In [2]:
```
#1) Importing Libraries

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

In [3]:
```
import warnings
warnings.filterwarnings(action='ignore')
```

In [4]:
```
#View setting
pd.set_option('display.max_rows', 1000)
```

In [54]:
```
#2) Importing data sets
appln_data= pd.read_csv('application_data.csv') # application data
pre_appln_data= pd.read_csv('previous_application.csv') # Previous application data
```

In [6]:
```
appln_data.head()
```

Out[6]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 122 columns

In [7]:
```
appln_data.shape
```

Out[7]: (47151, 122)

In [8]:
```
appln_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47151 entries, 0 to 47150
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(63), int64(43), object(16)
memory usage: 43.9+ MB
```

In [9]:
```
appln_data.describe()
```

Out[9]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AM
count	47151.000000	47151.000000	47151.000000	4.715100e+04	4.715100e+04	47151.000000	
mean	428179.370427	0.078959	0.417404	1.686382e+05	6.005510e+05	27114.000954	
std	19705.926674	0.269678	0.722962	1.001564e+05	4.046380e+05	14509.205143	
min	100002.000000	0.000000	0.000000	2.655000e+04	4.500000e+04	1615.500000	
25%	415500.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16551.000000	
50%	428826.000000	0.000000	0.000000	1.485000e+05	5.179275e+05	24930.000000	
75%	442611.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34573.500000	
max	456255.000000	1.000000	19.000000	4.500000e+06	4.050000e+06	225000.000000	

8 rows × 106 columns

In [10]:
```
appln_data.isna().sum()
```

Out[10]:

```
SK_ID_CURR                         0
TARGET                             0
NAME_CONTRACT_TYPE                 0
CODE_GENDER                        0
FLAG_OWN_CAR                       0
FLAG_OWN_REALTY                    0
CNT_CHILDREN                       0
AMT_INCOME_TOTAL                   0
AMT_CREDIT                         0
AMT_ANNUITY                        0
AMT_GOODS_PRICE                    0
NAME_TYPE_SUITE                    0
NAME_INCOME_TYPE                   0
NAME_EDUCATION_TYPE                0
NAME_FAMILY_STATUS                 0
NAME_HOUSING_TYPE                  0
REGION_POPULATION_RELATIVE         0
DAYS_BIRTH                         0
DAYS_EMPLOYED                      0
DAYS_REGISTRATION                  0
DAYS_ID_PUBLISH                    0
OWN_CAR_AGE                     3678
FLAG_MOBIL                         0
FLAG_EMP_PHONE                     0
FLAG_WORK_PHONE                    0
FLAG_CONT_MOBILE                   0
FLAG_PHONE                         0
FLAG_EMAIL                         0
OCCUPATION_TYPE                  148
CNT_FAM_MEMBERS                    0
REGION_RATING_CLIENT               0
REGION_RATING_CLIENT_W_CITY        0
WEEKDAY_APPR_PROCESS_START         0
HOUR_APPR_PROCESS_START            0
REG_REGION_NOT_LIVE_REGION         0
REG_REGION_NOT_WORK_REGION         0
LIVE_REGION_NOT_WORK_REGION        0
REG_CITY_NOT_LIVE_CITY             0
REG_CITY_NOT_WORK_CITY             0
LIVE_CITY_NOT_WORK_CITY            0
ORGANIZATION_TYPE                  0
EXT_SOURCE_1                    1525
EXT_SOURCE_2                       0
EXT_SOURCE_3                      30
APARTMENTS_AVG                   894
BASEMENTAREA_AVG                1854
YEARS_BEGINEXPLUATATION_AVG      747
YEARS_BUILD_AVG                 3800
COMMONAREA_AVG                  5051
ELEVATORS_AVG                   1117
ENTRANCES_AVG                    871
FLOORSMAX_AVG                    824
FLOORSMIN_AVG                   4273
LANDAREA_AVG                    2006
LIVINGAPARTMENTS_AVG            4429
LIVINGAREA_AVG                   823
NONLIVINGAPARTMENTS_AVG         4866
NONLIVINGAREA_AVG               1359
APARTMENTS_MODE                  894
```

```
BASEMENTAREA_MODE                1854
YEARS_BEGINEXPLUATATION_MODE      747
YEARS_BUILD_MODE                 3800
COMMONAREA_MODE                  5051
ELEVATORS_MODE                   1117
ENTRANCES_MODE                    871
FLOORSMAX_MODE                    824
FLOORSMIN_MODE                   4273
LANDAREA_MODE                    2006
LIVINGAPARTMENTS_MODE            4429
LIVINGAREA_MODE                   823
NONLIVINGAPARTMENTS_MODE         4866
NONLIVINGAREA_MODE               1359
APARTMENTS_MEDI                   894
BASEMENTAREA_MEDI                1854
YEARS_BEGINEXPLUATATION_MEDI      747
YEARS_BUILD_MEDI                 3800
COMMONAREA_MEDI                  5051
ELEVATORS_MEDI                   1117
ENTRANCES_MEDI                    871
FLOORSMAX_MEDI                    824
FLOORSMIN_MEDI                   4273
LANDAREA_MEDI                    2006
LIVINGAPARTMENTS_MEDI            4429
LIVINGAREA_MEDI                   823
NONLIVINGAPARTMENTS_MEDI         4866
NONLIVINGAREA_MEDI               1359
FONDKAPREMONT_MODE               4446
HOUSETYPE_MODE                    837
TOTALAREA_MODE                    701
WALLSMATERIAL_MODE                896
EMERGENCYSTATE_MODE               643
OBS_30_CNT_SOCIAL_CIRCLE            2
DEF_30_CNT_SOCIAL_CIRCLE            2
OBS_60_CNT_SOCIAL_CIRCLE            2
DEF_60_CNT_SOCIAL_CIRCLE            2
DAYS_LAST_PHONE_CHANGE              0
FLAG_DOCUMENT_2                     0
FLAG_DOCUMENT_3                     0
FLAG_DOCUMENT_4                     0
FLAG_DOCUMENT_5                     0
FLAG_DOCUMENT_6                     0
FLAG_DOCUMENT_7                     0
FLAG_DOCUMENT_8                     0
FLAG_DOCUMENT_9                     0
FLAG_DOCUMENT_10                    0
FLAG_DOCUMENT_11                    0
FLAG_DOCUMENT_12                    0
FLAG_DOCUMENT_13                    0
FLAG_DOCUMENT_14                    0
FLAG_DOCUMENT_15                    0
FLAG_DOCUMENT_16                    0
FLAG_DOCUMENT_17                    0
FLAG_DOCUMENT_18                    0
FLAG_DOCUMENT_19                    0
FLAG_DOCUMENT_20                    0
FLAG_DOCUMENT_21                    0
AMT_REQ_CREDIT_BUREAU_HOUR         18
AMT_REQ_CREDIT_BUREAU_DAY          18
```

```
AMT_REQ_CREDIT_BUREAU_WEEK        18
AMT_REQ_CREDIT_BUREAU_MON         18
AMT_REQ_CREDIT_BUREAU_QRT         18
AMT_REQ_CREDIT_BUREAU_YEAR        18
dtype: int64
```

In [56]:
```
appln_data.isna().mean().sort_values(ascending=False)*100
```

Out[56]:
```
COMMONAREA_MEDI                 10.712392
COMMONAREA_AVG                  10.712392
COMMONAREA_MODE                 10.712392
NONLIVINGAPARTMENTS_MODE        10.320036
NONLIVINGAPARTMENTS_MEDI        10.320036
NONLIVINGAPARTMENTS_AVG         10.320036
FONDKAPREMONT_MODE               9.429280
LIVINGAPARTMENTS_MEDI            9.393226
LIVINGAPARTMENTS_MODE            9.393226
LIVINGAPARTMENTS_AVG             9.393226
FLOORSMIN_MEDI                   9.062374
FLOORSMIN_MODE                   9.062374
FLOORSMIN_AVG                    9.062374
YEARS_BUILD_MEDI                 8.059214
YEARS_BUILD_AVG                  8.059214
YEARS_BUILD_MODE                 8.059214
OWN_CAR_AGE                      7.800471
LANDAREA_MODE                    4.254417
LANDAREA_AVG                     4.254417
LANDAREA_MEDI                    4.254417
BASEMENTAREA_MEDI                3.932048
BASEMENTAREA_AVG                 3.932048
BASEMENTAREA_MODE                3.932048
EXT_SOURCE_1                     3.234290
NONLIVINGAREA_MEDI               2.882229
NONLIVINGAREA_AVG                2.882229
NONLIVINGAREA_MODE               2.882229
ELEVATORS_MODE                   2.368985
ELEVATORS_AVG                    2.368985
ELEVATORS_MEDI                   2.368985
WALLSMATERIAL_MODE               1.900278
APARTMENTS_MODE                  1.896036
APARTMENTS_AVG                   1.896036
APARTMENTS_MEDI                  1.896036
ENTRANCES_MEDI                   1.847257
ENTRANCES_MODE                   1.847257
ENTRANCES_AVG                    1.847257
HOUSETYPE_MODE                   1.775148
FLOORSMAX_MODE                   1.747577
FLOORSMAX_MEDI                   1.747577
FLOORSMAX_AVG                    1.747577
LIVINGAREA_MEDI                  1.745456
LIVINGAREA_MODE                  1.745456
LIVINGAREA_AVG                   1.745456
YEARS_BEGINEXPLUATATION_MEDI     1.584272
YEARS_BEGINEXPLUATATION_AVG      1.584272
YEARS_BEGINEXPLUATATION_MODE     1.584272
TOTALAREA_MODE                   1.486713
EMERGENCYSTATE_MODE              1.363704
OCCUPATION_TYPE                  0.313885
EXT_SOURCE_3                     0.063625
AMT_REQ_CREDIT_BUREAU_QRT        0.038175
AMT_REQ_CREDIT_BUREAU_YEAR       0.038175
AMT_REQ_CREDIT_BUREAU_DAY        0.038175
AMT_REQ_CREDIT_BUREAU_WEEK       0.038175
AMT_REQ_CREDIT_BUREAU_MON        0.038175
AMT_REQ_CREDIT_BUREAU_HOUR       0.038175
OBS_30_CNT_SOCIAL_CIRCLE         0.004242
OBS_60_CNT_SOCIAL_CIRCLE         0.004242
```

```
DEF_60_CNT_SOCIAL_CIRCLE        0.004242
DEF_30_CNT_SOCIAL_CIRCLE        0.004242
DAYS_REGISTRATION               0.000000
DAYS_ID_PUBLISH                 0.000000
FLAG_MOBIL                      0.000000
FLAG_CONT_MOBILE                0.000000
FLAG_EMP_PHONE                  0.000000
FLAG_WORK_PHONE                 0.000000
DAYS_BIRTH                      0.000000
FLAG_PHONE                      0.000000
FLAG_EMAIL                      0.000000
CNT_FAM_MEMBERS                 0.000000
DAYS_EMPLOYED                   0.000000
NAME_HOUSING_TYPE               0.000000
REGION_POPULATION_RELATIVE      0.000000
AMT_INCOME_TOTAL                0.000000
TARGET                          0.000000
NAME_CONTRACT_TYPE              0.000000
CODE_GENDER                     0.000000
FLAG_OWN_CAR                    0.000000
FLAG_OWN_REALTY                 0.000000
CNT_CHILDREN                    0.000000
AMT_CREDIT                      0.000000
REGION_RATING_CLIENT_W_CITY     0.000000
AMT_ANNUITY                     0.000000
AMT_GOODS_PRICE                 0.000000
NAME_TYPE_SUITE                 0.000000
NAME_INCOME_TYPE                0.000000
NAME_EDUCATION_TYPE             0.000000
NAME_FAMILY_STATUS              0.000000
REGION_RATING_CLIENT            0.000000
REG_REGION_NOT_LIVE_REGION      0.000000
WEEKDAY_APPR_PROCESS_START      0.000000
FLAG_DOCUMENT_14                0.000000
DAYS_LAST_PHONE_CHANGE          0.000000
FLAG_DOCUMENT_2                 0.000000
FLAG_DOCUMENT_3                 0.000000
FLAG_DOCUMENT_4                 0.000000
FLAG_DOCUMENT_5                 0.000000
FLAG_DOCUMENT_6                 0.000000
FLAG_DOCUMENT_7                 0.000000
FLAG_DOCUMENT_8                 0.000000
FLAG_DOCUMENT_9                 0.000000
FLAG_DOCUMENT_10                0.000000
FLAG_DOCUMENT_11                0.000000
FLAG_DOCUMENT_12                0.000000
FLAG_DOCUMENT_13                0.000000
FLAG_DOCUMENT_15                0.000000
HOUR_APPR_PROCESS_START         0.000000
FLAG_DOCUMENT_16                0.000000
FLAG_DOCUMENT_17                0.000000
FLAG_DOCUMENT_18                0.000000
FLAG_DOCUMENT_19                0.000000
FLAG_DOCUMENT_20                0.000000
FLAG_DOCUMENT_21                0.000000
EXT_SOURCE_2                    0.000000
ORGANIZATION_TYPE               0.000000
LIVE_CITY_NOT_WORK_CITY         0.000000
REG_CITY_NOT_WORK_CITY          0.000000
```

```
REG_CITY_NOT_LIVE_CITY         0.000000
LIVE_REGION_NOT_WORK_REGION    0.000000
REG_REGION_NOT_WORK_REGION     0.000000
SK_ID_CURR                     0.000000
dtype: float64
```

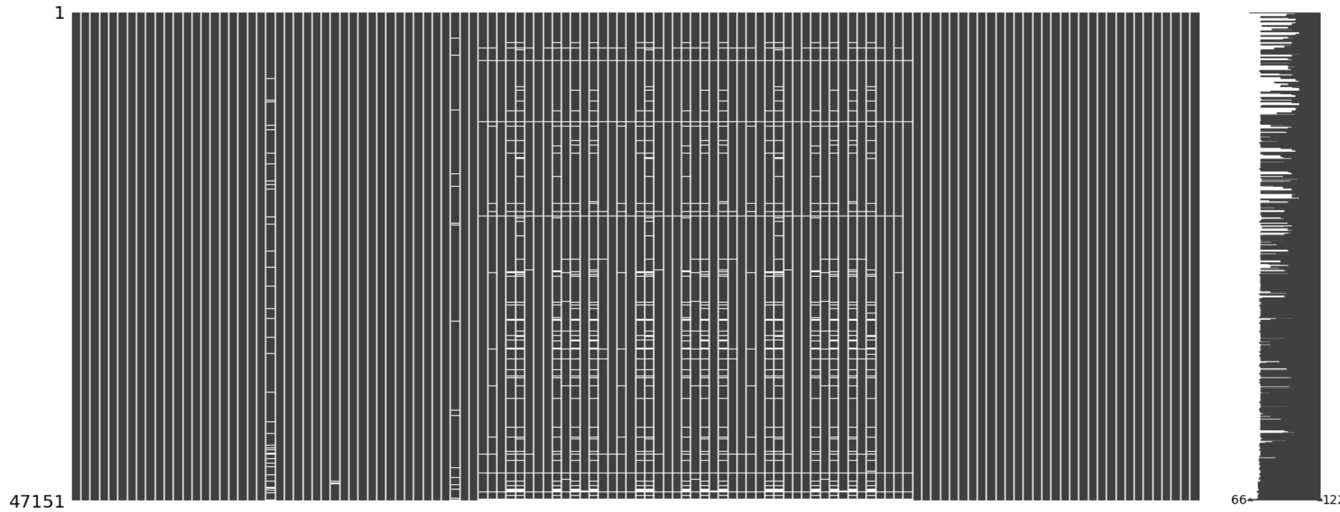
In [34]:
```
pip install missingno
```

```
Collecting missingno
  Downloading https://files.pythonhosted.org/packages/17/a2/be45b3bd2fe14cf9173f2337ab8
7a0f877d6847cf097e641eab4811a8b02/missingno-0.5.1-py3-none-any.whl
Requirement already satisfied: numpy in c:\users\parashu\anaconda3\lib\site-packages (f
rom missingno) (1.16.5)
Requirement already satisfied: matplotlib in c:\users\parashu\anaconda3\lib\site-packag
es (from missingno) (3.1.1)
Requirement already satisfied: scipy in c:\users\parashu\anaconda3\lib\site-packages (f
rom missingno) (1.3.1)
Requirement already satisfied: seaborn in c:\users\parashu\anaconda3\lib\site-packages
(from missingno) (0.9.0)
Requirement already satisfied: cycler>=0.10 in c:\users\parashu\anaconda3\lib\site-pack
ages (from matplotlib->missingno) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\parashu\anaconda3\lib\site
-packages (from matplotlib->missingno) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\par
ashu\anaconda3\lib\site-packages (from matplotlib->missingno) (2.4.2)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\parashu\anaconda3\lib\s
ite-packages (from matplotlib->missingno) (2.8.0)
Requirement already satisfied: pandas>=0.15.2 in c:\users\parashu\anaconda3\lib\site-pa
ckages (from seaborn->missingno) (0.25.1)
Requirement already satisfied: six in c:\users\parashu\anaconda3\lib\site-packages (fro
m cycler>=0.10->matplotlib->missingno) (1.12.0)
Requirement already satisfied: setuptools in c:\users\parashu\anaconda3\lib\site-packag
es (from kiwisolver>=1.0.1->matplotlib->missingno) (41.4.0)
Requirement already satisfied: pytz>=2017.2 in c:\users\parashu\anaconda3\lib\site-pack
ages (from pandas>=0.15.2->seaborn->missingno) (2019.3)
Installing collected packages: missingno
Successfully installed missingno-0.5.1
Note: you may need to restart the kernel to use updated packages.
```

In [11]:
```
import missingno as mn
```

In [12]:
```python
mn.matrix(appln_data)
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x248efe34e08>



In [13]:
```python
appln_data.groupby('OCCUPATION_TYPE').OCCUPATION_TYPE.count().sort_values(ascending=False)
```

Out[13]:
```
OCCUPATION_TYPE
Laborers                 12233
Sales staff               7256
Core staff                6104
Managers                  4706
Drivers                   4107
High skill tech staff     2591
Accountants               2184
Medicine staff            1895
Security staff            1473
Cooking staff             1307
Cleaning staff            1063
Private service staff      593
Low-skill Laborers         465
Waiters/barmen staff       305
Secretaries                287
Realty agents              172
HR staff                   141
IT staff                   121
Name: OCCUPATION_TYPE, dtype: int64
```

In [57]:
```python
appln_data['OCCUPATION_TYPE'].mode()[0]
appln_data['OCCUPATION_TYPE']=appln_data['OCCUPATION_TYPE'].fillna(appln_data['OCCUPATION_TYPE'].mode()[0])
```

In [58]:

```
# Continous columns: replacing with Median
for i in ['EXT_SOURCE_1', 'EXT_SOURCE_3', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR']:
    appln_data[i]=appln_data[i].fillna(appln_data[i].median())

# Creating the 'TARGET_PERCENT' Column. Multiplying 'TARGET' column by 100.
appln_data['TARGET_PERCENT']=appln_data['TARGET'].apply(lambda x:100 if x==1 else 0)
aappln_data1=appln_data.copy()
```

In [16]:
```
appln_data.isna().mean().sort_values(ascending=False)*100
```

Out[16]:

```
COMMONAREA_AVG                  10.712392
COMMONAREA_MODE                 10.712392
COMMONAREA_MEDI                 10.712392
NONLIVINGAPARTMENTS_AVG         10.320036
NONLIVINGAPARTMENTS_MODE        10.320036
NONLIVINGAPARTMENTS_MEDI        10.320036
FONDKAPREMONT_MODE               9.429280
LIVINGAPARTMENTS_AVG             9.393226
LIVINGAPARTMENTS_MODE            9.393226
LIVINGAPARTMENTS_MEDI            9.393226
FLOORSMIN_MEDI                   9.062374
FLOORSMIN_AVG                    9.062374
FLOORSMIN_MODE                   9.062374
YEARS_BUILD_AVG                  8.059214
YEARS_BUILD_MEDI                 8.059214
YEARS_BUILD_MODE                 8.059214
OWN_CAR_AGE                      7.800471
LANDAREA_MODE                    4.254417
LANDAREA_MEDI                    4.254417
LANDAREA_AVG                     4.254417
BASEMENTAREA_MODE                3.932048
BASEMENTAREA_MEDI                3.932048
BASEMENTAREA_AVG                 3.932048
NONLIVINGAREA_MEDI               2.882229
NONLIVINGAREA_MODE               2.882229
NONLIVINGAREA_AVG                2.882229
ELEVATORS_MEDI                   2.368985
ELEVATORS_AVG                    2.368985
ELEVATORS_MODE                   2.368985
WALLSMATERIAL_MODE               1.900278
APARTMENTS_MODE                  1.896036
APARTMENTS_MEDI                  1.896036
APARTMENTS_AVG                   1.896036
ENTRANCES_MODE                   1.847257
ENTRANCES_AVG                    1.847257
ENTRANCES_MEDI                   1.847257
HOUSETYPE_MODE                   1.775148
FLOORSMAX_AVG                    1.747577
FLOORSMAX_MODE                   1.747577
FLOORSMAX_MEDI                   1.747577
LIVINGAREA_MEDI                  1.745456
LIVINGAREA_AVG                   1.745456
LIVINGAREA_MODE                  1.745456
YEARS_BEGINEXPLUATATION_MODE     1.584272
YEARS_BEGINEXPLUATATION_MEDI     1.584272
YEARS_BEGINEXPLUATATION_AVG      1.584272
TOTALAREA_MODE                   1.486713
EMERGENCYSTATE_MODE              1.363704
CODE_GENDER                      0.000000
WEEKDAY_APPR_PROCESS_START       0.000000
HOUR_APPR_PROCESS_START          0.000000
REG_REGION_NOT_LIVE_REGION       0.000000
FLAG_OWN_REALTY                  0.000000
NAME_CONTRACT_TYPE               0.000000
REGION_RATING_CLIENT_W_CITY      0.000000
REG_REGION_NOT_WORK_REGION       0.000000
CNT_CHILDREN                     0.000000
FLAG_OWN_CAR                     0.000000
TARGET                           0.000000
```

```
NAME_HOUSING_TYPE               0.000000
AMT_INCOME_TOTAL                0.000000
AMT_CREDIT                      0.000000
DAYS_BIRTH                      0.000000
DAYS_EMPLOYED                   0.000000
DAYS_REGISTRATION               0.000000
DAYS_ID_PUBLISH                 0.000000
FLAG_MOBIL                      0.000000
FLAG_EMP_PHONE                  0.000000
FLAG_WORK_PHONE                 0.000000
FLAG_CONT_MOBILE                0.000000
FLAG_PHONE                      0.000000
FLAG_EMAIL                      0.000000
OCCUPATION_TYPE                 0.000000
CNT_FAM_MEMBERS                 0.000000
REGION_RATING_CLIENT            0.000000
NAME_FAMILY_STATUS              0.000000
NAME_EDUCATION_TYPE             0.000000
NAME_INCOME_TYPE                0.000000
REG_CITY_NOT_LIVE_CITY          0.000000
NAME_TYPE_SUITE                 0.000000
AMT_GOODS_PRICE                 0.000000
REGION_POPULATION_RELATIVE      0.000000
AMT_ANNUITY                     0.000000
LIVE_REGION_NOT_WORK_REGION     0.000000
TARGET_PERCENT                  0.000000
REG_CITY_NOT_WORK_CITY          0.000000
FLAG_DOCUMENT_18                0.000000
FLAG_DOCUMENT_11                0.000000
FLAG_DOCUMENT_12                0.000000
FLAG_DOCUMENT_13                0.000000
FLAG_DOCUMENT_14                0.000000
FLAG_DOCUMENT_15                0.000000
FLAG_DOCUMENT_16                0.000000
FLAG_DOCUMENT_17                0.000000
FLAG_DOCUMENT_19                0.000000
LIVE_CITY_NOT_WORK_CITY         0.000000
FLAG_DOCUMENT_20                0.000000
FLAG_DOCUMENT_21                0.000000
AMT_REQ_CREDIT_BUREAU_HOUR      0.000000
AMT_REQ_CREDIT_BUREAU_DAY       0.000000
AMT_REQ_CREDIT_BUREAU_WEEK      0.000000
AMT_REQ_CREDIT_BUREAU_MON       0.000000
AMT_REQ_CREDIT_BUREAU_QRT       0.000000
FLAG_DOCUMENT_10                0.000000
FLAG_DOCUMENT_9                 0.000000
FLAG_DOCUMENT_8                 0.000000
FLAG_DOCUMENT_7                 0.000000
ORGANIZATION_TYPE               0.000000
EXT_SOURCE_1                    0.000000
EXT_SOURCE_2                    0.000000
EXT_SOURCE_3                    0.000000
AMT_REQ_CREDIT_BUREAU_YEAR      0.000000
OBS_30_CNT_SOCIAL_CIRCLE        0.000000
DEF_30_CNT_SOCIAL_CIRCLE        0.000000
OBS_60_CNT_SOCIAL_CIRCLE        0.000000
DEF_60_CNT_SOCIAL_CIRCLE        0.000000
DAYS_LAST_PHONE_CHANGE          0.000000
FLAG_DOCUMENT_2                 0.000000
```

```
FLAG_DOCUMENT_3                 0.000000
FLAG_DOCUMENT_4                 0.000000
FLAG_DOCUMENT_5                 0.000000
FLAG_DOCUMENT_6                 0.000000
SK_ID_CURR                      0.000000
dtype: float64
```

In [17]:
```
appln_data.head()
```

Out[17]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 123 columns

In [59]:
```
appln_data['NO_CONTACT_INFO']=appln_data[['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHO
NE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL']].sum(axis=1)
appln_data=appln_data.drop(columns=['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',
'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL'])
```

In [19]:
```
appln_data.head()
```

Out[19]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 118 columns

In [61]:
```python
appln_data['CLIENT_REGION_RATING']=appln_data[['REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY']].mean(axis=1)
appln_data=appln_data.drop(columns=['REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY'])
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-61-7a90d7bfdd13> in <module>
----> 1 appln_data['CLIENT_REGION_RATING']=appln_data[['REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY']].mean(axis=1)
      2 appln_data=appln_data.drop(columns=['REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY'])

~\Anaconda3\lib\site-packages\pandas\core\frame.py in __getitem__(self, key)
   2984             if is_iterator(key):
   2985                 key = list(key)
-> 2986             indexer = self.loc._convert_to_indexer(key, axis=1, raise_missing=True)
   2987 
   2988         # take() does not accept boolean indexers

~\Anaconda3\lib\site-packages\pandas\core\indexing.py in _convert_to_indexer(self, obj, axis, is_setter, raise_missing)
   1283                 # When setting, missing keys are not allowed, even with .loc:
   1284                 kwargs = {"raise_missing": True if is_setter else raise_missing}
-> 1285                 return self._get_listlike_indexer(obj, axis, **kwargs)[1]
   1286         else:
   1287             try:

~\Anaconda3\lib\site-packages\pandas\core\indexing.py in _get_listlike_indexer(self, key, axis, raise_missing)
   1090 
   1091         self._validate_read_indexer(
-> 1092             keyarr, indexer, o._get_axis_number(axis), raise_missing=raise_missing
   1093         )
   1094         return keyarr, indexer

~\Anaconda3\lib\site-packages\pandas\core\indexing.py in _validate_read_indexer(self, key, indexer, axis, raise_missing)
   1175                 raise KeyError(
   1176                     "None of [{key}] are in the [{axis}]".format(
-> 1177                         key=key, axis=self.obj._get_axis_name(axis)
   1178                     )
   1179                 )

KeyError: "None of [Index(['REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY'], dtype='object')] are in the [columns]"
```

In [21]:
```
appln_data.head()
```

Out[21]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 117 columns

In [62]:
```
appln_data['PERCENTAGE_ADDRESS_MATCH']=(appln_data[['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']].mean(axis=1))*100
appln_data['PERCENTAGE_ADDRESS_MATCH']=100-appln_data['PERCENTAGE_ADDRESS_MATCH']
appln_data=appln_data.drop(columns=['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'])
```

In [23]:
```
appln_data.head()
```

Out[23]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 112 columns

In [63]:
```
appln_data['EXT_SOURCE']=appln_data[['EXT_SOURCE_2', 'EXT_SOURCE_3']].mean(axis=1)
appln_data=appln_data.drop(columns=['EXT_SOURCE_2', 'EXT_SOURCE_3'])
```

In [25]:
```
appln_data.head()
```

Out[25]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 111 columns

In [64]:
```
FLAG_DOCUMENTS=list(appln_data.columns)[31:51]
appln_data['TOTAL_DOC_GIVEN']=appln_data[FLAG_DOCUMENTS].sum(axis=1)
appln_data=appln_data.drop(columns=FLAG_DOCUMENTS)
```

In [27]:
```
appln_data.head()
```

Out[27]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	100002	1	Cash loans	Male	N	Y
1	100003	0	Cash loans	Female	N	N
2	100004	0	Revolving loans	Male	Y	Y
3	100006	0	Cash loans	Female	N	Y
4	100007	0	Cash loans	Male	N	Y

5 rows × 92 columns

In [81]:
```python
#Converting the Age in Negative Days to Positive Years in 'DAYS_BIRTH' column
appln_data['AGE']=(round(appln_data['DAYS_BIRTH']/365))*-1
appln_data=appln_data.drop(columns=['DAYS_BIRTH'])
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get_loc(self, key, method,
tolerance)
   2896             try:
-> 2897                 return self._engine.get_loc(key)
   2898             except KeyError:

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get
_item()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get
_item()

KeyError: 'DAYS_BIRTH'

During handling of the above exception, another exception occurred:

KeyError                                  Traceback (most recent call last)
<ipython-input-81-473047bb1159> in <module>
      1 #Converting the Age in Negative Days to Positive Years in 'DAYS_BIRTH' column
----> 2 appln_data['AGE']=(round(appln_data['DAYS_BIRTH']/365))*-1
      3 appln_data=appln_data.drop(columns=['DAYS_BIRTH'])

~\Anaconda3\lib\site-packages\pandas\core\frame.py in __getitem__(self, key)
   2978             if self.columns.nlevels > 1:
   2979                 return self._getitem_multilevel(key)
-> 2980             indexer = self.columns.get_loc(key)
   2981             if is_integer(indexer):
   2982                 indexer = [indexer]

~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in get_loc(self, key, method,
tolerance)
   2897                 return self._engine.get_loc(key)
   2898             except KeyError:
-> 2899                 return self._engine.get_loc(self._maybe_cast_indexer(key))
   2900         indexer = self.get_indexer([key], method=method, tolerance=tolerance)
   2901         if indexer.ndim > 1 or indexer.size > 1:

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get
_item()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectHashTable.get
_item()

KeyError: 'DAYS_BIRTH'
```

In [82]:
```
appln_data['AGE']
```

Out[82]:
```
0        20-30
1        40-50
2        50-60
3        50-60
4        50-60
         ...
47146    50-60
47147    30-40
47148    20-30
47149    50-60
47150    50-60
Name: AGE, Length: 47151, dtype: category
Categories (5, object): [20-30 < 30-40 < 40-50 < 50-60 < 60+]
```

In [67]:
```
#Converting the Negative Values of 'DAYS_REGISTRATION' to Positive
appln_data['DAYS_REGISTRATION']=appln_data['DAYS_REGISTRATION'].apply(lambda x:x*-1)
```

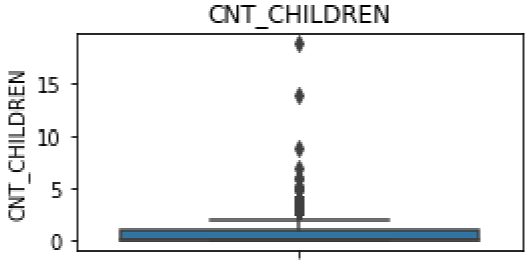
In [68]:
```
#Converting the negative values of 'DAYS_LAST_PHONE_CHANGE' to Positive
appln_data['DAYS_LAST_PHONE_CHANGE']=appln_data['DAYS_LAST_PHONE_CHANGE'].apply(lambda
x:x*-1)
```

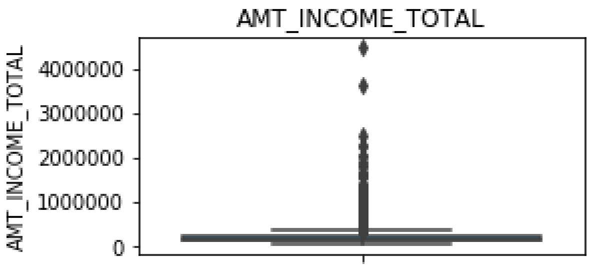
In [ ]:
```
#Creating the column 'Repayer_or_Defaulter'
#0 from TARGET column as Repayers & 1 from TARGET column as Defaulters
```

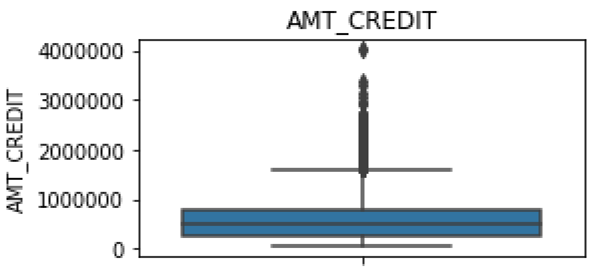
In [69]:
```
appln_data['Repayer_or_Defaulter']=appln_data['TARGET'].apply(lambda x:'Repayer' if x==0
else 'Defaulter')
```

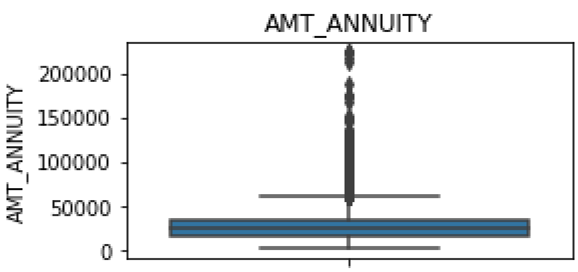
In [70]:

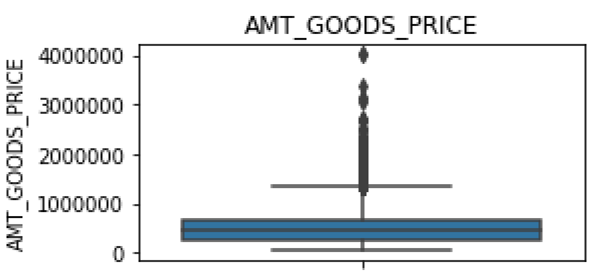
```
#Outlier Check by using Box plot
appln_data_continous = ['CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION',
'DAYS_ID_PUBLISH', 'CNT_FAM_MEMBERS', 'DAYS_LAST_PHONE_CHANGE', 'CLIENT_REGION_RATING',
'EXT_SOURCE', 'TOTAL_DOC_GIVEN', 'AGE']
appln_data_categorical=['TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_F
AMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE', 'ORGANIZATION_TYPE', 'NO_CONTACT_
INFO', 'PERCENTAGE_ADDRESS_MATCH']
j=1
for i in appln_data_continous:
    plt.figure(figsize=(4,2))
    sns.boxplot(y=appln_data[i])
    plt.title(i)
    plt.show()
```

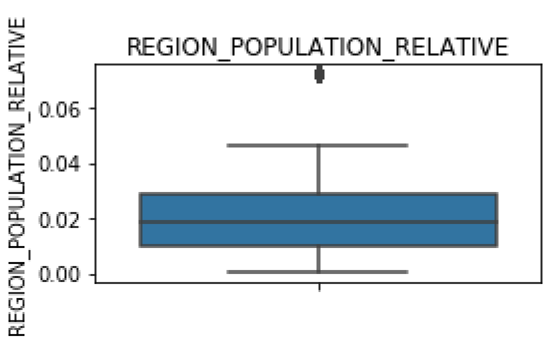

CNT_CHILDREN
CNT_CHILDREN
0
5
10
15

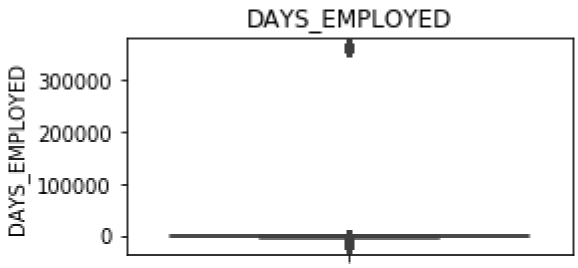

AMT_INCOME_TOTAL
AMT_INCOME_TOTAL
0
1000000
2000000
3000000
4000000

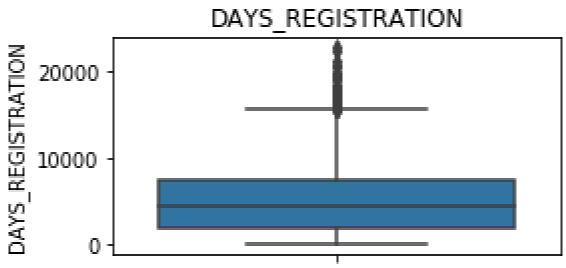

AMT_CREDIT
AMT_CREDIT
0
1000000
2000000
3000000
4000000

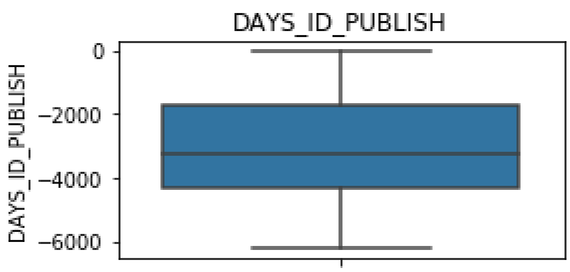

AMT_ANNUITY
AMT_ANNUITY
0
50000
100000
150000
200000

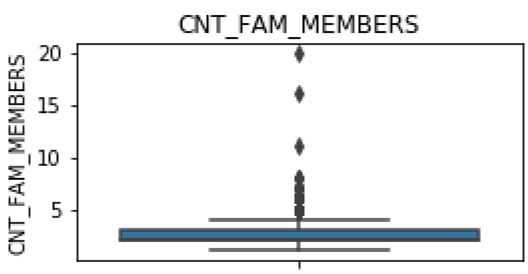

AMT_GOODS_PRICE
AMT_GOODS_PRICE
0
1000000
2000000
3000000
4000000

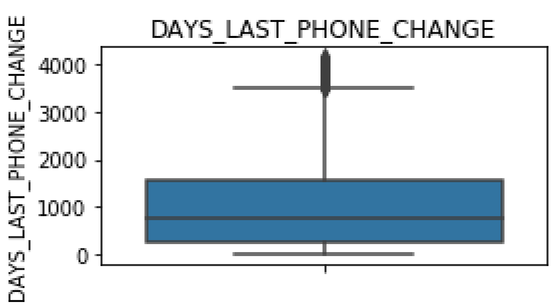

REGION_POPULATION_RELATIVE
REGION_POPULATION_RELATIVE
0.00
0.02
0.04
0.06

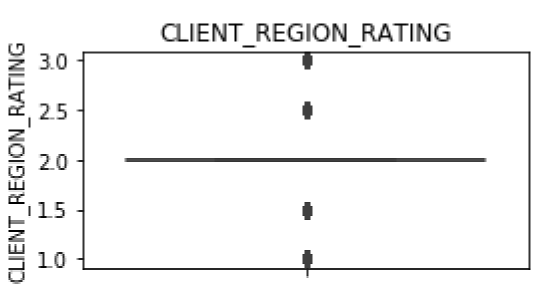

DAYS_EMPLOYED
DAYS_EMPLOYED
300000
200000
100000
0

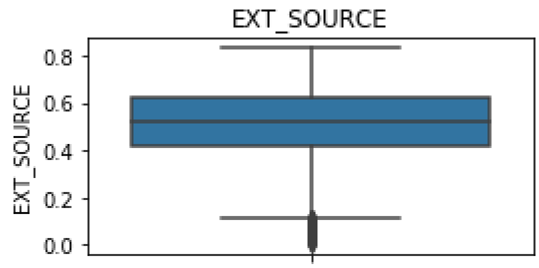

DAYS_REGISTRATION
DAYS_REGISTRATION
20000
10000
0

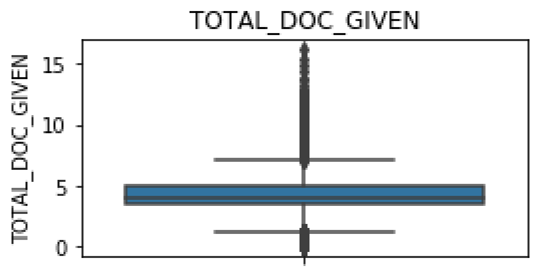

DAYS_ID_PUBLISH
DAYS_ID_PUBLISH
0
−2000
−4000
−6000

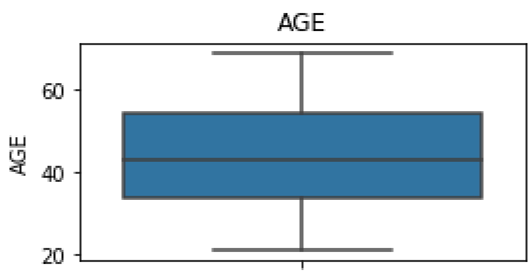

CNT_FAM_MEMBERS
CNT_FAM_MEMBERS
20
15
10
5


DAYS_LAST_PHONE_CHANGE
DAYS_LAST_PHONE_CHANGE
4000
3000
2000
1000
0


CLIENT_REGION_RATING
CLIENT_REGION_RATING
3.0
2.5
2.0
1.5
1.0







In [ ]:

```
#Insights:-
#1) CNT_CHILDREN:- Few applicants have more than 2-4 children which are outliers in this case
#2) AMT_INCOME_TOTAL:- Few applicants/clients are having very high income
#3) AMT_CREDIT:- Few applicants are asking for high loan credit (AMT_CREDIT) because of higher value of AMT_GOODS_PRICE
#4) AMT_ANNUITY:- As there are clients who are asking for high AMT_CREDIT, Amount of anual repayment also goes high
#5) AMT_GOODS_PRICE:- Few clients are applying for high goods price
#6) REGION_POPULATION_RELATIVE:- No much outliers
#7) DAYS_EMPLOYED:- Some outliers beyond 350000 days which can be considered as ERROR
#8) DAYS_REGISTRATION:- There are outliers which are still valid
#9) CNT_FAM_MEMBERS:- Few clients have family members more than 5
#10) DAYS_LAST_PHONE_CHANGE:- There are outliers which are still valid
#11) CLIENT_REGION_RATING:- Few of the clients have very good rating and very less rating at the same time. Not strong insight.
#12) EXT_SOURCE:- Few clients have very less normalized score from external source
#13)  TOTAL_DOC_GIVEN:- Majority of the clients have given single document only. Few have given more than 1 or not given at all.
#14) AGE:- No outliers in AGE column
```

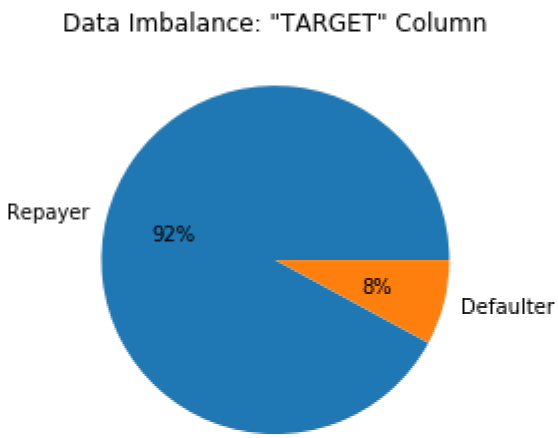
In [71]:

```
# Ratio of Repayers to Defaulters
di=(appln_data['Repayer_or_Defaulter'].value_counts(normalize=True)*100)
di[0]/di[1]
```

Out[71]:

```
11.664786462530218
```

In [72]:
```
plt.pie(di, labels= di.index, autopct='%.0f%%')
plt.title('Data Imbalance: "TARGET" Column')
plt.show()
```

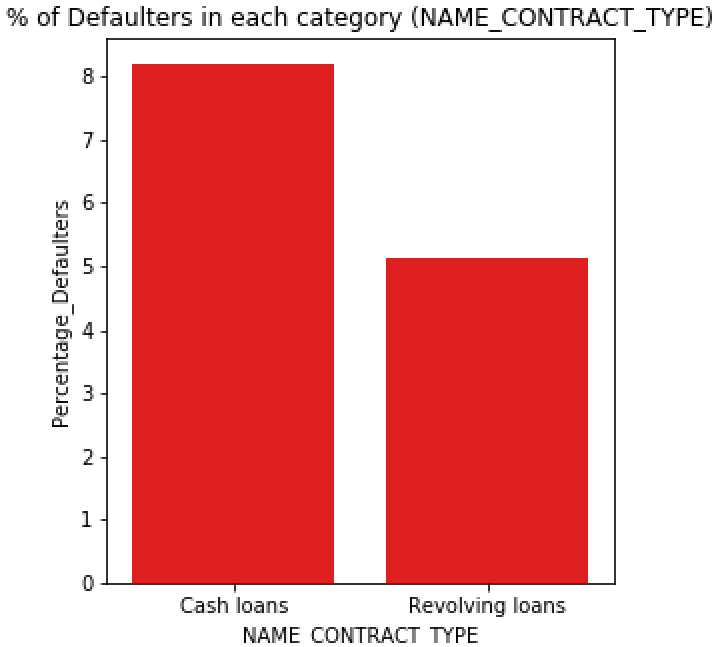


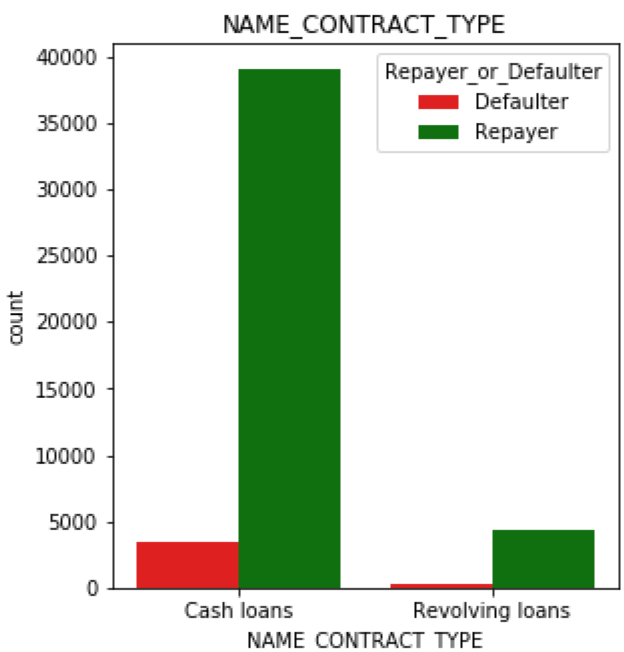
In [ ]:
```
#Here 91.92% of the clients are Repayers and 8.07% of the clients are Defaulters
#Ratio of Repayers (0) to Defaulters (1) is 11.4:1
```

In [ ]:
```
#Univariate Analysis target: TARGET column
```

In [73]:
```
def appln_data_univariate_categorical(x):
    chart1=pd.DataFrame(appln_data[x].value_counts())
    chart1=chart1.rename(columns={x: 'Value_Counts'})
    defaulters=appln_data.groupby(x).sum()['TARGET']
    chart=pd.concat([chart1,defaulters], axis=1)
    chart=chart.rename(columns={'TARGET': 'Defaulters'})
    chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
    chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
    chart.index.name=x
    chart=chart.reset_index()
    chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
    plt.figure(figsize=(10,5))
    plt.subplot(1,2,1)
    sns.barplot(data=chart, x=x, y='Percentage_Defaulters', color='Red')
    plt.title('% of Defaulters in each category '+'('+x+')')
    plt.show()

    plt.figure(figsize=(10,5))
    plt.subplot(1,2,2)
    sns.countplot(appln_data[x], hue=appln_data['Repayer_or_Defaulter'], palette=['Red',
'Green'])
    plt.title(x)
    plt.show()
```

In [74]:
```
#NAME_CONTRACT_TYPE
appln_data_univariate_categorical('NAME_CONTRACT_TYPE')
```



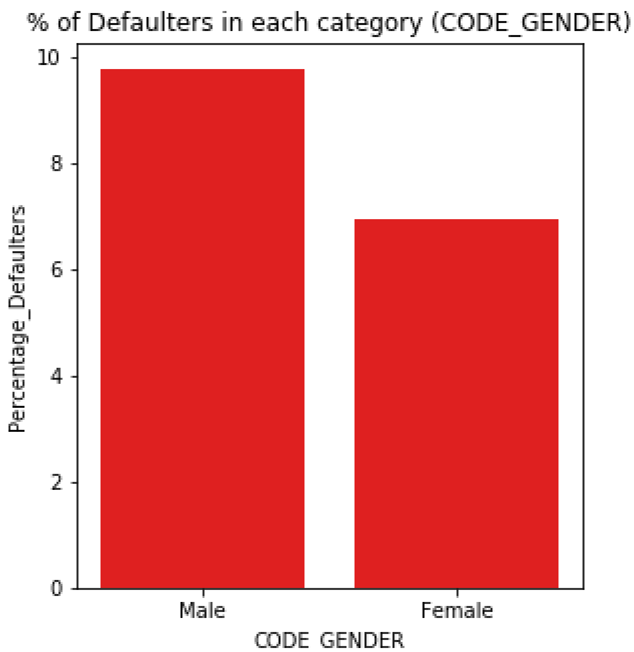


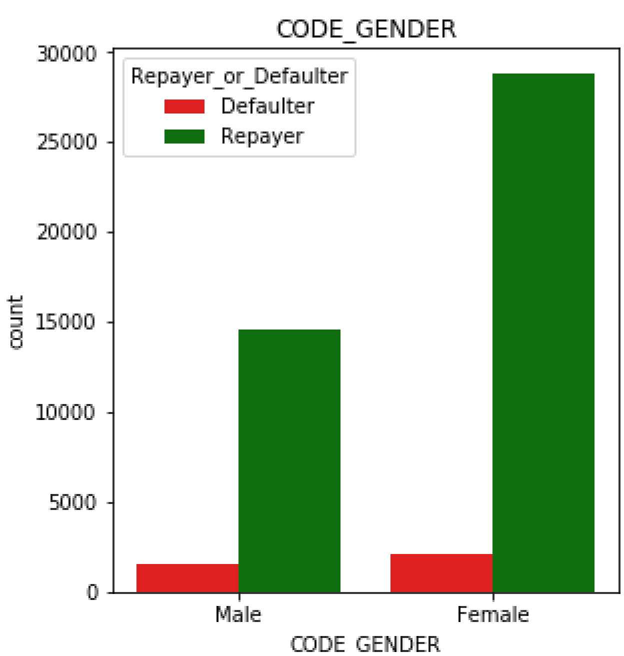
In [ ]:
```
##Insights
#1)More than 8% of the clients under cash loans are defaulters, whereas >5% of the clien
ts under revolving loans are defaulters
#2)Less risk is associated with revolving loans type
```

In [75]:
```
appln_data['CODE_GENDER']
```

Out[75]:
```
0          Male
1        Female
2          Male
3        Female
4          Male
          ...
47146      Male
47147    Female
47148    Female
47149    Female
47150    Female
Name: CODE_GENDER, Length: 47151, dtype: object
```

In [77]:
```
appln_data_univariate_categorical('CODE_GENDER')
```



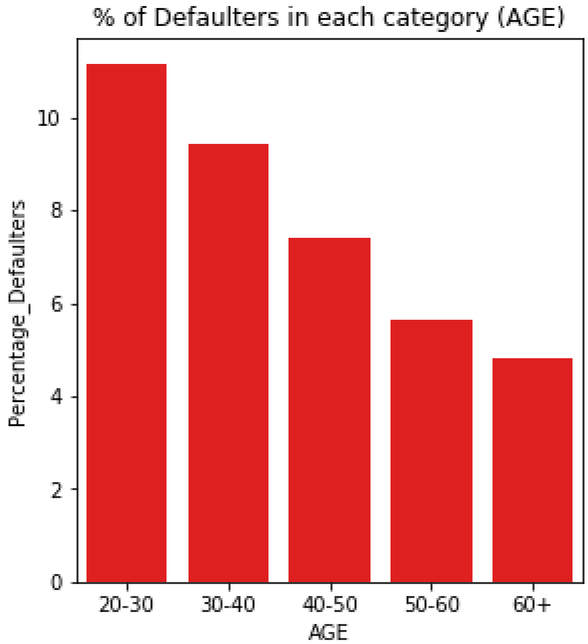


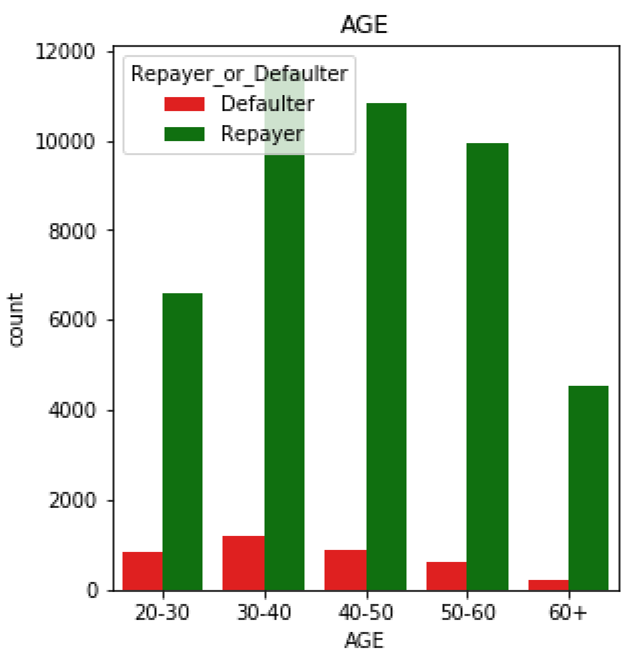
In [ ]:
```
#Insigits:-
#10% of the male clients are defaulters and 7% of the female clients are defaulters
#Less risk is associated with female clients
```

In [83]:
```
#AGE
appln_data[appln_data['AGE'] < 20] #No clients whose age is less than 20 years
appln_data['AGE']=pd.cut(appln_data['AGE'], [20,30,40,50,60,999], labels=['20-30', '30-40', '40-50', '50-60', '60+'])
appln_data_univariate_categorical('AGE')
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-83-3bc1d67034d3> in <module>
      1 #AGE
----> 2 appln_data[appln_data['AGE'] < 20] #No clients whose age is less than 20 years
      3 appln_data['AGE']=pd.cut(appln_data['AGE'], [20,30,40,50,60,999], labels=['20-30', '30-40', '40-50', '50-60', '60+'])
      4 appln_data_univariate_categorical('AGE')

~\Anaconda3\lib\site-packages\pandas\core\ops\__init__.py in wrapper(self, other, axis)
   1145             # Dispatch to Categorical implementation; pd.CategoricalIndex
   1146             # behavior is non-canonical GH#19513
-> 1147             res_values = dispatch_to_index_op(op, self, other, pd.Categorical)
   1148             return self._constructor(res_values, index=self.index, name=res_name)
   1149 

~\Anaconda3\lib\site-packages\pandas\core\ops\__init__.py in dispatch_to_index_op(op, left, right, index_class)
    628         left_idx = left_idx._shallow_copy(freq=None)
    629     try:
--> 630         result = op(left_idx, right)
    631     except NullFrequencyError:
    632         # DatetimeIndex and TimedeltaIndex with freq == None raise ValueError

~\Anaconda3\lib\site-packages\pandas\core\arrays\categorical.py in f(self, other)
    140                         "scalar, which is not a category."
    141                     )
--> 142                 raise TypeError(msg.format(op=op))
    143         else:
    144 

TypeError: Cannot compare a Categorical for op __lt__ with a scalar, which is not a category.
```

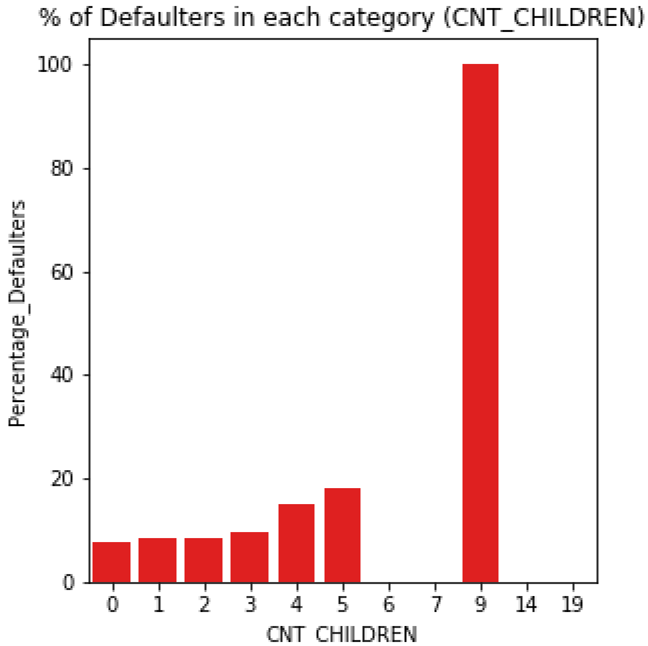
In [84]:
```
appln_data_univariate_categorical('AGE')
```

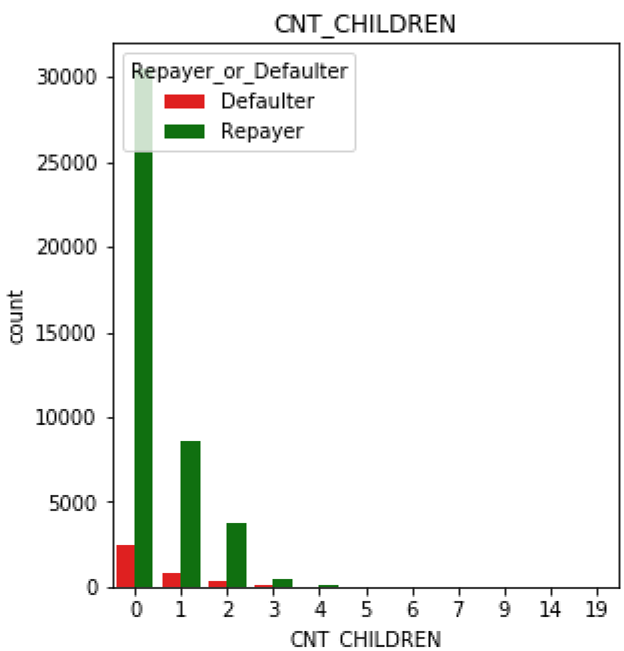




In [ ]:
```
## Insigits:-
#1)10% of the 20-40 age group clients are defaulters, 7% of the 40-60 age group clients
are defaulters and 5% of 60+ age groups are defaulters
#2)More the age of the client, less is the defaulting rate
#3)Less risk is associated with older people
```

In [85]:
```
appln_data_univariate_categorical('CNT_CHILDREN')
```

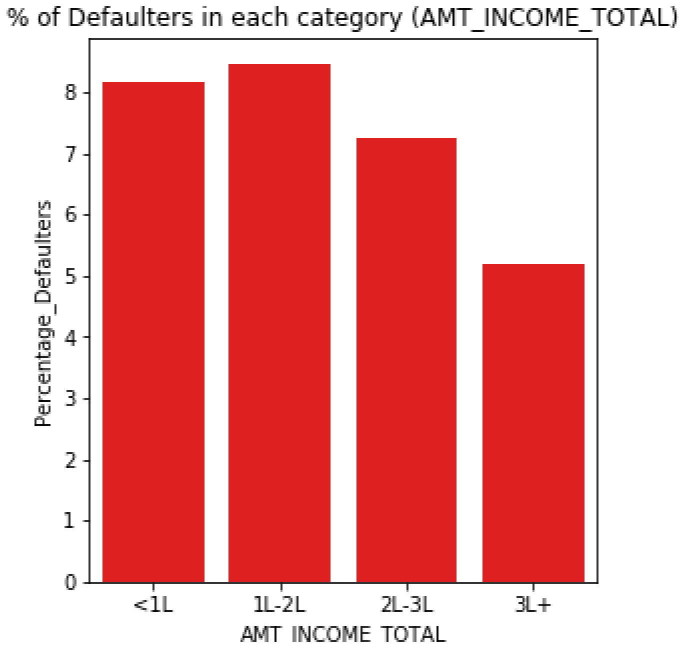


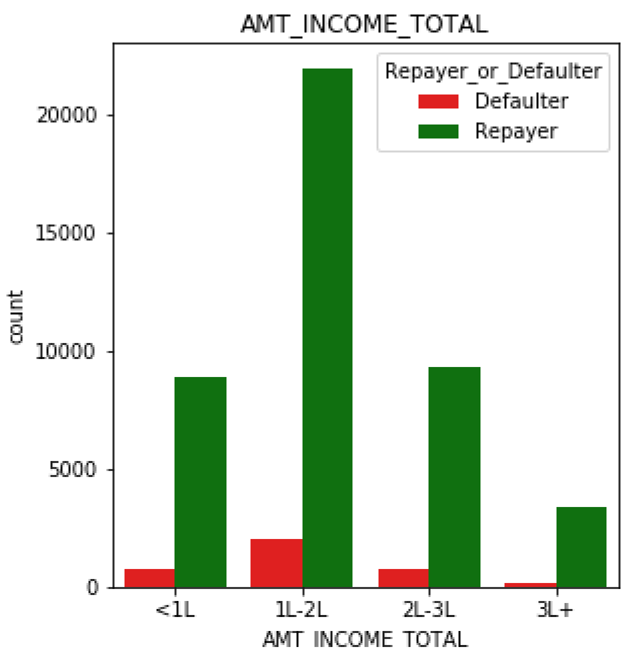


In [ ]:
```
#Insigits:-
#1)Clients with children <=3 have less defaulters (<=10%)
#2)Not strong insights, as less data is available for children more than 5
```

In [88]:
```
appln_data['AMT_INCOME_TOTAL'].describe()
appln_data['AMT_INCOME_TOTAL']=pd.cut(appln_data['AMT_INCOME_TOTAL'], [0,100000,200000,3
00000,9999999999], labels=['<1L', '1L-2L', '2L-3L', '3L+'])
```

In [89]:
```
appln_data_univariate_categorical('AMT_INCOME_TOTAL')
```

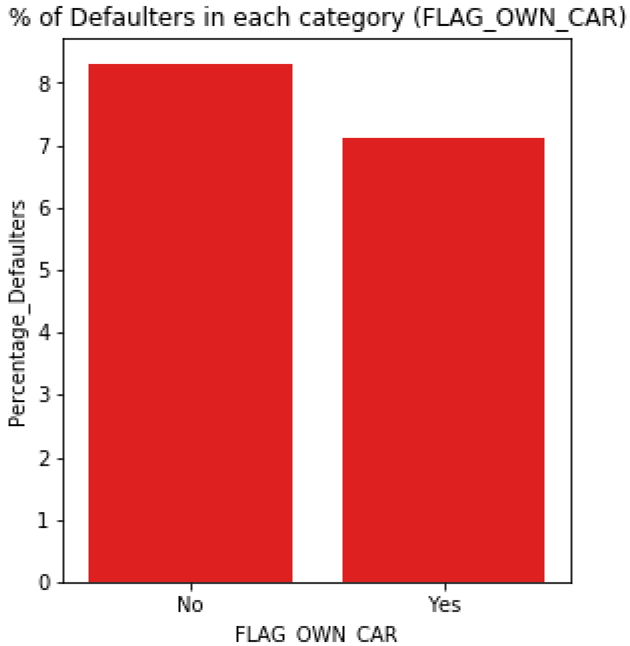


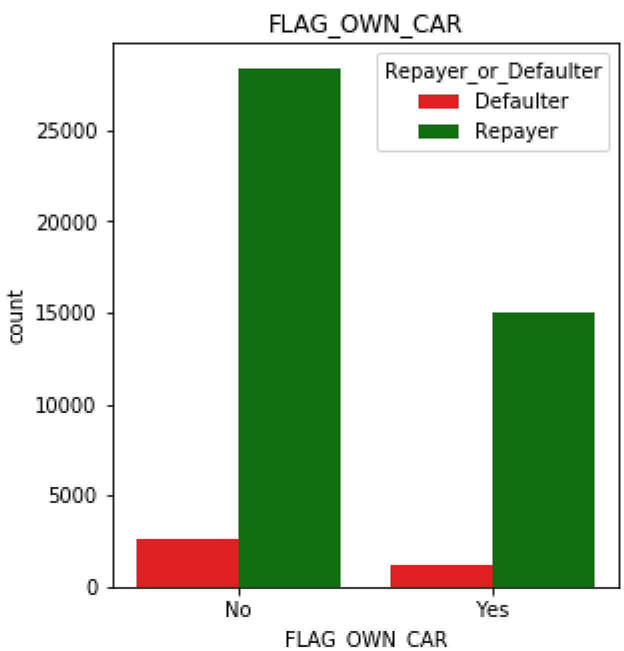


In [ ]:
```
#Insights:-
#1)Clients having total income more than 3 Lakhs have less defaulting rate (less risk as
sociated)
#2)Clients having total income less than 2 Lakhs have more defaulting rate
#3)More the income less is the defaulting rate of the clients
```

In [90]:
```
appln_data['FLAG_OWN_CAR']=appln_data['FLAG_OWN_CAR'].apply(lambda x:'Yes' if x=='Y' els
e 'No')
```

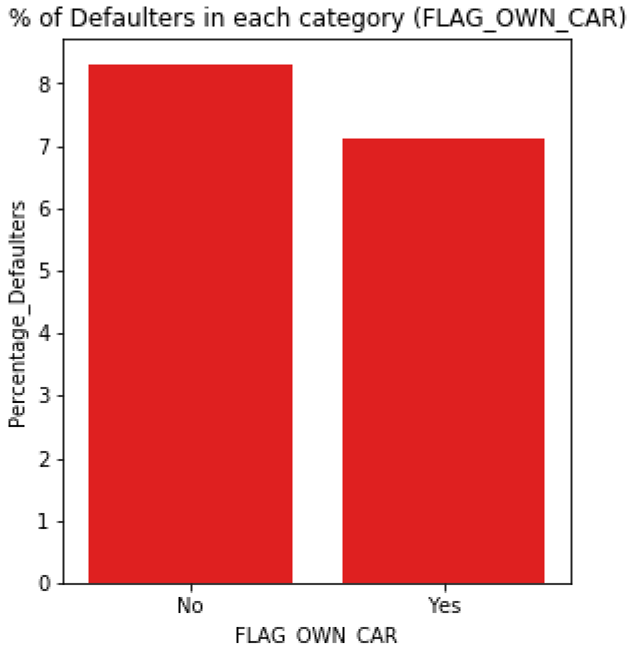
In [91]:
```
appln_data_univariate_categorical('FLAG_OWN_CAR')
```

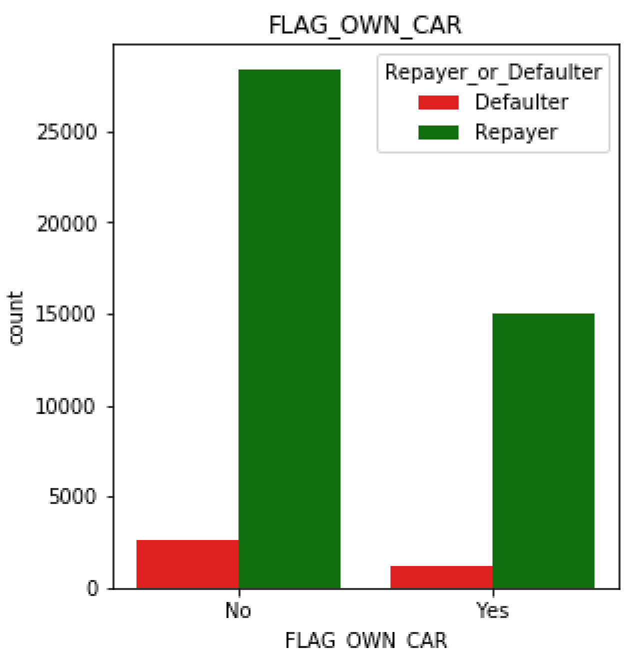




In [ ]:
```
#Insigits:-
#1)More than 8% of clients without car are defaulters and 7% of clents with car are defa
ulters
#2)No strong insights from this as there is not much difference
```

In [92]:
```
appln_data['FLAG_OWN_REALTY']=appln_data['FLAG_OWN_REALTY'].apply(lambda x:'Yes' if x=
='Y' else 'No')
appln_data_univariate_categorical('FLAG_OWN_CAR')
```



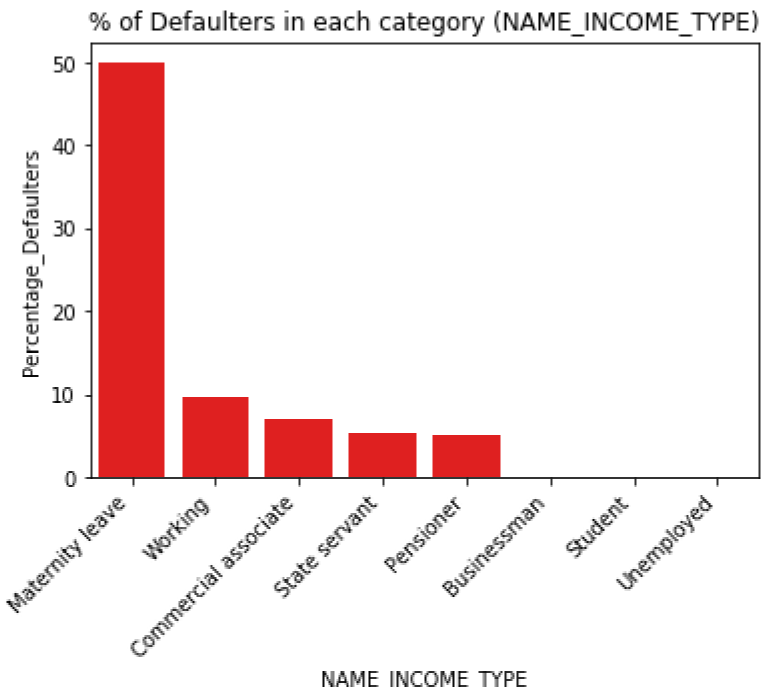


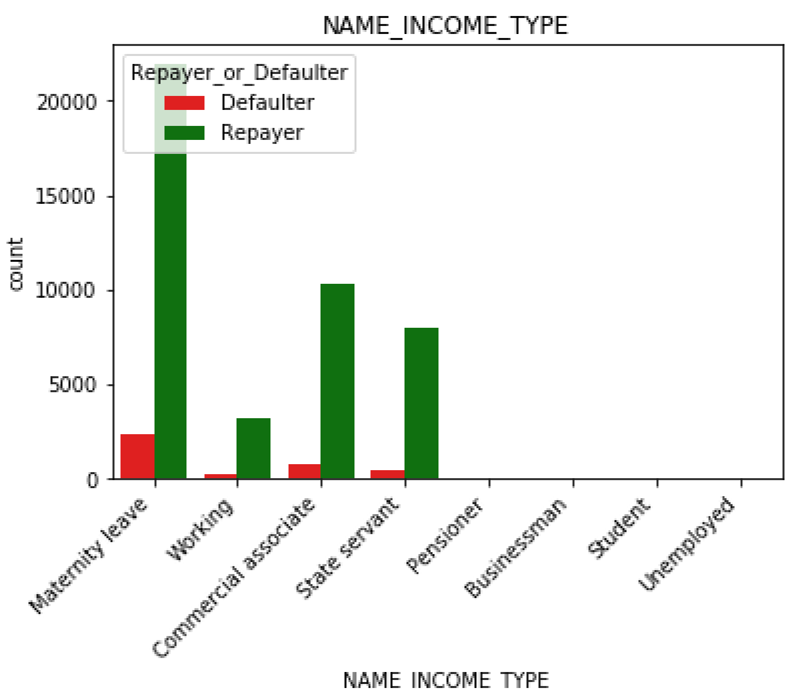
In [ ]:
```
#Insigits:-
#1)More than 8% of clients without House/Flat are defaulters and 7% of clents with Hous
e/Flat are defaulters
#2)No strong insights from this as there is not much difference
```

In [ ]:
```
#NAME_INCOME_TYPE
```

In [93]:

```
chart1=pd.DataFrame(appln_data['NAME_INCOME_TYPE'].value_counts()).rename(columns={'NAME
_INCOME_TYPE': 'Value_Counts'})
defaulters=appln_data.groupby('NAME_INCOME_TYPE').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='NAME_INCOME_TYPE'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
a=sns.barplot(data=chart, x='NAME_INCOME_TYPE', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(NAME_INCOME_TYPE)')
plt.show()
b=sns.countplot(appln_data['NAME_INCOME_TYPE'], hue=appln_data['Repayer_or_Defaulter'],
palette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('NAME_INCOME_TYPE')
plt.show()
```

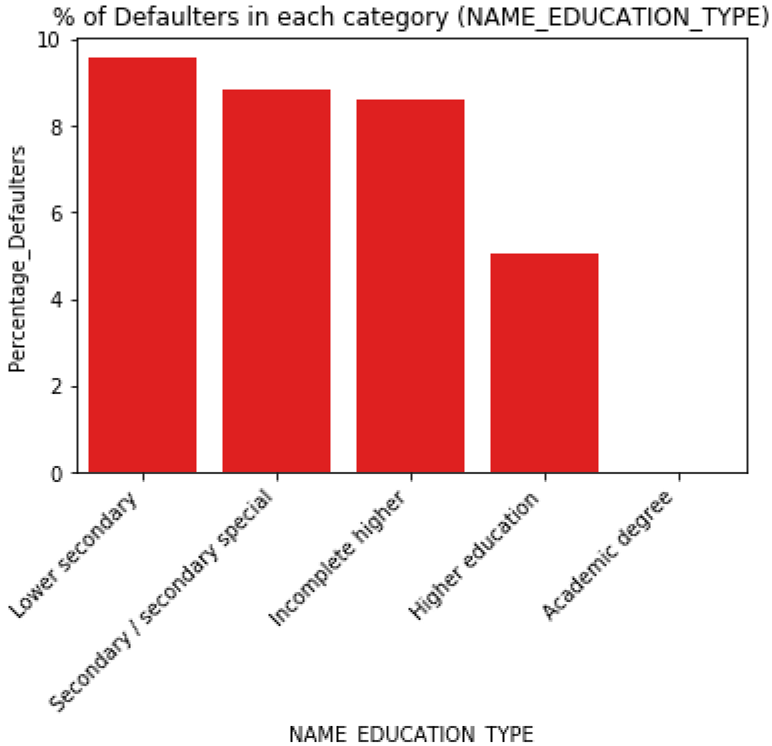


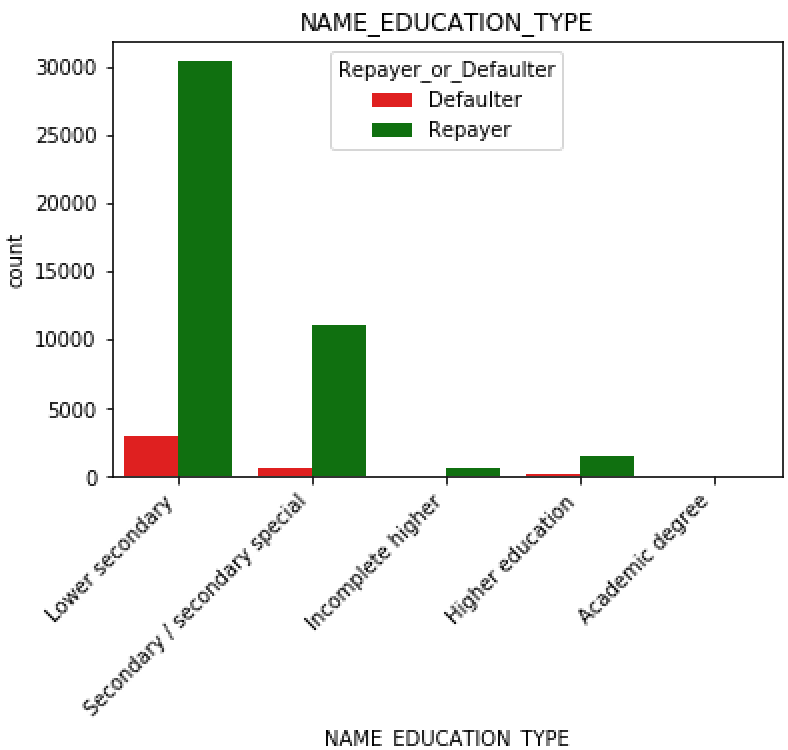


In [ ]:
```
#Insigits:-
#1)Very high % of defaulters in 'Maternity Leave' category. But the counts are very les
s, so can be ignored.
#2)Working professionals and commercial associates have litter higher default rate
#3)Pensioners and State Servants has less default rate comparatively (Less risk with the
m)
```

In [ ]:
```
#NAME_EDUCATION_TYPE
```

In [94]:
```
chart1=pd.DataFrame(appln_data['NAME_EDUCATION_TYPE'].value_counts()).rename(columns={'NAME_EDUCATION_TYPE': 'Value_Counts'})
defaulters=appln_data.groupby('NAME_EDUCATION_TYPE').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='NAME_EDUCATION_TYPE'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
a=sns.barplot(data=chart, x='NAME_EDUCATION_TYPE', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(NAME_EDUCATION_TYPE)')
plt.show()
b=sns.countplot(appln_data['NAME_EDUCATION_TYPE'], hue=appln_data['Repayer_or_Defaulter'], palette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('NAME_EDUCATION_TYPE')
plt.show()
```

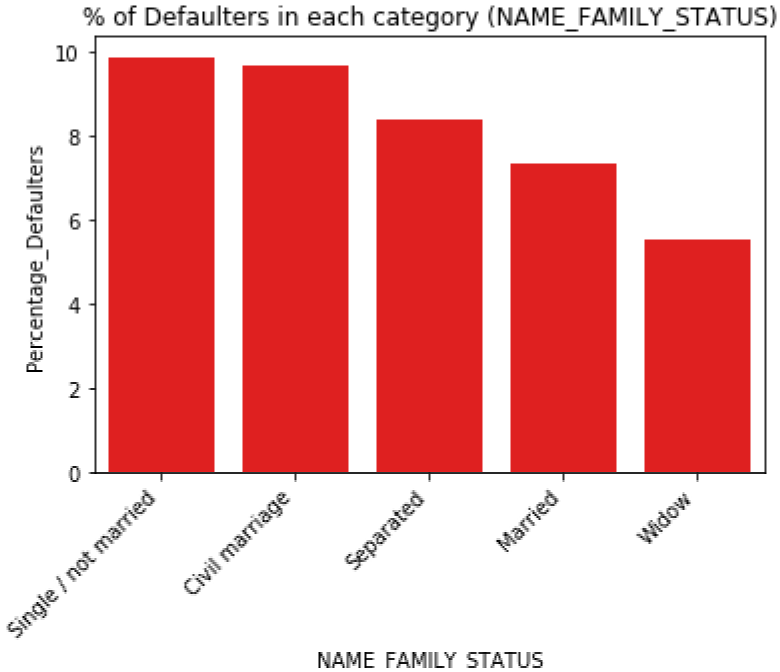


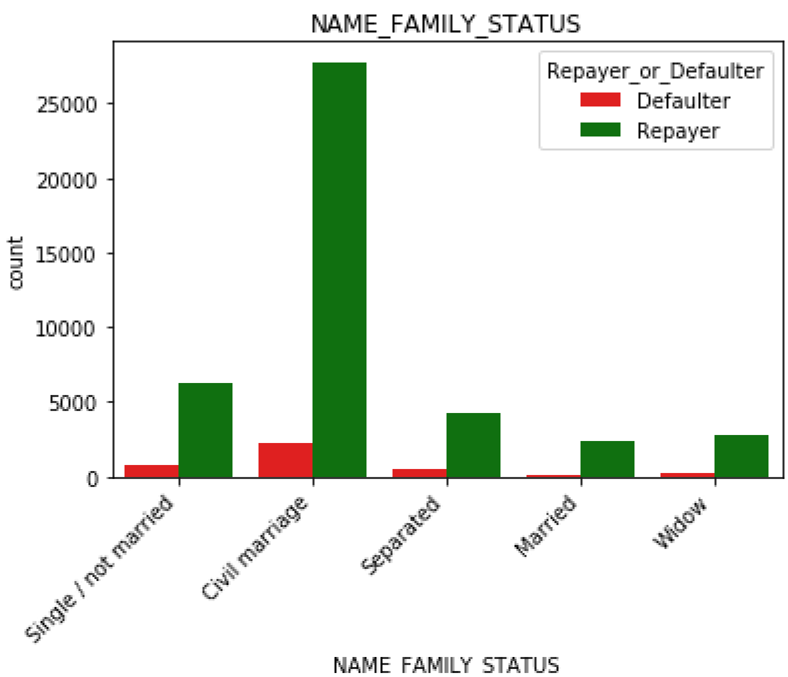


In [ ]:
```
#Insigits:-
#1)Clients have higher default rate who have lower secondary, secondary special or Incom
plete higher education type
#2)Clients with Academic degree or Higher education tend to default less
#3)Less risk associated is with Academic degree and Higher education holders
```

In [ ]:
```
#NAME_FAMILY_STATUS
```

In [95]:
```
chart1=pd.DataFrame(appln_data['NAME_FAMILY_STATUS'].value_counts()).rename(columns={'NAME_FAMILY_STATUS': 'Value_Counts'})
defaulters=appln_data.groupby('NAME_FAMILY_STATUS').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='NAME_FAMILY_STATUS'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
a=sns.barplot(data=chart, x='NAME_FAMILY_STATUS', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(NAME_FAMILY_STATUS)')
plt.show()
b=sns.countplot(appln_data['NAME_FAMILY_STATUS'], hue=appln_data['Repayer_or_Defaulter'], palette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('NAME_FAMILY_STATUS')
plt.show()
```



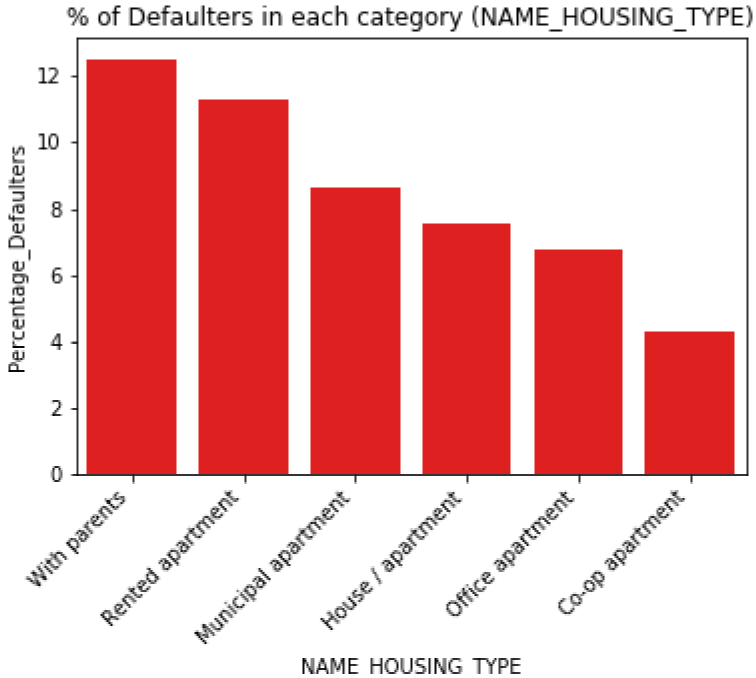


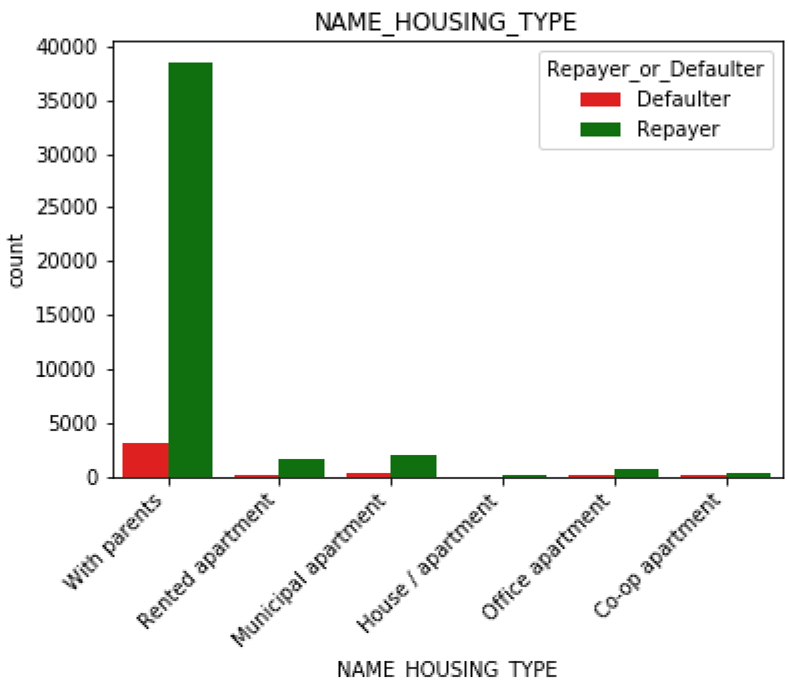
In [ ]:
```
#Insigits:-
#1)Single and Civil married clients have more defaulting rate
#2)Clients who are Widow have less defaulting rate (Less risk), Married clients are also
in the acceptable range (6-8%)
```

In [ ]:
```
#NAME_HOUSING_TYPE
```

In [97]:

```
chart1=pd.DataFrame(appln_data['NAME_HOUSING_TYPE'].value_counts()).rename(columns={'NAM
E_HOUSING_TYPE': 'Value_Counts'})
defaulters=appln_data.groupby('NAME_HOUSING_TYPE').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='NAME_HOUSING_TYPE'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
a=sns.barplot(data=chart, x='NAME_HOUSING_TYPE', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(NAME_HOUSING_TYPE)')
plt.show()
b=sns.countplot(appln_data['NAME_HOUSING_TYPE'], hue=appln_data['Repayer_or_Defaulter'],
palette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('NAME_HOUSING_TYPE')
plt.show()
```





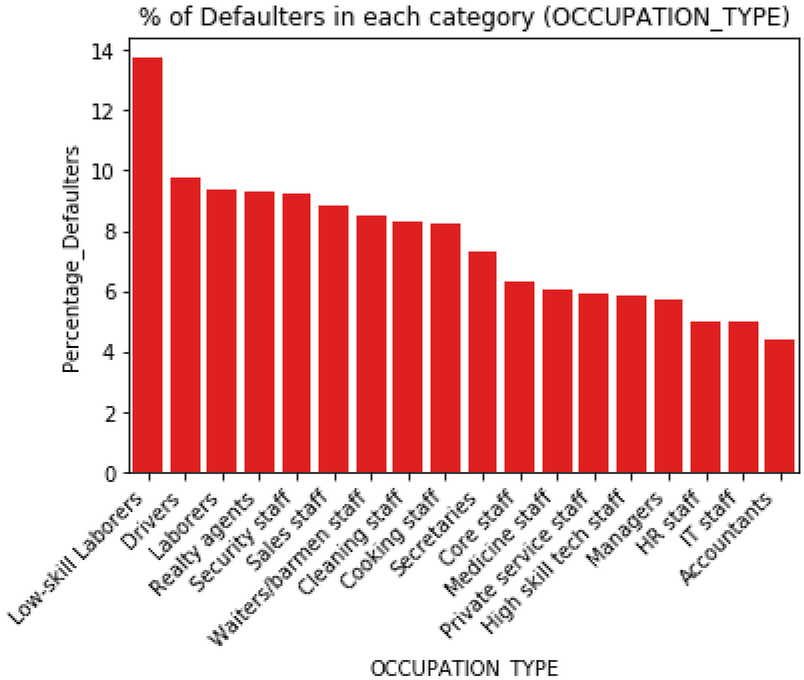
In [ ]:

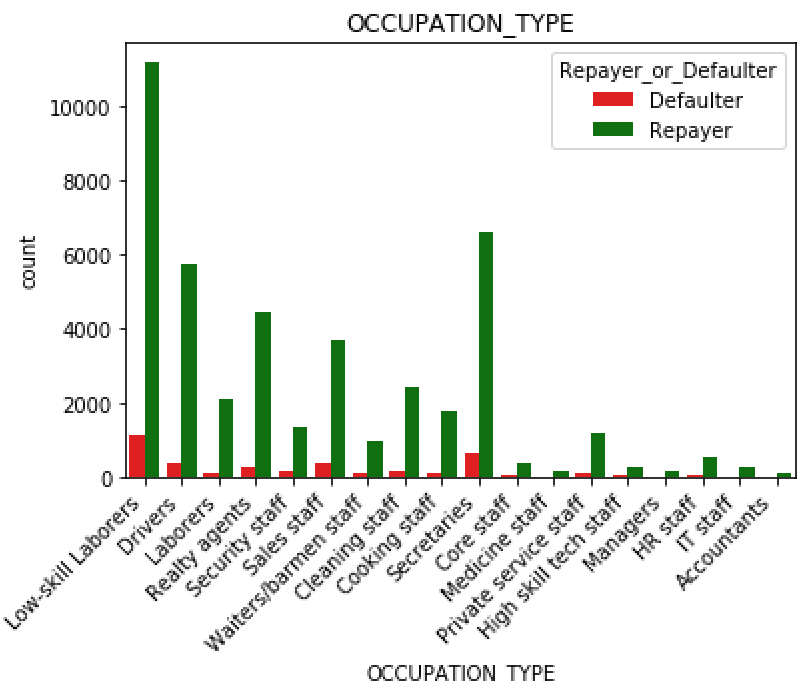
```
#Insigits:-
#1)Clients living in Rented apartments or With parents have higher defaulting rate
#2)Clients living in Office apartments (Less counts) or owning a House/apartment have le
ss defaulting rate (less risk associated)
```

In [ ]:

```
#OCCUPATION_TYPE
```

In [98]:
```
chart1=pd.DataFrame(appln_data['OCCUPATION_TYPE'].value_counts()).rename(columns={'OCCUP
ATION_TYPE': 'Value_Counts'})
defaulters=appln_data.groupby('OCCUPATION_TYPE').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='OCCUPATION_TYPE'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
a=sns.barplot(data=chart, x='OCCUPATION_TYPE', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(OCCUPATION_TYPE)')
plt.show()
b=sns.countplot(appln_data['OCCUPATION_TYPE'], hue=appln_data['Repayer_or_Defaulter'], p
alette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=45, horizontalalignment='right')
plt.title('OCCUPATION_TYPE')
plt.show()
```





In [ ]:

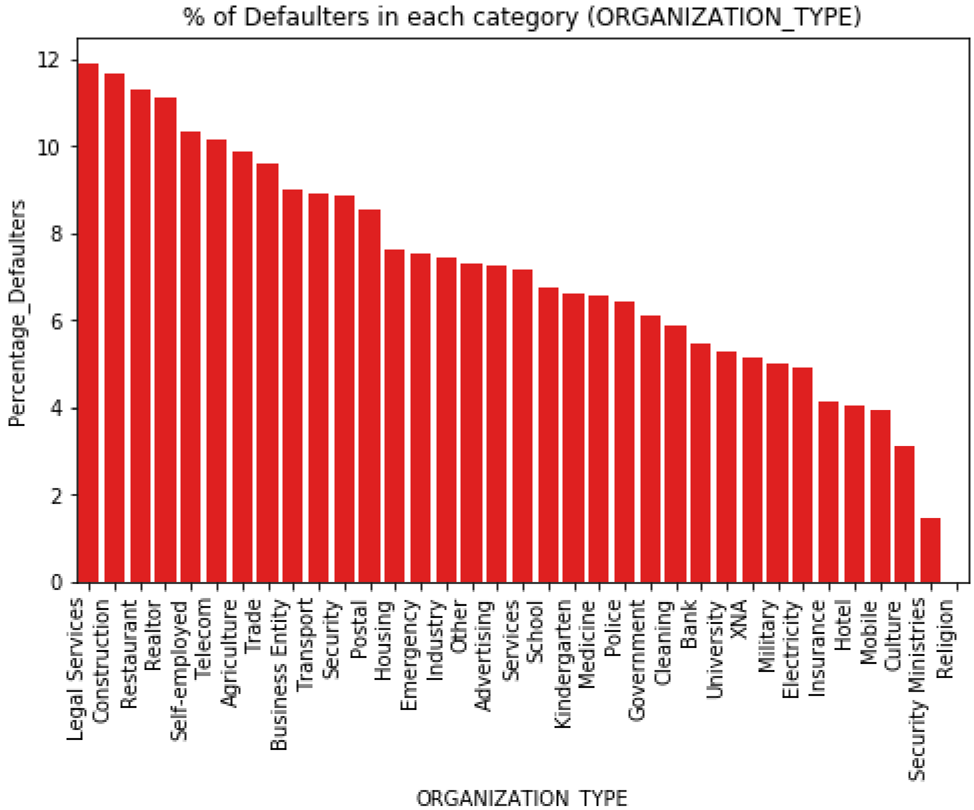
```
#Insigits:-
#1)Sales staffs, Drivers, Security staffs, Cooking staffs, low-skill Laborers (Very hig
h), Waiters/barmen staffs have high defaulting rate
#2)Core staffs, Managers, High skill tech staffs, Accountants, Medicines, Private servic
e, Seceretaries, HR & IT staffs have less defaulting rate (Less risk associated)
#3)Others are in the acceptable range (7.5-9)
```

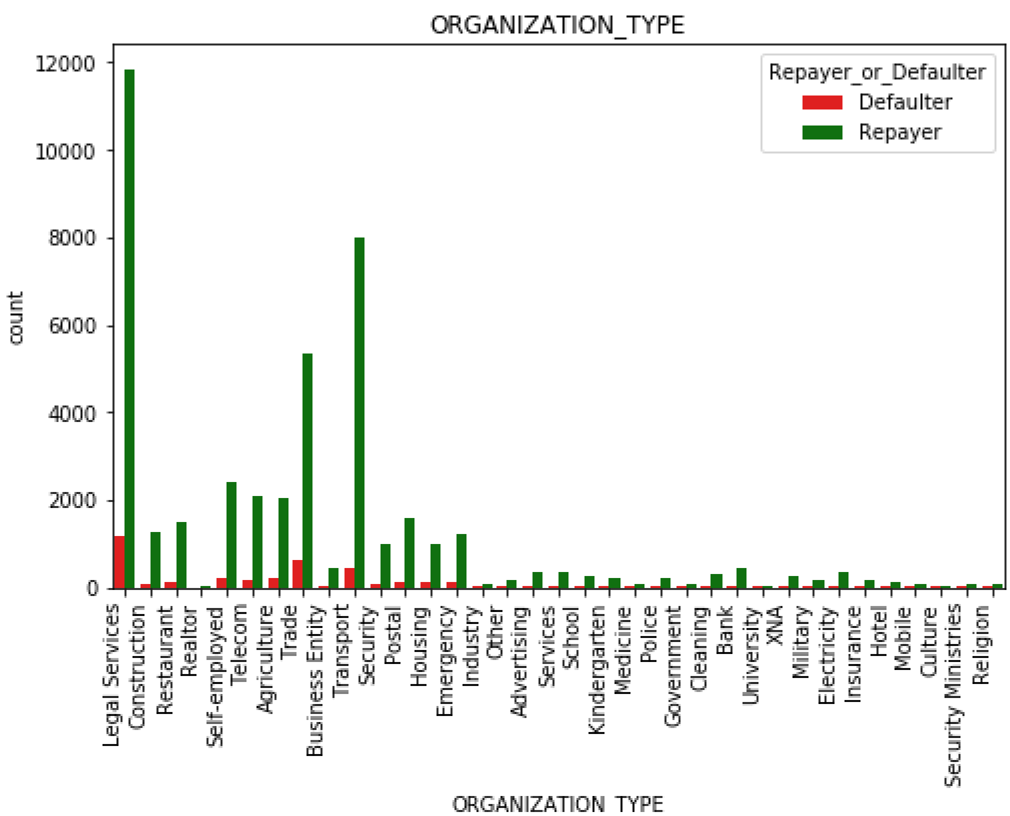
In [ ]:

```
#ORGANIZATION_TYPE
```

In [100]:

```
appln_data['ORGANIZATION_TYPE']=appln_data['ORGANIZATION_TYPE'].apply(lambda x:'Industr
y' if 'Industry' in x else x)
appln_data['ORGANIZATION_TYPE']=appln_data['ORGANIZATION_TYPE'].apply(lambda x:'Transpor
t' if 'Transport' in x else x)
appln_data['ORGANIZATION_TYPE']=appln_data['ORGANIZATION_TYPE'].apply(lambda x:'Trade' i
f 'Trade' in x else x)
appln_data['ORGANIZATION_TYPE']=appln_data['ORGANIZATION_TYPE'].apply(lambda x:'Business
Entity' if 'Business' in x else x)
chart1=pd.DataFrame(appln_data['ORGANIZATION_TYPE'].value_counts()).rename(columns={'ORG
ANIZATION_TYPE': 'Value_Counts'})
defaulters=appln_data.groupby('ORGANIZATION_TYPE').sum()['TARGET']
chart=pd.concat([chart1,defaulters], axis=1).rename(columns={'TARGET': 'Defaulters'})
chart['Percentage_Defaulters']=(chart['Defaulters']/chart['Value_Counts'])*100
chart=chart.drop(columns=['Value_Counts', 'Defaulters'])
chart.index.name='ORGANIZATION_TYPE'
chart=chart.reset_index()
chart.sort_values('Percentage_Defaulters', ascending=False, inplace=True)
plt.figure(figsize=(8,5))
a=sns.barplot(data=chart, x='ORGANIZATION_TYPE', y='Percentage_Defaulters', color='Red')
a.set_xticklabels(a.get_xticklabels(), rotation=90, horizontalalignment='right')
plt.title('% of Defaulters in each category '+'(ORGANIZATION_TYPE)')
plt.show()
plt.figure(figsize=(8,5))
b=sns.countplot(appln_data['ORGANIZATION_TYPE'], hue=appln_data['Repayer_or_Defaulter'],
palette=['Red', 'Green'])
b.set_xticklabels(a.get_xticklabels(), rotation=90, horizontalalignment='right')
plt.title('ORGANIZATION_TYPE')
plt.show()
```

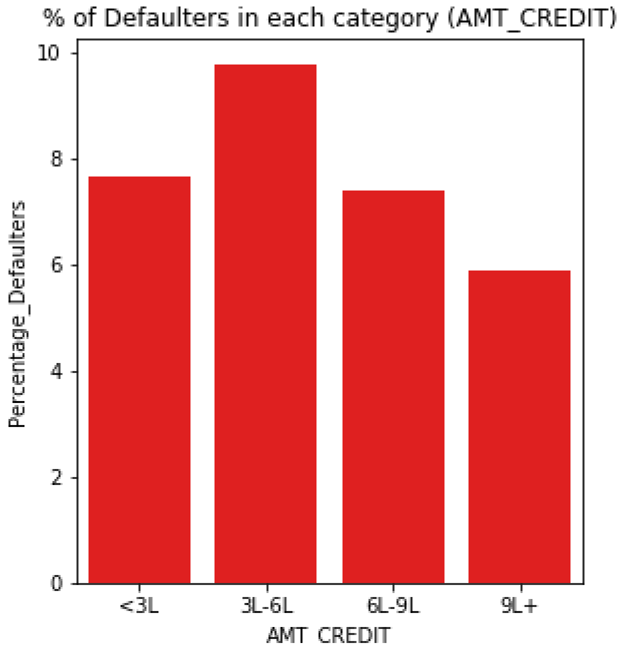


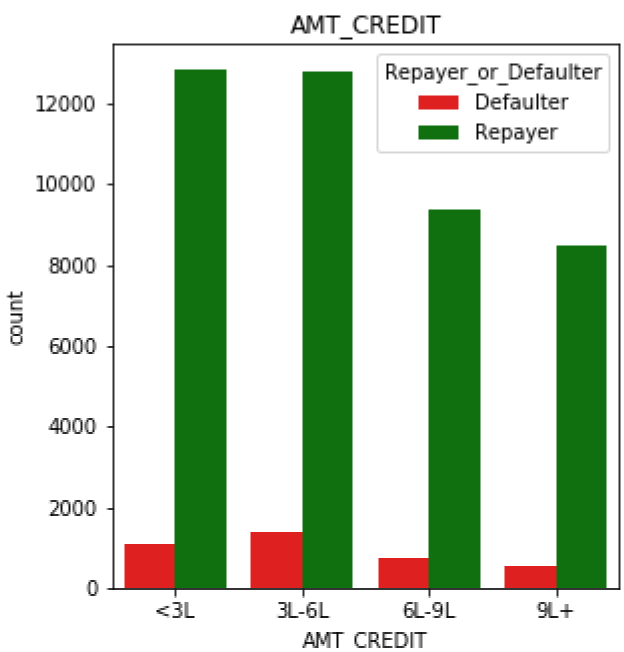


In [ ]:

```
#Insigits:-
#1)Less risk (<6%) associated with clients coming from Educational Universities, Medicin
e, Military, Bank, Police, Security Ministers, Insurance & Cultural organizations type
#2)Very high risk (>10%) in Self-employed, Transport, Construction, Agriculture, Restaur
ants, Relator, Cleaning organizations type
#3)Others are in the acceptable range but can be provided with high interest
```

In [102]:
```
appln_data['AMT_CREDIT']=pd.cut(appln_data['AMT_CREDIT'], [0,300000,600000,900000,999999
99999], labels=['<3L', '3L-6L', '6L-9L', '9L+'])
appln_data_univariate_categorical('AMT_CREDIT')
```

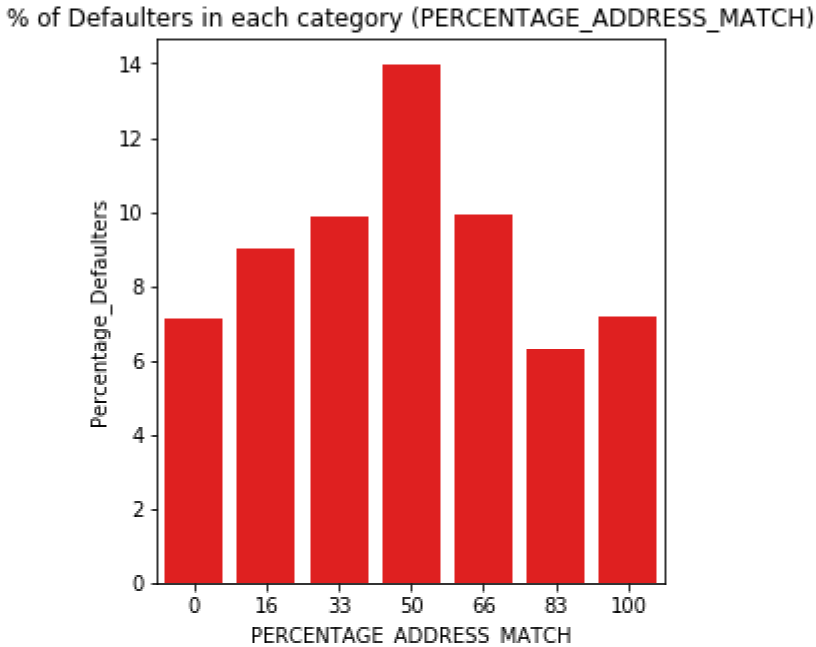


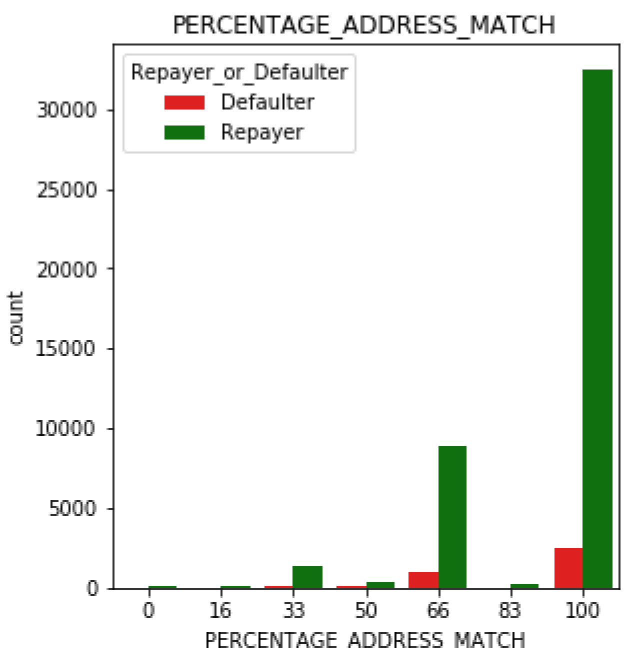


In [ ]:
```
#Insights:-
#1)Clients who have requested for credit between 3-6 Lakhs have more defaulting rate (>
9%)
#2)Clients who have requested for credit more than 9 lakhs have less defaulting rate (<
6%)
#3)Others are in the acceptable range
```

In [ ]:
```
##PERCENTAGE_ADDRESS_MATCH
```

In [103]:
```
appln_data['PERCENTAGE_ADDRESS_MATCH']=appln_data['PERCENTAGE_ADDRESS_MATCH'].apply(lamb
da x:int(round(x,1)))
appln_data_univariate_categorical('PERCENTAGE_ADDRESS_MATCH')
```

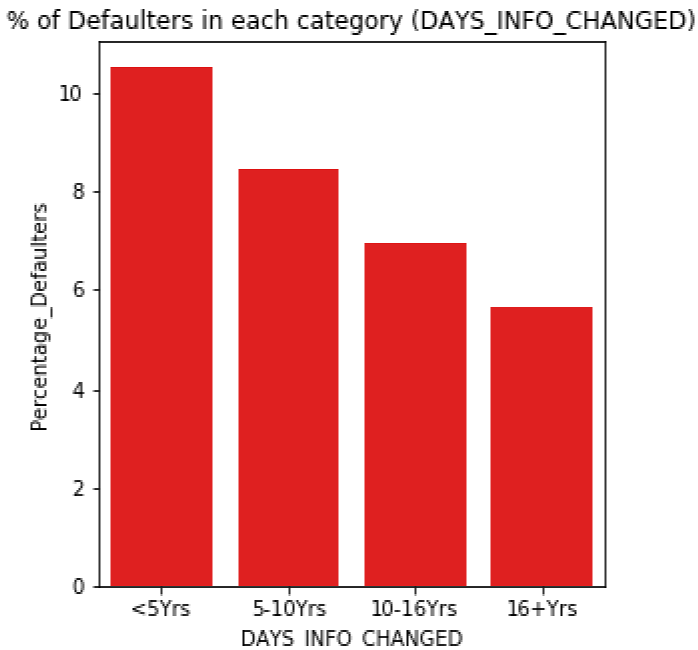


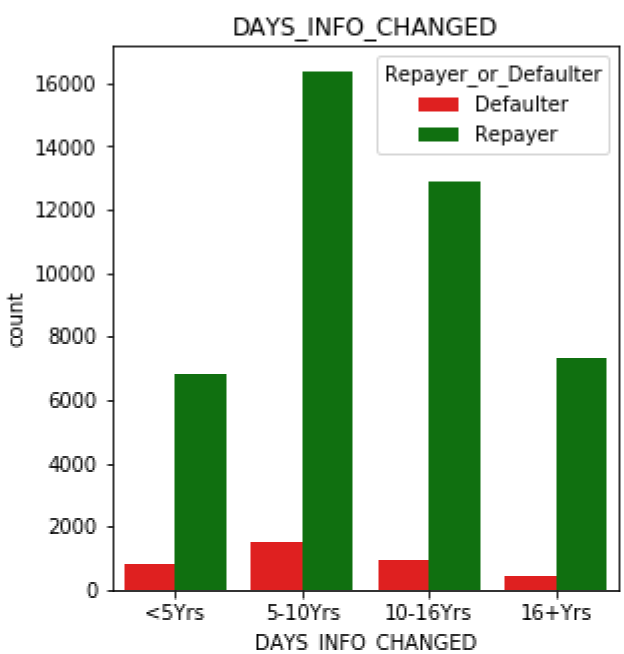


In [ ]:
```
#Insigits:-
#1)Clients whose address match percent <50% have more defaulting rate
#2)Clients whose address match percent is 100% have less defaulting rate (<8%)
```

In [ ]:
```
## DAYS_INFO_CHANGED (Registration & ID)
```

In [104]:
```
appln_data['DAYS_REGISTRATION']=appln_data['DAYS_REGISTRATION'].apply(lambda x:int(x))
appln_data['DAYS_ID_PUBLISH']=appln_data['DAYS_ID_PUBLISH'].apply(lambda x:int(x*-1))
appln_data['DAYS_INFO_CHANGED']=appln_data[['DAYS_REGISTRATION', 'DAYS_ID_PUBLISH']].mea
n(axis=1)
appln_data['DAYS_INFO_CHANGED'].describe()
appln_data['DAYS_INFO_CHANGED']=pd.cut(appln_data['DAYS_INFO_CHANGED'], [0,2000,4000,600
0,999999], labels=['<5Yrs', '5-10Yrs', '10-16Yrs', '16+Yrs'])
appln_data_univariate_categorical('DAYS_INFO_CHANGED')
```

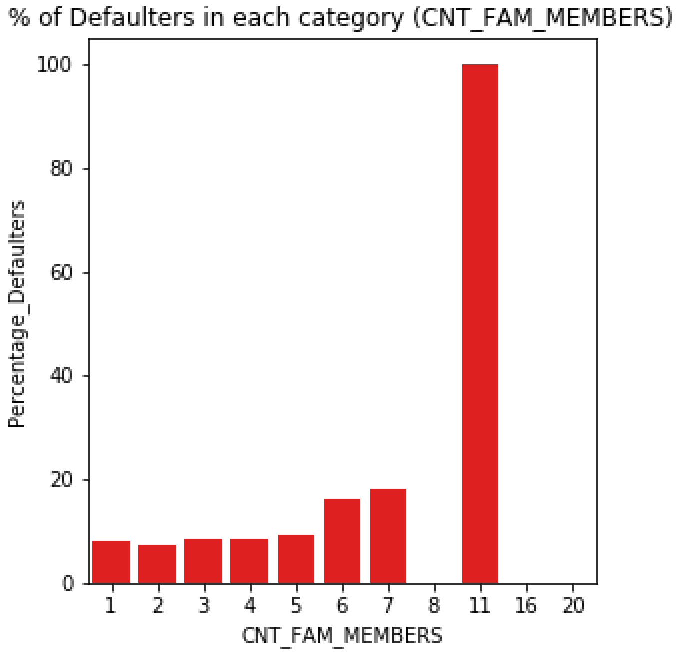


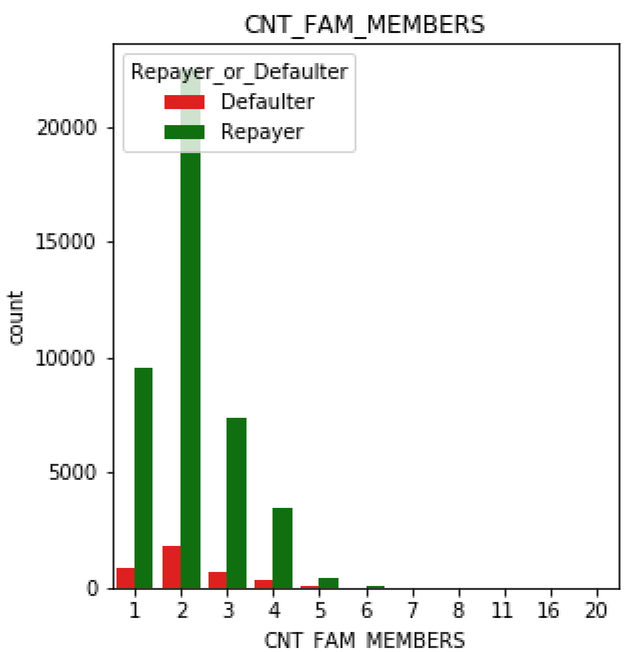


In [ ]:
```
#Insights:-
#1)Clients who have changed their information <5 years have more defaulting rate
#2)Clients who have changed their information >5 years have less defaulting rate
#3)Clients who have changed their information >16 years age have very less defaulting ra
te (Less risk asccociated)
```

In [ ]:
```
##CNT_FAM_MEMBERS
```

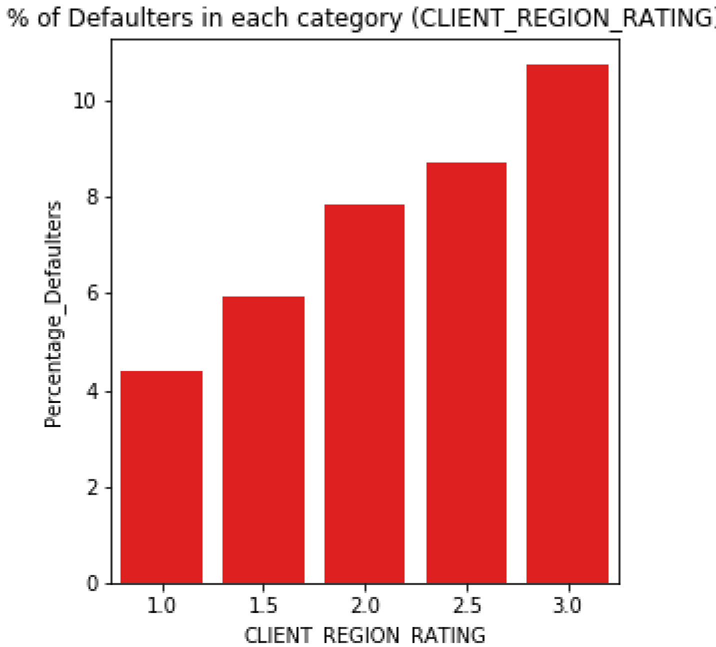
In [105]:
```
appln_data['CNT_FAM_MEMBERS']=appln_data['CNT_FAM_MEMBERS'].astype(int)
appln_data_univariate_categorical('CNT_FAM_MEMBERS')
```

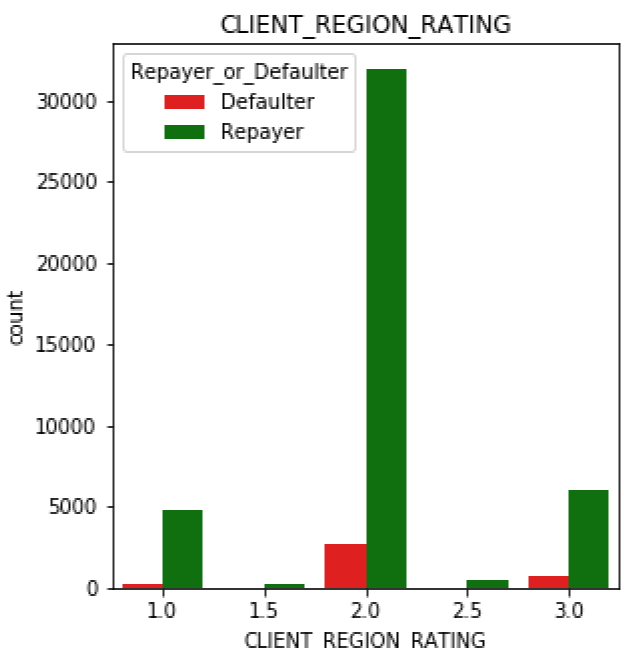




In [ ]:
```
#Insights:-
#Clients having the family members <=5 have lesser defaulting rate
```

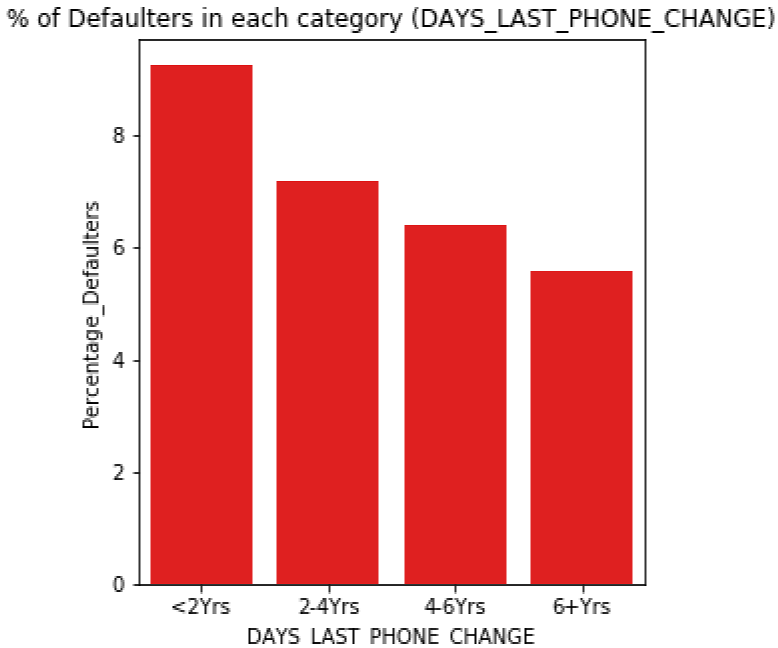
In [106]:
```
#CLIENT_REGION_RATING (1-3, 1:-Low & 3:-High)
appln_data_univariate_categorical('CLIENT_REGION_RATING')
```

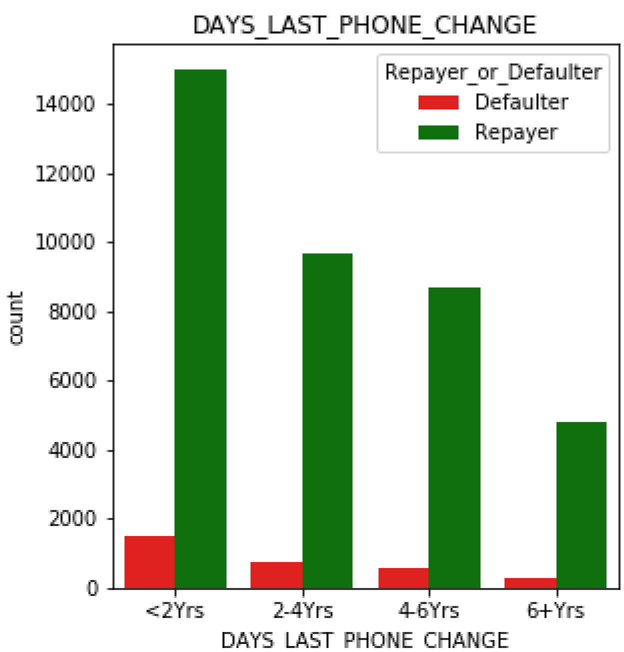




In [ ]:
```
#Insights:-
#1)Clients from region that has 3 rating have higher defaulting rate
#2)Clients from region that has <2 rating have lesser defaulting rate
#3)Clients from region that has 2 rating have medium defaulting rate (Acceptable range)
```

In [107]:
```
#DAYS_LAST_PHONE_CHANGE
appln_data['DAYS_LAST_PHONE_CHANGE']=pd.cut(appln_data['DAYS_LAST_PHONE_CHANGE'], [0,700,1400,2100,999999], labels=['<2Yrs', '2-4Yrs', '4-6Yrs', '6+Yrs'])
appln_data_univariate_categorical('DAYS_LAST_PHONE_CHANGE')
```





In [ ]:
```
#nsights:-
#1)Clients who have changed their phone numbers within 2 years from the date of loan application have higher defaulting rate
#2)Clients who have changed their phone numbers long back (>6 years) have lesser defaulting rate
#3)More the years of last phone change, lesser is the defaulting rate
```

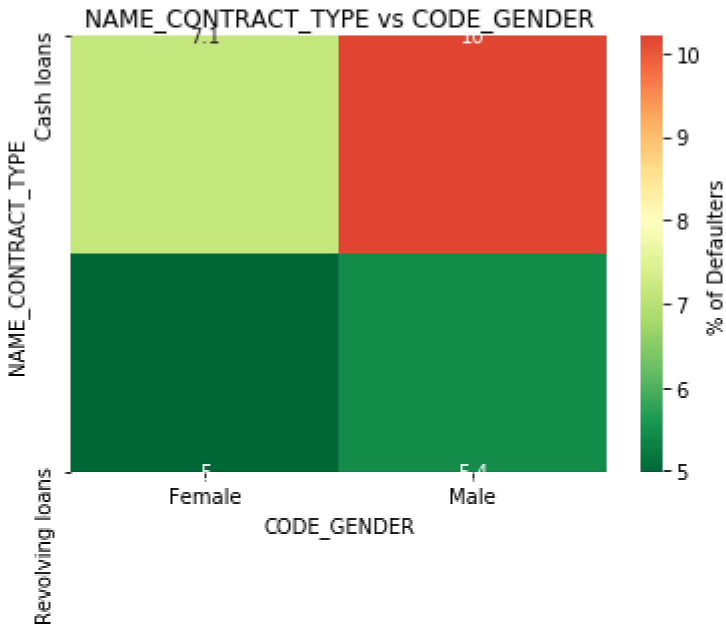
In [ ]:
```
##Bivariate Analysis
#target: TARGET column
```

In [ ]:
```
#function to call heatmap
```

In [124]:
```
def appln_data_heatmap(x,y):
    a=appln_data.pivot_table(index=x,columns=y,values='TARGET_PERCENT')
    sns.heatmap(a, cmap='RdYlGn_r', center=8, annot=True ,cbar_kws={'label': '% of Defau
lters'})
    plt.title(x+' vs '+y)
    plt.show()
```

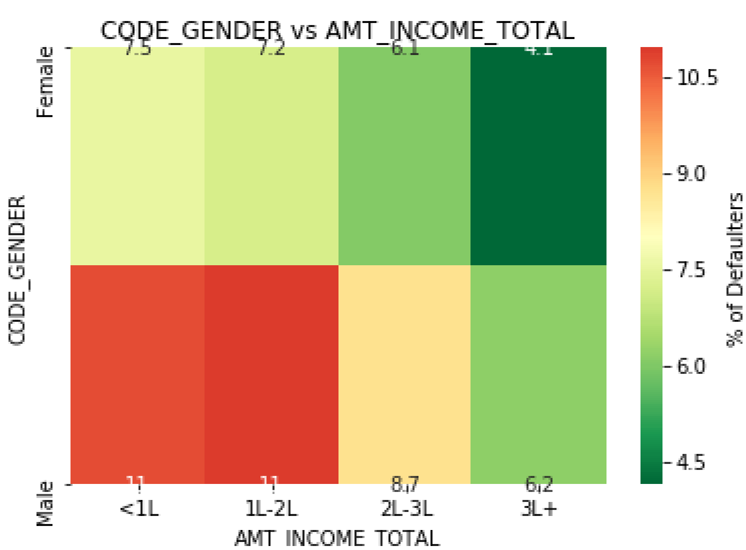
In [ ]:
```
#NAME_CONTRACT_TYPE vs CODE_GENDER
```

In [125]:
```
appln_data_heatmap('NAME_CONTRACT_TYPE', 'CODE_GENDER')
```



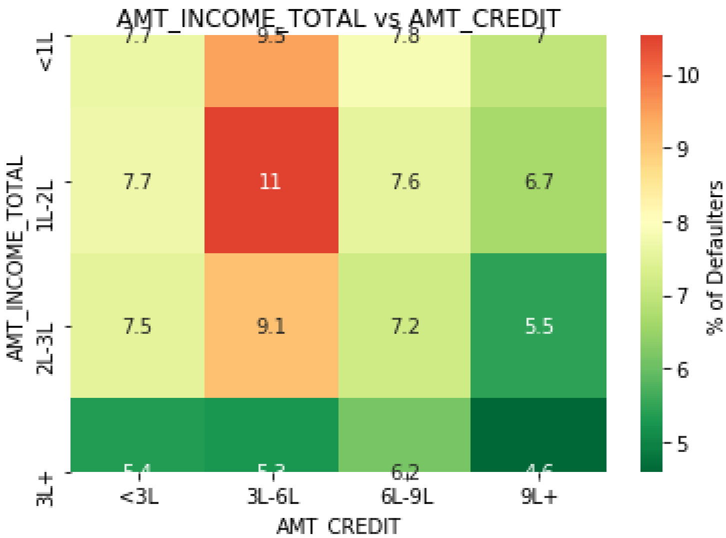
In [ ]:
```
#Insights:-
#1)High defaulting rate under Male - Cash loans category (10%)
#2)Low defaulting rate under Female - Revolving loans category (5%)
#3)Female-Cash loans category are in acceptable range (7.1%)
```

In [126]:
```
#CODE_GENDER vs AMT_INCOME_TOTAL
appln_data_heatmap('CODE_GENDER', 'AMT_INCOME_TOTAL')
```



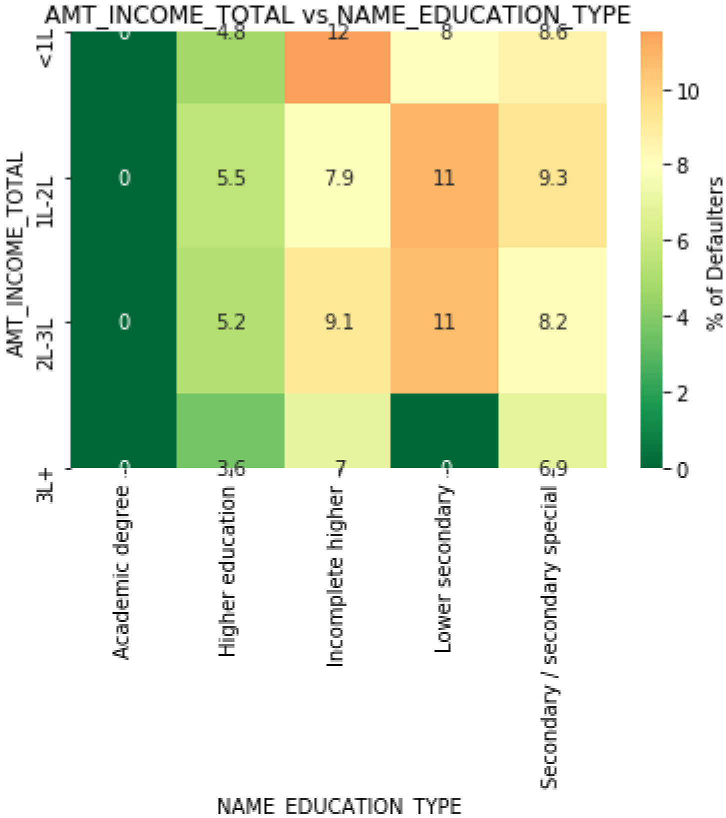
In [ ]:
```
#Insights:-
#1)Male clients with income <1 Lakh have high defaulting rate (11%)
#2)Female clients with income >3 Lakh have less defaulting rate(4.1%)
```

In [127]:
```
#AMT_INCOME_TOTAL vs AMT_CREDIT
appln_data_heatmap('AMT_INCOME_TOTAL', 'AMT_CREDIT')
```



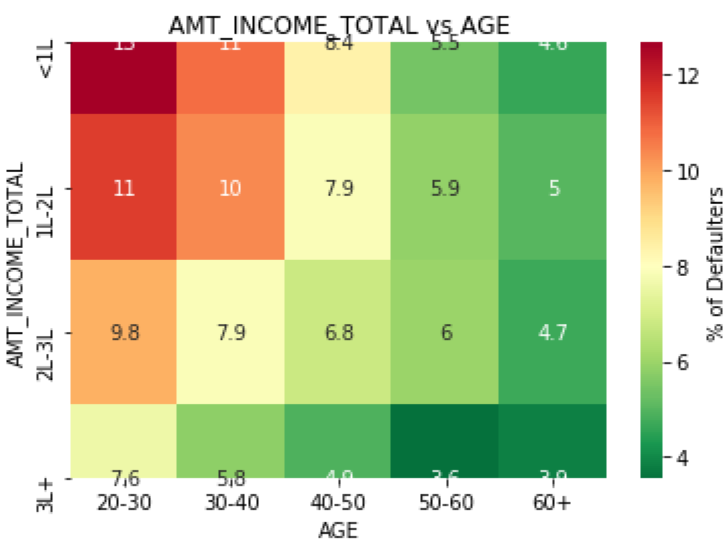
In [ ]:
```
#Insights:-
#1)Clients with less income and credit amount requested higher than their income have hi
gh defaulting rate (11%)
#2)Clients with more salary and equivalent credit amount requested have less defaulting
rate (5-6%) (Less risk)
```

In [128]:
```
#AMT_INCOME_TOTAL vs NAME_EDUCATION_TYPE
appln_data_heatmap('AMT_INCOME_TOTAL', 'NAME_EDUCATION_TYPE')
```



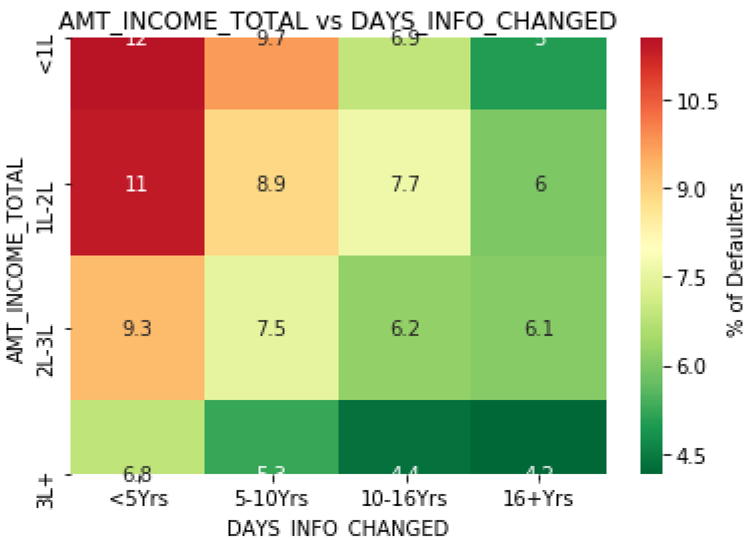
In [ ]:
```
#Insights:-
#1)Clients with Academic degree and Higher education with all income levels have very le
ss defaulting rate
#2)Clients with other education types (with all income levels) have little higher defaul
ting rate comparatively
```

In [130]:
```
#AMT_INCOME_TOTAL vs AGE
appln_data_heatmap('AMT_INCOME_TOTAL', 'AGE')
```



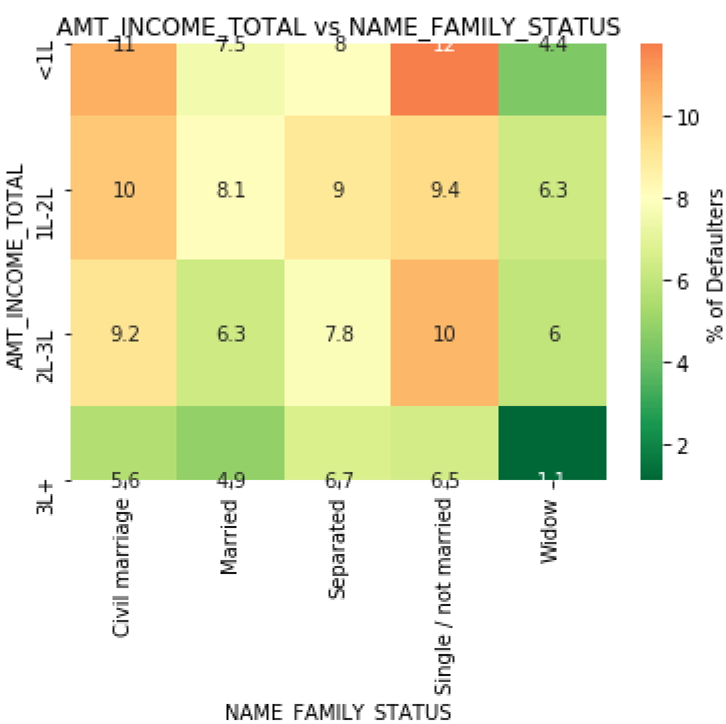
In [ ]:
```
#Insights:-
#1)Young clients whose age is 20-40 with income level <2-3 Lakh have high defaulting rat
es
#2)Clients whose age is more than 50 with all income levels have less defaulting rate (L
ess risk)
#3)More the age and more the income, lesser is the defaulting rate
```

In [131]:
```
appln_data_heatmap('AMT_INCOME_TOTAL', 'DAYS_INFO_CHANGED')
```



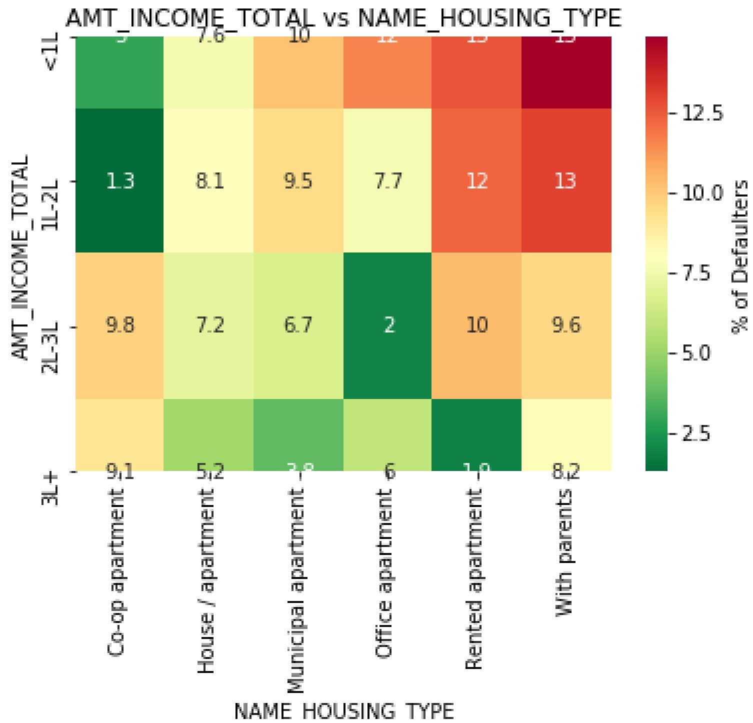
In [ ]:
```
# Insights:-
#1)Clients with lower salary and who have changed their documents in <5 years have high
defaulting rate
#2)Clients with all levels of salary and who haven't changed their documents from long t
ime (>10 years) have lesser defaulting rate (less risk associated)
```

In [132]:
```
appln_data_heatmap('AMT_INCOME_TOTAL', 'NAME_FAMILY_STATUS')
```



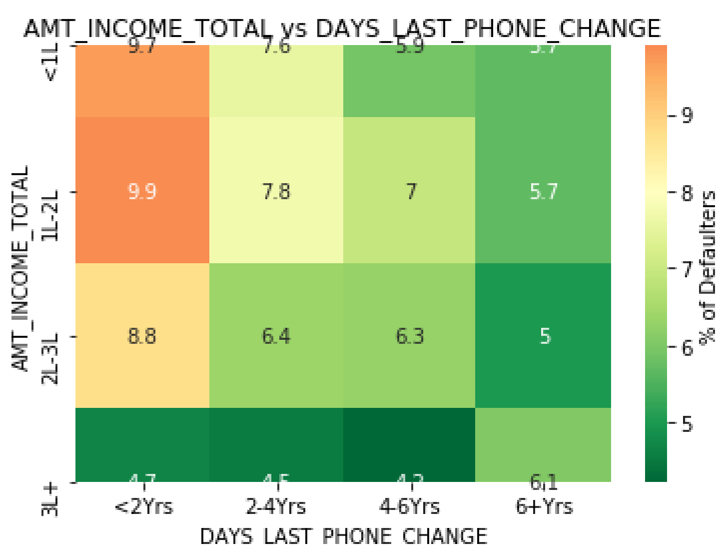
In [ ]:
```
#Insights:-
#1)Widow clients with all types of income levels have less defaulting rate (4-6%)
#2)All types of clients with high income level have average defaulting rate (6-7%)
```

In [133]:
```
appln_data_heatmap('AMT_INCOME_TOTAL', 'NAME_HOUSING_TYPE')
```



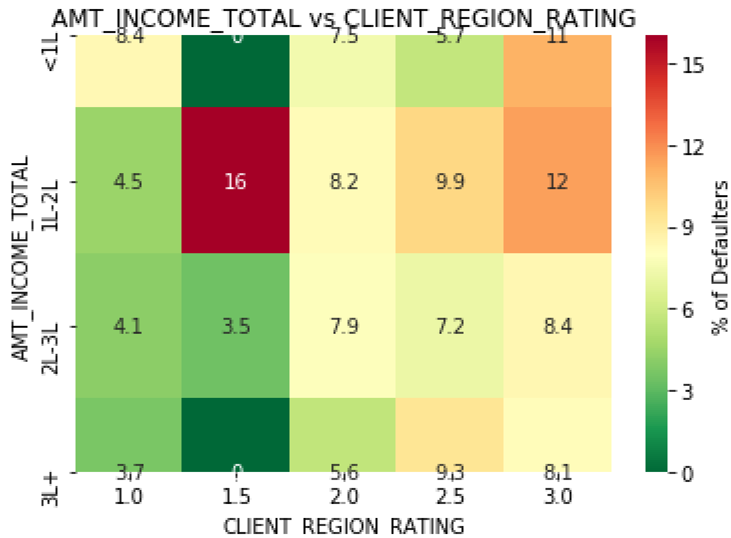
In [ ]:
```
#Insights:-
#1)Clients with income <2 Lakhs who have either rented apartment or with their parents h
ave very high defaulting rate (10-13%)
#2)Other clients who have owned apartment / office apartments have average defaulting ra
te (6-8%)
#3)Clients with office apartment or owned house/apartment with high income have very les
s defaulting rate (3-6%)
```

In [134]:
```
appln_data_heatmap('AMT_INCOME_TOTAL', 'DAYS_LAST_PHONE_CHANGE')
```



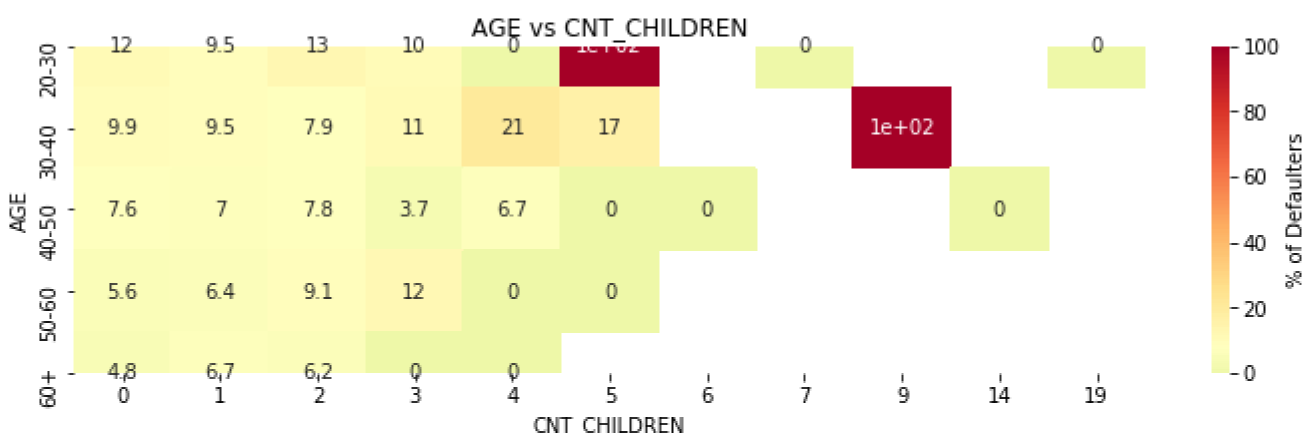
In [ ]:
```
#Insights
#1)Clients who have changed their phone number in <2-3 years have high defaulting rates
#2)Clients holding their phone number for longer duration (>5-6 years) have less default
ing rate (Less risk associated)
```

In [135]:
```
appln_data_heatmap('AMT_INCOME_TOTAL', 'CLIENT_REGION_RATING')
```



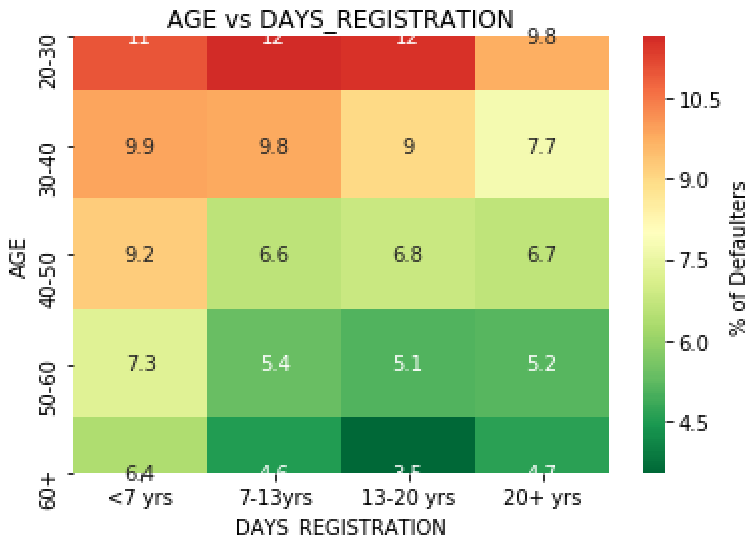
In [ ]:
```
#Insights:-
#1)Clients whose region rating is <=1 with all levels of income have less defaulting rat
e
#2)Clients whose region rating is between 1.5-2.5 have acceptable defaulting rate
#3)Clients from region rated with 3 (of all income levels) have high defaulting rates
```

In [136]:
```
plt.figure(figsize=(12,3))
appln_data_heatmap('AGE', 'CNT_CHILDREN')
plt.show()
```



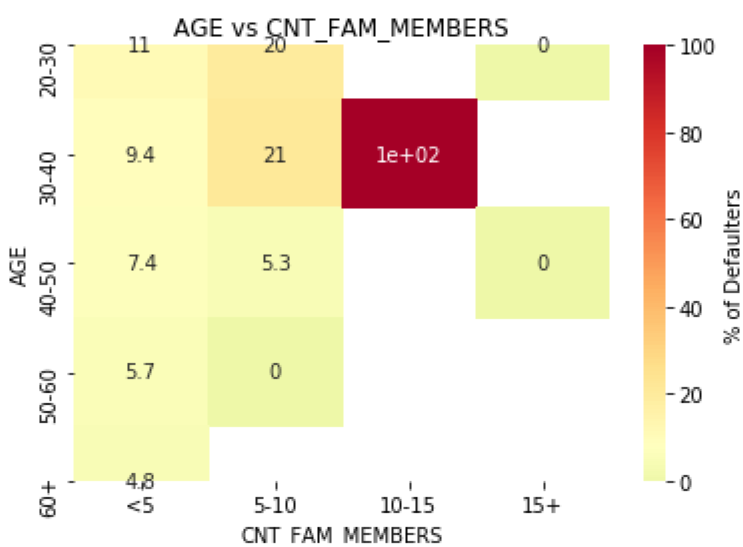
In [ ]:
```
#Insights
#1)Young Clients with more children have high defaulting rate
#2)Older clients with less children have less defaulting rate (Less risk associated)
```

In [137]:
```python
appln_data['DAYS_REGISTRATION']=pd.cut(appln_data['DAYS_REGISTRATION'], [0,2500,5000,7500,99999999], labels=['<7 yrs', '7-13yrs', '13-20 yrs', '20+ yrs'])
appln_data_heatmap('AGE', 'DAYS_REGISTRATION')
```



In [ ]:
```python
#Insights
#1)Young Clients who have changed their registration within 7-10 years have high defaulting rate
#2)Older clients who have changed their registration 15-20 years ago have less defaulting rate (Less risk associated)
```

In [138]:
```python
appln_data['CNT_FAM_MEMBERS']=pd.cut(appln_data['CNT_FAM_MEMBERS'], [0,5,10,15,200], labels=['<5', '5-10', '10-15', '15+'])
appln_data_heatmap('AGE', 'CNT_FAM_MEMBERS')
```



In [ ]:
```python
#Insights
#1)Mid & older clients with family members <5 have less defaulting rate (Less risk associated)
#2)Others have high defaulting rate or less/no data
```

In [ ]:
```python
#Previous Applications Data
```

In [142]:
```
pre_appln_data.head()
```

Out[142]:

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

5 rows × 37 columns

In [144]:
```
pre_appln_data.shape
```

Out[144]:
```
(1670214, 37)
```

In [145]:
```
pre_appln_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):
SK_ID_PREV                     1670214 non-null int64
SK_ID_CURR                     1670214 non-null int64
NAME_CONTRACT_TYPE             1670214 non-null object
AMT_ANNUITY                    1297979 non-null float64
AMT_APPLICATION                1670214 non-null float64
AMT_CREDIT                     1670213 non-null float64
AMT_DOWN_PAYMENT               774370 non-null float64
AMT_GOODS_PRICE                1284699 non-null float64
WEEKDAY_APPR_PROCESS_START     1670214 non-null object
HOUR_APPR_PROCESS_START        1670214 non-null int64
FLAG_LAST_APPL_PER_CONTRACT    1670214 non-null object
NFLAG_LAST_APPL_IN_DAY         1670214 non-null int64
RATE_DOWN_PAYMENT              774370 non-null float64
RATE_INTEREST_PRIMARY          5951 non-null float64
RATE_INTEREST_PRIVILEGED       5951 non-null float64
NAME_CASH_LOAN_PURPOSE         1670214 non-null object
NAME_CONTRACT_STATUS           1670214 non-null object
DAYS_DECISION                  1670214 non-null int64
NAME_PAYMENT_TYPE              1670214 non-null object
CODE_REJECT_REASON             1670214 non-null object
NAME_TYPE_SUITE                849809 non-null object
NAME_CLIENT_TYPE               1670214 non-null object
NAME_GOODS_CATEGORY            1670214 non-null object
NAME_PORTFOLIO                 1670214 non-null object
NAME_PRODUCT_TYPE              1670214 non-null object
CHANNEL_TYPE                   1670214 non-null object
SELLERPLACE_AREA               1670214 non-null int64
NAME_SELLER_INDUSTRY           1670214 non-null object
CNT_PAYMENT                    1297984 non-null float64
NAME_YIELD_GROUP               1670214 non-null object
PRODUCT_COMBINATION            1669868 non-null object
DAYS_FIRST_DRAWING             997149 non-null float64
DAYS_FIRST_DUE                 997149 non-null float64
DAYS_LAST_DUE_1ST_VERSION      997149 non-null float64
DAYS_LAST_DUE                  997149 non-null float64
DAYS_TERMINATION               997149 non-null float64
NFLAG_INSURED_ON_APPROVAL      997149 non-null float64
dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB
```

In [146]:
```
pre_appln_data.describe()
```
Out[146]:

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

8 rows × 21 columns

In [ ]:
```
#Handling Missing Values & Data Sanity Check
```

In [150]:
```
pre_appln_data.isna().sum().sort_values(ascending=False)
```

Out[150]:
```
RATE_INTEREST_PRIVILEGED       1664263
RATE_INTEREST_PRIMARY          1664263
RATE_DOWN_PAYMENT               895844
AMT_DOWN_PAYMENT                895844
NAME_TYPE_SUITE                 820405
DAYS_TERMINATION                673065
NFLAG_INSURED_ON_APPROVAL       673065
DAYS_FIRST_DRAWING              673065
DAYS_FIRST_DUE                  673065
DAYS_LAST_DUE_1ST_VERSION       673065
DAYS_LAST_DUE                   673065
AMT_GOODS_PRICE                 385515
AMT_ANNUITY                     372235
CNT_PAYMENT                     372230
PRODUCT_COMBINATION                346
AMT_CREDIT                           1
SK_ID_CURR                           0
NAME_CONTRACT_TYPE                   0
WEEKDAY_APPR_PROCESS_START           0
HOUR_APPR_PROCESS_START              0
FLAG_LAST_APPL_PER_CONTRACT          0
NFLAG_LAST_APPL_IN_DAY               0
AMT_APPLICATION                      0
NAME_PAYMENT_TYPE                    0
NAME_CASH_LOAN_PURPOSE               0
NAME_CONTRACT_STATUS                 0
DAYS_DECISION                        0
CODE_REJECT_REASON                   0
NAME_CLIENT_TYPE                     0
NAME_GOODS_CATEGORY                  0
NAME_PORTFOLIO                       0
NAME_PRODUCT_TYPE                    0
CHANNEL_TYPE                         0
SELLERPLACE_AREA                     0
NAME_SELLER_INDUSTRY                 0
NAME_YIELD_GROUP                     0
SK_ID_PREV                           0
dtype: int64
```

In [ ]:
```
#% of missing values
```

In [154]:
```
pre_appln_data.isna().mean().sort_values(ascending=False)*100
```

Out[154]:
```
RATE_INTEREST_PRIVILEGED      99.643698
RATE_INTEREST_PRIMARY         99.643698
RATE_DOWN_PAYMENT             53.636480
AMT_DOWN_PAYMENT              53.636480
NAME_TYPE_SUITE               49.119754
DAYS_TERMINATION              40.298129
NFLAG_INSURED_ON_APPROVAL     40.298129
DAYS_FIRST_DRAWING            40.298129
DAYS_FIRST_DUE                40.298129
DAYS_LAST_DUE_1ST_VERSION     40.298129
DAYS_LAST_DUE                 40.298129
AMT_GOODS_PRICE               23.081773
AMT_ANNUITY                   22.286665
CNT_PAYMENT                   22.286366
PRODUCT_COMBINATION            0.020716
AMT_CREDIT                     0.000060
SK_ID_CURR                     0.000000
NAME_CONTRACT_TYPE             0.000000
WEEKDAY_APPR_PROCESS_START     0.000000
HOUR_APPR_PROCESS_START        0.000000
FLAG_LAST_APPL_PER_CONTRACT    0.000000
NFLAG_LAST_APPL_IN_DAY         0.000000
AMT_APPLICATION                0.000000
NAME_PAYMENT_TYPE              0.000000
NAME_CASH_LOAN_PURPOSE         0.000000
NAME_CONTRACT_STATUS           0.000000
DAYS_DECISION                  0.000000
CODE_REJECT_REASON             0.000000
NAME_CLIENT_TYPE               0.000000
NAME_GOODS_CATEGORY            0.000000
NAME_PORTFOLIO                 0.000000
NAME_PRODUCT_TYPE              0.000000
CHANNEL_TYPE                   0.000000
SELLERPLACE_AREA               0.000000
NAME_SELLER_INDUSTRY           0.000000
NAME_YIELD_GROUP               0.000000
SK_ID_PREV                     0.000000
dtype: float64
```

In [ ]:
```
#Dropping Columns with Missing Values >40%
```

In [155]:
```
col_null_40_pre_appln_data=pre_appln_data.columns[pre_appln_data.isna().mean()*100>40]
pre_appln_data.drop(columns=col_null_40_pre_appln_data, inplace=True) #Dropped the colum
ns that had the null values >40%
```

In [156]:
```
pre_appln_data.isna().mean().sort_values(ascending=False)*100
```

Out[156]:
```
AMT_GOODS_PRICE               23.081773
AMT_ANNUITY                   22.286665
CNT_PAYMENT                   22.286366
PRODUCT_COMBINATION            0.020716
AMT_CREDIT                     0.000060
NAME_CASH_LOAN_PURPOSE         0.000000
SK_ID_CURR                     0.000000
NAME_CONTRACT_TYPE             0.000000
AMT_APPLICATION                0.000000
WEEKDAY_APPR_PROCESS_START     0.000000
HOUR_APPR_PROCESS_START        0.000000
FLAG_LAST_APPL_PER_CONTRACT    0.000000
NFLAG_LAST_APPL_IN_DAY         0.000000
NAME_CONTRACT_STATUS           0.000000
NAME_YIELD_GROUP               0.000000
DAYS_DECISION                  0.000000
NAME_PAYMENT_TYPE              0.000000
CODE_REJECT_REASON             0.000000
NAME_CLIENT_TYPE               0.000000
NAME_GOODS_CATEGORY            0.000000
NAME_PORTFOLIO                 0.000000
NAME_PRODUCT_TYPE              0.000000
CHANNEL_TYPE                   0.000000
SELLERPLACE_AREA               0.000000
NAME_SELLER_INDUSTRY           0.000000
SK_ID_PREV                     0.000000
dtype: float64
```

In [157]:
```
#Dealing the Null Values of 'AMT_CREDIT' Column
pre_appln_data=pre_appln_data[~pre_appln_data['AMT_CREDIT'].isna()]
```

In [ ]:
```
#Imputing the Null Values of the 'AMT_ANNUITY' Column (22.28% Null values)
#W.r.t the 'AMT_CREDIT' on average or median (here), applicants have Annual 10 installem
ents
#Therefore replacing the null values of 'AMT_ANNUITY' by dividing 'AMT_CREDIT' with 10
```

In [159]:
```
annual_installments=int((pre_appln_data['AMT_CREDIT']/pre_appln_data['AMT_ANNUITY']).med
ian())
pre_appln_data['AMT_ANNUITY'].fillna(pre_appln_data['AMT_CREDIT']/annual_installments, i
nplace=True)
```

In [ ]:
```
#Imputing the Null Values of 'AMT_GOODS_PRICE' column (23.08% Null values)
#As 'AMT_APPLICATION' will be based on 'AMT_GOODS_PRICE', filling the null values of 'AM
T_GOODS_PRICE' with the values of 'AMT_APPLICATION' column
```

In [160]:
```
pre_appln_data['AMT_GOODS_PRICE']=pre_appln_data['AMT_GOODS_PRICE'].fillna(pre_appln_dat
a['AMT_APPLICATION'])
```

In [ ]:
```
#Imputing the Null Values of 'CNT_PAYMENT' column (22.28% Null values)
#As 'CNT_PAYMENT' column is about the duration between the application and previous loan
credit. If the previous loan status is 'Canceled' or 'Refused' or 'Unused offer', then
'CNT_PAYMENT' will be Zero.
```

In [161]:
```
#Checking for the Loan status from 'NAME_CONTRACT_STATUS' column at the null places of 'CNT_PAYMENT' column
pre_appln_data[pre_appln_data['CNT_PAYMENT'].isna()]['NAME_CONTRACT_STATUS'].value_counts()
```

Out[161]:
```
Canceled        305805
Refused          40897
Unused offer     25524
Approved             4
Name: NAME_CONTRACT_STATUS, dtype: int64
```

In [162]:
```
# As the 'NAME_CONTRACT_STATUS' are in ['Canceled', 'Refused', 'Unused offer']
# Replacing null values with 0
pre_appln_data['CNT_PAYMENT']=pre_appln_data['CNT_PAYMENT'].fillna(0)
```

In [ ]:
```
#Dealing with the Null Values of 'PRODUCT_COMBINATION' column (0.02% Null values)¶
#Dropping the rows that has null values in the column 'PRODUCT_COMBINATION'
```

In [163]:
```
pre_appln_data=pre_appln_data[~pre_appln_data['PRODUCT_COMBINATION'].isna()]
```

In [164]:
```
#Final Check for the Null Values of all the Columns
pre_appln_data.isna().mean()*100
```

Out[164]:
```
SK_ID_PREV                     0.0
SK_ID_CURR                     0.0
NAME_CONTRACT_TYPE             0.0
AMT_ANNUITY                    0.0
AMT_APPLICATION                0.0
AMT_CREDIT                     0.0
AMT_GOODS_PRICE                0.0
WEEKDAY_APPR_PROCESS_START     0.0
HOUR_APPR_PROCESS_START        0.0
FLAG_LAST_APPL_PER_CONTRACT    0.0
NFLAG_LAST_APPL_IN_DAY         0.0
NAME_CASH_LOAN_PURPOSE         0.0
NAME_CONTRACT_STATUS           0.0
DAYS_DECISION                  0.0
NAME_PAYMENT_TYPE              0.0
CODE_REJECT_REASON             0.0
NAME_CLIENT_TYPE               0.0
NAME_GOODS_CATEGORY            0.0
NAME_PORTFOLIO                 0.0
NAME_PRODUCT_TYPE              0.0
CHANNEL_TYPE                   0.0
SELLERPLACE_AREA               0.0
NAME_SELLER_INDUSTRY           0.0
CNT_PAYMENT                    0.0
NAME_YIELD_GROUP               0.0
PRODUCT_COMBINATION            0.0
dtype: float64
```

In [165]:
```
pre_appln_data.head()
```

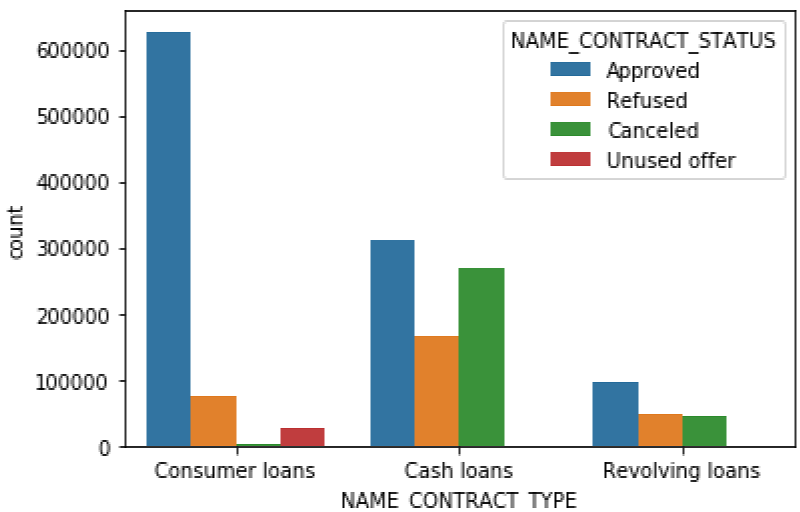
Out[165]:

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

5 rows × 26 columns

In [ ]:
```
#Univariate & Multivariate Analysis
#Target:- 'NAME_CONTRACT_STATUS'
```

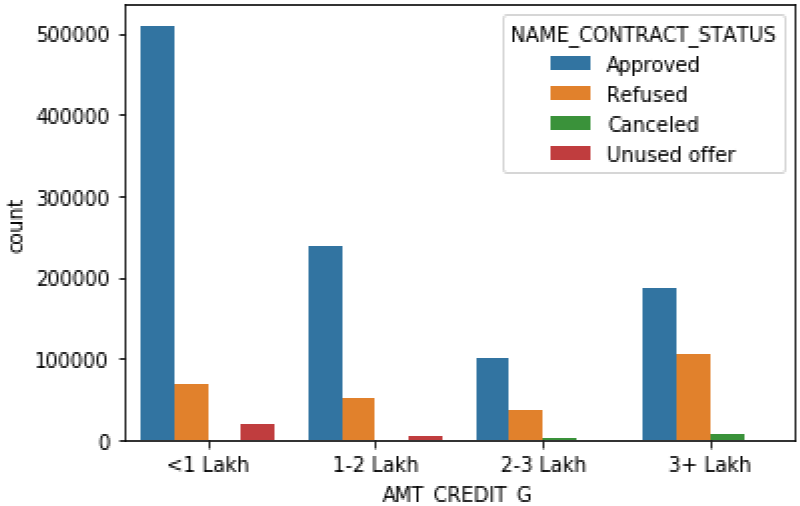
In [166]:
```
#NAME_CONTRACT_TYPE
sns.countplot(data=pre_appln_data, x=pre_appln_data['NAME_CONTRACT_TYPE'], hue=pre_appln
_data['NAME_CONTRACT_STATUS'])
plt.show()
```



In [ ]:
```
#Insights:-
#1)More clients are cancelling the loans themselves under cash loans category
#2)Consumer loans has the highest approval rate and lowest cancellations by the clients
```

In [167]:

```
#AMT_CREDIT_G ('AMT_CREDIT' grouped
pre_appln_data['AMT_CREDIT_G']=pd.cut(pre_appln_data['AMT_CREDIT'], [0,100000,200000,300000,9999999999], labels=['<1 Lakh','1-2 Lakh', '2-3 Lakh', '3+ Lakh'])
sns.countplot(data=pre_appln_data, x=pre_appln_data['AMT_CREDIT_G'], hue=pre_appln_data['NAME_CONTRACT_STATUS'])
plt.show()
```

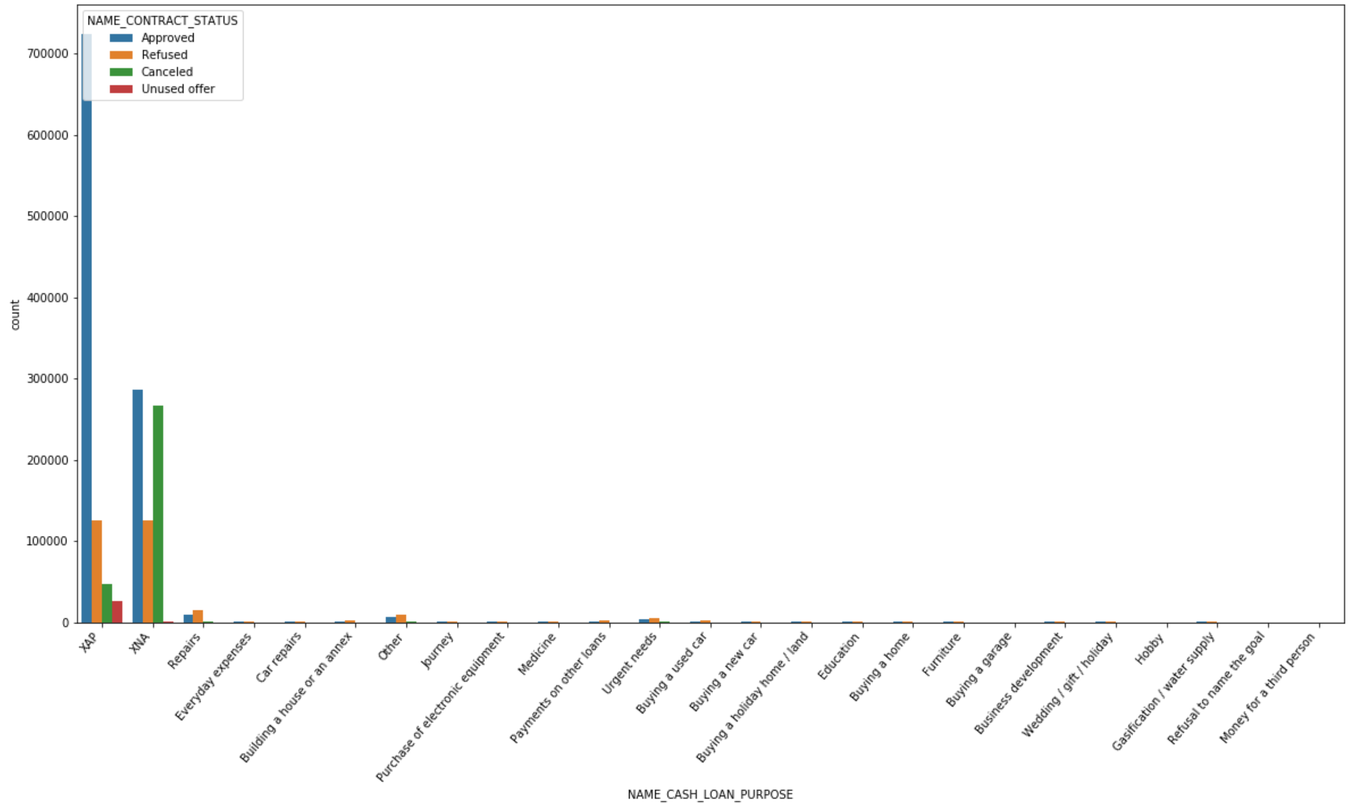


In [ ]:

```
#Insights:-
#1)High approval rate for credit amount less than 1 lakh
#2)Less approval rate for credit amount more than 3 lakh
```

In [168]:

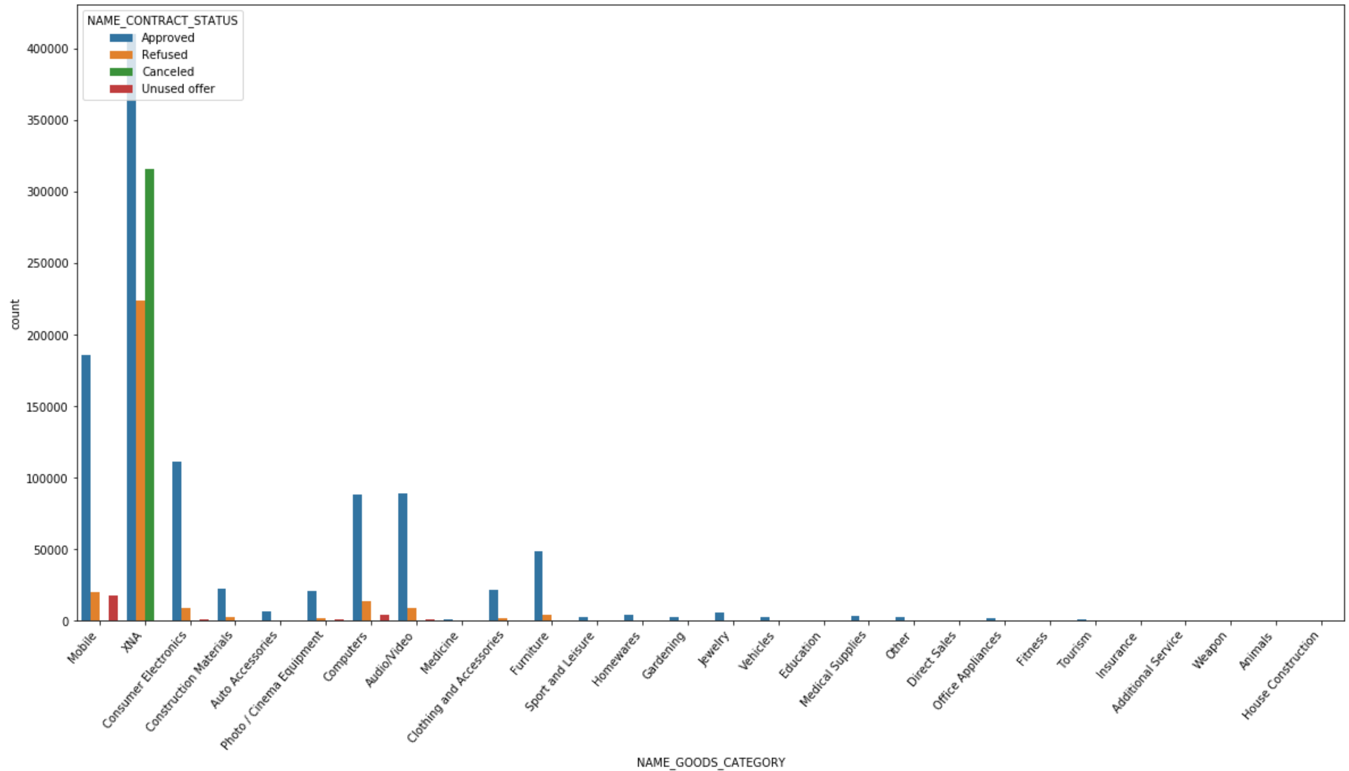
```
#NAME_CASH_LOAN_PURPOSE
plt.figure(figsize=(20,10))
plot=sns.countplot(data=pre_appln_data, x=pre_appln_data['NAME_CASH_LOAN_PURPOSE'], hue=
pre_appln_data['NAME_CONTRACT_STATUS'])
plot.set_xticklabels(plot.get_xticklabels(), rotation=50, horizontalalignment='right')
plt.show()
```



In [ ]:

```
#Insights:-
#Since majority of the values are XAP & XNA, not much useful insight was seen from this
plot
```

In [169]:
```
#NAME_GOODS_CATEGORY
plt.figure(figsize=(20,10))
plot=sns.countplot(data=pre_appln_data, x=pre_appln_data['NAME_GOODS_CATEGORY'], hue=pre_appln_data['NAME_CONTRACT_STATUS'])
plot.set_xticklabels(plot.get_xticklabels(), rotation=50, horizontalalignment='right')
plt.show()
```



In [ ]:
```
#Insights:-
#1)High approval rate can be expected for goods of mobile, consumer electronics, computers, clothing and furnitures, construction materials (Estimated based on the quantity of the data available)
#2)Again most of the data are XNA here
```

In [ ]:
```
#Merge the data
```

In [170]:
```
merged_appln_data_pre_appln_data=appln_data.merge(pre_appln_data,how='inner',on='SK_ID_CURR')
```

In [172]:
```
merged_appln_data_pre_appln_data.head()
```

Out[172]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE_x	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALT
0	100002	1	Cash loans	Male	No	Ye
1	100003	0	Cash loans	Female	No	N
2	100003	0	Cash loans	Female	No	N
3	100003	0	Cash loans	Female	No	N
4	100004	0	Revolving loans	Male	Yes	Ye

5 rows × 120 columns

In [174]:
```
merged_appln_data_pre_appln_data.shape
```

Out[174]:
```
(213341, 120)
```

In [175]:
```
merged_appln_data_pre_appln_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 213341 entries, 0 to 213340
Columns: 120 entries, SK_ID_CURR to AMT_CREDIT_G
dtypes: category(8), float64(46), int64(34), object(32)
memory usage: 185.6+ MB
```

In [176]:
```
merged_appln_data_pre_appln_data.describe()
```

Out[176]:

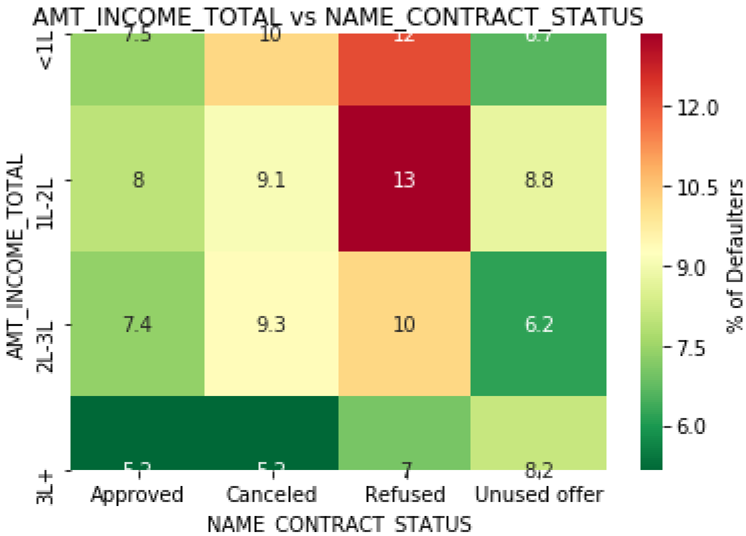
	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_ANNUITY_x	AMT_GOODS_PRICE_x	REGION_POP
count	213341.000000	213341.000000	213341.000000	213341.000000	2.133410e+05	
mean	428878.590974	0.085605	0.400073	27031.732107	5.288645e+05	
std	19443.192047	0.279780	0.712374	13938.301299	3.536244e+05	
min	100002.000000	0.000000	0.000000	1615.500000	4.050000e+04	
25%	417284.000000	0.000000	0.000000	16852.500000	2.385000e+05	
50%	429307.000000	0.000000	0.000000	24939.000000	4.500000e+05	
75%	442823.000000	0.000000	1.000000	34474.500000	6.795000e+05	
max	456255.000000	1.000000	19.000000	216589.500000	3.375000e+06	

8 rows × 80 columns

In [ ]:
```
#AMT_INCOME_TOTAL vs NAME_CONTRACT_STATUS (Target:- 'TARGET')
```

In [178]:

```
pivot=merged_appln_data_pre_appln_data.pivot_table(index='AMT_INCOME_TOTAL', columns='NAME_CONTRACT_STATUS', values='TARGET_PERCENT')
sns.heatmap(data=pivot, cmap='RdYlGn_r', annot=True, cbar_kws={'label':'% of Defaulters'})
plt.title('AMT_INCOME_TOTAL vs NAME_CONTRACT_STATUS')
plt.show()
```



In [ ]:

```
#Insights:-
#1)More defaulters have total income <1.75 Lakh who were rejected before
#2)Previously Rejected clients with income level less than 3 Lakh have high defaulting rate (>11%)
#3)Previously Approved clients with almost all income level have less defaulting rate (<7.5%)
```

In [ ]: