning & Manipulation

2.1 Null Values

```
#checking how many null values are present in each of the columns

#creating a function to find null values for the dataframe
def null_values(df):
    return round((df.isnull().sum()*100/len(df)).sort_values(ascending = False),2)


null_values(appl_data)
```

```
COMMONAREA_MEDI              69.87
COMMONAREA_AVG               69.87
COMMONAREA_MODE              69.87
NONLIVINGAPARTMENTS_MODE     69.43
NONLIVINGAPARTMENTS_MEDI     69.43
NONLIVINGAPARTMENTS_AVG      69.43
FONDKAPREMONT_MODE           68.39
LIVINGAPARTMENTS_MEDI        68.35
LIVINGAPARTMENTS_MODE        68.35
LIVINGAPARTMENTS_AVG         68.35
FLOORSMIN_MEDI               67.85
FLOORSMIN_MODE               67.85
FLOORSMIN_AVG                67.85
YEARS_BUILD_MEDI             66.50
YEARS_BUILD_AVG              66.50
YEARS_BUILD_MODE             66.50
OWN_CAR_AGE                  65.99
LANDAREA_MODE                59.38
LANDAREA_AVG                 59.38
LANDAREA_MEDI                59.38
BASEMENTAREA_MEDI            58.52
BASEMENTAREA_AVG             58.52
BASEMENTAREA_MODE            58.52
EXT_SOURCE_1                 56.38
NONLIVINGAREA_MEDI           55.18
NONLIVINGAREA_AVG            55.18
NONLIVINGAREA_MODE           55.18
ELEVATORS_MODE               53.30
ELEVATORS_AVG                53.30
ELEVATORS_MEDI               53.30
WALLSMATERIAL_MODE           50.84
APARTMENTS_MODE              50.75
APARTMENTS_AVG               50.75
APARTMENTS_MEDI              50.75
ENTRANCES_MEDI               50.35
ENTRANCES_MODE               50.35
ENTRANCES_AVG                50.35
LIVINGAREA_MEDI              50.19
LIVINGAREA_MODE              50.19
```

LIVINGAREA_AVG	50.19
HOUSETYPE_MODE	50.18
FLOORSMAX_MODE	49.76
FLOORSMAX_MEDI	49.76
FLOORSMAX_AVG	49.76
YEARS_BEGINEXPLUATATION_MEDI	48.78
YEARS_BEGINEXPLUATATION_AVG	48.78
YEARS_BEGINEXPLUATATION_MODE	48.78
TOTALAREA_MODE	48.27
EMERGENCYSTATE_MODE	47.40
OCCUPATION_TYPE	31.35
EXT_SOURCE_3	19.83
AMT_REQ_CREDIT_BUREAU_QRT	13.50
AMT_REQ_CREDIT_BUREAU_YEAR	13.50
AMT_REQ_CREDIT_BUREAU_WEEK	13.50
AMT_REQ_CREDIT_BUREAU_MON	13.50
AMT_REQ_CREDIT_BUREAU_DAY	13.50
AMT_REQ_CREDIT_BUREAU_HOUR	13.50
NAME_TYPE_SUITE	0.42
OBS_30_CNT_SOCIAL_CIRCLE	0.33
OBS_60_CNT_SOCIAL_CIRCLE	0.33
DEF_60_CNT_SOCIAL_CIRCLE	0.33
DEF_30_CNT_SOCIAL_CIRCLE	0.33
EXT_SOURCE_2	0.21
AMT_GOODS_PRICE	0.09
AMT_ANNUITY	0.00
CNT_FAM_MEMBERS	0.00
DAYS_LAST_PHONE_CHANGE	0.00
AMT_CREDIT	0.00
FLAG_OWN_CAR	0.00
FLAG_EMAIL	0.00
TARGET	0.00
FLAG_PHONE	0.00
FLAG_CONT_MOBILE	0.00
FLAG_WORK_PHONE	0.00
FLAG_EMP_PHONE	0.00
FLAG_MOBIL	0.00
NAME_CONTRACT_TYPE	0.00
CODE_GENDER	0.00
FLAG_OWN_REALTY	0.00
AMT_INCOME_TOTAL	0.00
DAYS_ID_PUBLISH	0.00
DAYS_REGISTRATION	0.00
DAYS_EMPLOYED	0.00
DAYS_BIRTH	0.00
REGION_POPULATION_RELATIVE	0.00
REGION_RATING_CLIENT	0.00
NAME_FAMILY_STATUS	0.00
NAME_EDUCATION_TYPE	0.00
NAME_INCOME_TYPE	0.00
CNT_CHILDREN	0.00

```
NAME_HOUSING_TYPE               0.00
REG_REGION_NOT_LIVE_REGION      0.00
REGION_RATING_CLIENT_W_CITY     0.00
WEEKDAY_APPR_PROCESS_START      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
ORGANIZATION_TYPE               0.00
LIVE_CITY_NOT_WORK_CITY         0.00
REG_CITY_NOT_WORK_CITY          0.00
REG_CITY_NOT_LIVE_CITY          0.00
LIVE_REGION_NOT_WORK_REGION     0.00
REG_REGION_NOT_WORK_REGION      0.00
HOUR_APPR_PROCESS_START         0.00
SK_ID_CURR                      0.00
dtype: float64
```

2.1.1 Dealing with Null values more than 50 %

```
#creating a variable null_col_50 for storing null columns having missing values more than 50%

null_col_50 = null_values(appl_data)[null_values(appl_data)>50]

#revieving null_col_50

print(null_col_50)
print()
print("Num of columns having missing values more than 50% :",len(null_col_50))
```

COMMONAREA_MEDI 69.87 COMMONAREA_AVG 69.87 COMMONAREA_MODE 69.87 NONLIVINGAPARTMENTS_MODE 69.43 NONLIVINGAPARTMENTS_MEDI 69.43 NONLIVINGAPARTMENTS_AVG 69.43 FONDKAPREMONT_MODE 68.39 LIVINGAPARTMENTS_MEDI 68.35 LIVINGAPARTMENTS_MODE 68.35 LIVINGAPARTMENTS_AVG 68.35 FLOORSMIN_MEDI 67.85 FLOORSMIN_MODE 67.85 FLOORSMIN_AVG 67.85 YEARS_BUILD_MEDI 66.50 YEARS_BUILD_AVG 66.50 YEARS_BUILD_MODE 66.50 OWN_CAR_AGE 65.99 LANDAREA_MODE 59.38 LANDAREA_AVG

59.38 LANDAREA_MEDI 59.38 BASEMENTAREA_MEDI 58.52 BASEMENTAREA_AVG 58.52 BASEMENTAREA_MODE 58.52 EXT_SOURCE_1 56.38 NONLIVINGAREA_MEDI 55.18 NONLIVINGAREA_AVG 55.18 NONLIVINGAREA_MODE 55.18 ELEVATORS_MODE 53.30 ELEVATORS_AVG 53.30 ELEVATORS_MEDI 53.30 WALLSMATERIAL_MODE 50.84 APARTMENTS_MODE 50.75 APARTMENTS_AVG 50.75 APARTMENTS_MEDI 50.75 ENTRANCES_MEDI 50.35 ENTRANCES_MODE 50.35 ENTRANCES_AVG 50.35 LIVINGAREA_MEDI 50.19 LIVINGAREA_MODE 50.19 LIVINGAREA_AVG 50.19 HOUSETYPE_MODE 50.18 dtype: float64
Num of columns having missing values more than 50% : 41

INSIGHT

- **There are 41 columns having null values more than 50% which are related to different area sizes on apartment owned/rented by the loan applicant**

```
null_col_50.index  # Will drop all these columns
```

Index(['COMMONAREA_MEDI', 'COMMONAREA_AVG', 'COMMONAREA_MODE', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAPARTMENTS_MEDI', 'NONLIVINGAPARTMENTS_AVG', 'FONDKAPREMONT_MODE', 'LIVINGAPARTMENTS_MEDI', 'LIVINGAPARTMENTS_MODE', 'LIVINGAPARTMENTS_AVG', 'FLOORSMIN_MEDI', 'FLOORSMIN_MODE', 'FLOORSMIN_AVG', 'YEARS_BUILD_MEDI', 'YEARS_BUILD_AVG', 'YEARS_BUILD_MODE', 'OWN_CAR_AGE', 'LANDAREA_MODE', 'LANDAREA_AVG', 'LANDAREA_MEDI', 'BASEMENTAREA_MEDI', 'BASEMENTAREA_AVG', 'BASEMENTAREA_MODE', 'EXT_SOURCE_1', 'NONLIVINGAREA_MEDI', 'NONLIVINGAREA_AVG', 'NONLIVINGAREA_MODE', 'ELEVATORS_MODE', 'ELEVATORS_AVG', 'ELEVATORS_MEDI', 'WALLSMATERIAL_MODE', 'APARTMENTS_MODE', 'APARTMENTS_AVG', 'APARTMENTS_MEDI', 'ENTRANCES_MEDI', 'ENTRANCES_MODE', 'ENTRANCES_AVG', 'LIVINGAREA_MEDI', 'LIVINGAREA_MODE', 'LIVINGAREA_AVG', 'HOUSETYPE_MODE'], dtype='object')

```
# Now lets drop all the columns having missing values more than 50% that is 41 columns

appl_data.drop(columns = null_col_50.index, inplace = True)
```

```
appl_data.shape  # Now there are 81 columns remaining
```

(307511, 81)

- **After after dropping 41 columns we are left with 81 columns**

2.1.2 Dealing with null values more than 15%

```
# now we will deal with null values more than 15%

null_col_15 = null_values(appl_data)[null_values(appl_data)>15]
```

```
null_col_15
```

```
FLOORSMAX_AVG                  49.76
FLOORSMAX_MEDI                 49.76
FLOORSMAX_MODE                 49.76
YEARS_BEGINEXPLUATATION_AVG    48.78
YEARS_BEGINEXPLUATATION_MEDI   48.78
YEARS_BEGINEXPLUATATION_MODE   48.78
TOTALAREA_MODE                 48.27
EMERGENCYSTATE_MODE            47.40
OCCUPATION_TYPE                31.35
```

EXT_SOURCE_3   19.83
dtype: float64

- **from the columns dictionary we can conclude that only 'OCCUPATION_TYPE', 'EXT_SOURCE_3 looks relevant to TARGET column.thus dropping all other columns except 'OCCUPATION_TYPE','EXT_SOURCE_3**

```
#removing 'OCCUPATION_TYPE', 'EXT_SOURCE_3' from "null_col_15" so that we can drop all other at once.

null_col_15.drop(["OCCUPATION_TYPE","EXT_SOURCE_3"], inplace = True)
```

```
print(null_col_15)
print()
print("No of columns having missing values more than 15% and are not reletable:",len(null_col_15))
```

FLOORSMAX_AVG 49.76 FLOORSMAX_MEDI 49.76 FLOORSMAX_MODE 49.76 YEARS_BEGINEXPLUATATION_AVG 48.78 YEARS_BEGINEXPLUATATION_MEDI 48.78 YEARS_BEGINEXPLUATATION_MODE 48.78 TOTALAREA_MODE 48.27 EMERGENCYSTATE_MODE 47.40 dtype: float64 No of columns having missing values more than 15% and are not reletable: 8

```
#thus removing columns having missing values more than 15% and which are not reletable to TARGET column.

appl_data.drop(null_col_15.index,axis=1, inplace = True)
```

```
appl_data.shape  # After dropping null_col_15, we have left with 73 columns
```

(307511, 73)

- **After after dropping 8 columns we are left with 73 columns**
- **There are 2 more Columns with missing values more than 15%**

```
null_values(appl_data).head(10)
```

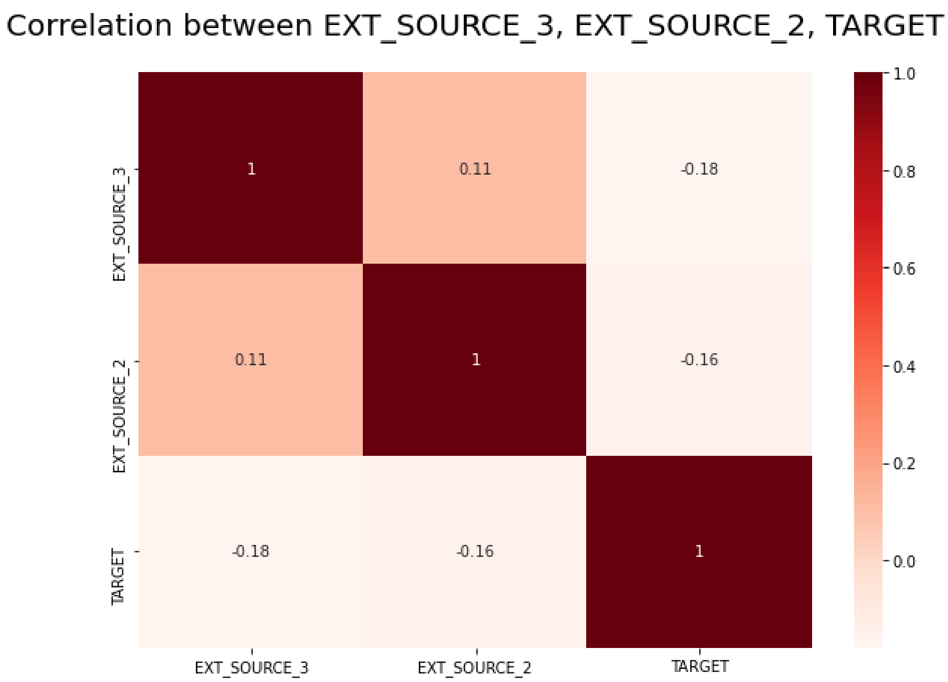
OCCUPATION_TYPE   31.35
EXT_SOURCE_3   19.83
AMT_REQ_CREDIT_BUREAU_YEAR   13.50
AMT_REQ_CREDIT_BUREAU_MON   13.50
AMT_REQ_CREDIT_BUREAU_WEEK   13.50
AMT_REQ_CREDIT_BUREAU_DAY   13.50
AMT_REQ_CREDIT_BUREAU_HOUR   13.50
AMT_REQ_CREDIT_BUREAU_QRT   13.50
NAME_TYPE_SUITE   0.42
OBS_30_CNT_SOCIAL_CIRCLE   0.33
dtype: float64

2.2 Analyse & Removing Unneccsary Columns

2.2.1 Starting with EXT_SOURCE_3 , EXT_SOURCE_2. As they have normalised values, now we will understand the relation between these columns with TARGET column using a heatmap

```
irrev = ["EXT_SOURCE_3","EXT_SOURCE_2"]  # putting irrevlent columns in varibale "irrev"

plt.figure(figsize= [10,7])
```

```
sns.heatmap(appl_data[irrev+["TARGET"]].corr(), cmap="Reds",annot=True)

plt.title("Correlation between EXT_SOURCE_3, EXT_SOURCE_2, TARGET", fontdict={"fontsize":20}, pad=25)
plt.show()
```



- **There seems to be no linear correlation and also from columns description we decided to remove these columns.**
- **Also we are aware correation doesn't cause causation**

```
#dropping above columns as decided

appl_data.drop(irrev, axis=1, inplace= True)

appl_data.shape  # Now we are left with 71 columns
```

(307511, 71)

```
null_values(appl_data).head(10)
```

```
OCCUPATION_TYPE              31.35
AMT_REQ_CREDIT_BUREAU_YEAR    13.50
AMT_REQ_CREDIT_BUREAU_MON     13.50
AMT_REQ_CREDIT_BUREAU_WEEK    13.50
AMT_REQ_CREDIT_BUREAU_DAY     13.50
AMT_REQ_CREDIT_BUREAU_HOUR    13.50
AMT_REQ_CREDIT_BUREAU_QRT     13.50
NAME_TYPE_SUITE               0.42
OBS_30_CNT_SOCIAL_CIRCLE      0.33
DEF_30_CNT_SOCIAL_CIRCLE      0.33
dtype: float64
```

2.2.2 Now we will check columns with FLAGS and their relation with TARGET columns to remove irrelevant ones

For this we will create a dataframe containig all FLAG columns and then plot bar graphs for each column with respect to TARGET column for which "0" will represent as Repayer and "1" will represent as Defaulter

```
# adding all flags coloumns in variable "flag_columns"

flag_columns = [col for col in appl_data.columns if "FLAG" in col]

flag_columns  # Viewing all FLAG columns
```

```
['FLAG_OWN_CAR',
 'FLAG_OWN_REALTY',
 'FLAG_MOBIL',
 'FLAG_EMP_PHONE',
 'FLAG_WORK_PHONE',
 'FLAG_CONT_MOBILE',
 'FLAG_PHONE',
 'FLAG_EMAIL',
 'FLAG_DOCUMENT_2',
 'FLAG_DOCUMENT_3',
 'FLAG_DOCUMENT_4',
 'FLAG_DOCUMENT_5',
 'FLAG_DOCUMENT_6',
 'FLAG_DOCUMENT_7',
 'FLAG_DOCUMENT_8',
 'FLAG_DOCUMENT_9',
 'FLAG_DOCUMENT_10',
 'FLAG_DOCUMENT_11',
 'FLAG_DOCUMENT_12',
 'FLAG_DOCUMENT_13',
 'FLAG_DOCUMENT_14',
 'FLAG_DOCUMENT_15',
 'FLAG_DOCUMENT_16',
 'FLAG_DOCUMENT_17',
 'FLAG_DOCUMENT_18',
 'FLAG_DOCUMENT_19',
 'FLAG_DOCUMENT_20',
 'FLAG_DOCUMENT_21']
```

```
# creating flag_df dataframe having all FLAG columns and TARGET column

flag_df = appl_data[flag_columns+["TARGET"]]

# replacing "0" as repayer and "1" as defaulter for TARGET column

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

# as stated in columnn description replacing "1" as Y being TRUE and "0" as N being False

for i in flag_df:
```

```
    if i!= "TARGET":
        flag_df[i] = flag_df[i].replace({1:"Y", 0:"N"})

flag_df.head()

import itertools # using itertools for efficient looping plotting subplots

# Plotting all the graph to find the relation and evaluting for dropping such columns

plt.figure(figsize = [20,24])

for i,j in itertools.zip_longest(flag_columns,range(len(flag_columns))):
    plt.subplot(7,4,j+1)
    ax = sns.countplot(flag_df[i], hue = flag_df["TARGET"], palette = ["r","b"])
    #plt.yticks(fontsize=8)
    plt.xlabel("")
    plt.ylabel("")
    plt.title(i)
```

INSIGHT

- **Columns (FLAG_OWN_REALTY, FLAG_MOBIL ,FLAG_EMP_PHONE, FLAG_CONT_MOBILE, FLAG_DOCUMENT_3) have more repayers than defaulter and from**

these keeping FLAG_DOCUMENT_3,FLAG_OWN_REALTY, FLAG_MOBIL more sense thus we can include these columns and remove all other FLAG columns for furhter analysis.

```
# removing required columns from "flag_df" such that we can remove the irrelevent columns from "appl_data" dataset.

flag_df.drop(["TARGET","FLAG_OWN_REALTY","FLAG_MOBIL","FLAG_DOCUMENT_3"], axis=1 , inplace = True)
```

```
len(flag_df.columns)
```

```
25
```

```
# dropping the columns of "flag_df" dataframe that is removing more 25 columns from "appl_data" dataframe

appl_data.drop(flag_df.columns, axis=1, inplace= True)
```

```
appl_data.shape    # Now we are left 46 revelent columns
```

```
(307511, 46)
```

INSIGHT

- **After removing uneccsarry, irrelevent and missing columns. We are left with 46 columns**

3. Imputing values

Now that we have removed all the unneccesarry columns, we will proced with imputing values for relevent missing columns whereever required

```
null_values(appl_data).head(10)
```

```
OCCUPATION_TYPE              31.35
AMT_REQ_CREDIT_BUREAU_YEAR    13.50
AMT_REQ_CREDIT_BUREAU_QRT     13.50
AMT_REQ_CREDIT_BUREAU_MON     13.50
AMT_REQ_CREDIT_BUREAU_WEEK    13.50
AMT_REQ_CREDIT_BUREAU_DAY     13.50
AMT_REQ_CREDIT_BUREAU_HOUR    13.50
NAME_TYPE_SUITE               0.42
DEF_60_CNT_SOCIAL_CIRCLE      0.33
OBS_60_CNT_SOCIAL_CIRCLE      0.33
dtype: float64
```

Insight

- **Now we have only 7 columns which have missing values more than 1%. Thus, we will only impute them for further analysis and such columns are: OCCUPATION_TYPE, AMT_REQ_CREDIT_BUREAU_YEAR, AMT_REQ_CREDIT_BUREAU_QRT, AMT_REQ_CREDIT_BUREAU_MON, AMT_REQ_CREDIT_BUREAU_WEEK, AMT_REQ_CREDIT_BUREAU_DAY, AMT_REQ_CREDIT_BUREAU_HOUR**

3.1 Imputing for "OCCUPATION_TYPE" column

```
#Percentage of each category present in "OCCUPATION_TYPE"

appl_data["OCCUPATION_TYPE"].value_counts(normalize=True)*100
```

```
Laborers                 26.139636
Sales staff              15.205570
Core staff               13.058924
Managers                 10.122679
Drivers                   8.811576
High skill tech staff     5.390299
Accountants               4.648067
Medicine staff            4.043672
Security staff            3.183498
Cooking staff             2.816408
Cleaning staff            2.203960
Private service staff     1.256158
Low-skill Laborers        0.991379
Waiters/barmen staff      0.638499
Secretaries               0.618132
Realty agents             0.355722
HR staff                  0.266673
IT staff                  0.249147
Name: OCCUPATION_TYPE, dtype: float64
```

Insight:

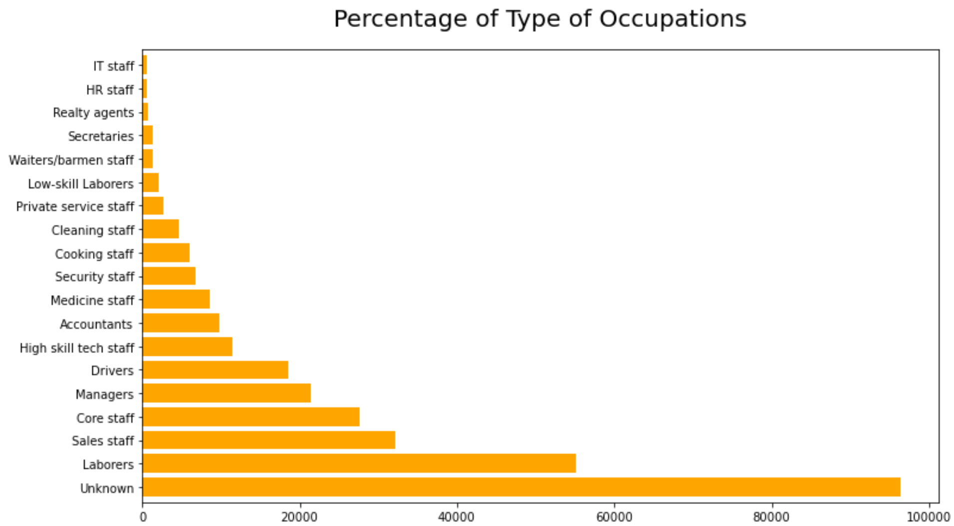
- **from above it looks like this columnn is categorical one and have missing values of 31.35%. to fix this we will impute another category as "Unknown" for the missing values.**

```
# imputing null values with "Unknown"

appl_data["OCCUPATION_TYPE"] = appl_data["OCCUPATION_TYPE"].fillna("Unknown")
```

```
appl_data["OCCUPATION_TYPE"].isnull().sum() # Now we have zero null values
```

```
0
```

```
# Plotting a percentage graph having each category of "OCCUPATION_TYPE"

plt.figure(figsize = [12,7])
(appl_data["OCCUPATION_TYPE"].value_counts()).plot.barh(color= "orange",width = .8)
plt.title("Percentage of Type of Occupations", fontdict={"fontsize":20}, pad =20)
plt.show()
```



- **Highest percentage of values belongs to Unknown group and Secons belongs to Laborers**

3.2 Now let's move to other 6 columns :
AMT_REQ_CREDIT_BUREAU_YEAR", "AMT_REQ_CREDIT_BUREAU_QRT","AMT_REQ_CREDIT_BUREAU_MON", "AMT_REQ_CREDIT_BUREAU_WEEK","AMT_REQ_CREDIT_BUREAU_DAY", "AMT_REQ_CREDIT_BUREAU_HOUR"

```
appl_data[["AMT_REQ_CREDIT_BUREAU_YEAR","AMT_REQ_CREDIT_BUREAU_QRT","AMT_REQ_CREDIT_BUREAU_MON","AMT_REQ_CREDIT_BUREAU_WEEK",
"AMT_REQ_CREDIT_BUREAU_DAY","AMT_REQ_CREDIT_BUREAU_HOUR"]].describe()
```

These above columns represent number of enquries made for the customer(which should be discrete and not continous). from above describe results we see that all values are numerical and can conclude that for imputing missing we should not use mean as it is in decimal form, hence for imputing purpose we will use median for all these columns.

```
#creating "amt_credit" variable having these columns "AMT_REQ_CREDIT_BUREAU_YEAR","AMT_REQ_CREDIT_BUREAU_QRT","AMT_REQ_CREDIT_BUREAU_MON","AMT_REQ_CREDIT_BUREAU_WEEK",
#"AMT_REQ_CREDIT_BUREAU_DAY","AMT_REQ_CREDIT_BUREAU_HOUR"

amt_credit = ["AMT_REQ_CREDIT_BUREAU_YEAR","AMT_REQ_CREDIT_BUREAU_QRT","AMT_REQ_CREDIT_BUREAU_MON","AMT_REQ_CREDIT_BUREAU_WEEK",
"AMT_REQ_CREDIT_BUREAU_DAY","AMT_REQ_CREDIT_BUREAU_HOUR"]

#filling missing values with median values

appl_data.fillna(appl_data[amt_credit].median(),inplace = True)

null_values(appl_data).head(10)
```

```
NAME_TYPE_SUITE          0.42
DEF_60_CNT_SOCIAL_CIRCLE    0.33
OBS_60_CNT_SOCIAL_CIRCLE    0.33
DEF_30_CNT_SOCIAL_CIRCLE    0.33
```

```
OBS_30_CNT_SOCIAL_CIRCLE    0.33
AMT_GOODS_PRICE             0.09
AMT_ANNUITY                 0.00
CNT_FAM_MEMBERS             0.00
DAYS_LAST_PHONE_CHANGE      0.00
DAYS_EMPLOYED               0.00
dtype: float64
```

Still there some missing value coloumns but we will not impute them as the missing value count very less.

4. Standardising values

```
appl_data.describe()
```

Insights:

from above describe result we can see that

- **columns AMT_INCOME_TOTAL, AMT_CREDIT, AMT_GOODS_PRICE have very high values, thus will make these numerical columns in categorical columns for better understanding.**
- **columns DAYS_BIRTH, DAYS_EMPLOYED, DAYS_REGISTRATION, DAYS_ID_PUBLISH, DAYS_LAST_PHONE_CHANGE which counts days have negative values. thus will correct those values**
- **convert DAYS_BIRTH to AGE in years , DAYS_EMPLOYED to YEARS EMPLOYED**

4.1 Taking care of columns: AMT_INCOME_TOTAL, AMT_CREDIT, AMT_GOODS_PRICE

```
# Binning Numerical Columns to create a categorical column

# Creating bins for income amount in term of Lakhs
appl_data['AMT_INCOME_TOTAL']=appl_data['AMT_INCOME_TOTAL']/100000

bins = [0,1,2,3,4,5,6,7,8,9,10,11]
slot = ['0-1L','1L-2L', '2L-3L','3L-4L','4L-5L','5L-6L','6L-7L','7L-8L','8L-9L','9L-10L','10L Above']

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

```
round((appl_data["AMT_INCOME_RANGE"].value_counts(normalize = True)*100),2)
```

```
1L-2L       50.73
2L-3L       21.21
0-1L        20.73
3L-4L        4.78
4L-5L        1.74
5L-6L        0.36
6L-7L        0.28
8L-9L        0.10
7L-8L        0.05
9L-10L       0.01
10L Above    0.01
Name: AMT_INCOME_RANGE, dtype: float64
```

```
# Creating bins for Credit amount in term of Lakhs
appl_data['AMT_CREDIT']=appl_data['AMT_CREDIT']/100000
```

```
bins = [0,1,2,3,4,5,6,7,8,9,10,100]
slots = ['0-1L','1L-2L', '2L-3L','3L-4L','4L-5L','5L-6L','6L-7L','7L-8L','8L-9L','9L-10L','10L Above']

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

```
round((appl_data["AMT_CREDIT_RANGE"].value_counts(normalize = True)*100),2)
```

```
2L-3L       17.82
10L Above   16.25
5L-6L       11.13
4L-5L       10.42
1L-2L        9.80
3L-4L        8.56
6L-7L        7.82
8L-9L        7.09
7L-8L        6.24
9L-10L       2.90
0-1L         1.95
Name: AMT_CREDIT_RANGE, dtype: float64
```

```
# Creating bins for Price of Goods in term of Lakhs
appl_data['AMT_GOODS_PRICE']=appl_data['AMT_GOODS_PRICE']/100000

bins = [0,1,2,3,4,5,6,7,8,9,10,100]
slots = ['0-1L','1L-2L', '2L-3L','3L-4L','4L-5L','5L-6L','6L-7L','7L-8L','8L-9L','9L-10L','10L Above']

appl_data['AMT_GOODS_PRICE_RANGE']=pd.cut(appl_data['AMT_GOODS_PRICE'],bins=bins,labels=sl
ots)
```

```
round((appl_data["AMT_GOODS_PRICE_RANGE"].value_counts(normalize = True)*100),2)
```

```
2L-3L       20.43
4L-5L       18.54
6L-7L       13.03
10L Above   11.11
1L-2L       10.73
8L-9L        6.99
3L-4L        6.91
5L-6L        4.27
0-1L         2.83
7L-8L        2.64
9L-10L       2.53
Name: AMT_GOODS_PRICE_RANGE, dtype: float64
```

4.2 Dealing with columns :
DAYS_BIRTH, DAYS_EMPLOYED, DAYS_REGISTRATION, DAYS_ID_PUBLISH, DAYS_LAST_PHONE_CHANGE

```
# creating "days_col" varibale to store all days columns
days_col = ["DAYS_BIRTH", "DAYS_EMPLOYED", "DAYS_REGISTRATION", "DAYS_ID_PUBLISH",
"DAYS_LAST_PHONE_CHANGE"]

appl_data[days_col].describe()
```

- **from describe we get that days are in negative that is not usual, so to correct it we use absolute function as below**

```
#using abs() function to correct the days values

appl_data[days_col]= abs(appl_data[days_col])

# Data is correct now

appl_data[days_col].describe()
```

4.3. now convert DAYS_BIRTH, DAYS_EMPLOYED columns in terms of Years and binning years for better understanding, that is adding two more categorical column

```
appl_data["AGE"] = appl_data["DAYS_BIRTH"]/365
bins = [0,20,25,30,35,40,45,50,55,60,100]
slots = ["0-20","20-25","25-30","30-35","35-40","40-45","45-50","50-55","55-60","60 Above"]

appl_data["AGE_GROUP"] = pd.cut(appl_data["AGE"], bins=bins, labels=slots)

appl_data["AGE_GROUP"].value_counts(normalize= True)*100
```

```
35-40      13.940314
40-45      13.464884
30-35      12.825557
60 Above   11.569993
45-50      11.425608
50-55      11.362846
55-60      10.770346
25-30      10.686447
20-25       3.954005
0-20        0.000000
Name: AGE_GROUP, dtype: float64
```

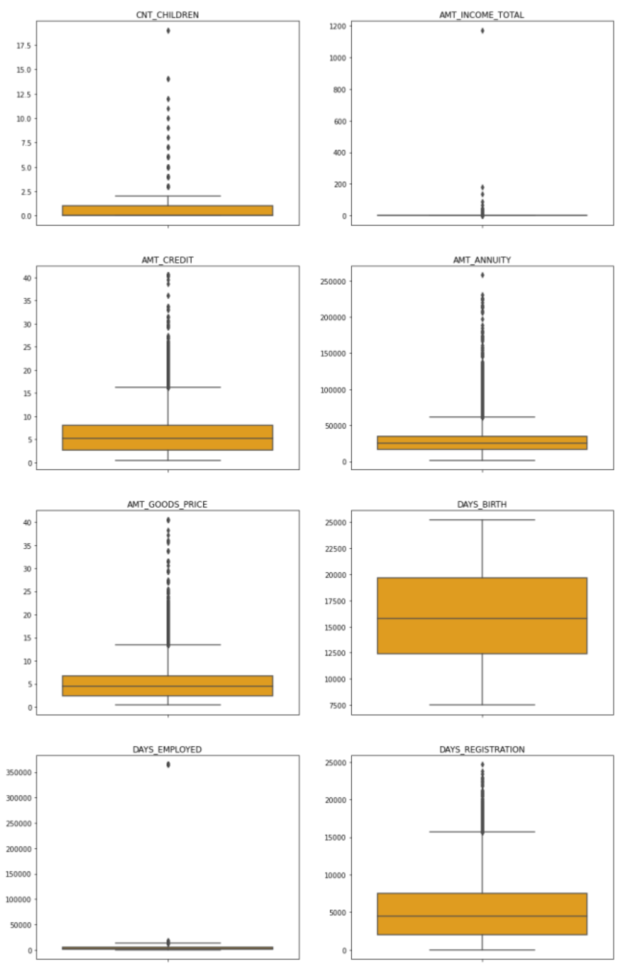
```
#creating column "EMPLOYEMENT_YEARS" from "DAYS_EMPLOYED"

appl_data["YEARS_EMPLOYED"] = appl_data["DAYS_EMPLOYED"]/365
bins = [0,5,10,15,20,25,30,50]
slots = ["0-5","5-10","10-15","15-20","20-25","25-30","30 Above"]

appl_data["EMPLOYEMENT_YEARS"] = pd.cut(appl_data["YEARS_EMPLOYED"], bins=bins,
labels=slots)

appl_data["EMPLOYEMENT_YEARS"].value_counts(normalize= True)*100
```

```
0-5        54.061911
5-10       25.729074
10-15      10.926289
15-20       4.302854
20-25       2.476054
25-30       1.311996
30 Above    1.191822
Name: EMPLOYEMENT_YEARS, dtype: float64
```

5. Identifying Outliers
appl_data.describe()

- **from describe we could find all the columns those wo have high difference between max and 75 percentile and the ones which makes no sense having max value to be so high are captured below:**

```
outlier_col = ["CNT_CHILDREN","AMT_INCOME_TOTAL", "AMT_CREDIT", "AMT_ANNUITY", "AMT_GOODS_PRICE",
              "DAYS_BIRTH", "DAYS_EMPLOYED", "DAYS_REGISTRATION"]

plt.figure(figsize=[15,25])
for i,j in itertools.zip_longest(outlier_col, range(len(outlier_col))):
    plt.subplot(4,2,j+1)
    sns.boxplot(y = appl_data[i], orient = "h", color = "orange")
    #plt.yticks(fontsize=8)
    plt.xlabel("")
    plt.ylabel("")
    plt.title(i)
```



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.**

appl_data.nunique().sort_values()

```
LIVE_REGION_NOT_WORK_REGION        2
TARGET                             2
NAME_CONTRACT_TYPE                 2
REG_REGION_NOT_LIVE_REGION         2
FLAG_OWN_REALTY                    2
LIVE_CITY_NOT_WORK_CITY            2
REG_CITY_NOT_WORK_CITY             2
REG_CITY_NOT_LIVE_CITY             2
FLAG_DOCUMENT_3                    2
REG_REGION_NOT_WORK_REGION         2
FLAG_MOBIL                         2
REGION_RATING_CLIENT               3
CODE_GENDER                        3
REGION_RATING_CLIENT_W_CITY        3
NAME_EDUCATION_TYPE                5
AMT_REQ_CREDIT_BUREAU_HOUR         5
NAME_FAMILY_STATUS                 6
NAME_HOUSING_TYPE                  6
EMPLOYEMENT_YEARS                  7
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
AGE_GROUP                          9
DEF_30_CNT_SOCIAL_CIRCLE          10
AMT_REQ_CREDIT_BUREAU_QRT         11
AMT_INCOME_RANGE                  11
AMT_CREDIT_RANGE                  11
AMT_GOODS_PRICE_RANGE             11
CNT_CHILDREN                      15
CNT_FAM_MEMBERS                   17
OCCUPATION_TYPE                   19
AMT_REQ_CREDIT_BUREAU_MON         24
HOUR_APPR_PROCESS_START           24
AMT_REQ_CREDIT_BUREAU_YEAR        25
OBS_60_CNT_SOCIAL_CIRCLE          33
OBS_30_CNT_SOCIAL_CIRCLE          33
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
YEARS_EMPLOYED 12574
AMT_ANNUITY 13672
DAYS_REGISTRATION 15688
DAYS_BIRTH 17460
AGE 17460
SK_ID_CURR 307511
dtype: int64

#Checking the number of unique values each column possess to identify categorical columns

appl_data.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 307511 entries, 0 to 307510 Data columns (total 53 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_REALTY 307511 non-null object 5 CNT_CHILDREN 307511 non-null int64 6 AMT_INCOME_TOTAL 307511 non-null float64 7 AMT_CREDIT 307511 non-null float64 8 AMT_ANNUITY 307499 non-null float64 9 AMT_GOODS_PRICE 307233 non-null float64 10 NAME_TYPE_SUITE 306219 non-null object 11 NAME_INCOME_TYPE 307511 non-null object 12 NAME_EDUCATION_TYPE 307511 non-null object 13 NAME_FAMILY_STATUS 307511 non-null object 14 NAME_HOUSING_TYPE 307511 non-null object 15 REGION_POPULATION_RELATIVE 307511 non-null float64 16 DAYS_BIRTH 307511 non-null float64 17 DAYS_EMPLOYED 307511 non-null float64 18 DAYS_REGISTRATION 307511 non-null float64 19 DAYS_ID_PUBLISH 307511 non-null float64 20 FLAG_MOBIL 307511 non-null int64 21 OCCUPATION_TYPE 307511 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 307511 non-null float64 41 AMT_REQ_CREDIT_BUREAU_DAY 307511 non-null float64 42 AMT_REQ_CREDIT_BUREAU_WEEK 307511 non-null float64 43 AMT_REQ_CREDIT_BUREAU_MON 307511 non-null float64 44 AMT_REQ_CREDIT_BUREAU_QRT 307511 non-null float64 45 AMT_REQ_CREDIT_BUREAU_YEAR 307511 non-null float64 46 AMT_INCOME_RANGE 307279 non-null category 47 AMT_CREDIT_RANGE 307511 non-null category 48 AMT_GOODS_PRICE_RANGE 307233 non-null category 49 AGE 307511 non-null float64 50 AGE_GROUP 307511 non-null category 51 YEARS_EMPLOYED 307511 non-null float64 52 EMPLOYEMENT_YEARS 252135 non-null category dtypes: category(5), float64(23), int64(14), object(11) memory usage: 114.1+ MB

6. Converting Desired columns from Object to categorical column
appl_data.columns

Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3', 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR', 'AMT_INCOME_RANGE', 'AMT_CREDIT_RANGE', 'AMT_GOODS_PRICE_RANGE', 'AGE', 'AGE_GROUP', 'YEARS_EMPLOYED', 'EMPLOYEMENT_YEARS'],
dtype='object')

```
#from the list, we have taken out the desired columns for conversion

categorical_columns = ['NAME_CONTRACT_TYPE','CODE_GENDER','NAME_TYPE_SUITE','NAME_INCOME_TYPE','NAME_EDUCATION_TYPE',
                       'NAME_FAMILY_STATUS','NAME_HOUSING_TYPE','OCCUPATION_TYPE','WEEKDAY_APPR_PROCESS_START',
                       'ORGANIZATION_TYPE','FLAG_OWN_REALTY','LIVE_CITY_NOT_WORK_CITY',
                       'REG_CITY_NOT_LIVE_CITY','REG_CITY_NOT_WORK_CITY','REG_REGION_NOT_WORK_REGION',
                       'LIVE_REGION_NOT_WORK_REGION','REGION_RATING_CLIENT','WEEKDAY_APPR_PROCESS_START',
                       'REGION_RATING_CLIENT_W_CITY','CNT_CHILDREN','CNT_FAM_MEMBERS']

for col in categorical_columns:
    appl_data[col] = pd.Categorical(appl_data[col])
```

```
len(categorical_columns) # Converting total of 21 columns to categorical one
```

21

```
appl_data.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 307511 entries, 0 to 307510 Data columns (total 53 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_REALTY 307511 non-null category 5 CNT_CHILDREN 307511 non-null category 6 AMT_INCOME_TOTAL 307511 non-null float64 7 AMT_CREDIT 307511 non-null float64 8 AMT_ANNUITY 307499 non-null float64 9 AMT_GOODS_PRICE 307233 non-null float64 10 NAME_TYPE_SUITE 306219 non-null category 11 NAME_INCOME_TYPE 307511 non-null category 12 NAME_EDUCATION_TYPE 307511 non-null category 13 NAME_FAMILY_STATUS 307511 non-null category 14 NAME_HOUSING_TYPE 307511 non-null category 15 REGION_POPULATION_RELATIVE 307511 non-null float64 16 DAYS_BIRTH 307511 non-null float64 17 DAYS_EMPLOYED 307511 non-null float64 18 DAYS_REGISTRATION 307511 non-null float64 19 DAYS_ID_PUBLISH 307511 non-null float64 20 FLAG_MOBIL 307511 non-null int64 21 OCCUPATION_TYPE 307511 non-null category 22 CNT_FAM_MEMBERS 307509 non-null category 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 307511 non-null float64 41 AMT_REQ_CREDIT_BUREAU_DAY 307511 non-null float64 42 AMT_REQ_CREDIT_BUREAU_WEEK 307511 non-null float64 43 AMT_REQ_CREDIT_BUREAU_MON 307511 non-null float64 44 AMT_REQ_CREDIT_BUREAU_QRT 307511 non-null float64 45 AMT_REQ_CREDIT_BUREAU_YEAR 307511 non-null float64 46 AMT_INCOME_RANGE 307279 non-null category 47 AMT_CREDIT_RANGE 307511 non-null category 48 AMT_GOODS_PRICE_RANGE 307233 non-null category 49 AGE 307511 non-null float64 50 AGE_GROUP 307511 non-null category 51 YEARS_EMPLOYED 307511 non-null float64 52 EMPLOYEMENT_YEARS 252135 non-null category dtypes: category(25), float64(22), int64(6) memory usage: 73.0 MB

Insight

- **After imputing we have 53 columns and we will move ahead with Data Analysis on these columns**

Dataset 2 - "previous_application.csv"
Note: Have followed similar steps done for application_data.csv

```
# importing previous_application.csv

prev_appl = pd.read_csv("previous_application.csv")


prev_appl.head()
```

```
#Checking rows and columns of the raw data
prev_appl.shape
```

(1670214, 37)

#Checking information of all the columns like data types
prev_appl.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 1670214 entries, 0 to 1670213 Data columns (total 37 columns): # Column Non-Null Count Dtype --- ------ -------------- ----- 0 SK_ID_PREV 1670214 non-null int64 1 SK_ID_CURR 1670214 non-null int64 2 NAME_CONTRACT_TYPE 1670214 non-null object 3 AMT_ANNUITY 1297979 non-null float64 4 AMT_APPLICATION 1670214 non-null float64 5 AMT_CREDIT 1670213 non-null float64 6 AMT_DOWN_PAYMENT 774370 non-null float64 7 AMT_GOODS_PRICE 1284699 non-null float64 8 WEEKDAY_APPR_PROCESS_START 1670214 non-null object 9 HOUR_APPR_PROCESS_START 1670214 non-null int64 10 FLAG_LAST_APPL_PER_CONTRACT 1670214 non-null object 11 NFLAG_LAST_APPL_IN_DAY 1670214 non-null int64 12 RATE_DOWN_PAYMENT 774370 non-null float64 13 RATE_INTEREST_PRIMARY 5951 non-null float64 14 RATE_INTEREST_PRIVILEGED 5951 non-null float64 15 NAME_CASH_LOAN_PURPOSE 1670214 non-null object 16 NAME_CONTRACT_STATUS 1670214 non-null object 17 DAYS_DECISION 1670214 non-null int64 18 NAME_PAYMENT_TYPE 1670214 non-null object 19 CODE_REJECT_REASON 1670214 non-null object 20 NAME_TYPE_SUITE 849809 non-null object 21 NAME_CLIENT_TYPE 1670214 non-null object 22 NAME_GOODS_CATEGORY 1670214 non-null object 23 NAME_PORTFOLIO 1670214 non-null object 24 NAME_PRODUCT_TYPE 1670214 non-null object 25 CHANNEL_TYPE 1670214 non-null object 26 SELLERPLACE_AREA 1670214 non-null int64 27 NAME_SELLER_INDUSTRY 1670214 non-null object 28 CNT_PAYMENT 1297984 non-null float64 29 NAME_YIELD_GROUP 1670214 non-null object 30 PRODUCT_COMBINATION 1669868 non-null object 31 DAYS_FIRST_DRAWING 997149 non-null float64 32 DAYS_FIRST_DUE 997149 non-null float64 33 DAYS_LAST_DUE_1ST_VERSION 997149 non-null float64 34 DAYS_LAST_DUE 997149 non-null float64 35 DAYS_TERMINATION 997149 non-null float64 36 NFLAG_INSURED_ON_APPROVAL 997149 non-null float64 dtypes: float64(15), int64(6), object(16) memory usage: 471.5+ MB

- **There are 37 columns having various data types like object, int, float and 1670214 rows.**

 # Checking the numeric variables of the dataframes
prev_appl.describe()

Insight

- **there are 37 columns and 1679214 rows.**
- **there columns having negative, postive values which includes days. fixing is required**

#checking how many null values are present in each of the columns in percentage
null_values(prev_appl)

RATE_INTEREST_PRIVILEGED	99.64
RATE_INTEREST_PRIMARY	99.64
RATE_DOWN_PAYMENT	53.64
AMT_DOWN_PAYMENT	53.64
NAME_TYPE_SUITE	49.12
DAYS_TERMINATION	40.30
NFLAG_INSURED_ON_APPROVAL	40.30
DAYS_FIRST_DRAWING	40.30
DAYS_FIRST_DUE	40.30
DAYS_LAST_DUE_1ST_VERSION	40.30
DAYS_LAST_DUE	40.30
AMT_GOODS_PRICE	23.08
AMT_ANNUITY	22.29

```
CNT_PAYMENT                  22.29
PRODUCT_COMBINATION           0.02
AMT_CREDIT                    0.00
SK_ID_CURR                    0.00
NAME_CONTRACT_TYPE            0.00
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
AMT_APPLICATION               0.00
NAME_PAYMENT_TYPE             0.00
NAME_CASH_LOAN_PURPOSE        0.00
NAME_CONTRACT_STATUS          0.00
DAYS_DECISION                 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
NAME_YIELD_GROUP              0.00
SK_ID_PREV                    0.00
dtype: float64
```

```
#creating a variable p_null_col_50 for storing null columns having missing values more than 50%

p_null_col_50 = null_values(prev_appl)[null_values(prev_appl)>50]
```

```
p_null_col_50 # There only 4 columns with missing valus more than 50%
```

```
RATE_INTEREST_PRIVILEGED    99.64
RATE_INTEREST_PRIMARY       99.64
RATE_DOWN_PAYMENT           53.64
AMT_DOWN_PAYMENT            53.64
dtype: float64
```

```
#dropping null columns having missing values more than 50%

prev_appl.drop(columns = p_null_col_50.index, inplace = True)
```

```
#creating a variable p_null_col_15 for storing null columns having missing values more than 15%

p_null_col_15 = null_values(prev_appl)[null_values(prev_appl)>15]
```

```
p_null_col_15
```

```
NAME_TYPE_SUITE              49.12
DAYS_FIRST_DUE               40.30
DAYS_TERMINATION             40.30
DAYS_FIRST_DRAWING           40.30
NFLAG_INSURED_ON_APPROVAL    40.30
```

```
DAYS_LAST_DUE_1ST_VERSION    40.30
DAYS_LAST_DUE                40.30
AMT_GOODS_PRICE              23.08
AMT_ANNUITY                  22.29
CNT_PAYMENT                  22.29
dtype: float64
```

```
prev_appl[p_null_col_15.index]
```

```
prev_appl.columns
```

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

```
# Listing down columns which are not needed
Unnecessary_prev =
['WEEKDAY_APPR_PROCESS_START','HOUR_APPR_PROCESS_START','FLAG_LAST_APPL_PER_
CONTRACT','NFLAG_LAST_APPL_IN_DAY']
```

```
prev_appl.drop(Unnecessary_prev,axis =1, inplace = True)
```

```
prev_appl.shape
```

```
(1670214, 29)
```

```
# IMputing values "Unknown" as this a categorical column
prev_appl["NAME_TYPE_SUITE"] = prev_appl["NAME_TYPE_SUITE"].fillna("Unknown")
```

```
null_values(prev_appl)
```

```
NFLAG_INSURED_ON_APPROVAL    40.30
DAYS_LAST_DUE                40.30
DAYS_LAST_DUE_1ST_VERSION    40.30
DAYS_FIRST_DUE               40.30
DAYS_FIRST_DRAWING           40.30
DAYS_TERMINATION             40.30
AMT_GOODS_PRICE              23.08
AMT_ANNUITY                  22.29
CNT_PAYMENT                  22.29
PRODUCT_COMBINATION           0.02
AMT_CREDIT                    0.00
NAME_CONTRACT_STATUS          0.00
NAME_CASH_LOAN_PURPOSE        0.00
```

```
NAME_CONTRACT_TYPE          0.00
AMT_APPLICATION             0.00
NAME_PAYMENT_TYPE           0.00
SK_ID_CURR                  0.00
DAYS_DECISION               0.00
NAME_GOODS_CATEGORY         0.00
CODE_REJECT_REASON          0.00
NAME_TYPE_SUITE             0.00
NAME_CLIENT_TYPE            0.00
NAME_PORTFOLIO              0.00
NAME_PRODUCT_TYPE           0.00
CHANNEL_TYPE                0.00
SELLERPLACE_AREA            0.00
NAME_SELLER_INDUSTRY        0.00
NAME_YIELD_GROUP            0.00
SK_ID_PREV                  0.00
dtype: float64
```

- **There are missing values in columns 'DAYS_FIRST_DUE', 'DAYS_TERMINATION', 'DAYS_FIRST_DRAWING','DAYS_LAST_DUE_1ST_VERSION', 'DAYS_LAST_DUE' and these columns count days thus will keeping null values as they are**

```
#Analying numerical columns using describe

prev_appl[p_null_col_15.index].describe()

# To convert negative days to postive days creating a varaible "p_days_col"

p_days_col = ['DAYS_DECISION','DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
'DAYS_LAST_DUE_1ST_VERSION', 'DAYS_LAST_DUE', 'DAYS_TERMINATION']

prev_appl[p_days_col].describe() # Analysis before conversion


# Converting Negative days to positive days

prev_appl[p_days_col] = abs(prev_appl[p_days_col])

prev_appl[p_null_col_15.index].describe() # analysing after conversion

#days group calculation e.g. 369 will be grouped as with in 2 years

bins = [0,1*365,2*365,3*365,4*365,5*365,6*365,7*365,10*365]
slots = ["1","2","3","4","5","6","7","7 above"]
prev_appl['YEARLY_DECISION'] = pd.cut(prev_appl['DAYS_DECISION'],bins,labels=slots)


prev_appl['YEARLY_DECISION'].value_counts(normalize=True)*100
```

```
1     34.351287
2     23.056806
3     12.855598
4      7.883181
```

```
5          6.128556
7          5.813806
7 above    5.060729
6          4.850037
Name: YEARLY_DECISION, dtype: float64
```

Insight:

- **Almost 35% loan applicatants have applied for a new loan within 1 year of previous loan decision**

prev_appl.nunique()

```
SK_ID_PREV                 1670214
SK_ID_CURR                  338857
NAME_CONTRACT_TYPE               4
AMT_ANNUITY                 357959
AMT_APPLICATION              93885
AMT_CREDIT                   86803
AMT_GOODS_PRICE              93885
NAME_CASH_LOAN_PURPOSE          25
NAME_CONTRACT_STATUS             4
DAYS_DECISION                 2922
NAME_PAYMENT_TYPE                4
CODE_REJECT_REASON               9
NAME_TYPE_SUITE                  8
NAME_CLIENT_TYPE                 4
NAME_GOODS_CATEGORY             28
NAME_PORTFOLIO                   5
NAME_PRODUCT_TYPE                3
CHANNEL_TYPE                     8
SELLERPLACE_AREA              2097
NAME_SELLER_INDUSTRY            11
CNT_PAYMENT                     49
NAME_YIELD_GROUP                 5
PRODUCT_COMBINATION             17
DAYS_FIRST_DRAWING            2838
DAYS_FIRST_DUE                2892
DAYS_LAST_DUE_1ST_VERSION     2803
DAYS_LAST_DUE                 2873
DAYS_TERMINATION              2830
NFLAG_INSURED_ON_APPROVAL        2
YEARLY_DECISION                  8
dtype: int64
```

null_values(prev_appl)

```
DAYS_TERMINATION             40.30
DAYS_LAST_DUE                40.30
DAYS_LAST_DUE_1ST_VERSION    40.30
DAYS_FIRST_DUE               40.30
DAYS_FIRST_DRAWING           40.30
NFLAG_INSURED_ON_APPROVAL    40.30
```

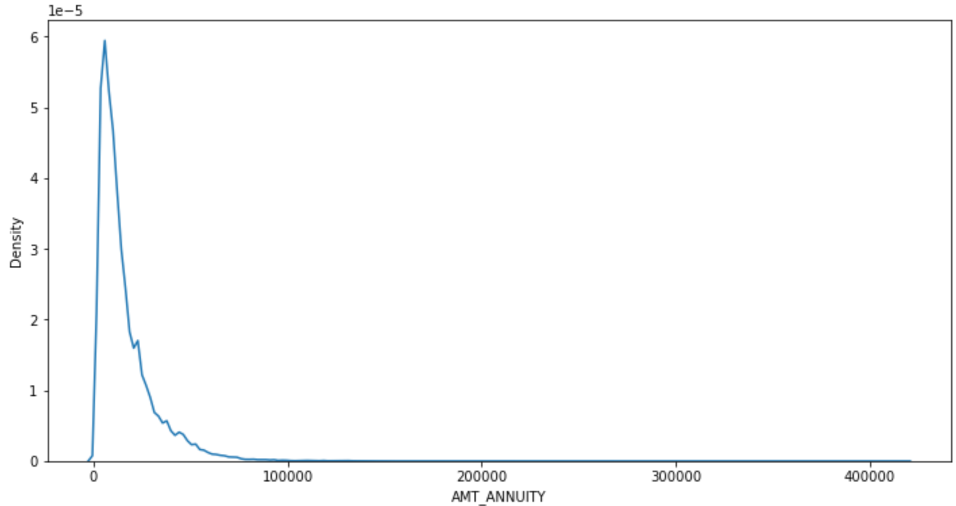
```
AMT_GOODS_PRICE            23.08
AMT_ANNUITY                22.29
CNT_PAYMENT                22.29
PRODUCT_COMBINATION         0.02
AMT_CREDIT                  0.00
NAME_CONTRACT_STATUS        0.00
NAME_CASH_LOAN_PURPOSE      0.00
YEARLY_DECISION             0.00
AMT_APPLICATION             0.00
NAME_CONTRACT_TYPE          0.00
NAME_PAYMENT_TYPE           0.00
SK_ID_CURR                  0.00
DAYS_DECISION               0.00
NAME_GOODS_CATEGORY         0.00
CODE_REJECT_REASON          0.00
NAME_TYPE_SUITE             0.00
NAME_CLIENT_TYPE            0.00
NAME_PORTFOLIO              0.00
NAME_PRODUCT_TYPE           0.00
CHANNEL_TYPE                0.00
SELLERPLACE_AREA            0.00
NAME_SELLER_INDUSTRY        0.00
NAME_YIELD_GROUP            0.00
SK_ID_PREV                  0.00
dtype: float64
```

Now dealing with continuos variables "AMT_ANNUITY", "AMT_GOODS_PRICE"

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.**

```
#plotting a kdeplot to understand distribution of "AMT_ANNUITY"

plt.figure(figsize=(12,6))
sns.kdeplot(prev_appl['AMT_ANNUITY'])
plt.show()
```

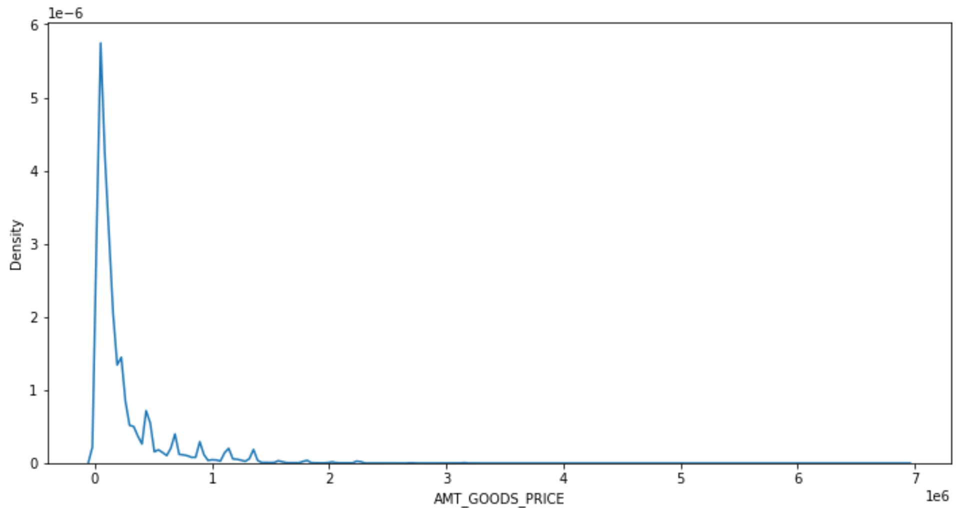


Insight:

- **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.**

```
#imputing missing values with median

prev_appl['AMT_ANNUITY'].fillna(prev_appl['AMT_ANNUITY'].median(),inplace = True)
```

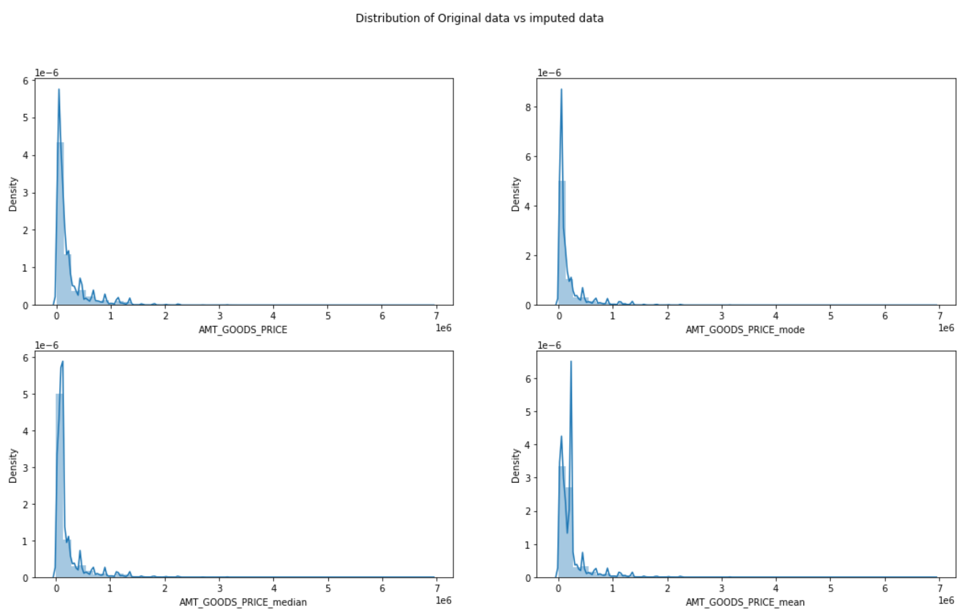
```
# Plotting kde plot for "AMT_GOODS_PRICE" to understand the distribution

plt.figure(figsize=(12,6))
sns.kdeplot(prev_appl['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.**

Creating new dataframe for "AMT_GOODS_PRICE" with columns imputed with mode, median and mean

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

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

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



- **The original distribution is closer with the distribution of data imputed with mode in this case, thus will impute mode for missing values**

```
# Imputing null values with mode

prev_appl['AMT_GOODS_PRICE'].fillna(prev_appl['AMT_GOODS_PRICE'].mode()[0], inplace=True)
```

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

```
#taking out values count for NAME_CONTRACT_STATUS categories where CNT_PAYMENT have null values.

prev_appl.loc[prev_appl['CNT_PAYMENT'].isnull(),'NAME_CONTRACT_STATUS'].value_counts()
```

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

```
#imputing null values as 0

prev_appl['CNT_PAYMENT'].fillna(0,inplace = True)
```

```
prev_appl.columns
```

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

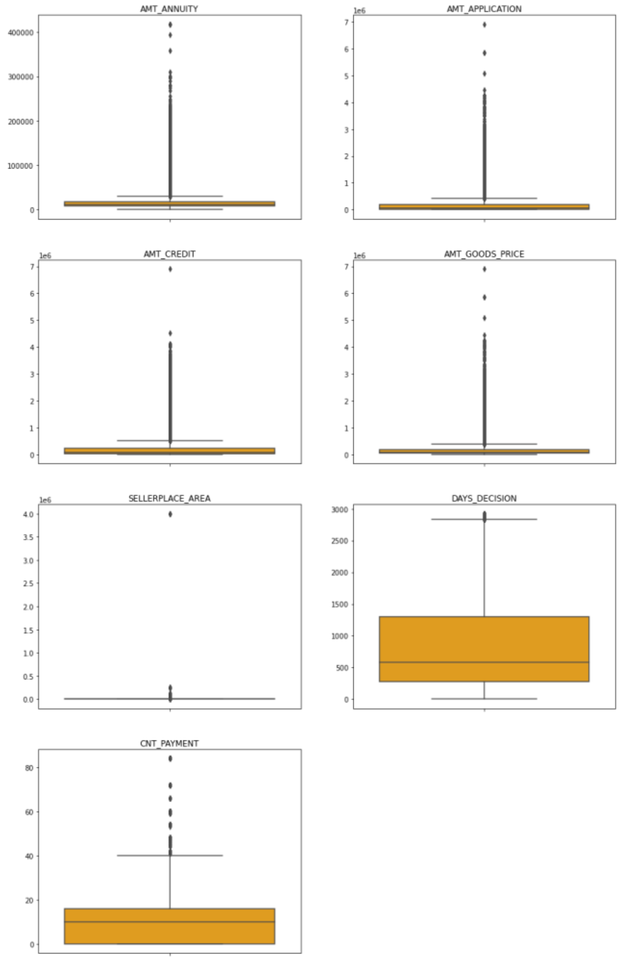
```
#Converting required categoical columns from Object to categorical

p_catgorical_col =
['NAME_CASH_LOAN_PURPOSE','NAME_CONTRACT_STATUS','NAME_PAYMENT_TYPE',

'CODE_REJECT_REASON','NAME_CLIENT_TYPE','NAME_GOODS_CATEGORY','NAME_PORTFOLIO',

'NAME_PRODUCT_TYPE','CHANNEL_TYPE','NAME_SELLER_INDUSTRY','NAME_YIELD_GROUP','PRODUCT_COMBINATION',
                    'NAME_CONTRACT_TYPE']


for col in p_catgorical_col:
    prev_appl[col] =pd.Categorical(prev_appl[col])
```

Finding outliers
prev_appl.describe()

- **from describe we could find all the columns those wo have high difference between max and 75 percentile and the ones which makes no sense having max value to be so high are captured below**

```
p_outlier_col = ['AMT_ANNUITY','AMT_APPLICATION','AMT_CREDIT','AMT_GOODS_PRICE',
                 'SELLERPLACE_AREA','DAYS_DECISION','CNT_PAYMENT']

plt.figure(figsize=[15,25])
for i,j in itertools.zip_longest(p_outlier_col, range(len(p_outlier_col))):
    plt.subplot(4,2,j+1)
    sns.boxplot(y = prev_appl[i], orient = "h", color = "orange")
    #plt.yticks(fontsize=8)
```

```
plt.xlabel("")
plt.ylabel("")
plt.title(i)
```



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

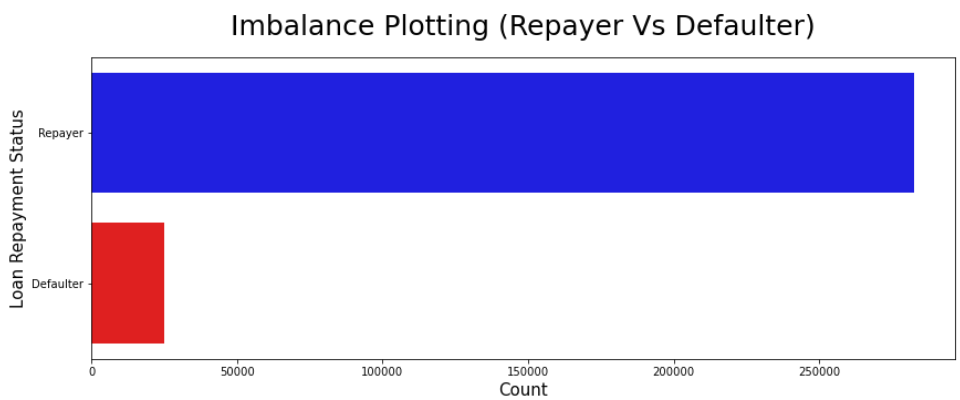
6. Data Analysis Time
Strategy: The data analysis flow has been planned in following way :

- 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

6.1 Imbalance Data

```
plt.figure(figsize= [14,5])
sns.barplot(y=["Repayer","Defaulter"], x = appl_data["TARGET"].value_counts(), palette =
["blue","r"],orient="h")
plt.ylabel("Loan Repayment Status",fontdict = {"fontsize":15})
plt.xlabel("Count",fontdict = {"fontsize":15})
plt.title("Imbalance Plotting (Repayer Vs Defaulter)", fontdict = {"fontsize":25}, pad = 20)
plt.show()
```




```
#Ratio of imbalance percentage with respect to defaulter and repayer is given below
repayer = round((appl_data["TARGET"].value_counts()[0]/len(appl_data)* 100),2)
print("Repayer Percentage is {}%".format(repayer))
defaluter = round((appl_data["TARGET"].value_counts()[1]/len(appl_data)* 100),2)
print("Defaulter Percentage is {}%".format(defaluter))
print("Imbalance Ratio with respect to Repayer and Defaulter is given: {0:.2f}/1
(approx)".format(repayer/defaluter))
```

Repayer Percentage is 91.93% Defaulter Percentage is 8.07% Imbalance Ratio with respect to Repayer and Defaulter is given: 11.39/1 (approx)

6.2 Plotting Functions

Important Function for Univariate analysis
Creating a function for plotting Variables to do univariate analysis. This function will create two plots

1. Count plot of given column w.r.t TARGET column
2. Percentage of defaulters within that column

The function is taking 6 arguments

3. dataset : to put the dataset we want to use
4. col : column name for which we need to the analysis
5. target_col : column name for with which we will be comparing
6. ylog : to have y-axis in log10 terms, in case the plot is not readable
7. x_label_angle : to maintain the orientation of x-axis labels
8. h_layout : to give horizontal layout of the subplots

```
# Creating a function to find if the column is categorical or numerical

def data_type(dataset,col):
    if dataset[col].dtype == np.int64 or dataset[col].dtype == np.float64:
        return "numerical"
    if dataset[col].dtype == "category":
        return "categorical"

# Creating a function "univariate" to perform analysis one single variable with respect to target variable

def univariate(dataset,col,target_col,ylog=False,x_label_angle=False,h_layout=True):
    if data_type(dataset,col) == "numerical":
        sns.distplot(dataset[col],hist=False)



    elif data_type(dataset,col) == "categorical":
        val_count = dataset[col].value_counts()
        df1 = pd.DataFrame({col: val_count.index,'count': val_count.values})



        target_1_percentage = dataset[[col, target_col]].groupby([col],as_index=False).mean()
        target_1_percentage[target_col] = target_1_percentage[target_col]*100
        target_1_percentage.sort_values(by=target_col,inplace = True)



# If the plot is not readable, use the log scale

        if(h_layout):
            fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(15,7))
        else:
            fig, (ax1, ax2) = plt.subplots(nrows=2, figsize=(25,35))



# 1. Subplot 1: Count plot of the column

        s = sns.countplot(ax=ax1, x=col, data=dataset, hue=target_col)
        ax1.set_title(col, fontsize = 20)
        ax1.legend(['Repayer','Defaulter'])
        ax1.set_xlabel(col,fontdict={'fontsize' : 15, 'fontweight' : 3})

        if(x_label_angle):
            s.set_xticklabels(s.get_xticklabels(),rotation=75)

# 2. Subplot 2: Percentage of defaulters within the column

        s = sns.barplot(ax=ax2, x = col, y=target_col, data=target_1_percentage)
        ax2.set_title("Defaulters % in "+col, fontsize = 20)
        ax2.set_xlabel(col,fontdict={'fontsize' : 15, 'fontweight' : 3})
        ax2.set_ylabel(target_col,fontdict={'fontsize' : 15, 'fontweight' : 3})
```

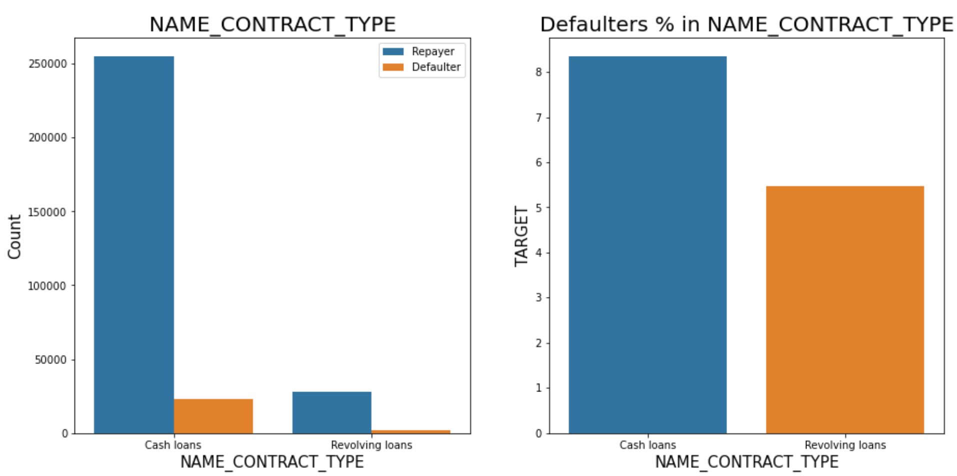
```
        if(x_label_angle):
            s.set_xticklabels(s.get_xticklabels(),rotation=75)


# If the plot is not readable, use the log scale

        if ylog:
            ax1.set_yscale('log')
            ax1.set_ylabel("Count (log)",fontdict={'fontsize' : 15, 'fontweight' : 3})
        else:
            ax1.set_ylabel("Count",fontdict={'fontsize' : 15, 'fontweight' : 3})



        plt.show()

# function for plotting repetitive rel plots in bivaritae numerical analysis

def bivariate_n(x,y,df,hue,kind,labels):
    plt.figure(figsize=[15,15])
    sns.relplot(x=x, y=y, data=df, hue=hue,kind=kind,legend = False)
    plt.legend(labels=labels)
    plt.xticks(rotation=45, ha='right')
    plt.show()



# function for plotting repetitive barplots in bivariate categorical analysis

def bivariate_c(x,y,df,hue,figsize,labels):

    plt.figure(figsize=figsize)
    sns.barplot(x=x,y=y,data=df, hue=hue)

    # Defining aesthetics of Labels and Title of the plot using style dictionaries
    plt.xlabel(x,fontsize = 15)
    plt.ylabel(y,fontsize = 15)
    plt.title(col,fontsize = 20)
    plt.xticks(rotation=45, ha='right')
    plt.legend(labels = labels )
    plt.show()


#function for plotting repetitive countplots in univariate categorical analysis on the merged df

def univariate_c_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)",fontsize=15)
    else:
        plt.ylabel("Count",fontsize=15)

    plt.title(col , fontsize=20)
    plt.legend(loc = "upper right")
    plt.xticks(rotation=45, ha='right')

    plt.show()


# Function to plot point plots

def pointplot(df,hue,x,y):
    plt.figure(figsize=(12,6))
    sns.pointplot(x=x, y=y, hue=hue, data=df)
    plt.title(x+" VS "+y,fontsize = 15)


# storing numnercial and categorical columns as list in belows varibles

cat_col = list(appl_data.select_dtypes(["category"]).columns)   # Categorical columns list
num_col = list(appl_data.select_dtypes(["int","float"]).columns)  #N Numerical Column list
```

6.3 Categorical Variables Analysis

6.3.1 Segmented Univariate Analysis

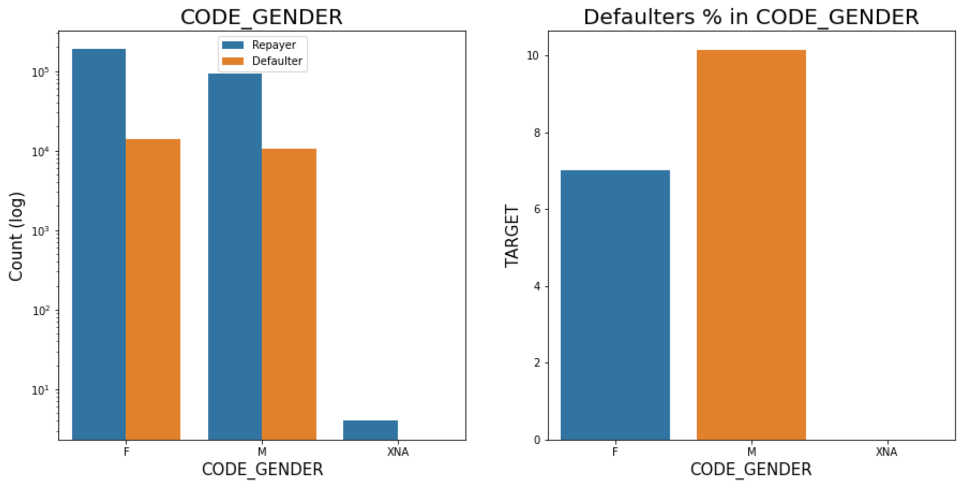
```
#1 Checking the contract type based on loan repayment status
univariate(appl_data,"NAME_CONTRACT_TYPE","TARGET",False,False,True)
```



Inferences: Contract type

- **Revolving loans are just a small fraction (10%) from the total number of loans**
- **Around 8-9% Cash loan applicants and 5-6% Revolving loan applicant are in defaulters**

```
#2 Checking the type of Gender on loan repayment status
univariate(appl_data,"CODE_GENDER","TARGET",True,False,True)
```

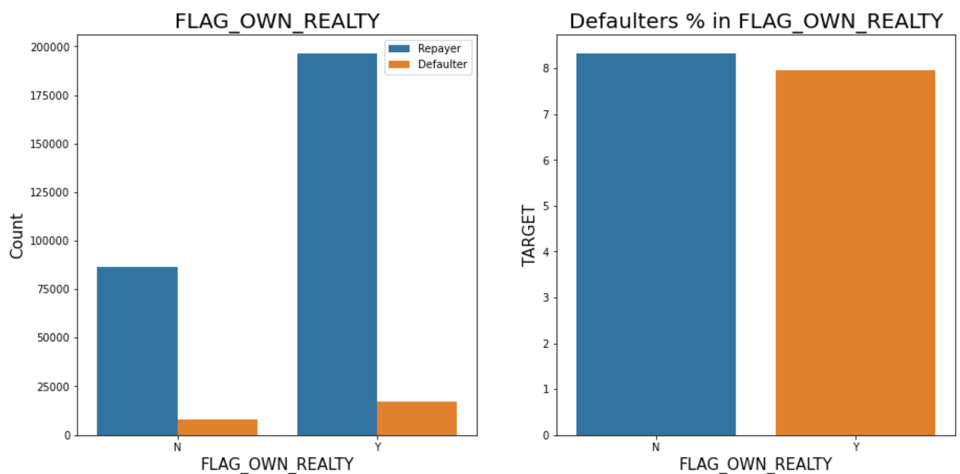


Inferences: Gender Type

- **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 about 10%, comparing with women about 7%**

#3 Checking if owning a real estate is related to loan repayment status

```
univariate(appl_data,"FLAG_OWN_REALTY","TARGET",False,False,True)
```

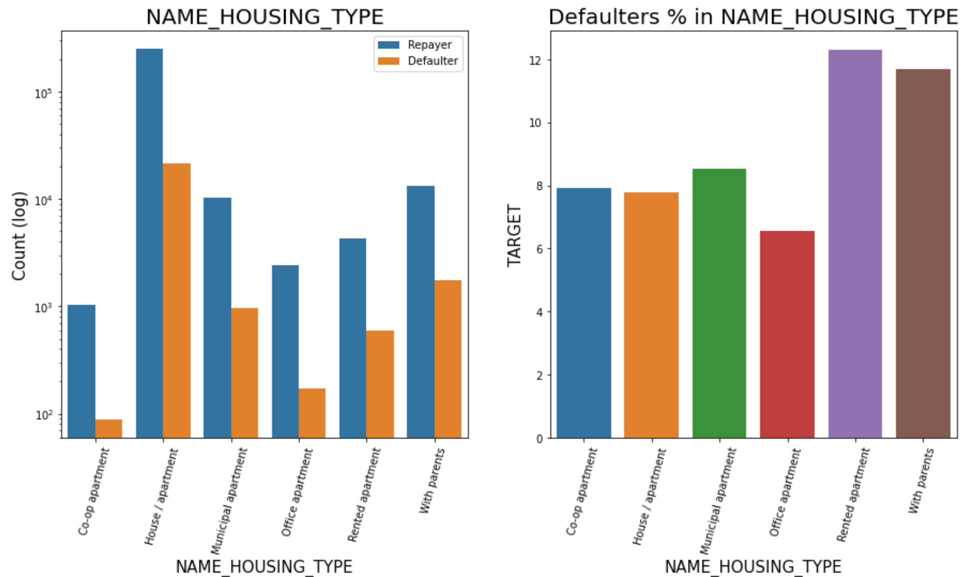


Inferences:

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

#4 Analyzing Housing Type based on loan repayment status

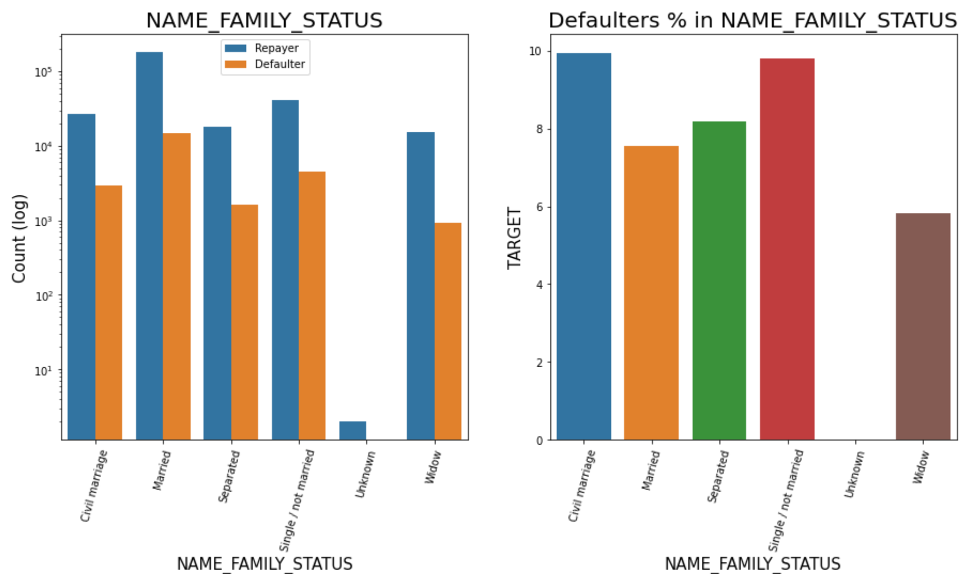
```
univariate(appl_data,"NAME_HOUSING_TYPE","TARGET",True,True,True)
```



Inferences: Applicant House type

- **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**

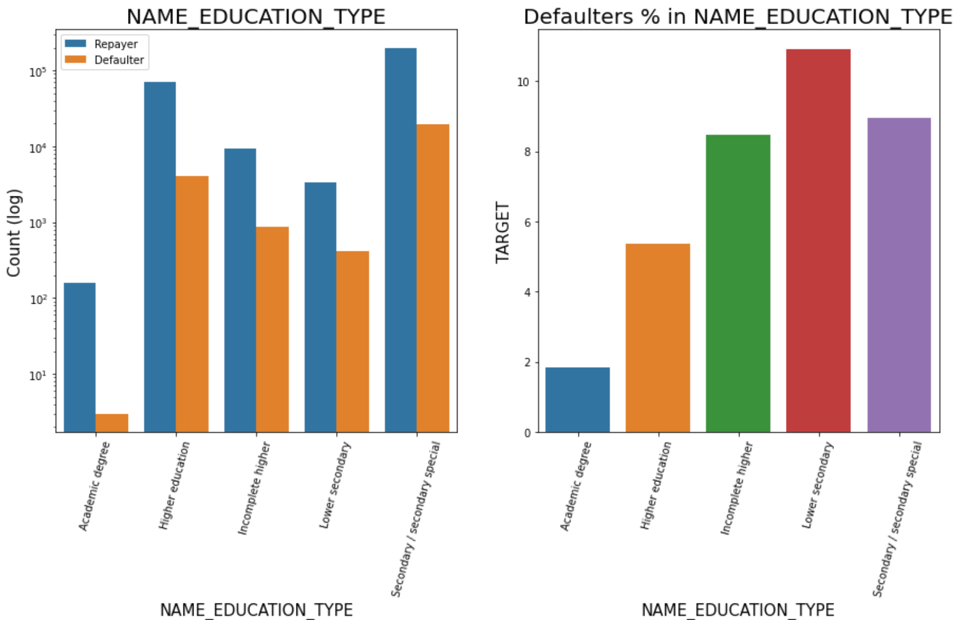
#5 Analyzing Family status based on loan repayment status
univariate(appl_data,"NAME_FAMILY_STATUS","TARGET",True,True,True)



Inferences:

- **Most of the people who have taken loan are married, followed by Single/not married and civil marriage**
- **In Percentage of defaulters, Civil marriage has the highest percent around (10%) and widow has the lowest around 6% (exception being Unknown).**

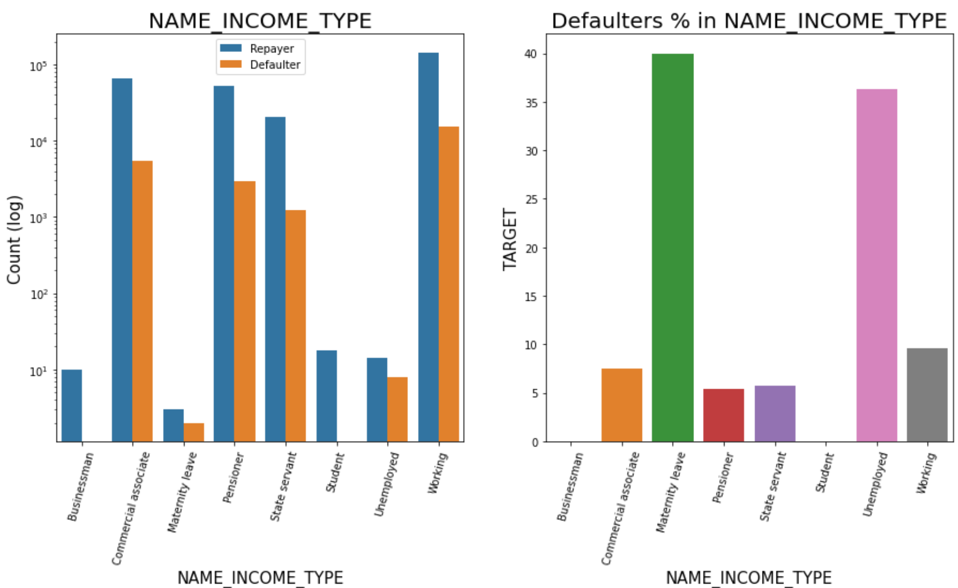
#6 Analyzing Education Type based on loan repayment status
univariate(appl_data,"NAME_EDUCATION_TYPE","TARGET",True,True,True)



Inferences: Education Type

- **Majority of clients have Secondary/secondary special education, followed by clients with Higher education.**
- **Very few clients have an academic degree**
- **Lower secondary category have highest rate of defaulting around 11%.**
- **People with Academic degree are least likely to default.**

#7 Analyzing Income Type based on loan repayment status
univariate(appl_data,"NAME_INCOME_TYPE","TARGET",True,True,True)



Inferences:

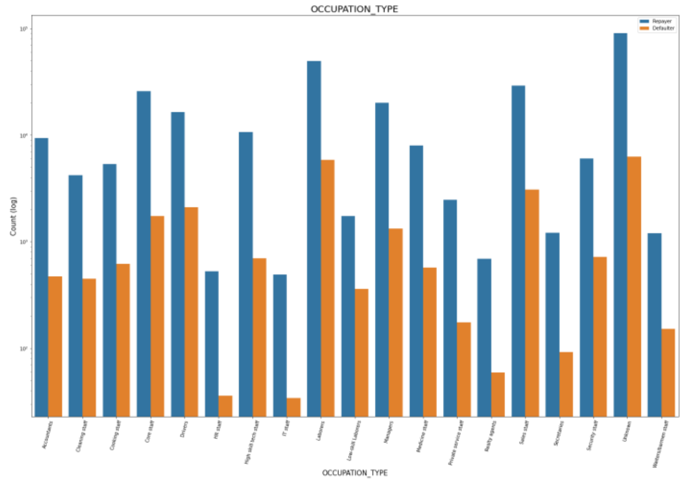
- **Most of applicants for loans income type is Working, followed by Commercial associate, Pensioner and State servant.**
- **The applicants who are on Maternity leave have defaulting percentage of 40% which is the highest, followed by Unemployed (37%). The rest under average around 10% defaultees.**
- **Student and Businessmen though less in numbers, do not have default record. Safest two categories for providing loan.**

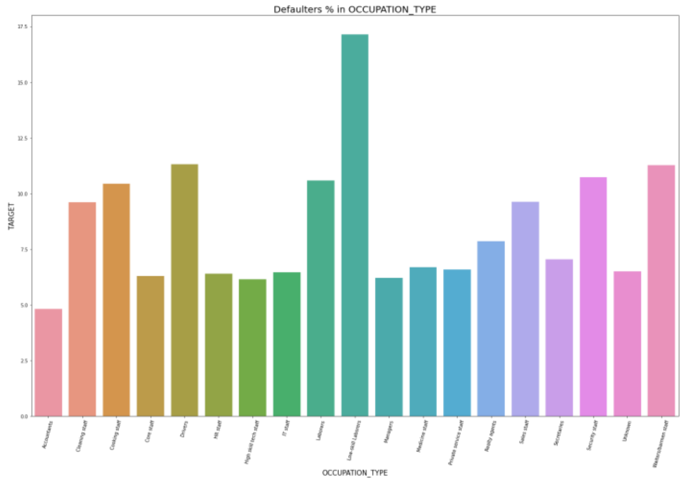
#8 Analyzing Region rating where applicant lives based on loan repayment status
univariate(appl_data,"REGION_RATING_CLIENT","TARGET",True,False,True)

Inferences:Client Region Rating

- **Most of the applicants are living in Region with 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**

#9 Analyzing Occupation Type where applicant lives based on loan repayment status
univariate(appl_data,"OCCUPATION_TYPE","TARGET",True,True,False)



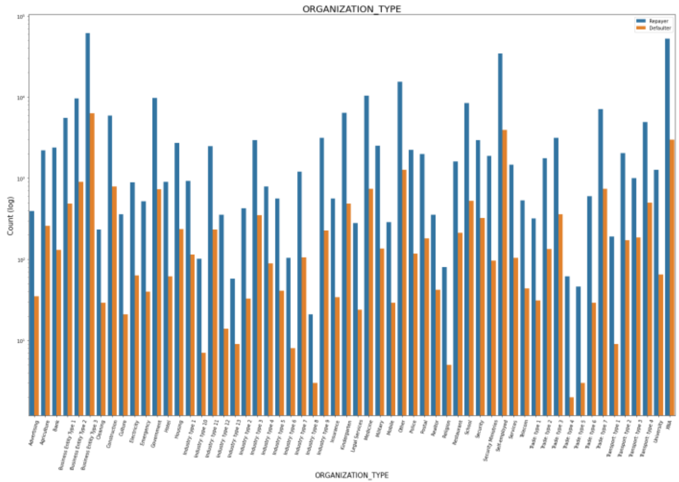


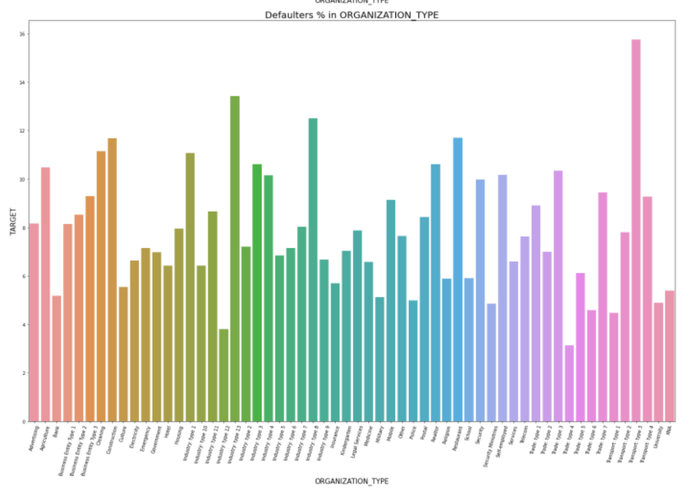
Inferences:

- **Most of the loans are taken by Laborers, followed by Sales staff.**
- **IT staff are less likely to apply for Loan.**
- **Category with highest percent of defautess are Low-skill Laborers (above 17%), followed by Drivers and Waiters/barmen staff, Security staff, Laborers and Cooking staff**

#10 Checking Loan repayment status based on Organization type

```
univariate(appl_data,"ORGANIZATION_TYPE","TARGET",True,True,False)
```

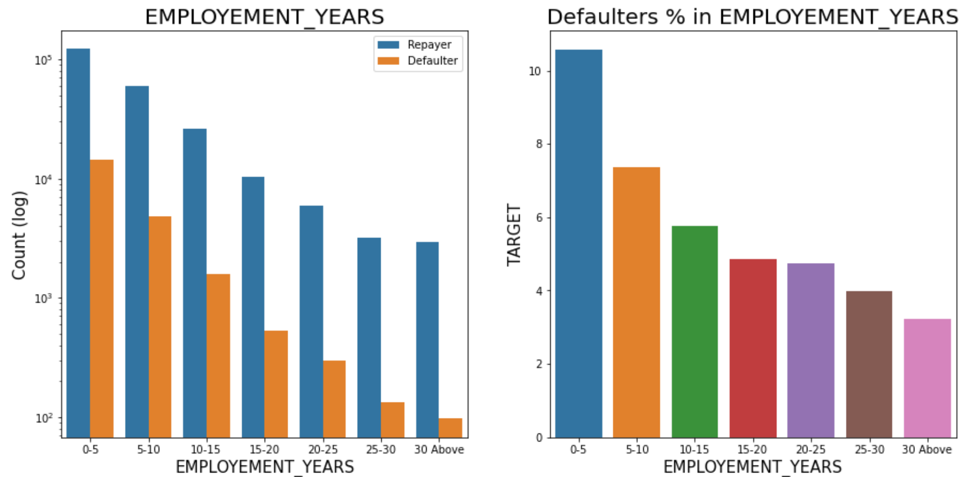




Inferences: Organization Type

- **Organizations with highest percent of defaultess 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,to be safer side loan disbursement should be avoided or provide loan with higher interest rate to mitigate the risk of defaulting.**
- **Most of the people application for loan are from Business Entity Type 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**

```
#11 Analyzing Employment_Year based on loan repayment status
univariate(appl_data,"EMPLOYEMENT_YEARS","TARGET",True,False,True)
```

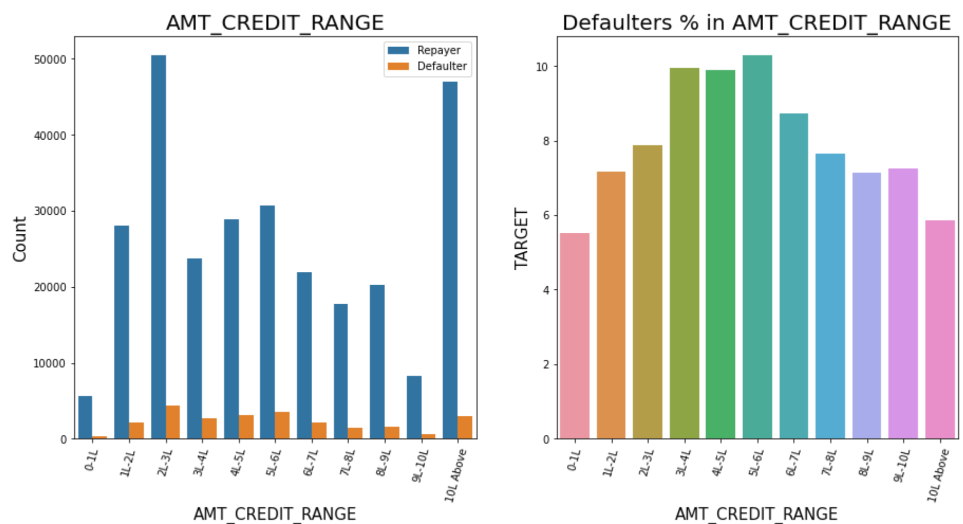


Inferences: Employment in Years

- **Majority of the applicants having working experience between 0-5 years are defaultees. The defaulting rating of this group is also the highest which is around 10%**
- **With increase of employment year, defaulting rate is radually decreasing.**
- **with people having 40+ year experience have less than 1% default rate**

#12 Analyzing Amount_Credit based on loan repayment status

univariate(appl_data,"AMT_CREDIT_RANGE","TARGET",False,True,True)

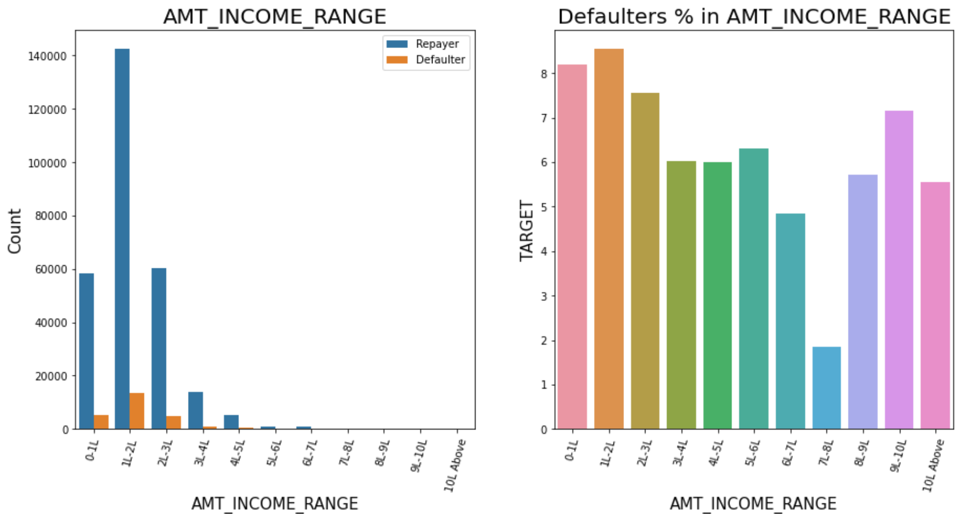


Inferences: Loan Amount

- **there are high number of applicants have loan in range of 2-3 Lakhs followed by 10 Lakh above range**
- **People who get loan for 3-6 Lakhs have most number of defaulters than other loan range.**

#13 Analyzing Amount_Income Range based on loan repayment status

univariate(appl_data,"AMT_INCOME_RANGE","TARGET",False,True,True)

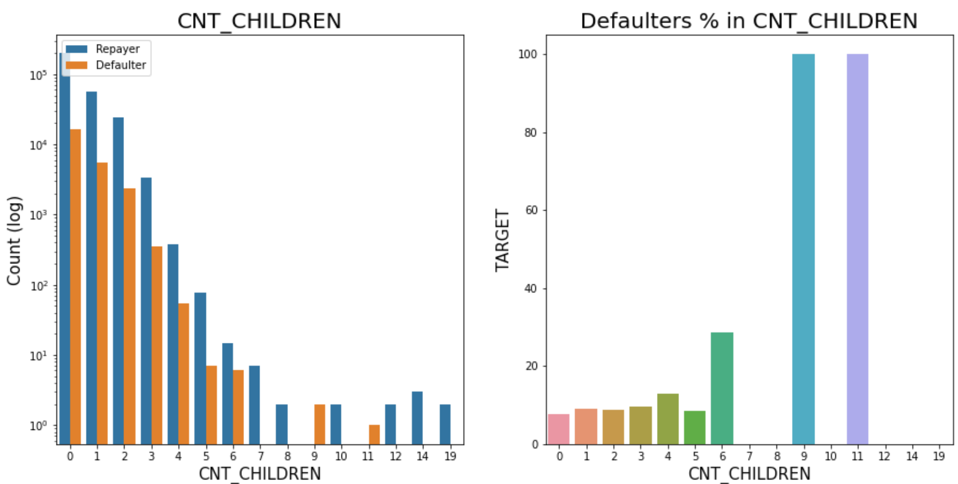


Inferences: Applicant Income

- **Majority of the applications have Income total less than 3 Lakhs.**
- **Application with Income less than 3 Lakhs has high probability of defaulting**
- **Applicant with Income 7-8 Lakhas are less likely to default.**

#14 Analyzing Number of children based on loan repayment status

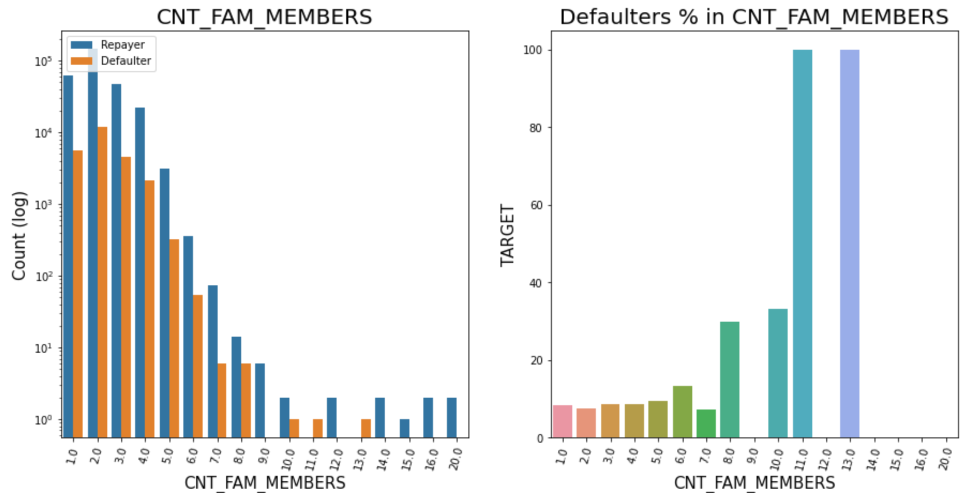
univariate(appl_data,"CNT_CHILDREN","TARGET",True,False,True)



Inferences: Client Children's Count

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

#15 Analyzing Number of family members based on loan repayment status
univariate(appl_data,"CNT_FAM_MEMBERS","TARGET",True,True,True)



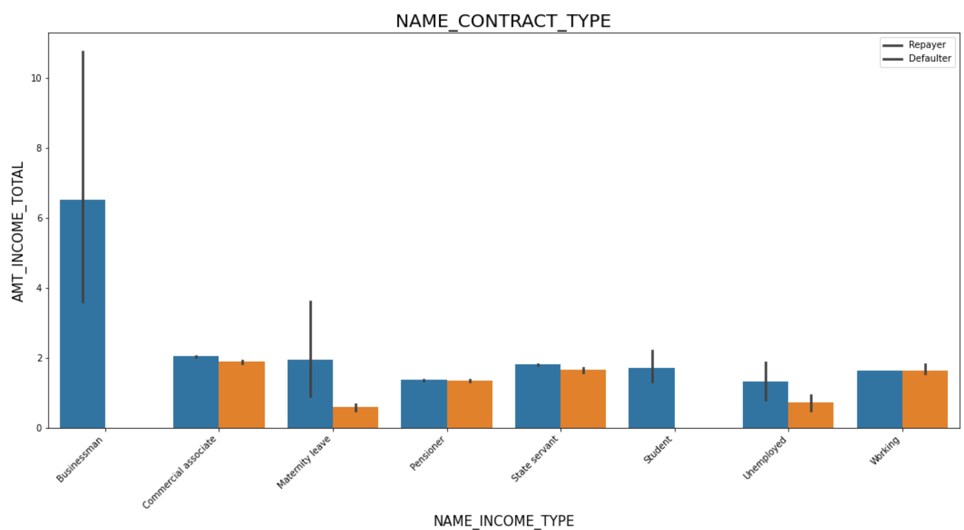
Inferences: Family Memembers Count

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

6.3.2 Categorical Bivariate or Multivariate Analysis

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

```
# Income type vs Income Amount Range on a Seaborn Barplot
bivariate_c("NAME_INCOME_TYPE","AMT_INCOME_TOTAL",appl_data,"TARGET",(18,8),['Repayer','
Defaulter'])
```



Inferences:

- **It can be seen that Businessman income is the highest and the estimated range with default 95% confidence level seem to indicate that the income of a Businessman could be in the range of slightly close to 4 lakhs and slightly above 10 lakhs**

6.3.3 Numeric Variables Analysis

Bisecting the app_data dataframe based on Target value 0 and 1 for correlation and other analysis

```
#Listing all the columnns of dataframe "appl_data"
appl_data.columns
```

Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'FLAG_MOBIL', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3', 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR', 'AMT_INCOME_RANGE', 'AMT_CREDIT_RANGE', 'AMT_GOODS_PRICE_RANGE', 'AGE', 'AGE_GROUP', 'YEARS_EMPLOYED', 'EMPLOYEMENT_YEARS'],
dtype='object')

```
# bisecting the app_data dataframe based on Target value 0 and 1 for correlation and other analysis

cols_for_correlation = ['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_REALTY',
                        'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',
                        'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
                        'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED',
                        'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
                        'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
                        'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
                        'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE',
                        'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_3',
                        'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
                        'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR']


# Repayers dataframe
Repayer_df = appl_data.loc[appl_data['TARGET']==0, cols_for_correlation]
```

```
# Defaulters dataframe
Defaulter_df = appl_data.loc[appl_data['TARGET']==1, cols_for_correlation]
```

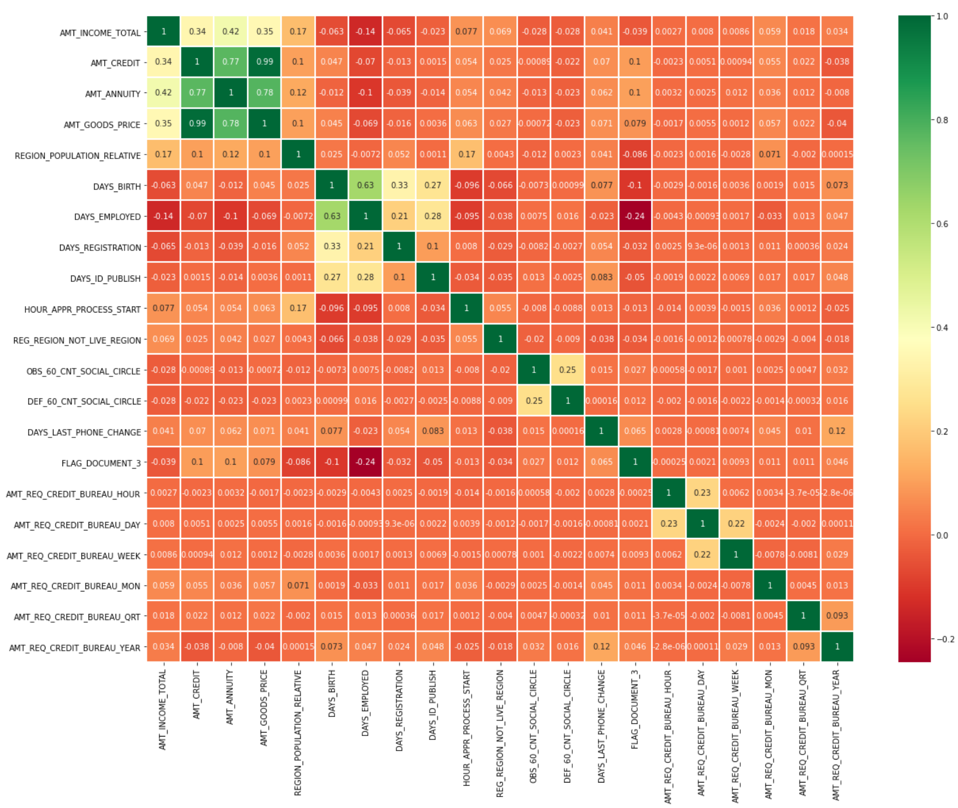
```
len(cols_for_correlation)
```

41

Correlation between numeric variable

```
# Getting  top 10 correlation for the Repayers dataframe

corr_repayer = Repayer_df.corr()
corr_df_repayer =
corr_repayer.where(np.triu(np.ones(corr_repayer.shape),k=1).astype(np.bool)).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)
```

```
#plotting heatmap to see linear correlation amoung Repayers

fig = plt.figure(figsize=(20,15))
ax = sns.heatmap(Repayer_df.corr(), cmap="RdYlGn",annot=True,linewidth =1)
```



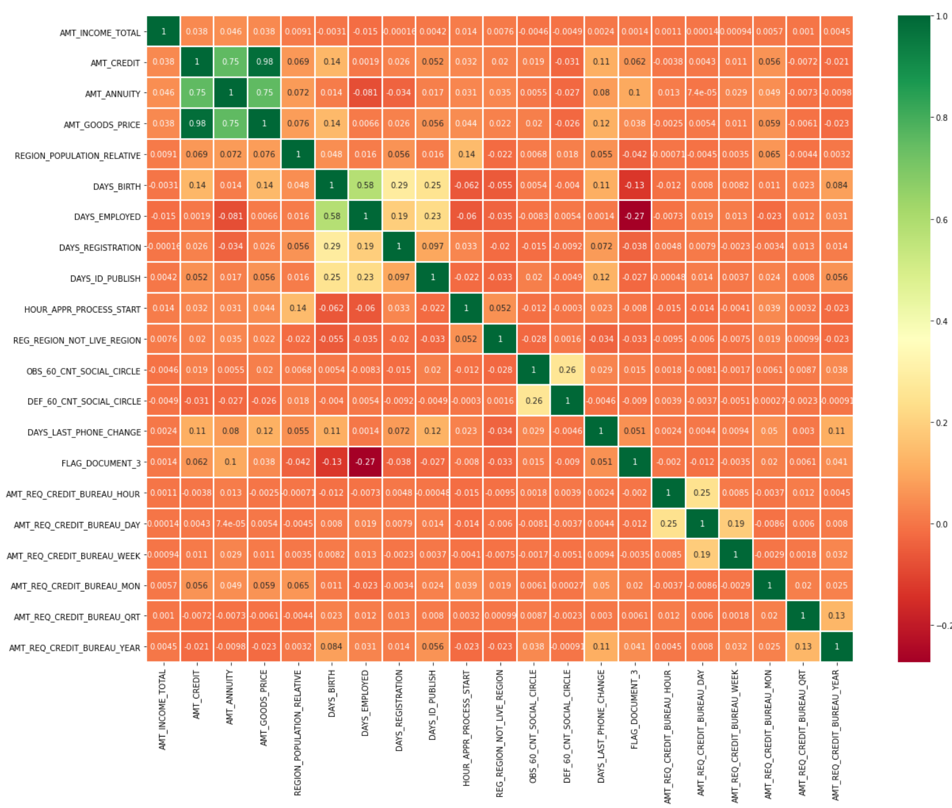
Inferences: Correlating factors amongst repayers

1. Credit amount is highly correlated with:

- **Goods Price Amount**
- **Loan Annuity**
- **Total Income**

2. We can also see that repayers have high correlation in number of days employed.

```
# Getting the top 10 correlation for the Defaulter data
corr_Defaulter = Defaulter_df.corr()
corr_Defaulter = corr_Defaulter.where(np.triu(np.ones(corr_Defaulter.shape),k=1).astype(np.bool))
corr_df_Defaulter = corr_Defaulter.unstack().reset_index()
corr_df_Defaulter.columns =['VAR1','VAR2','Correlation']
corr_df_Defaulter.dropna(subset = ["Correlation"], inplace = True)
corr_df_Defaulter["Correlation"]=corr_df_Defaulter["Correlation"].abs()
corr_df_Defaulter.sort_values(by='Correlation', ascending=False, inplace=True)
corr_df_Defaulter.head(10)

fig = plt.figure(figsize=(20,15))
ax = sns.heatmap(Defaulter_df.corr(), cmap="RdYlGn",annot=True,linewidth =1)
```



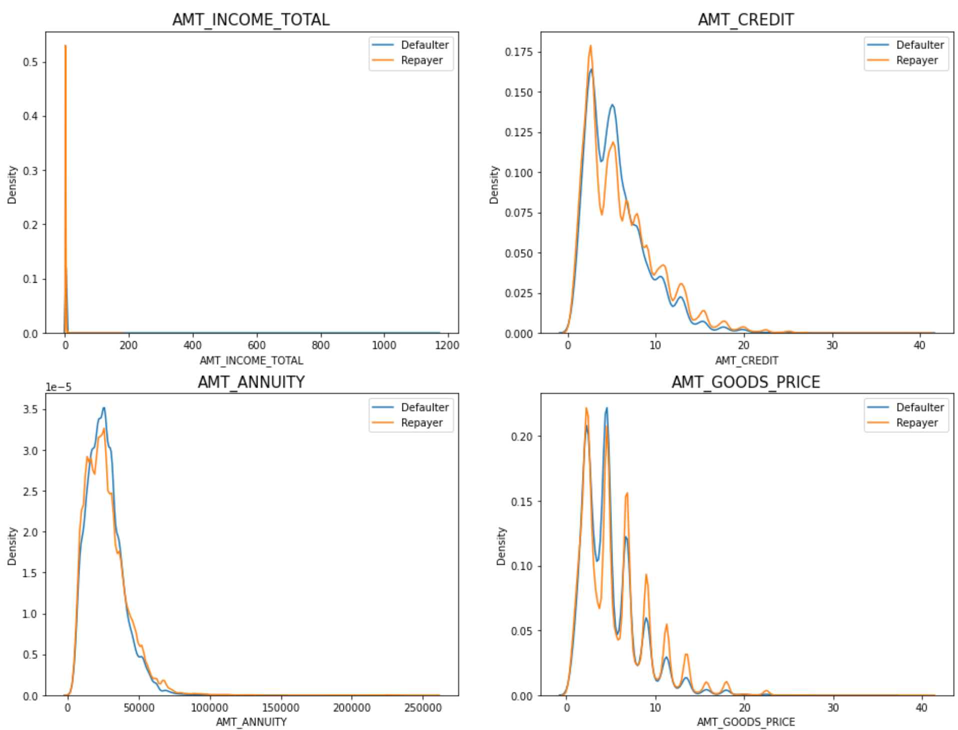
Inferences: Correlating factors amongst repayers

- **Credit amount is highly correlated with good price amount which is same as repayers.**
- **Loan annuity correlation with credit amount has slightly reduced in defaulters(0.75) when compared to repayers(0.77)**
- **We can also see that repayers have high correlation in number of days employed(0.62) when compared to defaulters(0.58).**
- **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.**

- **Days_birth and number of children correlation has reduced to 0.259 in defaulters when compared to 0.337 in repayers.**
- **There is a slight increase in defaulted to observed count in social circle among defaulters(0.264) when compared to repayers(0.254)**

6.3.4 Numerical Univariate Analysis

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

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

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


plt.show()
```



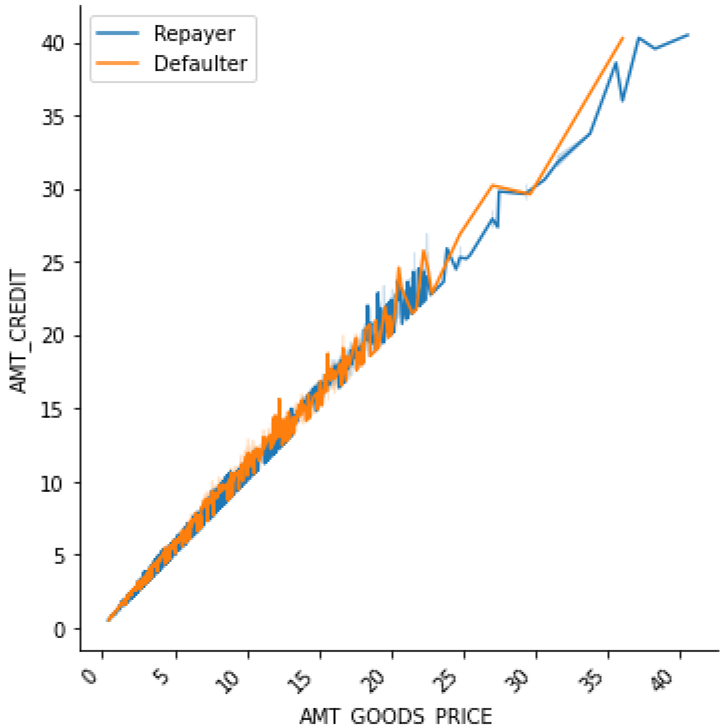
Inferences:

- **Most no of loans are given for goods price below 10 lakhs**
- **Most people pay annuity below 50K for the credit loan**
- **Credit amount of the loan is mostly less then 10 lakhs**
- **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**

6.3.5 Numerical Bivariate Analysis

```
# Checking the relationship between Goods price and credit and comparing with loan repayment staus
bivariate_n('AMT_GOODS_PRICE','AMT_CREDIT',appl_data,"TARGET", "line",['Repayer','Defaulter'])
```

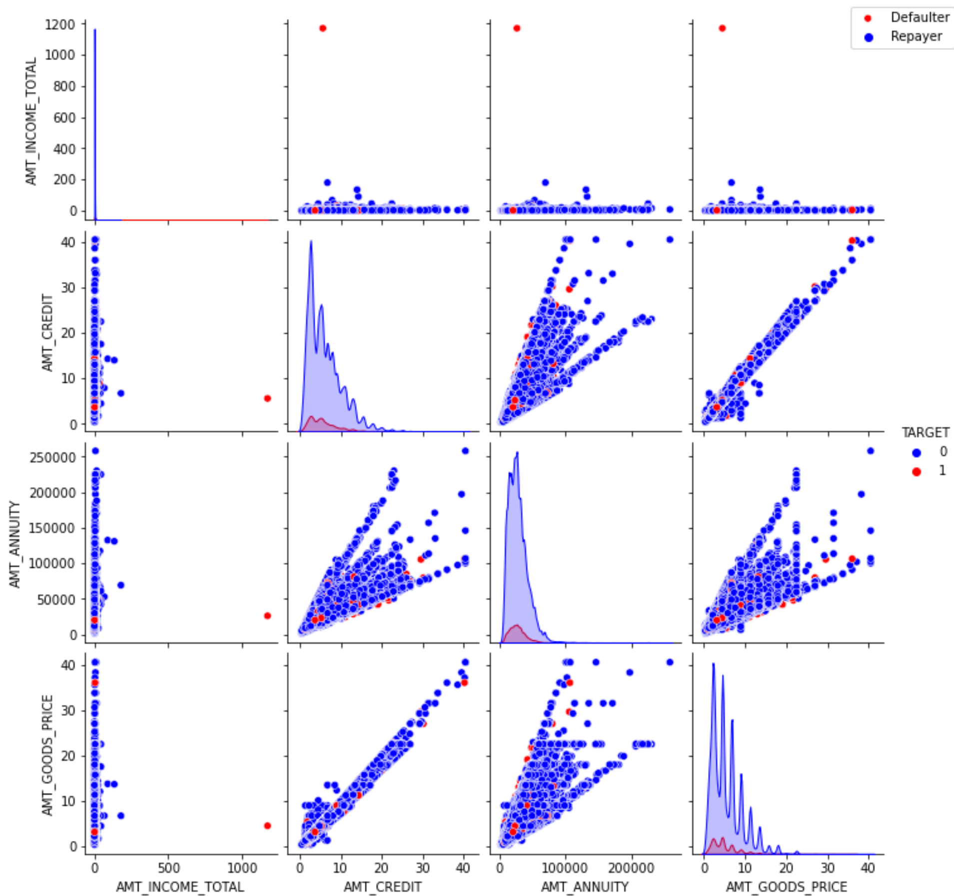
<Figure size 1080x1080 with 0 Axes>



Inferences:

- **When the credit amount goes beyond 30 Lakhs, there is an increase in defaulters.**

```
# Plotting pairplot between amount variable to draw reference against loan repayment status

amount = appl_data[[ 'AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY', 'AMT_GOODS_PRICE','TARGET']]
amount = amount[(amount["AMT_GOODS_PRICE"].notnull()) & (amount["AMT_ANNUITY"].notnull())]

ax= sns.pairplot(amount,hue="TARGET",palette=["b","r"])
ax.fig.legend(labels=['Defaulter','Repayer'])
plt.show()
```



Inferences:

- **When Annuity Amount > 15K and Good Price Amount > 20 Lakhs, there is a lesser chance of defaulters**
- **Loan Amount(AMT_CREDIT) and Goods price(AMT_GOODS_PRICE) are highly correlated as based on the scatterplot where most of the data are consolidated in form of a line**
- **There are very less defaulters for AMT_CREDIT >20 Lakhs**

7. Merged Dataframes Analysis

```
# merge both the dataframe on SK_ID_CURR with Inner Joins
loan_df = pd.merge(appl_data, prev_appl, how='inner', on='SK_ID_CURR')
loan_df.head()
```

```
#Checking the details of the merged dataframe
loan_df.shape
```

(1413701, 82)

```
# checking the columns and column types of the dataframe
loan_df.info()
```

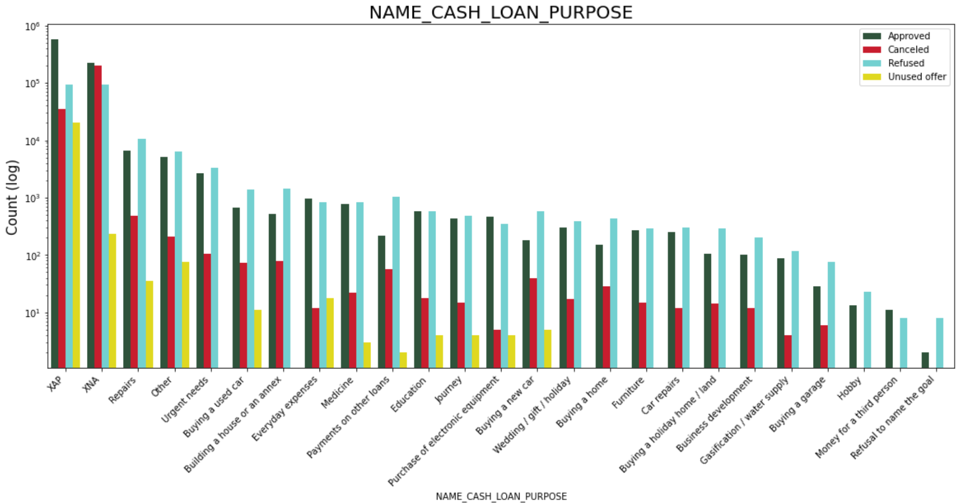
<class 'pandas.core.frame.DataFrame'> Int64Index: 1413701 entries, 0 to 1413700 Data columns (total 82 columns): # Column Non-Null Count Dtype --- ------ -------------- ----- 0 SK_ID_CURR 1413701 non-null int64 1 TARGET 1413701 non-null int64 2 NAME_CONTRACT_TYPE_x 1413701 non-null category 3 CODE_GENDER 1413701 non-null category 4 FLAG_OWN_REALTY 1413701 non-null category 5

CNT_CHILDREN 1413701 non-null category 6 AMT_INCOME_TOTAL 1413701 non-null float64 7 AMT_CREDIT_x 1413701 non-null float64 8 AMT_ANNUITY_x 1413608 non-null float64 9 AMT_GOODS_PRICE_x 1412493 non-null float64 10 NAME_TYPE_SUITE_x 1410175 non-null category 11 NAME_INCOME_TYPE 1413701 non-null category 12 NAME_EDUCATION_TYPE 1413701 non-null category 13 NAME_FAMILY_STATUS 1413701 non-null category 14 NAME_HOUSING_TYPE 1413701 non-null category 15 REGION_POPULATION_RELATIVE 1413701 non-null float64 16 DAYS_BIRTH 1413701 non-null float64 17 DAYS_EMPLOYED 1413701 non-null float64 18 DAYS_REGISTRATION 1413701 non-null float64 19 DAYS_ID_PUBLISH 1413701 non-null float64 20 FLAG_MOBIL 1413701 non-null int64 21 OCCUPATION_TYPE 1413701 non-null category 22 CNT_FAM_MEMBERS 1413701 non-null category 23 REGION_RATING_CLIENT 1413701 non-null category 24 REGION_RATING_CLIENT_W_CITY 1413701 non-null category 25 WEEKDAY_APPR_PROCESS_START 1413701 non-null category 26 HOUR_APPR_PROCESS_START 1413701 non-null int64 27 REG_REGION_NOT_LIVE_REGION 1413701 non-null int64 28 REG_REGION_NOT_WORK_REGION 1413701 non-null category 29 LIVE_REGION_NOT_WORK_REGION 1413701 non-null category 30 REG_CITY_NOT_LIVE_CITY 1413701 non-null category 31 REG_CITY_NOT_WORK_CITY 1413701 non-null category 32 LIVE_CITY_NOT_WORK_CITY 1413701 non-null category 33 ORGANIZATION_TYPE 1413701 non-null category 34 OBS_30_CNT_SOCIAL_CIRCLE 1410555 non-null float64 35 DEF_30_CNT_SOCIAL_CIRCLE 1410555 non-null float64 36 OBS_60_CNT_SOCIAL_CIRCLE 1410555 non-null float64 37 DEF_60_CNT_SOCIAL_CIRCLE 1410555 non-null float64 38 DAYS_LAST_PHONE_CHANGE 1413701 non-null float64 39 FLAG_DOCUMENT_3 1413701 non-null int64 40 AMT_REQ_CREDIT_BUREAU_HOUR 1413701 non-null float64 41 AMT_REQ_CREDIT_BUREAU_DAY 1413701 non-null float64 42 AMT_REQ_CREDIT_BUREAU_WEEK 1413701 non-null float64 43 AMT_REQ_CREDIT_BUREAU_MON 1413701 non-null float64 44 AMT_REQ_CREDIT_BUREAU_QRT 1413701 non-null float64 45 AMT_REQ_CREDIT_BUREAU_YEAR 1413701 non-null float64 46 AMT_INCOME_RANGE 1413024 non-null category 47 AMT_CREDIT_RANGE 1413701 non-null category 48 AMT_GOODS_PRICE_RANGE 1412493 non-null category 49 AGE 1413701 non-null float64 50 AGE_GROUP 1413701 non-null category 51 YEARS_EMPLOYED 1413701 non-null float64 52 EMPLOYEMENT_YEARS 1140109 non-null category 53 SK_ID_PREV 1413701 non-null int64 54 NAME_CONTRACT_TYPE_y 1413701 non-null category 55 AMT_ANNUITY_y 1413701 non-null float64 56 AMT_APPLICATION 1413701 non-null float64 57 AMT_CREDIT_y 1413700 non-null float64 58 AMT_GOODS_PRICE_y 1413701 non-null float64 59 NAME_CASH_LOAN_PURPOSE 1413701 non-null category 60 NAME_CONTRACT_STATUS 1413701 non-null category 61 DAYS_DECISION 1413701 non-null float64 62 NAME_PAYMENT_TYPE 1413701 non-null category 63 CODE_REJECT_REASON 1413701 non-null category 64 NAME_TYPE_SUITE_y 1413701 non-null object 65 NAME_CLIENT_TYPE 1413701 non-null category 66 NAME_GOODS_CATEGORY 1413701 non-null category 67 NAME_PORTFOLIO 1413701 non-null category 68 NAME_PRODUCT_TYPE 1413701 non-null category 69 CHANNEL_TYPE 1413701 non-null category 70 SELLERPLACE_AREA 1413701 non-null int64 71 NAME_SELLER_INDUSTRY 1413701 non-null category 72 CNT_PAYMENT 1413701 non-null float64 73 NAME_YIELD_GROUP 1413701 non-null category 74 PRODUCT_COMBINATION 1413388 non-null category 75 DAYS_FIRST_DRAWING 852595 non-null float64 76 DAYS_FIRST_DUE 852595 non-null float64 77 DAYS_LAST_DUE_1ST_VERSION 852595 non-null float64 78 DAYS_LAST_DUE 852595 non-null float64 79 DAYS_TERMINATION 852595 non-null float64 80 NFLAG_INSURED_ON_APPROVAL 852595 non-null float64 81 YEARLY_DECISION 1413701 non-null category dtypes: category(39), float64(34), int64(8), object(1) memory usage: 527.2+ MB

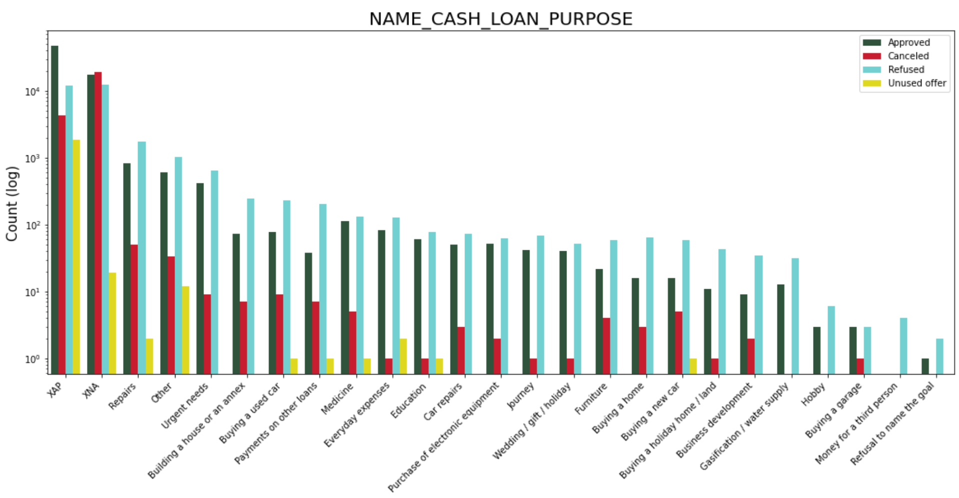
```
# Bisecting the "loan_df" dataframe based on Target value 0 and 1 for correlation and other analysis

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

Plotting Contract Status vs purpose of the loan

univariate_c_merged("NAME_CASH_LOAN_PURPOSE",L0,"NAME_CONTRACT_STATUS",["#295939", "#e40017","#64dfdf","#fff600"],True,(18,7))



univariate_c_merged("NAME_CASH_LOAN_PURPOSE",L1,"NAME_CONTRACT_STATUS",["#295939", "#e40017","#64dfdf","#fff600"],True,(18,7))



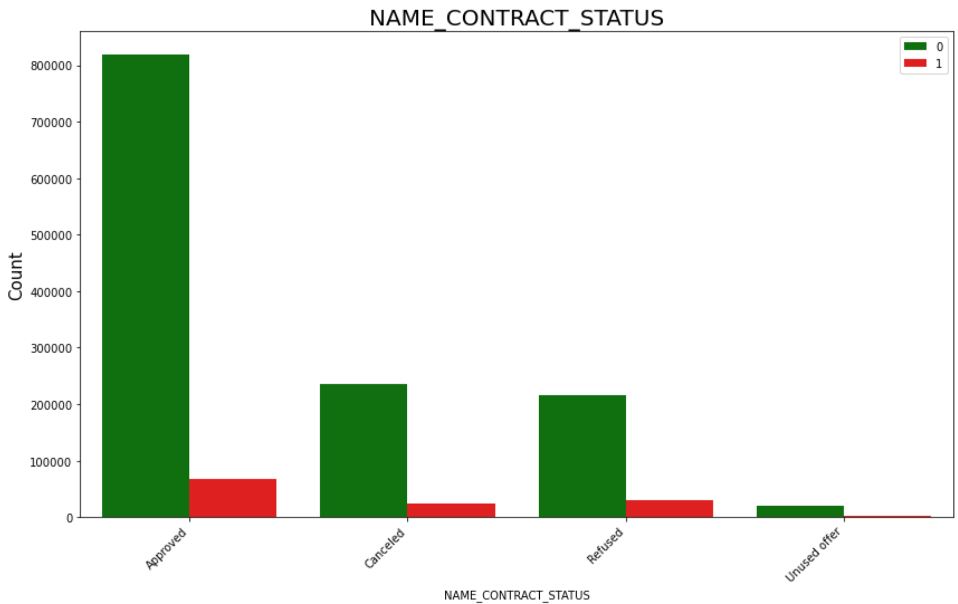
Inferences:

- **Loan purpose has high number of unknown values (XAP, XNA)**
- **Loan taken for the purpose of Repairs looks to have highest default rate**
- **Huge number application have been rejected by bank or refused by client which are applied for Repair or Other. from this we can infer that repair is considered high risk by bank. Also, either they are rejected or bank offers loan on high interest rate which is not feasible by the clients and they refuse the loan.**

 # Checking Contract Status based on loan repayment status whether there is any business loss or financial loss

univariate_c_merged("NAME_CONTRACT_STATUS",loan_df,"TARGET",['g','r'],False,(14,8))

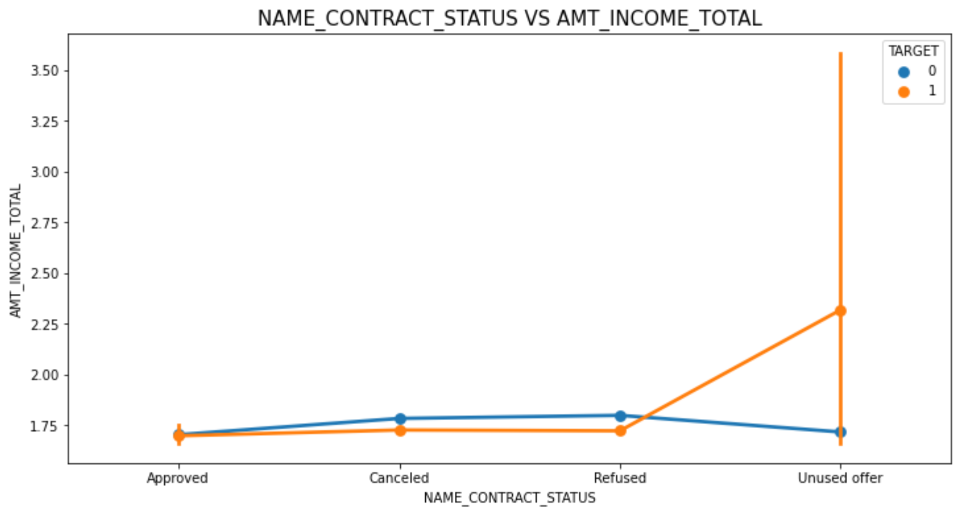
```
r = loan_df.groupby("NAME_CONTRACT_STATUS")["TARGET"]
df1 = pd.concat([r.value_counts(),round(r.value_counts(normalize=True).mul(100),2)],axis=1,
keys=('Counts','Percentage'))
df1['Percentage'] = df1['Percentage'].astype(str) +"%" # adding percentage symbol in the results for
understanding
df1
```



Inferences:

- **90% of the previously cancelled client have actually repayed the loan. Revising the interest rates would increase business opportunity for these clients**
- **88% of the clients who have been previously refused a loan has payed back the loan in current case.**
- **Refusal reason should be recorded for further analysis as these clients could turn into potential repaying customer.**

```
# plotting the relationship between income total and contact status

pointplot(loan_df,"TARGET","NAME_CONTRACT_STATUS",'AMT_INCOME_TOTAL')
```

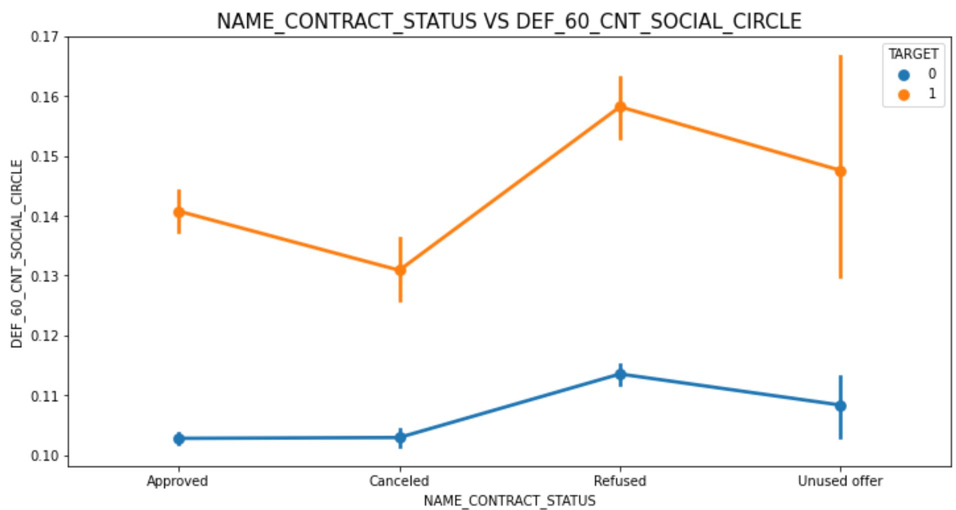


Inferences:

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

 # plotting the relationship between people who defaulted in last 60 days being in client's social circle and contact status

pointplot(loan_df,"TARGET","NAME_CONTRACT_STATUS",'DEF_60_CNT_SOCIAL_CIRCLE')



Inferences:

- **Clients who have average of 0.13 or higher their DEF_60_CNT_SOCIAL_CIRCLE score tend to default more and thus analysing client's social circle could help in disbursment of the loan.**