Importing Libraries

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

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

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

In [2]:
```
plt.rcParams['figure.figsize']=(10,5)
plt.style.use('ggplot')
```

In [3]:
```
pd.options.display.max_rows = 4000
pd.options.display.max_columns = 1000
```

Loading the data

In [4]:
```
data_dict = pd.read_csv("columns_description.csv")
data_dict.head(100)
```

Out[4]:

	Unnamed: 0	Table	Row	Description	Special
0	1	application_data	SK_ID_CURR	ID of loan in our sample	NaN
1	2	application_data	TARGET	Target variable (1 - client with payment diffi...	NaN
2	5	application_data	NAME_CONTRACT_TYPE	Identification if loan is cash or revolving	NaN
3	6	application_data	CODE_GENDER	Gender of the client	NaN
4	7	application_data	FLAG_OWN_CAR	Flag if the client owns a car	NaN
5	8	application_data	FLAG_OWN_REALTY	Flag if client owns a house or flat	NaN
6	9	application_data	CNT_CHILDREN	Number of children the client has	NaN
7	10	application_data	AMT_INCOME_TOTAL	Income of the client	NaN
8	11	application_data	AMT_CREDIT	Credit amount of the loan	NaN
9	12	application_data	AMT_ANNUITY	Loan annuity	NaN
10	13	application_data	AMT_GOODS_PRICE	For consumer loans it is the price of the good...	NaN
11	14	application_data	NAME_TYPE_SUITE	Who was accompanying client when he was applyi...	NaN
12	15	application_data	NAME_INCOME_TYPE	Clients income type (businessman, working, mat...	NaN
13	16	application_data	NAME_EDUCATION_TYPE	Level of highest education the client achieved	NaN
14	17	application_data	NAME_FAMILY_STATUS	Family status of the client	NaN
15	18	application_data	NAME_HOUSING_TYPE	What is the housing situation of the client (r...	NaN
16	19	application_data	REGION_POPULATION_RELATIVE	Normalized population of region where client l...	normalized
17	20	application_data	DAYS_BIRTH	Client's age in days at the time of application	time only relative to the application
18	21	application_data	DAYS_EMPLOYED	How many days before the application the perso...	time only relative to the application
19	22	application_data	DAYS_REGISTRATION	How many days before the application did clien...	time only relative to the application
20	23	application_data	DAYS_ID_PUBLISH	How many days before the application did clien...	time only relative to the application
21	24	application_data	OWN_CAR_AGE	Age of client's car	NaN
22	25	application_data	FLAG_MOBIL	Did client provide mobile phone (1=YES, 0=NO)	NaN
23	26	application_data	FLAG_EMP_PHONE	Did client provide work phone (1=YES, 0=NO)	NaN

	Unnamed: 0	Table	Row	Description	Special
24	27	application_data	FLAG_WORK_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
25	28	application_data	FLAG_CONT_MOBILE	Was mobile phone reachable (1=YES, 0=NO)	NaN
26	29	application_data	FLAG_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
27	30	application_data	FLAG_EMAIL	Did client provide email (1=YES, 0=NO)	NaN
28	31	application_data	OCCUPATION_TYPE	What kind of occupation does the client have	NaN
29	32	application_data	CNT_FAM_MEMBERS	How many family members does client have	NaN
30	33	application_data	REGION_RATING_CLIENT	Our rating of the region where client lives (1...	NaN
31	34	application_data	REGION_RATING_CLIENT_W_CITY	Our rating of the region where client lives wi...	NaN
32	35	application_data	WEEKDAY_APPR_PROCESS_START	On which day of the week did the client apply ...	NaN
33	36	application_data	HOUR_APPR_PROCESS_START	Approximately at what hour did the client appl...	rounded
34	37	application_data	REG_REGION_NOT_LIVE_REGION	Flag if client's permanent address does not ma...	NaN
35	38	application_data	REG_REGION_NOT_WORK_REGION	Flag if client's permanent address does not ma...	NaN
36	39	application_data	LIVE_REGION_NOT_WORK_REGION	Flag if client's contact address does not matc...	NaN
37	40	application_data	REG_CITY_NOT_LIVE_CITY	Flag if client's permanent address does not ma...	NaN
38	41	application_data	REG_CITY_NOT_WORK_CITY	Flag if client's permanent address does not ma...	NaN
39	42	application_data	LIVE_CITY_NOT_WORK_CITY	Flag if client's contact address does not matc...	NaN
40	43	application_data	ORGANIZATION_TYPE	Type of organization where client works	NaN
41	44	application_data	EXT_SOURCE_1	Normalized score from external data source	normalized
42	45	application_data	EXT_SOURCE_2	Normalized score from external data source	normalized
43	46	application_data	EXT_SOURCE_3	Normalized score from external data source	normalized
44	47	application_data	APARTMENTS_AVG	Normalized information about building where th...	normalized
45	48	application_data	BASEMENTAREA_AVG	Normalized information about building where th...	normalized
46	49	application_data	YEARS_BEGINEXPLUATATION_AVG	Normalized information about building where th...	normalized
47	50	application_data	YEARS_BUILD_AVG	Normalized information about building where th...	normalized

	Unnamed: 0	Table	Row	Description	Special
48	51	application_data	COMMONAREA_AVG	Normalized information about building where th...	normalized
49	52	application_data	ELEVATORS_AVG	Normalized information about building where th...	normalized
50	53	application_data	ENTRANCES_AVG	Normalized information about building where th...	normalized
51	54	application_data	FLOORSMAX_AVG	Normalized information about building where th...	normalized
52	55	application_data	FLOORSMIN_AVG	Normalized information about building where th...	normalized
53	56	application_data	LANDAREA_AVG	Normalized information about building where th...	normalized
54	57	application_data	LIVINGAPARTMENTS_AVG	Normalized information about building where th...	normalized
55	58	application_data	LIVINGAREA_AVG	Normalized information about building where th...	normalized
56	59	application_data	NONLIVINGAPARTMENTS_AVG	Normalized information about building where th...	normalized
57	60	application_data	NONLIVINGAREA_AVG	Normalized information about building where th...	normalized
58	61	application_data	APARTMENTS_MODE	Normalized information about building where th...	normalized
59	62	application_data	BASEMENTAREA_MODE	Normalized information about building where th...	normalized
60	63	application_data	YEARS_BEGINEXPLUATATION_MODE	Normalized information about building where th...	normalized
61	64	application_data	YEARS_BUILD_MODE	Normalized information about building where th...	normalized
62	65	application_data	COMMONAREA_MODE	Normalized information about building where th...	normalized
63	66	application_data	ELEVATORS_MODE	Normalized information about building where th...	normalized
64	67	application_data	ENTRANCES_MODE	Normalized information about building where th...	normalized
65	68	application_data	FLOORSMAX_MODE	Normalized information about building where th...	normalized
66	69	application_data	FLOORSMIN_MODE	Normalized information about building where th...	normalized
67	70	application_data	LANDAREA_MODE	Normalized information about building where th...	normalized
68	71	application_data	LIVINGAPARTMENTS_MODE	Normalized information about building where th...	normalized
69	72	application_data	LIVINGAREA_MODE	Normalized information about building where th...	normalized
70	73	application_data	NONLIVINGAPARTMENTS_MODE	Normalized information about building where th...	normalized
71	74	application_data	NONLIVINGAREA_MODE	Normalized information about building where th...	normalized

	Unnamed: 0	Table	Row	Description	Special
72	75	application_data	APARTMENTS_MEDI	Normalized information about building where th...	normalized
73	76	application_data	BASEMENTAREA_MEDI	Normalized information about building where th...	normalized
74	77	application_data	YEARS_BEGINEXPLUATATION_MEDI	Normalized information about building where th...	normalized
75	78	application_data	YEARS_BUILD_MEDI	Normalized information about building where th...	normalized
76	79	application_data	COMMONAREA_MEDI	Normalized information about building where th...	normalized
77	80	application_data	ELEVATORS_MEDI	Normalized information about building where th...	normalized
78	81	application_data	ENTRANCES_MEDI	Normalized information about building where th...	normalized
79	82	application_data	FLOORSMAX_MEDI	Normalized information about building where th...	normalized
80	83	application_data	FLOORSMIN_MEDI	Normalized information about building where th...	normalized
81	84	application_data	LANDAREA_MEDI	Normalized information about building where th...	normalized
82	85	application_data	LIVINGAPARTMENTS_MEDI	Normalized information about building where th...	normalized
83	86	application_data	LIVINGAREA_MEDI	Normalized information about building where th...	normalized
84	87	application_data	NONLIVINGAPARTMENTS_MEDI	Normalized information about building where th...	normalized
85	88	application_data	NONLIVINGAREA_MEDI	Normalized information about building where th...	normalized
86	89	application_data	FONDKAPREMONT_MODE	Normalized information about building where th...	normalized
87	90	application_data	HOUSETYPE_MODE	Normalized information about building where th...	normalized
88	91	application_data	TOTALAREA_MODE	Normalized information about building where th...	normalized
89	92	application_data	WALLSMATERIAL_MODE	Normalized information about building where th...	normalized
90	93	application_data	EMERGENCYSTATE_MODE	Normalized information about building where th...	normalized
91	94	application_data	OBS_30_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
92	95	application_data	DEF_30_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
93	96	application_data	OBS_60_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
94	97	application_data	DEF_60_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
95	98	application_data	DAYS_LAST_PHONE_CHANGE	How many days before application did client ch...	NaN

	Unnamed: 0	Table	Row	Description	Special
96	99	application_data	FLAG_DOCUMENT_2	Did client provide document 2	NaN
97	100	application_data	FLAG_DOCUMENT_3	Did client provide document 3	NaN
98	101	application_data	FLAG_DOCUMENT_4	Did client provide document 4	NaN
99	102	application_data	FLAG_DOCUMENT_5	Did client provide document 5	NaN

In [5]:
```
credit_data = pd.read_csv("application_data.csv")
credit_data.head(20)
```

Out[5]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CR
0	100002	1	Cash loans	M	N	Y	0	202500.000	406
1	100003	0	Cash loans	F	N	N	0	270000.000	1293
2	100004	0	Revolving loans	M	Y	Y	0	67500.000	135
3	100006	0	Cash loans	F	N	Y	0	135000.000	312
4	100007	0	Cash loans	M	N	Y	0	121500.000	513
5	100008	0	Cash loans	M	N	Y	0	99000.000	490
6	100009	0	Cash loans	F	Y	Y	1	171000.000	1560
7	100010	0	Cash loans	M	Y	Y	0	360000.000	1530
8	100011	0	Cash loans	F	N	Y	0	112500.000	1019
9	100012	0	Revolving loans	M	N	Y	0	135000.000	405
10	100014	0	Cash loans	F	N	Y	1	112500.000	652
11	100015	0	Cash loans	F	N	Y	0	38419.155	148
12	100016	0	Cash loans	F	N	Y	0	67500.000	80
13	100017	0	Cash loans	M	Y	N	1	225000.000	918
14	100018	0	Cash loans	F	N	Y	0	189000.000	773
15	100019	0	Cash loans	M	Y	Y	0	157500.000	299
16	100020	0	Cash loans	M	N	N	0	108000.000	509

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CR
17	100021	0	Revolving loans	F	N	Y	1	81000.000	270
18	100022	0	Revolving loans	F	N	Y	0	112500.000	157
19	100023	0	Cash loans	F	N	Y	1	90000.000	544

Data Wrangling

Inspecting the data

In [6]:
```
# checking the shape of the data

credit_data.shape
```

Out[6]:
```
(307511, 122)
```

In [7]:
```
# checking 5 point summary

credit_data.describe()
```

Out[7]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_REI
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307499.000000	3.072330e+05	307511.(
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.573909	5.383962e+05	0.(
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.737315	3.694465e+05	0.(
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	0.(
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.000000	2.385000e+05	0.(
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.000000	4.500000e+05	0.(
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.000000	6.795000e+05	0.(
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	0.(

In [8]:

```
null_perc=credit_data.isna().sum()*100/len(credit_data)
null_perc.sort_values(ascending=False)
```

Out[8]:
```
COMMONAREA_MEDI                69.872297
COMMONAREA_AVG                 69.872297
COMMONAREA_MODE                69.872297
NONLIVINGAPARTMENTS_MODE       69.432963
NONLIVINGAPARTMENTS_AVG        69.432963
NONLIVINGAPARTMENTS_MEDI       69.432963
FONDKAPREMONT_MODE             68.386172
LIVINGAPARTMENTS_MODE          68.354953
LIVINGAPARTMENTS_AVG           68.354953
LIVINGAPARTMENTS_MEDI          68.354953
FLOORSMIN_AVG                  67.848630
FLOORSMIN_MODE                 67.848630
FLOORSMIN_MEDI                 67.848630
YEARS_BUILD_MEDI               66.497784
YEARS_BUILD_MODE               66.497784
YEARS_BUILD_AVG                66.497784
OWN_CAR_AGE                    65.990810
LANDAREA_MEDI                  59.376738
LANDAREA_MODE                  59.376738
LANDAREA_AVG                   59.376738
BASEMENTAREA_MEDI              58.515956
BASEMENTAREA_AVG               58.515956
BASEMENTAREA_MODE              58.515956
EXT_SOURCE_1                   56.381073
NONLIVINGAREA_MODE             55.179164
NONLIVINGAREA_AVG              55.179164
NONLIVINGAREA_MEDI             55.179164
ELEVATORS_MEDI                 53.295980
ELEVATORS_AVG                  53.295980
ELEVATORS_MODE                 53.295980
WALLSMATERIAL_MODE             50.840783
APARTMENTS_MEDI                50.749729
APARTMENTS_AVG                 50.749729
APARTMENTS_MODE                50.749729
ENTRANCES_MEDI                 50.348768
ENTRANCES_AVG                  50.348768
ENTRANCES_MODE                 50.348768
LIVINGAREA_AVG                 50.193326
LIVINGAREA_MODE                50.193326
LIVINGAREA_MEDI                50.193326
HOUSETYPE_MODE                 50.176091
FLOORSMAX_MODE                 49.760822
FLOORSMAX_MEDI                 49.760822
FLOORSMAX_AVG                  49.760822
```

```
YEARS_BEGINEXPLUATATION_MODE    48.781019
YEARS_BEGINEXPLUATATION_MEDI    48.781019
YEARS_BEGINEXPLUATATION_AVG     48.781019
TOTALAREA_MODE                  48.268517
EMERGENCYSTATE_MODE             47.398304
OCCUPATION_TYPE                 31.345545
EXT_SOURCE_3                    19.825307
AMT_REQ_CREDIT_BUREAU_HOUR      13.501631
AMT_REQ_CREDIT_BUREAU_DAY       13.501631
AMT_REQ_CREDIT_BUREAU_WEEK      13.501631
AMT_REQ_CREDIT_BUREAU_MON       13.501631
AMT_REQ_CREDIT_BUREAU_QRT       13.501631
AMT_REQ_CREDIT_BUREAU_YEAR      13.501631
NAME_TYPE_SUITE                  0.420148
OBS_30_CNT_SOCIAL_CIRCLE         0.332021
DEF_30_CNT_SOCIAL_CIRCLE         0.332021
OBS_60_CNT_SOCIAL_CIRCLE         0.332021
DEF_60_CNT_SOCIAL_CIRCLE         0.332021
EXT_SOURCE_2                     0.214626
AMT_GOODS_PRICE                  0.090403
AMT_ANNUITY                      0.003902
CNT_FAM_MEMBERS                  0.000650
DAYS_LAST_PHONE_CHANGE           0.000325
CNT_CHILDREN                     0.000000
FLAG_DOCUMENT_8                  0.000000
NAME_CONTRACT_TYPE               0.000000
CODE_GENDER                      0.000000
FLAG_OWN_CAR                     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_9                  0.000000
FLAG_DOCUMENT_21                 0.000000
FLAG_DOCUMENT_10                 0.000000
FLAG_DOCUMENT_11                 0.000000
FLAG_OWN_REALTY                  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_18                 0.000000
FLAG_DOCUMENT_19                 0.000000
FLAG_DOCUMENT_20                 0.000000
FLAG_DOCUMENT_12                 0.000000
AMT_CREDIT                       0.000000
AMT_INCOME_TOTAL                 0.000000
FLAG_PHONE                       0.000000
LIVE_CITY_NOT_WORK_CITY          0.000000
REG_CITY_NOT_WORK_CITY           0.000000
TARGET                           0.000000
REG_CITY_NOT_LIVE_CITY           0.000000
LIVE_REGION_NOT_WORK_REGION      0.000000
REG_REGION_NOT_WORK_REGION       0.000000
REG_REGION_NOT_LIVE_REGION       0.000000
HOUR_APPR_PROCESS_START          0.000000
WEEKDAY_APPR_PROCESS_START       0.000000
REGION_RATING_CLIENT_W_CITY      0.000000
REGION_RATING_CLIENT             0.000000
FLAG_EMAIL                       0.000000
FLAG_CONT_MOBILE                 0.000000
ORGANIZATION_TYPE                0.000000
FLAG_WORK_PHONE                  0.000000
FLAG_EMP_PHONE                   0.000000
FLAG_MOBIL                       0.000000
DAYS_ID_PUBLISH                  0.000000
DAYS_REGISTRATION                0.000000
DAYS_EMPLOYED                    0.000000
DAYS_BIRTH                       0.000000
REGION_POPULATION_RELATIVE       0.000000
NAME_HOUSING_TYPE                0.000000
NAME_FAMILY_STATUS               0.000000
NAME_EDUCATION_TYPE              0.000000
NAME_INCOME_TYPE                 0.000000
SK_ID_CURR                       0.000000
dtype: float64
```

In [9]:

```
# filter top 60 columns with max null values

null_perc.sort_values(ascending=False).head(60)
```

Out[9]:

```
COMMONAREA_MEDI              69.872297
COMMONAREA_AVG               69.872297
COMMONAREA_MODE              69.872297
NONLIVINGAPARTMENTS_MODE     69.432963
NONLIVINGAPARTMENTS_AVG      69.432963
NONLIVINGAPARTMENTS_MEDI     69.432963
FONDKAPREMONT_MODE           68.386172
LIVINGAPARTMENTS_MODE        68.354953
LIVINGAPARTMENTS_AVG         68.354953
LIVINGAPARTMENTS_MEDI        68.354953
FLOORSMIN_AVG                67.848630
FLOORSMIN_MODE               67.848630
FLOORSMIN_MEDI               67.848630
YEARS_BUILD_MEDI             66.497784
YEARS_BUILD_MODE             66.497784
YEARS_BUILD_AVG              66.497784
OWN_CAR_AGE                  65.990810
LANDAREA_MEDI                59.376738
LANDAREA_MODE                59.376738
LANDAREA_AVG                 59.376738
BASEMENTAREA_MEDI            58.515956
BASEMENTAREA_AVG             58.515956
BASEMENTAREA_MODE            58.515956
EXT_SOURCE_1                 56.381073
NONLIVINGAREA_MODE           55.179164
NONLIVINGAREA_AVG            55.179164
NONLIVINGAREA_MEDI           55.179164
ELEVATORS_MEDI               53.295980
ELEVATORS_AVG                53.295980
ELEVATORS_MODE               53.295980
WALLSMATERIAL_MODE           50.840783
APARTMENTS_MEDI              50.749729
APARTMENTS_AVG               50.749729
APARTMENTS_MODE              50.749729
ENTRANCES_MEDI               50.348768
ENTRANCES_AVG                50.348768
ENTRANCES_MODE               50.348768
LIVINGAREA_AVG               50.193326
LIVINGAREA_MODE              50.193326
LIVINGAREA_MEDI              50.193326
HOUSETYPE_MODE               50.176091
FLOORSMAX_MODE               49.760822
FLOORSMAX_MEDI               49.760822
FLOORSMAX_AVG                49.760822
```

```
YEARS_BEGINEXPLUATATION_MODE    48.781019
YEARS_BEGINEXPLUATATION_MEDI    48.781019
YEARS_BEGINEXPLUATATION_AVG     48.781019
TOTALAREA_MODE                  48.268517
EMERGENCYSTATE_MODE             47.398304
OCCUPATION_TYPE                 31.345545
EXT_SOURCE_3                    19.825307
AMT_REQ_CREDIT_BUREAU_HOUR      13.501631
AMT_REQ_CREDIT_BUREAU_DAY       13.501631
AMT_REQ_CREDIT_BUREAU_WEEK      13.501631
AMT_REQ_CREDIT_BUREAU_MON       13.501631
AMT_REQ_CREDIT_BUREAU_QRT       13.501631
AMT_REQ_CREDIT_BUREAU_YEAR      13.501631
NAME_TYPE_SUITE                  0.420148
OBS_30_CNT_SOCIAL_CIRCLE         0.332021
DEF_30_CNT_SOCIAL_CIRCLE         0.332021
dtype: float64
```

In our case the columns which contains more than 45% null values will be discarded

Data Cleaning

Identifying and Removing null values > 45%

In [10]:
```
null_cols=credit_data.isna().sum().sort_values(ascending=False)
null_cols=null_cols[null_cols.values>(.45*len(credit_data))]

no=len(null_cols)
print("There are "+ str(no) + " columns with more than 45% NULLs")

null_cols
```

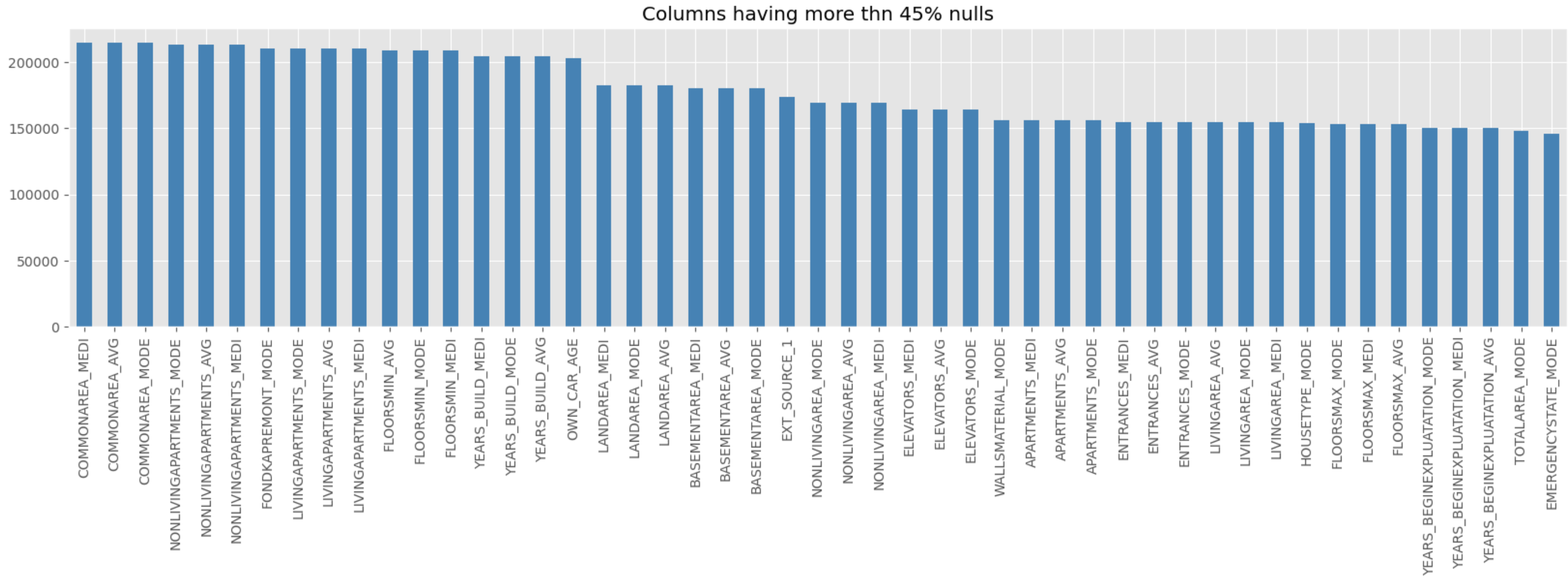
```
There are 49 columns with more than 45% NULLs
```

Out[10]:

```
COMMONAREA_MEDI              214865
COMMONAREA_AVG               214865
COMMONAREA_MODE              214865
NONLIVINGAPARTMENTS_MODE     213514
NONLIVINGAPARTMENTS_AVG      213514
NONLIVINGAPARTMENTS_MEDI     213514
FONDKAPREMONT_MODE           210295
LIVINGAPARTMENTS_MODE        210199
LIVINGAPARTMENTS_AVG         210199
LIVINGAPARTMENTS_MEDI        210199
FLOORSMIN_AVG                208642
FLOORSMIN_MODE               208642
FLOORSMIN_MEDI               208642
YEARS_BUILD_MEDI             204488
YEARS_BUILD_MODE             204488
YEARS_BUILD_AVG              204488
OWN_CAR_AGE                  202929
LANDAREA_MEDI                182590
LANDAREA_MODE                182590
LANDAREA_AVG                 182590
BASEMENTAREA_MEDI            179943
BASEMENTAREA_AVG             179943
BASEMENTAREA_MODE            179943
EXT_SOURCE_1                 173378
NONLIVINGAREA_MODE           169682
NONLIVINGAREA_AVG            169682
NONLIVINGAREA_MEDI           169682
ELEVATORS_MEDI               163891
ELEVATORS_AVG                163891
ELEVATORS_MODE               163891
WALLSMATERIAL_MODE           156341
APARTMENTS_MEDI              156061
APARTMENTS_AVG               156061
APARTMENTS_MODE              156061
ENTRANCES_MEDI               154828
ENTRANCES_AVG                154828
ENTRANCES_MODE               154828
LIVINGAREA_AVG               154350
LIVINGAREA_MODE              154350
LIVINGAREA_MEDI              154350
HOUSETYPE_MODE               154297
FLOORSMAX_MODE               153020
FLOORSMAX_MEDI               153020
FLOORSMAX_AVG                153020
```

```
YEARS_BEGINEXPLUATATION_MODE    150007
YEARS_BEGINEXPLUATATION_MEDI    150007
YEARS_BEGINEXPLUATATION_AVG     150007
TOTALAREA_MODE                  148431
EMERGENCYSTATE_MODE             145755
dtype: int64
```

In [11]:
```
# Let's visually look at the columns with NULLs>45% and there NULL counts

plt.figure(figsize=(20,4))
null_cols.plot(kind='bar', color="steelblue")
plt.title('Columns having more thn 45% nulls')
plt.show()
```



In [12]:
```
# Removal of Null columns > 45%

def remove_null_cols(data):
    perc=0.45
    df=data.copy()
    shape_before = df.shape
    remove_cols=(df.isna().sum()/len(df))
```

```
    remove_cols=list(remove_cols[remove_cols.values>=perc].index)
    df.drop(labels=remove_cols,axis=1,inplace=True)
    print("Number of Columns dropped\t: ",len(remove_cols))
    print("\nOld dataset rows,columns",shape_before,"\nNew dataset rows,columns",df.shape)
    return df
```

In [13]:
```
credit_data_1=remove_null_cols(credit_data)
```

```
Number of Columns dropped	:  49

Old dataset rows,columns (307511, 122)
New dataset rows,columns (307511, 73)
```

Imputing Missing Data

The below listed columns can be categorized into a group of columns with similar significance as they all represent number of queries made to the Credit Bureau

AMT_REQ_CREDIT_BUREAU_YEAR

AMT_REQ_CREDIT_BUREAU_MON

AMT_REQ_CREDIT_BUREAU_WEEK

AMT_REQ_CREDIT_BUREAU_DAY

AMT_REQ_CREDIT_BUREAU_HOUR

AMT_REQ_CREDIT_BUREAU_QRT

In [14]:
```
# Checking value counts for AMT_REQ_CREDIT_BUREAU_YEAR

credit_data_1.AMT_REQ_CREDIT_BUREAU_YEAR.value_counts()

# We see that there are 71k 0s
```

Out[14]:
```
0.0     71801
1.0     63405
2.0     50192
3.0     33628
4.0     20714
5.0     12052
6.0      6967
7.0      3869
8.0      2127
9.0      1096
11.0       31
12.0       30
10.0       22
13.0       19
14.0       10
17.0        7
15.0        6
19.0        4
18.0        4
16.0        3
25.0        1
23.0        1
22.0        1
21.0        1
20.0        1
Name: AMT_REQ_CREDIT_BUREAU_YEAR, dtype: int64
```

In [15]:
```
credit_data_1.AMT_REQ_CREDIT_BUREAU_YEAR.value_counts(normalize=True)*100

# so around 71K or approx 27% of the column contains 0
```

Out[15]:
```
0.0     26.993669
1.0     23.837183
2.0     18.869740
3.0     12.642485
4.0      7.787452
5.0      4.530963
6.0      2.619252
7.0      1.454555
8.0      0.799648
9.0      0.412042
11.0     0.011654
12.0     0.011279
10.0     0.008271
13.0     0.007143
14.0     0.003760
17.0     0.002632
15.0     0.002256
19.0     0.001504
18.0     0.001504
16.0     0.001128
25.0     0.000376
23.0     0.000376
22.0     0.000376
21.0     0.000376
20.0     0.000376
Name: AMT_REQ_CREDIT_BUREAU_YEAR, dtype: float64
```

In [16]:
```
# here used mode function to find out the most occured value in each column

print(credit_data_1.AMT_REQ_CREDIT_BUREAU_YEAR.mode())
print(credit_data_1.AMT_REQ_CREDIT_BUREAU_MON.mode())
print(credit_data_1.AMT_REQ_CREDIT_BUREAU_WEEK.mode())
print(credit_data_1.AMT_REQ_CREDIT_BUREAU_DAY.mode())
print(credit_data_1.AMT_REQ_CREDIT_BUREAU_HOUR.mode())
print(credit_data_1.AMT_REQ_CREDIT_BUREAU_QRT.mode())
```

```
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_YEAR, dtype: float64
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_MON, dtype: float64
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_WEEK, dtype: float64
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_DAY, dtype: float64
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_HOUR, dtype: float64
0    0.0
Name: AMT_REQ_CREDIT_BUREAU_QRT, dtype: float64
```

In [17]:
```
credit_data_2=credit_data_1.copy()
```

In [18]:
```
# Imputing null with 0s

impute_list = ['AMT_REQ_CREDIT_BUREAU_YEAR','AMT_REQ_CREDIT_BUREAU_MON','AMT_REQ_CREDIT_BUREAU_WEEK',
               'AMT_REQ_CREDIT_BUREAU_DAY','AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_QRT']

for i in impute_list:
        credit_data_2[i] = credit_data_1[i].fillna(credit_data_1[i].mode()[0])
```

In [19]:
```
# Verifying count of NULLs after imputaion

print(credit_data_2['AMT_REQ_CREDIT_BUREAU_YEAR'].isnull().sum())
print(credit_data_2['AMT_REQ_CREDIT_BUREAU_MON'].isnull().sum())
print(credit_data_2['AMT_REQ_CREDIT_BUREAU_WEEK'].isnull().sum())
print(credit_data_2['AMT_REQ_CREDIT_BUREAU_DAY'].isnull().sum())
print(credit_data_2['AMT_REQ_CREDIT_BUREAU_HOUR'].isnull().sum())
print(credit_data_2['AMT_REQ_CREDIT_BUREAU_QRT'].isnull().sum())
```

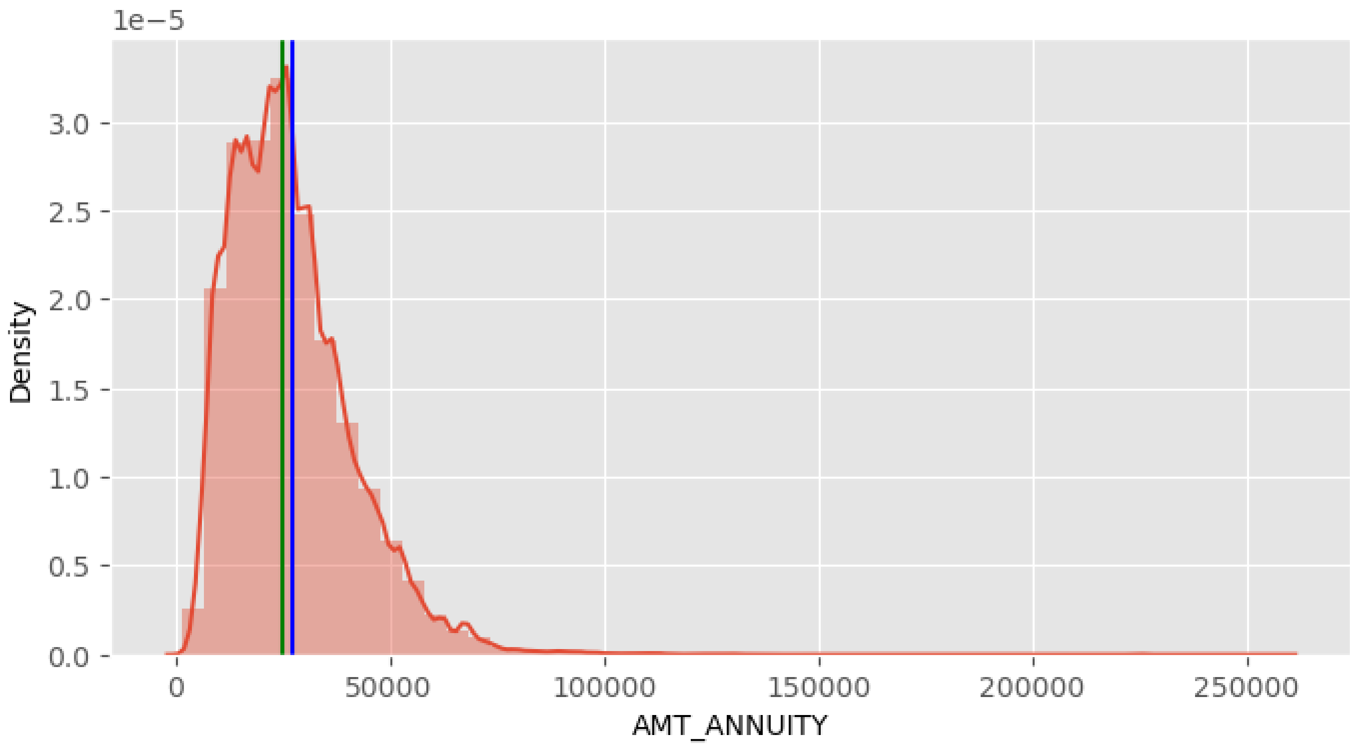
```
0
0
0
0
0
0
```

AMT_Annuity

In [20]:
```
credit_data_1.AMT_ANNUITY.describe()
```

Out[20]:
```
count    307499.000000
mean      27108.573909
std       14493.737315
min        1615.500000
25%       16524.000000
50%       24903.000000
75%       34596.000000
max      258025.500000
Name: AMT_ANNUITY, dtype: float64
```

In [21]:
```
plt.figure(figsize=(8,4))
sns.distplot(credit_data_1.AMT_ANNUITY)
plt.axvline(credit_data_1.AMT_ANNUITY.mean(),color='blue')
plt.axvline(credit_data_1.AMT_ANNUITY.median(),color='green')
plt.show()
```



In [22]:
```
credit_data_1.AMT_ANNUITY.skew()
```

Out[22]:
```
1.5797773638612507
```

A skewness value greater than 1 or less than -1 indicates a highly skewed distribution. A value between 0.5 and 1 or -0.5 and -1 is moderately skewed. A value between -0.5 and 0.5 indicates that the distribution is fairly symmetrical.

Because we see a huge skewness, we will fill the missing value by median.

In [23]:
```
credit_data_1.AMT_ANNUITY.median()
```

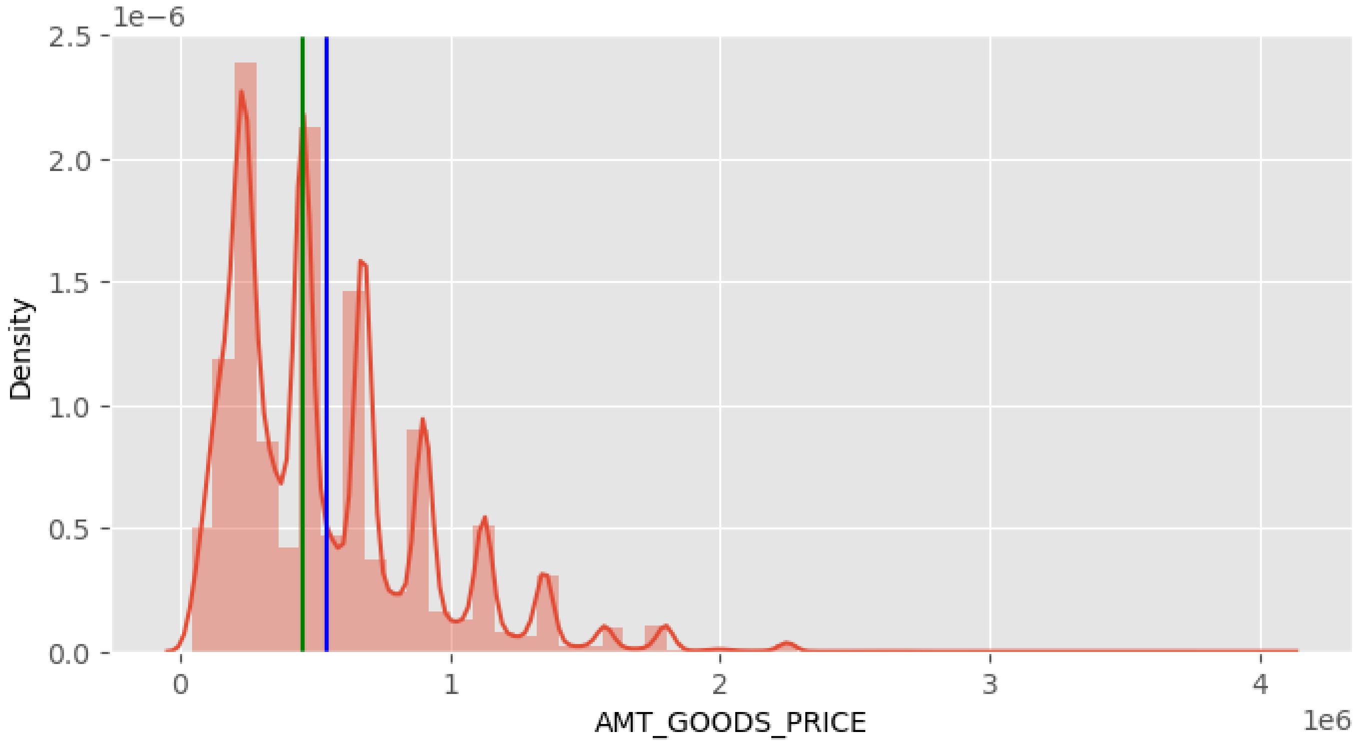
Out[23]:
```
24903.0
```

In [24]:
```
# Imputing NULLs with Median

credit_data_2['AMT_ANNUITY'] = credit_data_1['AMT_ANNUITY'].fillna(credit_data_1.AMT_ANNUITY.median())
credit_data_2['AMT_ANNUITY'].isnull().sum()
```

Out[24]:
```
0
```

AMT_GOODS_PRICE

In [25]:
```
plt.figure(figsize=(8,4))
sns.distplot(credit_data_1.AMT_GOODS_PRICE)
plt.axvline(credit_data_1.AMT_GOODS_PRICE.mean(),color='blue')
plt.axvline(credit_data_1.AMT_GOODS_PRICE.median(),color='green')
plt.show()
```



In [26]:
```
credit_data_1.AMT_GOODS_PRICE.skew()
```
Out[26]:
```
1.3490003414747445
```

hence here also we have to impute median

In [27]:
```
# Imputing NULLs with Median

credit_data_2['AMT_GOODS_PRICE'] = credit_data_1['AMT_GOODS_PRICE'].fillna(credit_data_1.AMT_GOODS_PRICE.median())
```

In [28]:
```
# Verifying count of NULLs to be 0

credit_data_2['AMT_GOODS_PRICE'].isnull().sum()
```
Out[28]:
```
0
```

Fixing Erroneous Data

As seen already with the help of describe function, we know that we need to treat -ve values in days columns.

In [29]:
```
# Confirming that all DAYS fields have -ve values

print(credit_data['DAYS_BIRTH'].unique())
print(credit_data['DAYS_EMPLOYED'].unique())
print(credit_data['DAYS_REGISTRATION'].unique())
print(credit_data['DAYS_ID_PUBLISH'].unique())
print(credit_data['DAYS_LAST_PHONE_CHANGE'].unique())
```

```
[ -9461 -16765 -19046 ...  -7951  -7857 -25061]
[  -637  -1188   -225 ... -12971 -11084  -8694]
[ -3648.  -1186.  -4260. ... -16396. -14558. -14798.]
[-2120  -291 -2531 ... -6194 -5854 -6211]
[-1134.  -828.  -815. ... -3988. -3899. -3538.]
```

In [30]:
```
# Preparing the list of columns to be treated

erroneous_cols = [cols for cols in credit_data_2 if cols.startswith('DAYS')]
erroneous_cols
```

Out[30]:
```
['DAYS_BIRTH',
 'DAYS_EMPLOYED',
 'DAYS_REGISTRATION',
 'DAYS_ID_PUBLISH',
 'DAYS_LAST_PHONE_CHANGE']
```

In [31]:
```
# Changing the column values with Absolute values using abs function

credit_data_2[erroneous_cols]= np.abs(credit_data_2[erroneous_cols])
```

In [32]:
```
# Verifying absence of -ve values in data

credit_data_2.describe()
```

Out[32]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_RE
count	307511.000000	307511.000000	307511.000000	3.075110e+05	3.075110e+05	307511.000000	3.075110e+05	307511.
mean	278180.518577	0.080729	0.417052	1.687979e+05	5.990260e+05	27108.487841	5.383163e+05	0.
std	102790.175348	0.272419	0.722121	2.371231e+05	4.024908e+05	14493.461065	3.692890e+05	0.
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	0.
25%	189145.500000	0.000000	0.000000	1.125000e+05	2.700000e+05	16524.000000	2.385000e+05	0.
50%	278202.000000	0.000000	0.000000	1.471500e+05	5.135310e+05	24903.000000	4.500000e+05	0.
75%	367142.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596.000000	6.795000e+05	0.
max	456255.000000	1.000000	19.000000	1.170000e+08	4.050000e+06	258025.500000	4.050000e+06	0.

Replacing XNAs for CODE_GENDER

In [33]:
```
credit_data_2['CODE_GENDER'].value_counts()
```

Out[33]:
```
F      202448
M      105059
XNA         4
Name: CODE_GENDER, dtype: int64
```

In [34]:
```
# Replacing XNAs with F

credit_data_2.loc[credit_data_2.CODE_GENDER == 'XNA','CODE_GENDER'] = 'F'
credit_data_2.CODE_GENDER.value_counts()
```

Out[34]:
```
F    202452
M    105059
Name: CODE_GENDER, dtype: int64
```

Replacing XNAs for ORGANIZATION_TYPE

In [35]:
```
# Checking value counts for ORGANIZATION_TYPE

credit_data_2.ORGANIZATION_TYPE.value_counts()
```

Out[35]:

```
Business Entity Type 3    67992
XNA                       55374
Self-employed             38412
Other                     16683
Medicine                  11193
Business Entity Type 2    10553
Government                10404
School                     8893
Trade: type 7              7831
Kindergarten               6880
Construction               6721
Business Entity Type 1     5984
Transport: type 4          5398
Trade: type 3              3492
Industry: type 9           3368
Industry: type 3           3278
Security                   3247
Housing                    2958
Industry: type 11          2704
Military                   2634
Bank                       2507
Agriculture                2454
Police                     2341
Transport: type 2          2204
Postal                     2157
Security Ministries        1974
Trade: type 2              1900
Restaurant                 1811
Services                   1575
University                 1327
Industry: type 7           1307
Transport: type 3          1187
Industry: type 1           1039
Hotel                       966
Electricity                 950
Industry: type 4            877
Trade: type 6               631
Industry: type 5            599
Insurance                   597
Telecom                     577
Emergency                   560
Industry: type 2            458
Advertising                 429
Realtor                     396
```

```
Culture                    379
Industry: type 12          369
Trade: type 1              348
Mobile                     317
Legal Services             305
Cleaning                   260
Transport: type 1          201
Industry: type 6           112
Industry: type 10          109
Religion                    85
Industry: type 13           67
Trade: type 4               64
Trade: type 5               49
Industry: type 8            24
Name: ORGANIZATION_TYPE, dtype: int64
```

In [36]:

```
 # Replacing XNAs with Nulls

credit_data_2['ORGANIZATION_TYPE'] = credit_data_1['ORGANIZATION_TYPE'].replace('XNA',np.NaN)
```

In [37]:

```
# Checking value counts for credit_data_2

credit_data_2.ORGANIZATION_TYPE.value_counts()
```

Out[37]:
```
Business Entity Type 3    67992
Self-employed             38412
Other                     16683
Medicine                  11193
Business Entity Type 2    10553
Government                10404
School                     8893
Trade: type 7              7831
Kindergarten               6880
Construction               6721
Business Entity Type 1     5984
Transport: type 4          5398
Trade: type 3              3492
Industry: type 9           3368
Industry: type 3           3278
Security                   3247
Housing                    2958
Industry: type 11          2704
Military                   2634
Bank                       2507
Agriculture                2454
Police                     2341
Transport: type 2          2204
Postal                     2157
Security Ministries        1974
Trade: type 2              1900
Restaurant                 1811
Services                   1575
University                 1327
Industry: type 7           1307
Transport: type 3          1187
Industry: type 1           1039
Hotel                       966
Electricity                 950
Industry: type 4            877
Trade: type 6               631
Industry: type 5            599
Insurance                   597
Telecom                     577
Emergency                   560
Industry: type 2            458
Advertising                 429
Realtor                     396
Culture                     379
```

```
Industry: type 12          369
Trade: type 1              348
Mobile                     317
Legal Services             305
Cleaning                   260
Transport: type 1          201
Industry: type 6           112
Industry: type 10          109
Religion                    85
Industry: type 13           67
Trade: type 4               64
Trade: type 5               49
Industry: type 8            24
Name: ORGANIZATION_TYPE, dtype: int64
```

Adding new columns by Binning Continuous Variables

In [38]:

```
credit_data_2['AMT_INCOME_TOTAL'].describe()
```

Out[38]:

```
count    3.075110e+05
mean     1.687979e+05
std      2.371231e+05
min      2.565000e+04
25%      1.125000e+05
50%      1.471500e+05
75%      2.025000e+05
max      1.170000e+08
Name: AMT_INCOME_TOTAL, dtype: float64
```

In [39]:

```
# Using pd.qcut function to bin AMT_INCOME_TOTAL into 5 categories

credit_data_2['AMT_INCOME_RANGE'] = pd.qcut(credit_data_2.AMT_INCOME_TOTAL,
                                            q=[0, 0.2, 0.5, 0.8, 0.95, 1],
                                            labels=['VERY_LOW', 'LOW', "MEDIUM", 'HIGH', 'VERY_HIGH'])
credit_data_2['AMT_INCOME_RANGE'].head(7)
```

Out[39]:
```
0      MEDIUM
1        HIGH
2    VERY_LOW
3         LOW
4         LOW
5    VERY_LOW
6      MEDIUM
Name: AMT_INCOME_RANGE, dtype: category
Categories (5, object): ['VERY_LOW' < 'LOW' < 'MEDIUM' < 'HIGH' < 'VERY_HIGH']
```

In [40]:
```
credit_data_2['AMT_INCOME_RANGE'].value_counts()
```

Out[40]:
```
MEDIUM       106633
LOW           90089
VERY_LOW      63671
HIGH          33083
VERY_HIGH     14035
Name: AMT_INCOME_RANGE, dtype: int64
```

Binning AMT_CREDIT

In [41]:
```
# Using pd.qcut function to bin AMT_CREDIT_RANGE into 5 categories

credit_data_2['AMT_CREDIT_RANGE'] = pd.qcut(credit_data_2.AMT_CREDIT, q=[0, 0.2, 0.5, 0.8, 0.95, 1],
                                            labels=['VERY_LOW', 'LOW', "MEDIUM", 'HIGH', 'VERY_HIGH'])
credit_data_2['AMT_CREDIT_RANGE'].head(7)
```

Out[41]:
```
0          LOW
1         HIGH
2     VERY_LOW
3          LOW
4          LOW
5          LOW
6    VERY_HIGH
Name: AMT_CREDIT_RANGE, dtype: category
Categories (5, object): ['VERY_LOW' < 'LOW' < 'MEDIUM' < 'HIGH' < 'VERY_HIGH']
```

In [42]:
```
credit_data_2['AMT_CREDIT_RANGE'].value_counts()
```

Out[42]:
```
MEDIUM       94750
LOW          88924
VERY_LOW     64925
HIGH         44878
VERY_HIGH    14034
Name: AMT_CREDIT_RANGE, dtype: int64
```

Binning DAYS_BIRTH

In [43]:
```
credit_data_2['DAYS_BIRTH']= (credit_data_2['DAYS_BIRTH']/365).astype(int)
credit_data_2['DAYS_BIRTH'].unique()
```

Out[43]:
```
array([25, 45, 52, 54, 46, 37, 51, 55, 39, 27, 36, 38, 23, 35, 26, 48, 31,
       50, 40, 30, 68, 43, 28, 41, 32, 33, 47, 57, 65, 44, 64, 21, 59, 49,
       56, 62, 53, 42, 29, 67, 63, 61, 58, 60, 34, 22, 24, 66, 69, 20])
```

In [44]:
```
# Using pd.qcut function to bin DAYS_BIRTH into 5 categories

credit_data_2['DAYS_BIRTH_BINS']=pd.cut(credit_data_2['DAYS_BIRTH'],
                                        bins=[19,25,35,60,100],
                                        labels=['Very_Young','Young', 'Middle_Age', 'Senior_Citizen'])
```

In [45]:
```
credit_data_2.head()
```

Out[45]:

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

In [46]:
```
# Checking value counts for DAYS_BIRTH_BINS
```

```
credit_data_2['DAYS_BIRTH_BINS'].value_counts()
```

Out[46]:
```
Middle_Age        185900
Young              75925
Senior_Citizen     29368
Very_Young         16318
Name: DAYS_BIRTH_BINS, dtype: int64
```

Splitting data based on TARGET

In [47]:
```
credit_data_2.TARGET.value_counts()
```

Out[47]:
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

In [48]:
```
# Splitting data as per TARGET into deafulter and non-defaulter datasets

defaulter = credit_data_2[credit_data_2.TARGET==1]
non_defaulter =  credit_data_2[credit_data_2.TARGET==0]
```

In [49]:
```
print(" Defaulter data shape - " + str(defaulter.shape) )
print(" Non-Defaulter data shape - " + str(non_defaulter.shape) )
```

```
 Defaulter data shape - (24825, 76)
 Non-Defaulter data shape - (282686, 76)
```

In [50]:
```
# Checking % of data split as per TARGET

print(" Defaulter data % - " + str(round(len(defaulter)*100/len(credit_data_2),2) ))
print(" Non-Defaulter data % - " + str(round(len(non_defaulter)*100/len(credit_data_2),2) ))
```

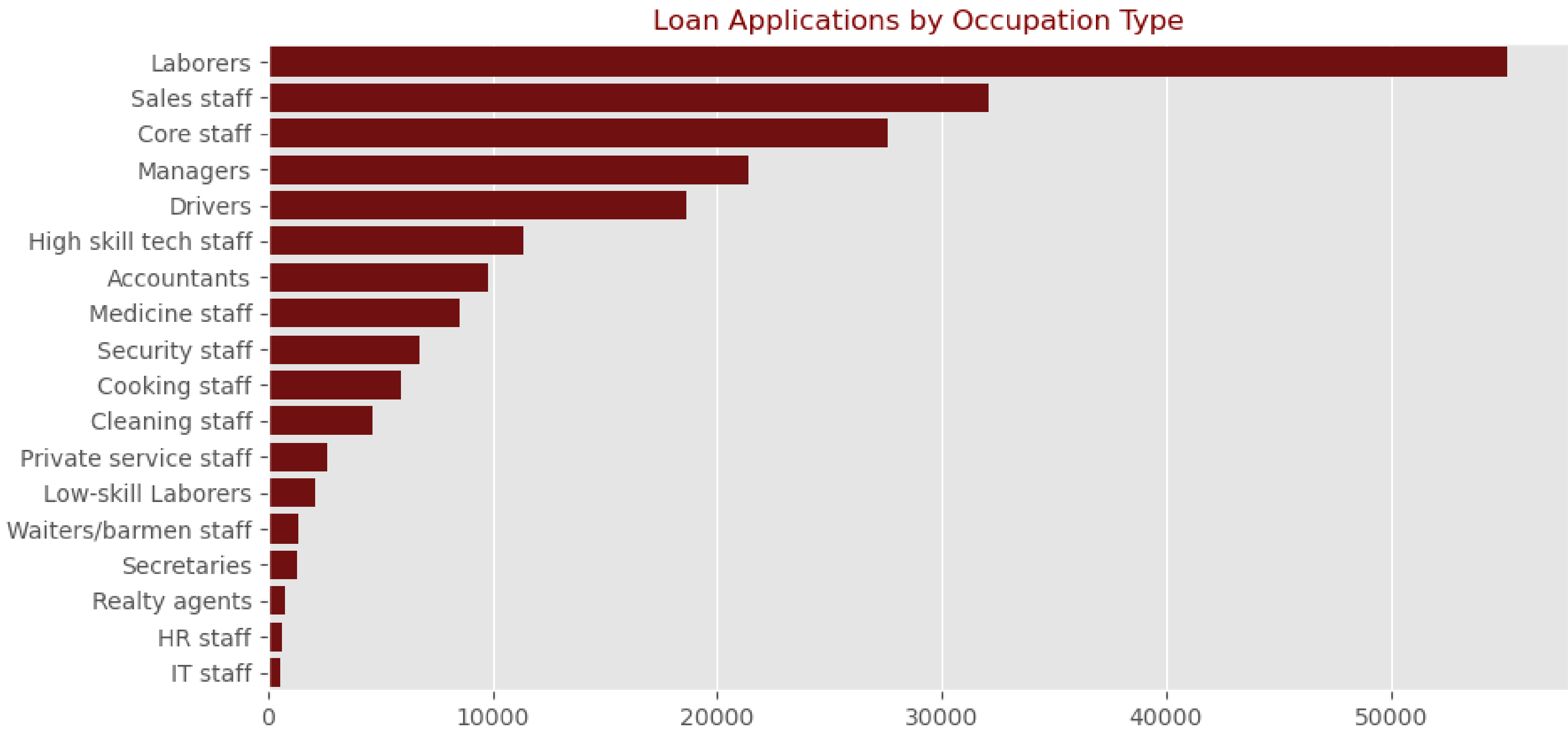
```
 Defaulter data % - 8.07
 Non-Defaulter data % - 91.93
```

Univariate Analysis

In [51]:
```
credit_data_2["OCCUPATION_TYPE"].value_counts()
```

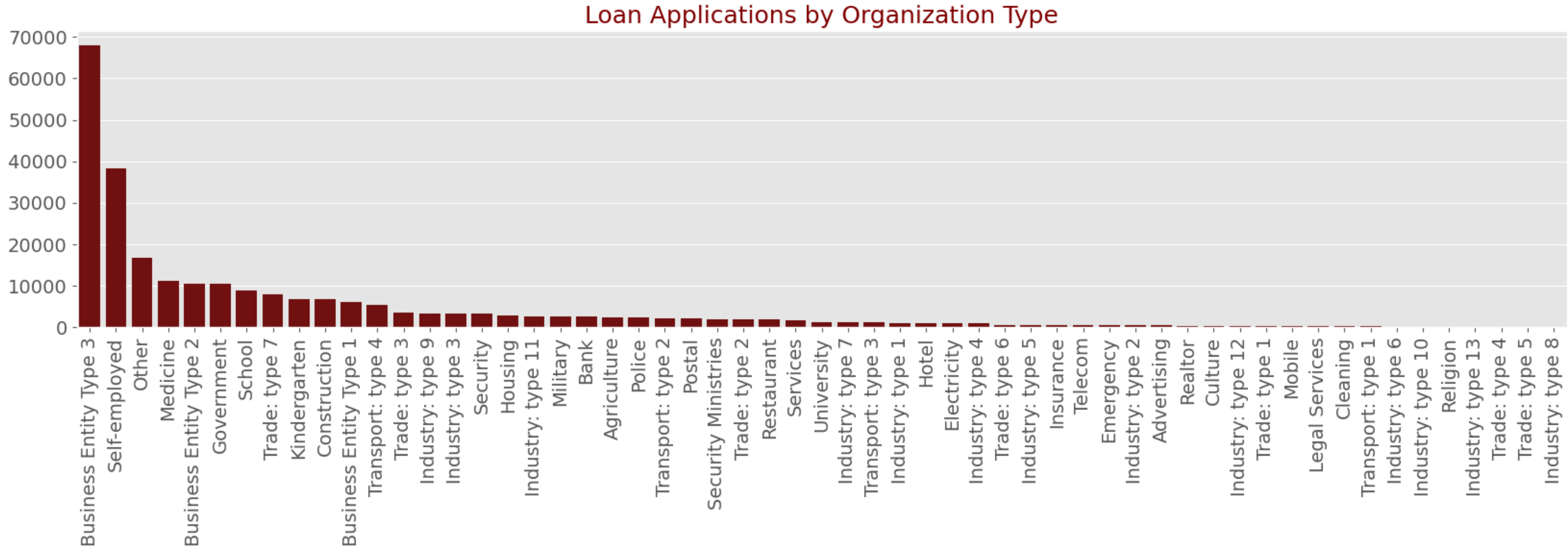
Out[51]:
```
Laborers                 55186
Sales staff              32102
Core staff               27570
Managers                 21371
Drivers                  18603
High skill tech staff    11380
Accountants               9813
Medicine staff            8537
Security staff            6721
Cooking staff             5946
Cleaning staff            4653
Private service staff     2652
Low-skill Laborers        2093
Waiters/barmen staff      1348
Secretaries               1305
Realty agents              751
HR staff                   563
IT staff                   526
Name: OCCUPATION_TYPE, dtype: int64
```

In [52]:
```
# Distribution of 'OCCUPATION_TYPE'

temp = credit_data_2["OCCUPATION_TYPE"].value_counts()
sns.barplot(y=temp.index, x = temp.values, color = 'maroon')
plt.xticks(size = 10)
plt.yticks( size = 10)
plt.title('Loan Applications by Occupation Type', size=12,color = 'maroon')
plt.show()
```



We can infer that most of the applications come for Labourers, Sales Staff and Core Staff.

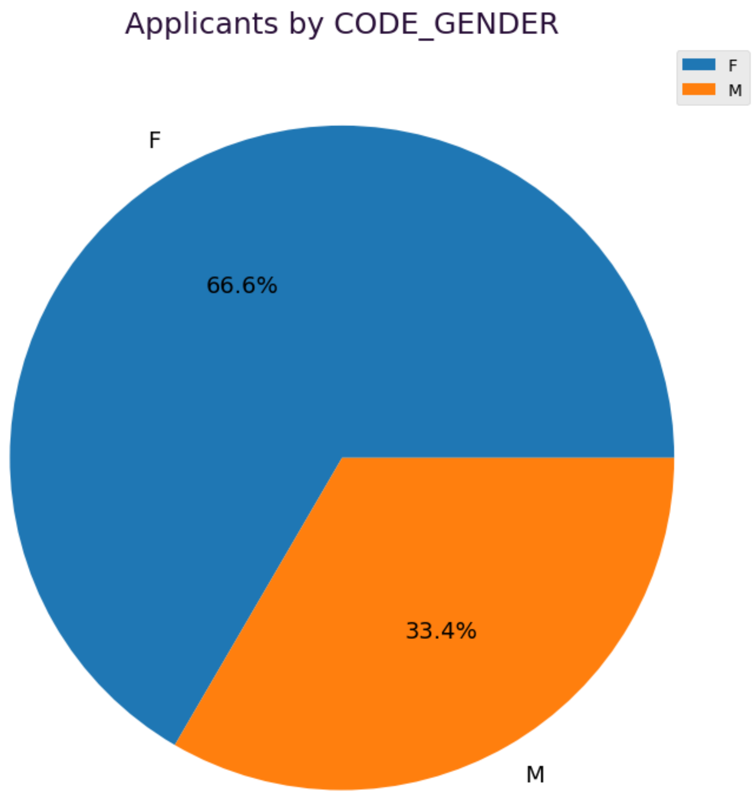
In [53]:
```
# Distribution of 'Organization Type'

plt.figure(figsize=(20,4))
temp = credit_data_2["ORGANIZATION_TYPE"].value_counts()
sns.barplot(x=temp.index, y = temp.values, color = 'maroon')
plt.xticks(rotation=90, size = 14)
plt.yticks( size = 14)
plt.title('Loan Applications by Organization Type', size=18,color = 'maroon')
plt.show()
```

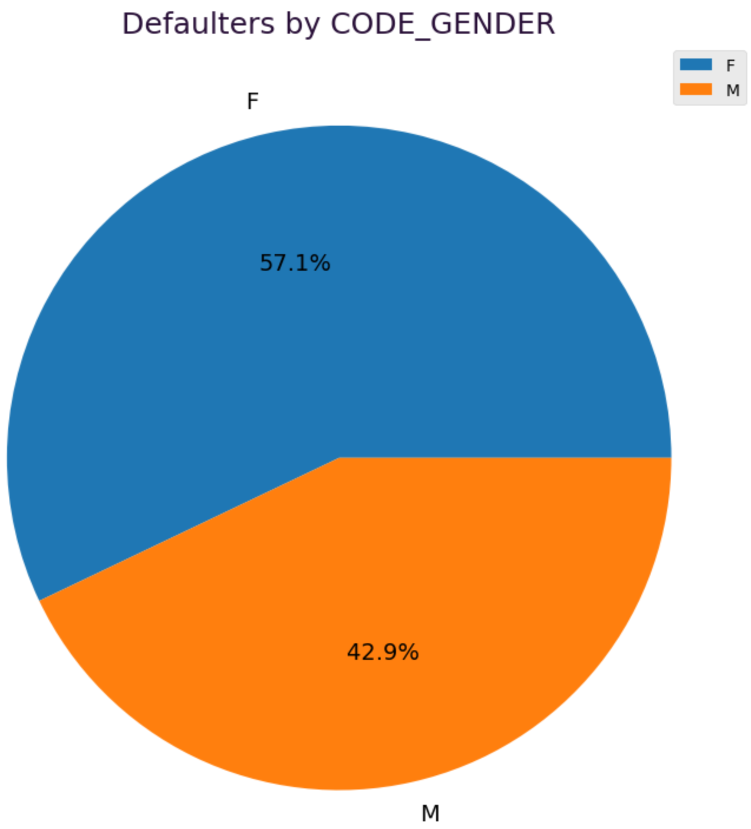


It is observed that majority of the applicants belong to Business Entity Type 3 and Self Employed.

Comparison of Gender Applicants Distribution among Defaulters and Non-Defaulters

In [54]:
```
colors = sns.color_palette('tab10')[0:5]

fig, ax=plt.subplots(nrows =1,ncols=2,figsize=(20,12))

data1=non_defaulter['CODE_GENDER'].value_counts()
ax[0].pie(data1.values, labels=data1.index.to_list(), colors = colors, autopct='%0.1f%%',textprops={'fontsize': 14})
ax[0].set_title('Applicants by CODE_GENDER', size=18,color = '#291038')
ax[0].legend()

data2=defaulter['CODE_GENDER'].value_counts()
ax[1].pie(data2.values, labels=data2.index.to_list(), colors = colors, autopct='%0.1f%%',textprops={'fontsize': 14})
ax[1].set_title('Defaulters by CODE_GENDER', size=18,color = '#291038')
ax[1].legend()

plt.show()
```





Insights -

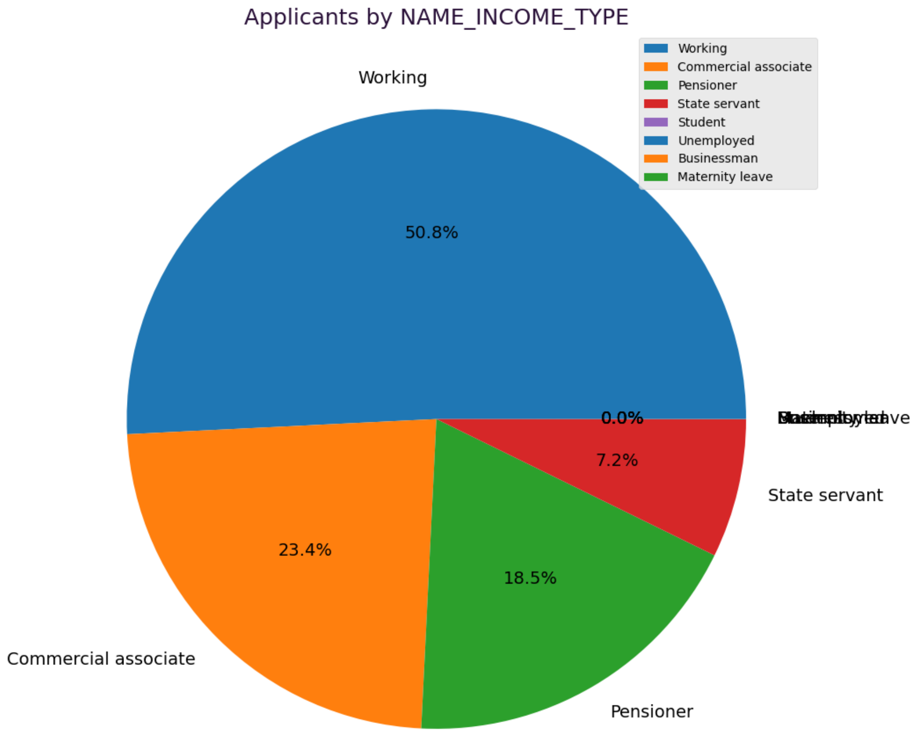
- There is majority of Female loan applicants.
- More Men deafult loans as compared to Women, since the % split has increased further for Men in case of Defaulter distribution.

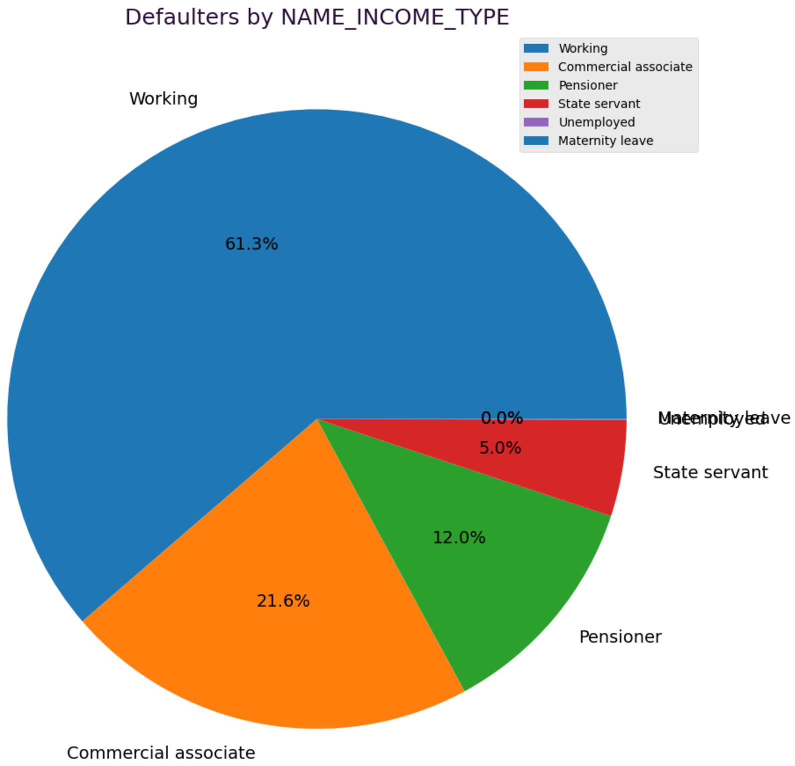
In [55]:
```
# Function for univariate comparison

def univariate_comparison(col,hue=None):
    colors = sns.color_palette('tab10')[0:5]

    fig, ax=plt.subplots(nrows =1,ncols=2,figsize=(25,18))

    data1=non_defaulter[col].value_counts()
    ax[0].pie(data1.values, labels=data1.index.to_list(), colors = colors, autopct='%0.1f%%',textprops={'fontsize': 14})
```

```
    ax[0].set_title('Applicants by '+col, size=18,color = '#291038')
    ax[0].legend()

    data2=defaulter[col].value_counts()
    ax[1].pie(data2.values, labels=data2.index.to_list(), colors = colors, autopct='%0.1f%%',textprops={'fontsize': 14})
    ax[1].set_title('Defaulters by '+col, size=18,color = '#291038')
    ax[1].legend()

    plt.show()
```

Comparison of Income Type Distribution among Defaulters and Non Defaulters

In [56]:
```
univariate_comparison('NAME_INCOME_TYPE')
```



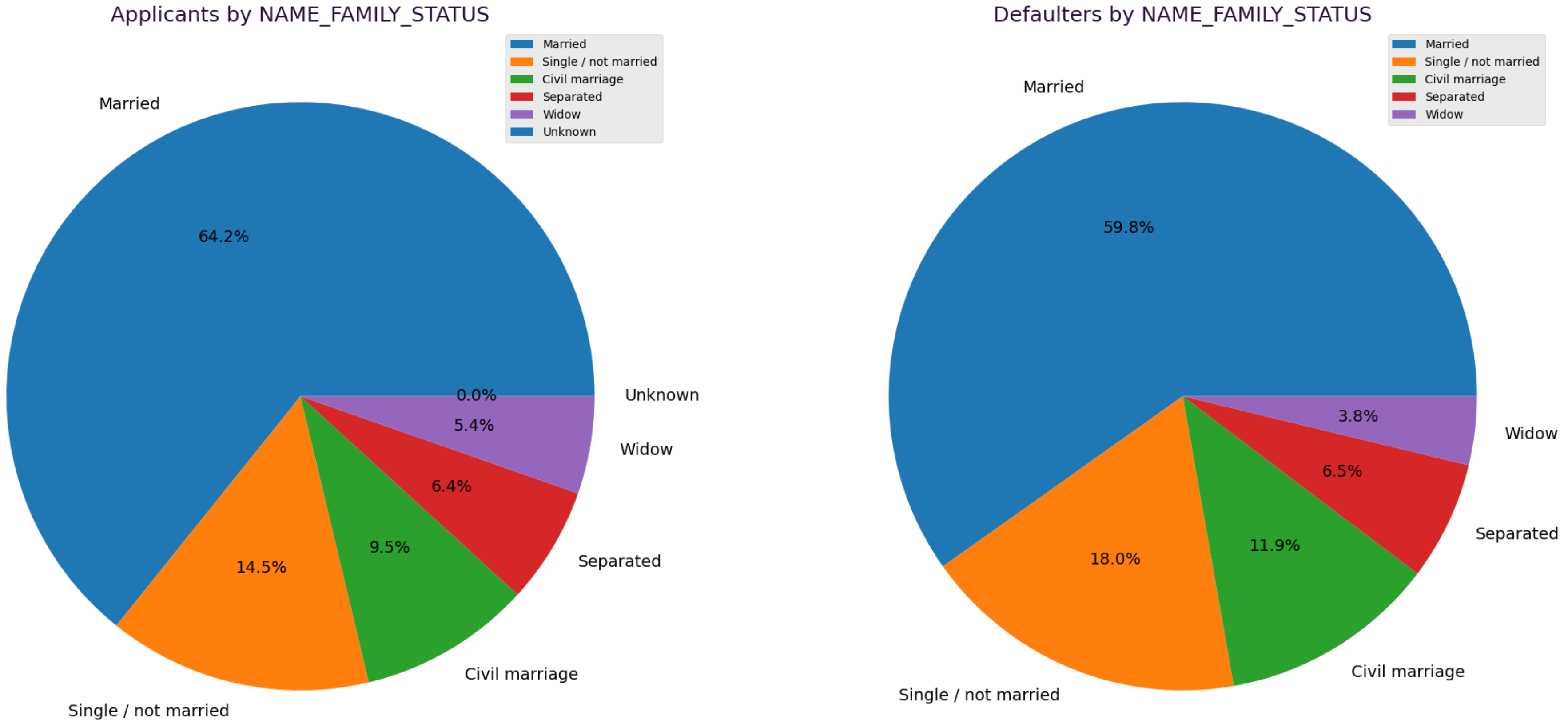


Insights -

- Almost half of the Loan applications come from Working professionals.
- Working professionals contribute more than expected to loan defaults. The % split has increased from 51% to 61%

Comparison of Family Status Distribution among Defaulters and Non Defaulters

In [57]:
```
univariate_comparison('NAME_FAMILY_STATUS')
```

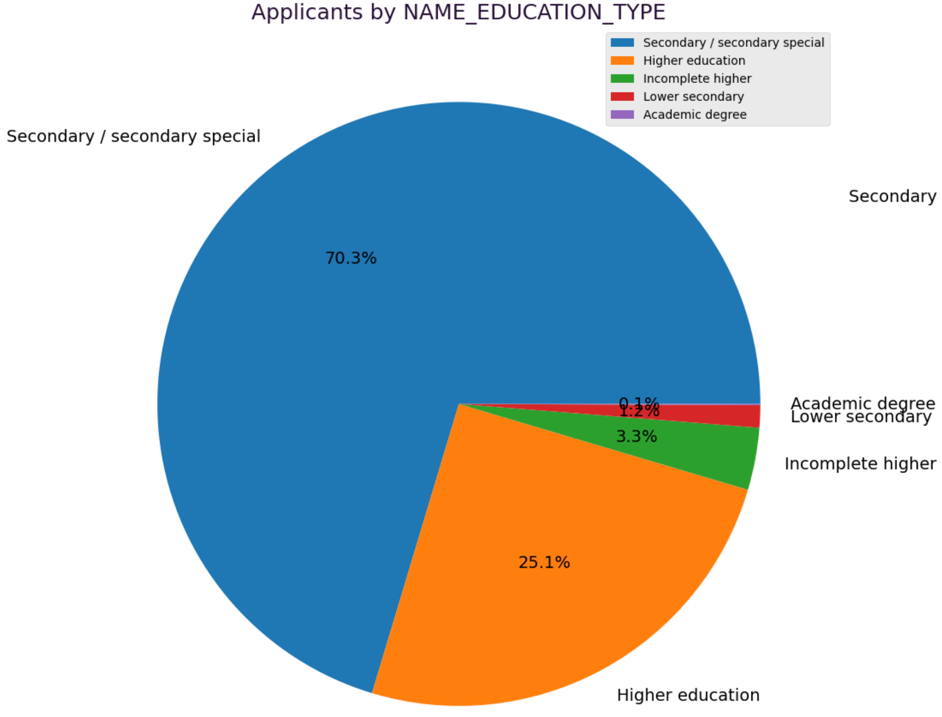


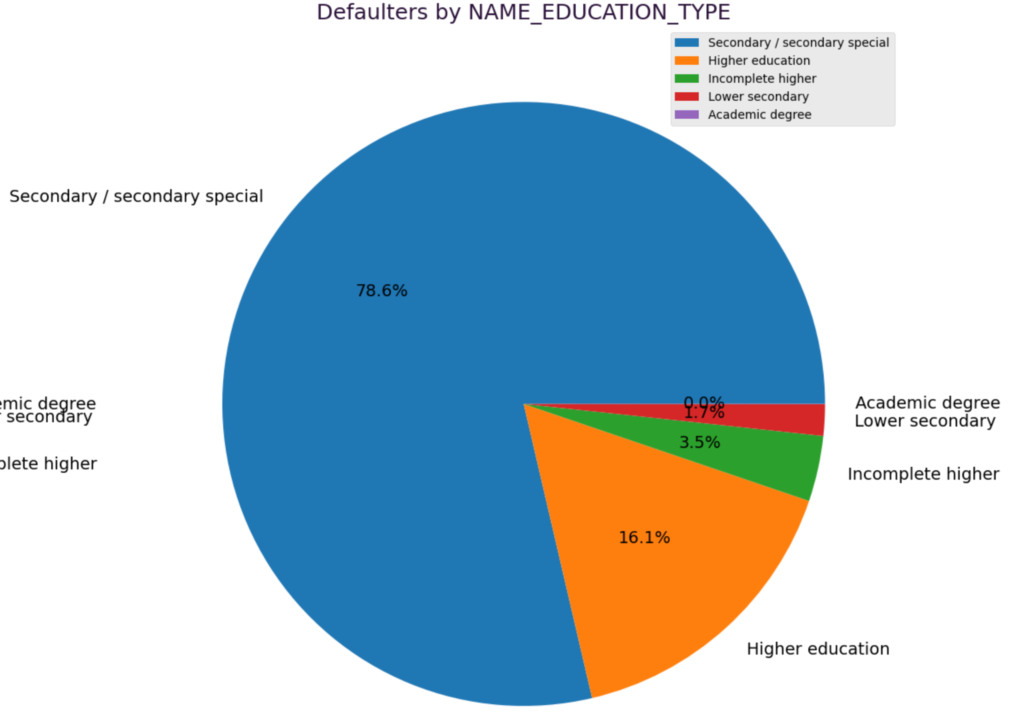
65 % of the Loan applicants are married.

Family Status doesn't play a significant role in determining whether there will be a loan defaulter.

Comparison of Education Type Distribution among Defaulters and Non Defaulters

In [58]:
```
univariate_comparison('NAME_EDUCATION_TYPE')
```



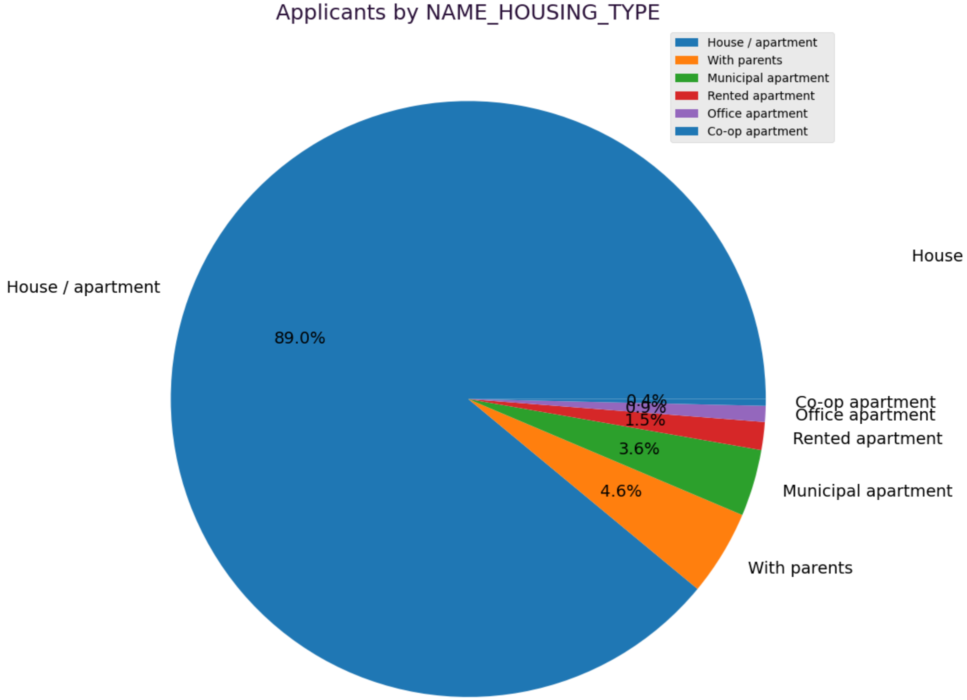


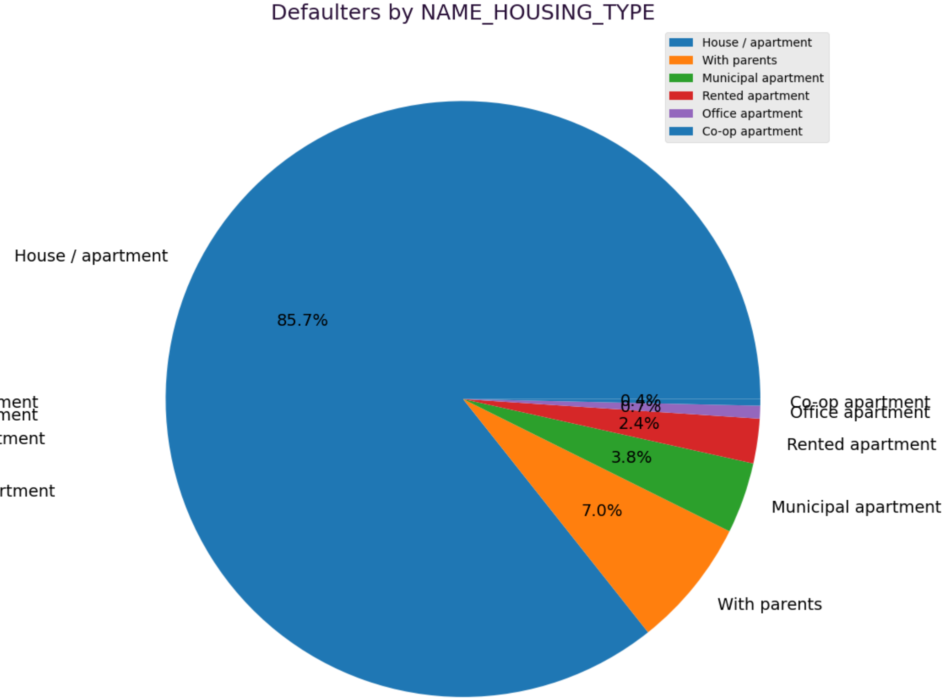
Insights-

- More than 2/3rds of Loan applicants have highest education as Secondary.
- Secondary Education class contribute majorly (more than expected too) for loan defaults.
- There is a considerable decrease in % split for loan defaults by people with higher education. (from 25% to 16%)

Comparison of Housing Type Distribution among Defaulters and Non Defaulters

In [59]:
```
univariate_comparison('NAME_HOUSING_TYPE')
```



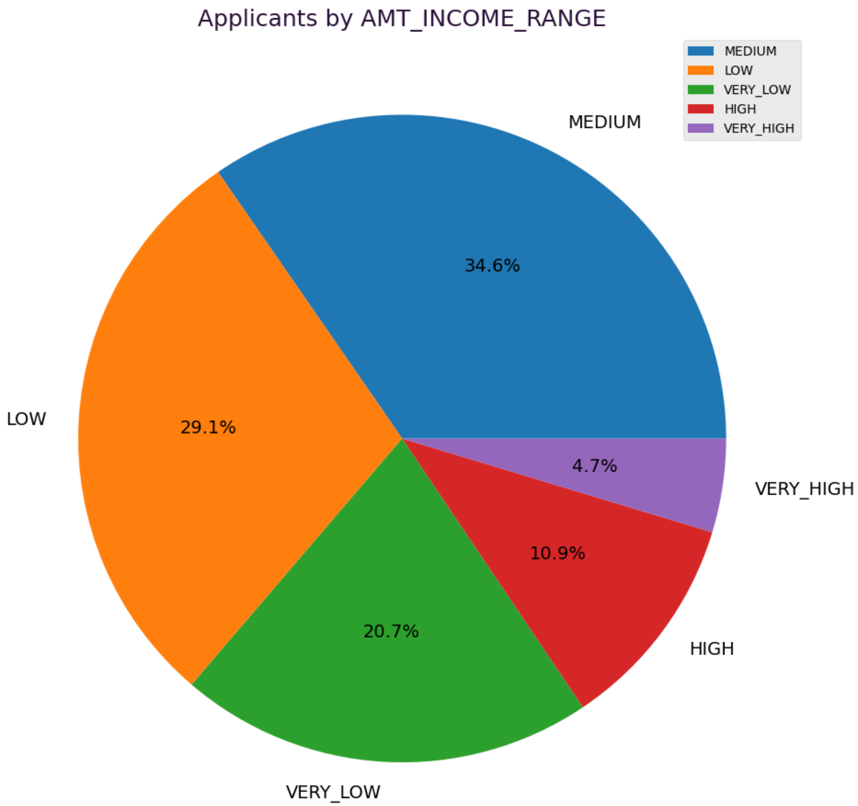


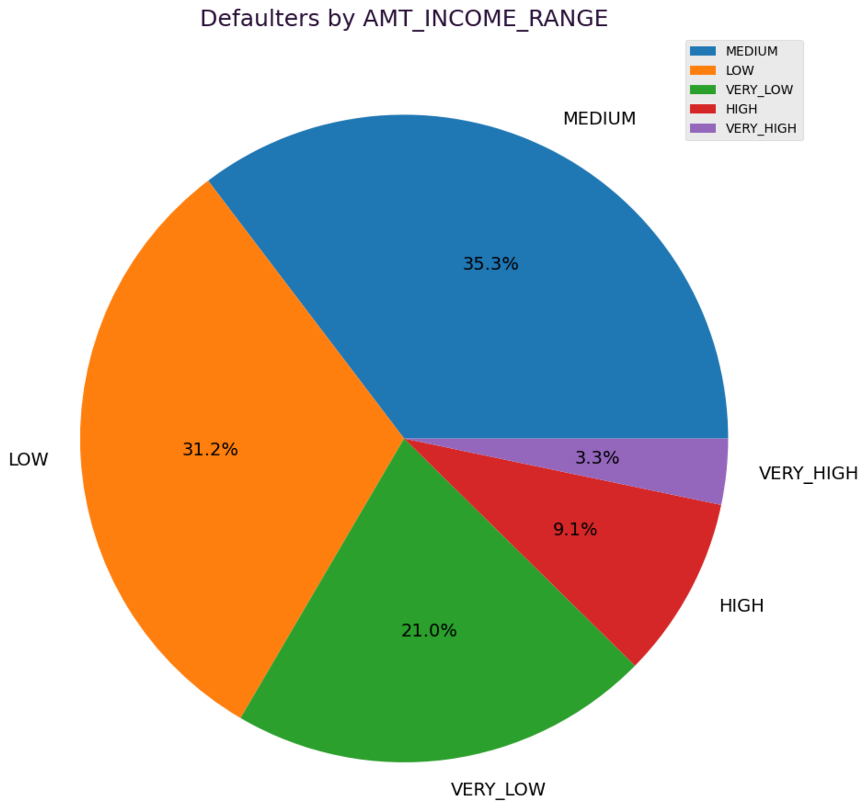
Almost 90% of Loan applicants have their own home.

Housing type doesn't play a significant role in determining whether there will be a loan defaulter.

Comparison of Income Range Distribution among Defaulters and Non Defaulters

In [60]:
```
univariate_comparison('AMT_INCOME_RANGE')
```



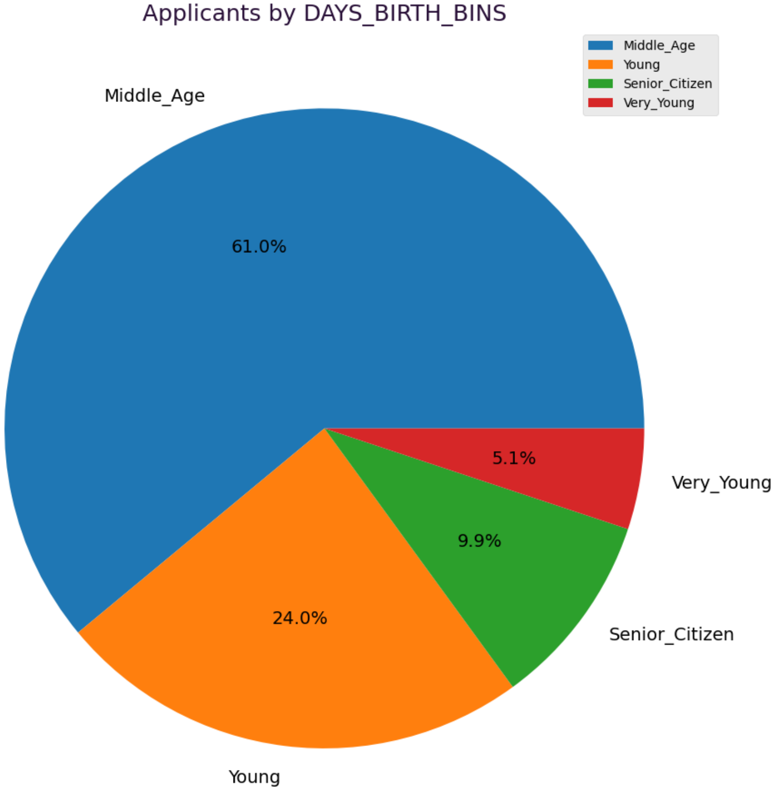


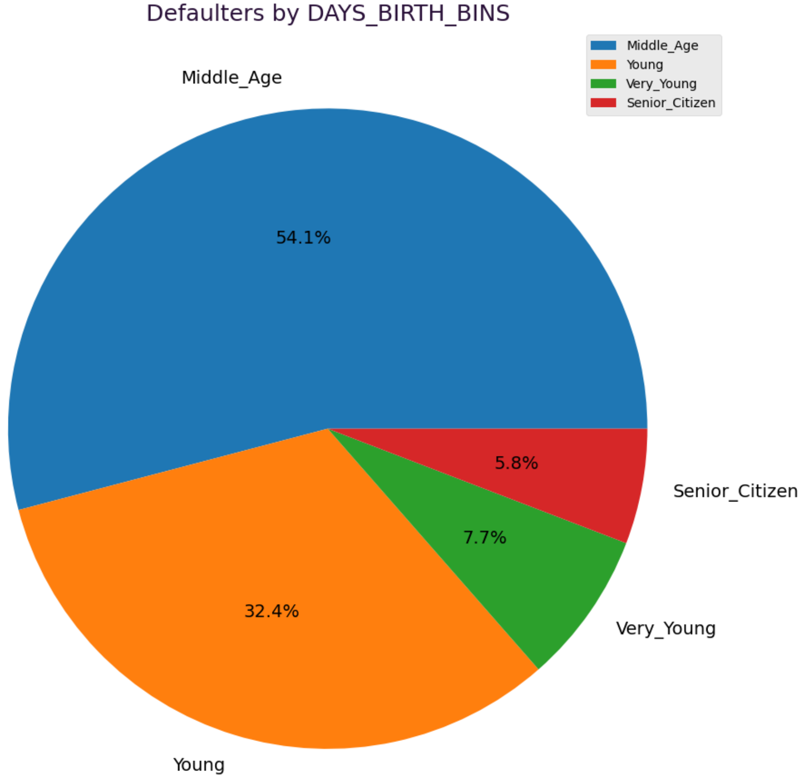
Insights-

- Here also, the % split is more or less unchanged for Defaulters. It suggests that Income doesn't play a significant role in loan defaults. Although, further drilldown analysis (later done in this notebook) would tell us a different story.

Comparison of Age Distribution among Defaulters and Non Defaulters

In [61]:
```
univariate_comparison('DAYS_BIRTH_BINS')
```



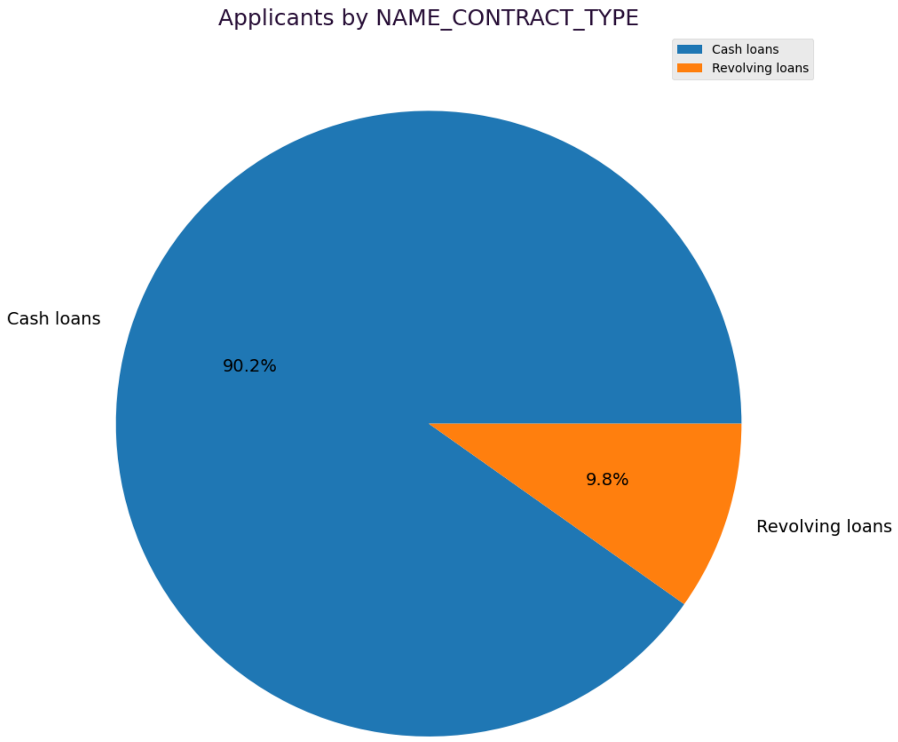


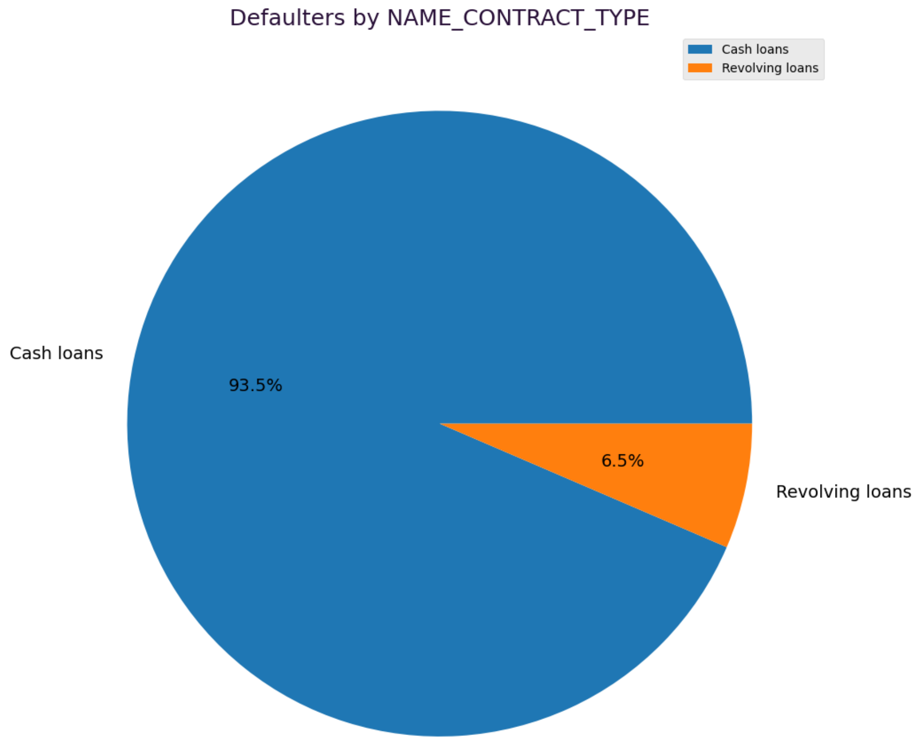
Insights -

- There is a significant shift in % split for Middle Age and Young applicants.
- Middle Aged applicants are contributing lesser to loan defaults
- Young applicants are more expected to default on a loan since there is a change in % split from 24% to 32%

Comparison of Loan Type Distribution among Defaulters and Non Defaulters

In [62]:
```
univariate_comparison('NAME_CONTRACT_TYPE')
```



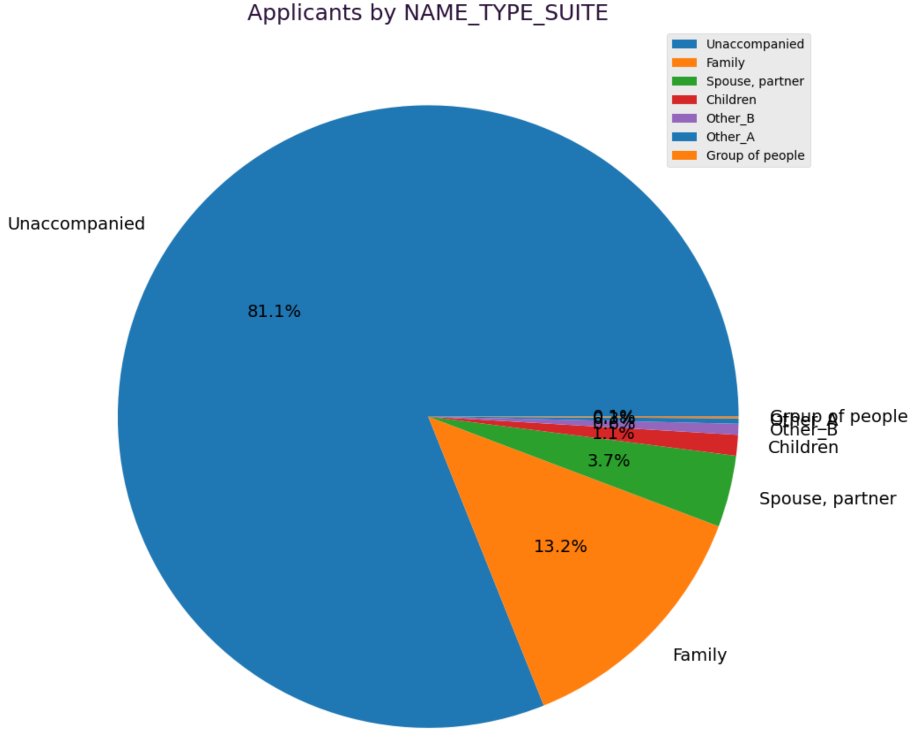


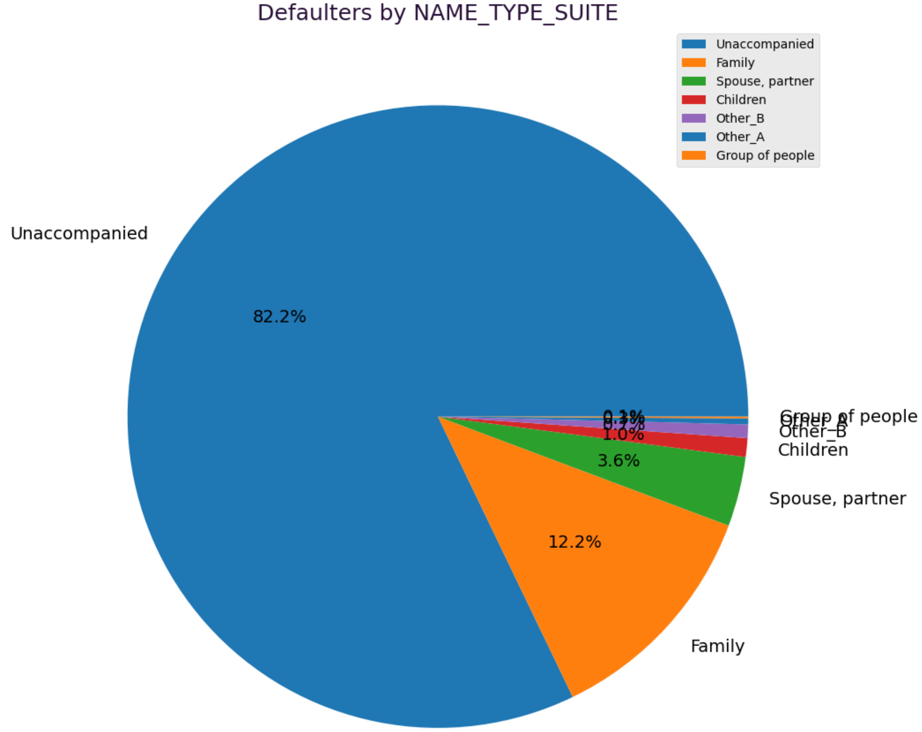
Insights-

- Cash loans are slightly more likely to be defaulted than revolving loans.

Comparison of Accompany Type Distribution among Defaulters and Non Defaulters

In [63]:
```
univariate_comparison('NAME_TYPE_SUITE')
```





Insights-

- Majority of loans are applied by single occupants
- This parameter doesn't have any impact on loan defaults as the % split is unchanged in both cases.

Univariate Analysis of Quantitative Variables

In [118…

```
# Defining function for Univariate Analysis of Quantitative Variables

def univariate_comparison_quant(col,hue=None):

    fig, axes=plt.subplots(nrows =2,ncols=2,figsize=(20,12))
    axes[0,0].set_title("Displot (Non-Defaulter) for  " + col )
    sns.distplot(non_defaulter[~non_defaulter[col].isna()][col],ax=axes[0,0], color="#4CB391")
```

```
    axes[0,1].set_title("Displot (Defaulter) for  " + col )
    sns.distplot(defaulter[~defaulter[col].isna()][col],ax=axes[0,1], color="#4CB391")

    axes[1,0].set_title("Boxplot (Non-Defaulter) for  " + col )
    sns.boxplot(x=non_defaulter[~non_defaulter[col].isna()][col],ax=axes[1,0], color="#4CB391")

    axes[1,1].set_title("Boxplot (Defaulter) for  " + col )
    sns.boxplot(x=defaulter[~defaulter[col].isna()][col],ax=axes[1,1], orient='h',color="#4CB391")

    plt.show()
```

In [119…

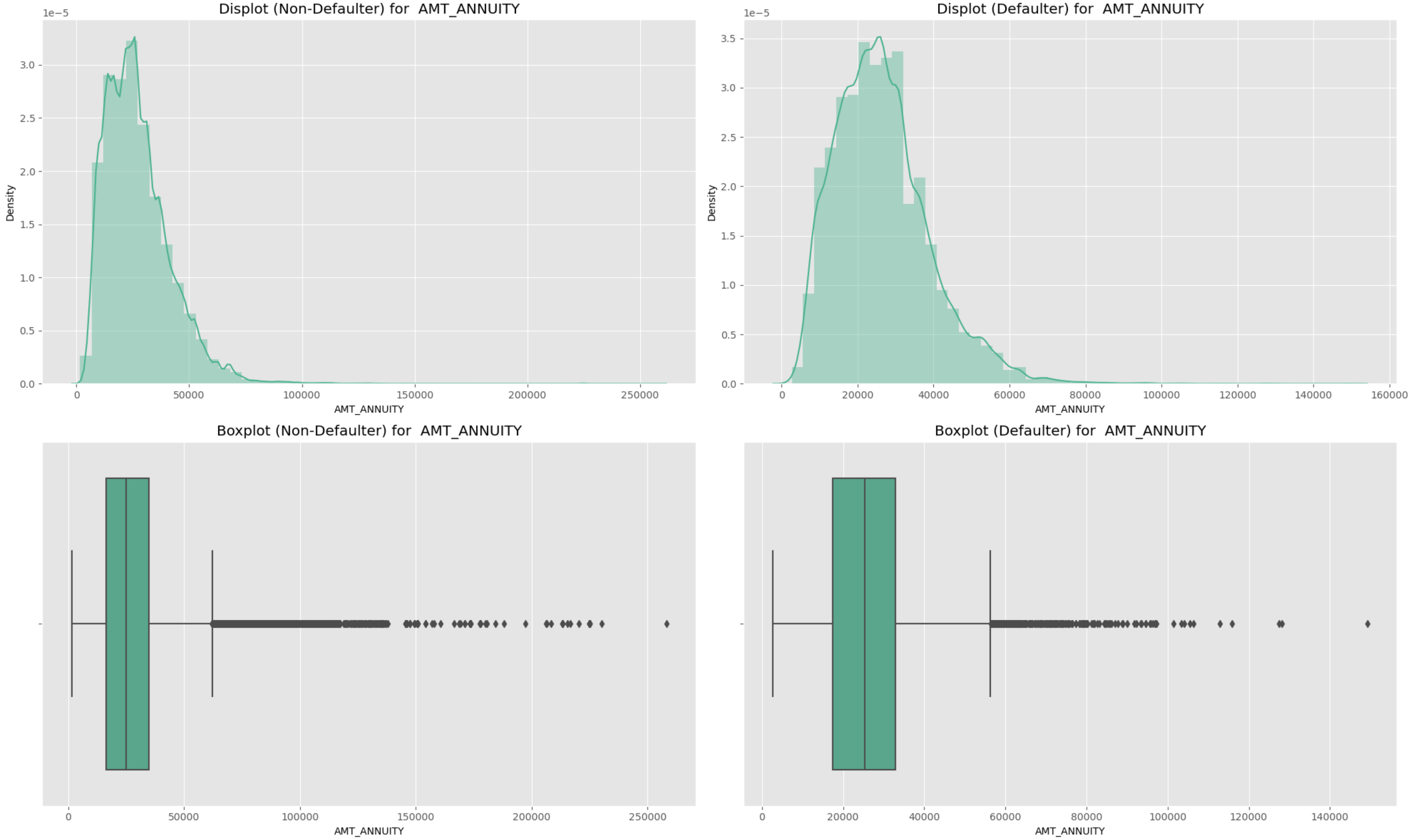
```
defaulter['AMT_ANNUITY']
```

Out[119]:

```
0         24700.5
26        27076.5
40        35028.0
42        16258.5
81        14593.5
           ...
307448    32746.5
307475    46809.0
307481    19975.5
307489    23089.5
307509    20205.0
Name: AMT_ANNUITY, Length: 24825, dtype: float64
```

In [66]:

```
# Univariate Analysis for Annuity Amount

univariate_comparison_quant('AMT_ANNUITY')
```

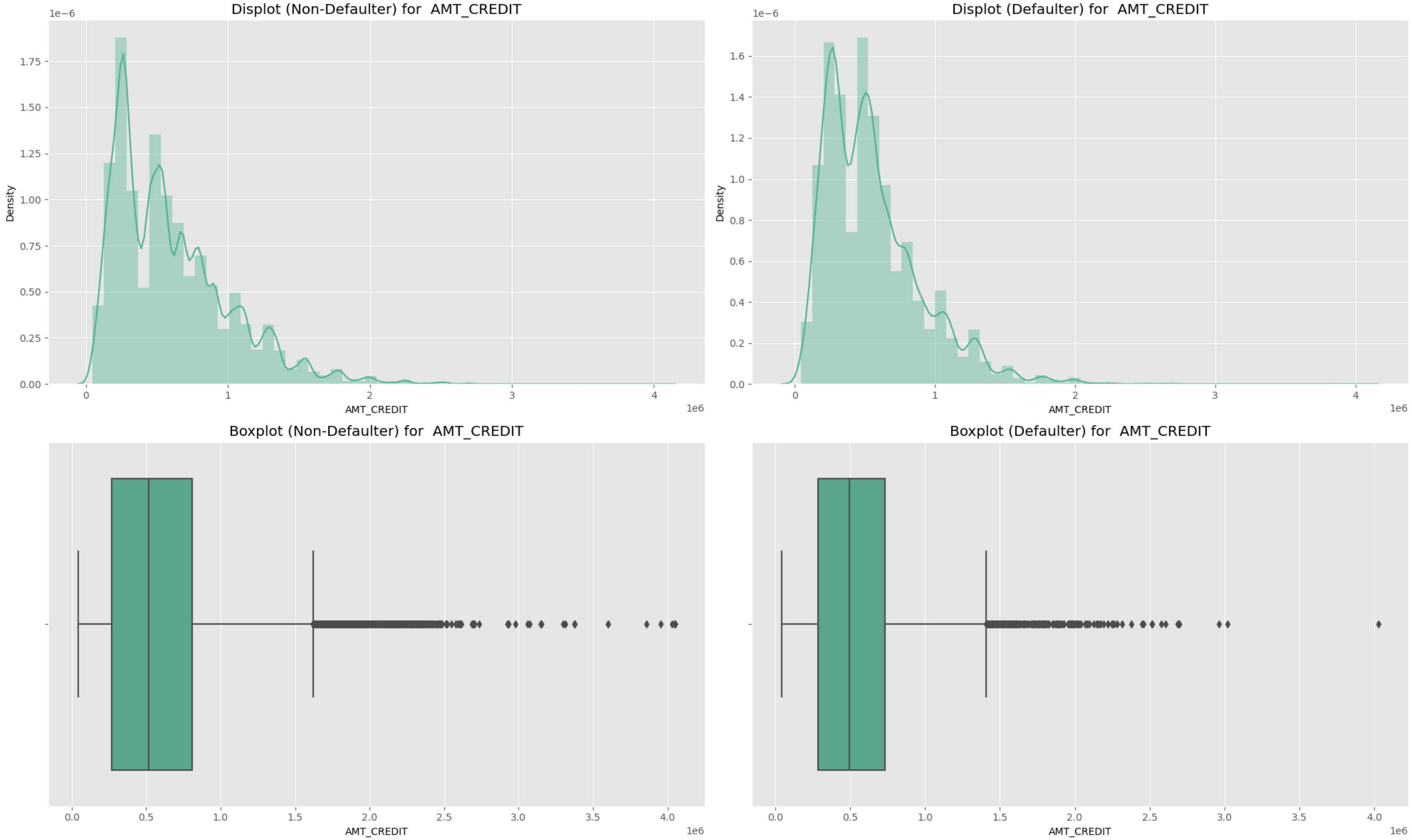


Insights -

- Applicants with lower Annuity Amount are slightly more likely to default on a loan.
- Majority of Loan applicants come from 1st quartile of Annuity data (Low salary people)

In [67]:
```
# Univariate Analysis for Loan Amount
```

```
univariate_comparison_quant('AMT_CREDIT')
```

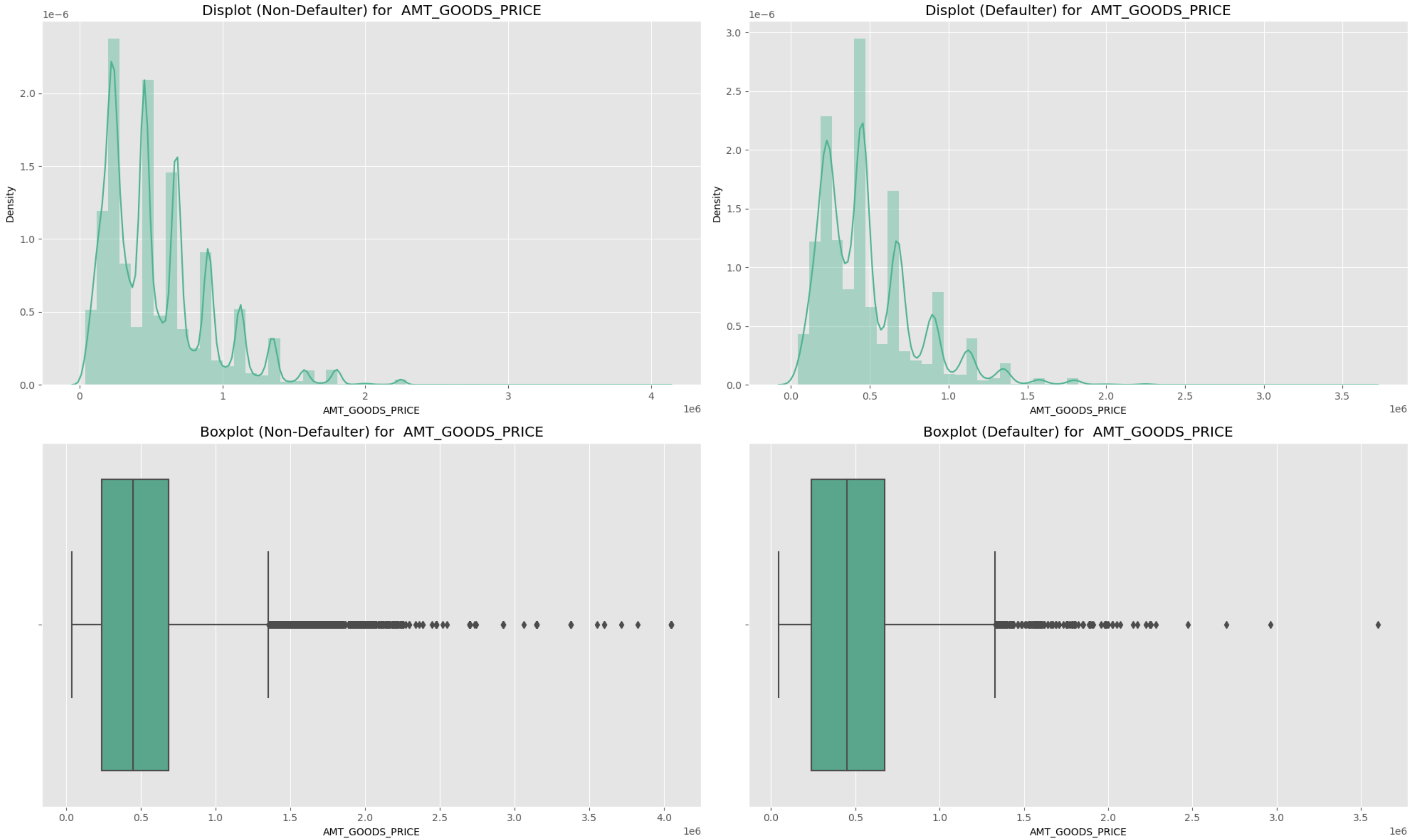


Insights-

- We can infer that Loan Amount doesn't correlate with Loan defaults since the Loan Amount has the exact quartile boundaries in two cases.

In [68]:
```
# Univariate Analysis for Goods Price Amount
```

```
univariate_comparison_quant(col='AMT_GOODS_PRICE')
```



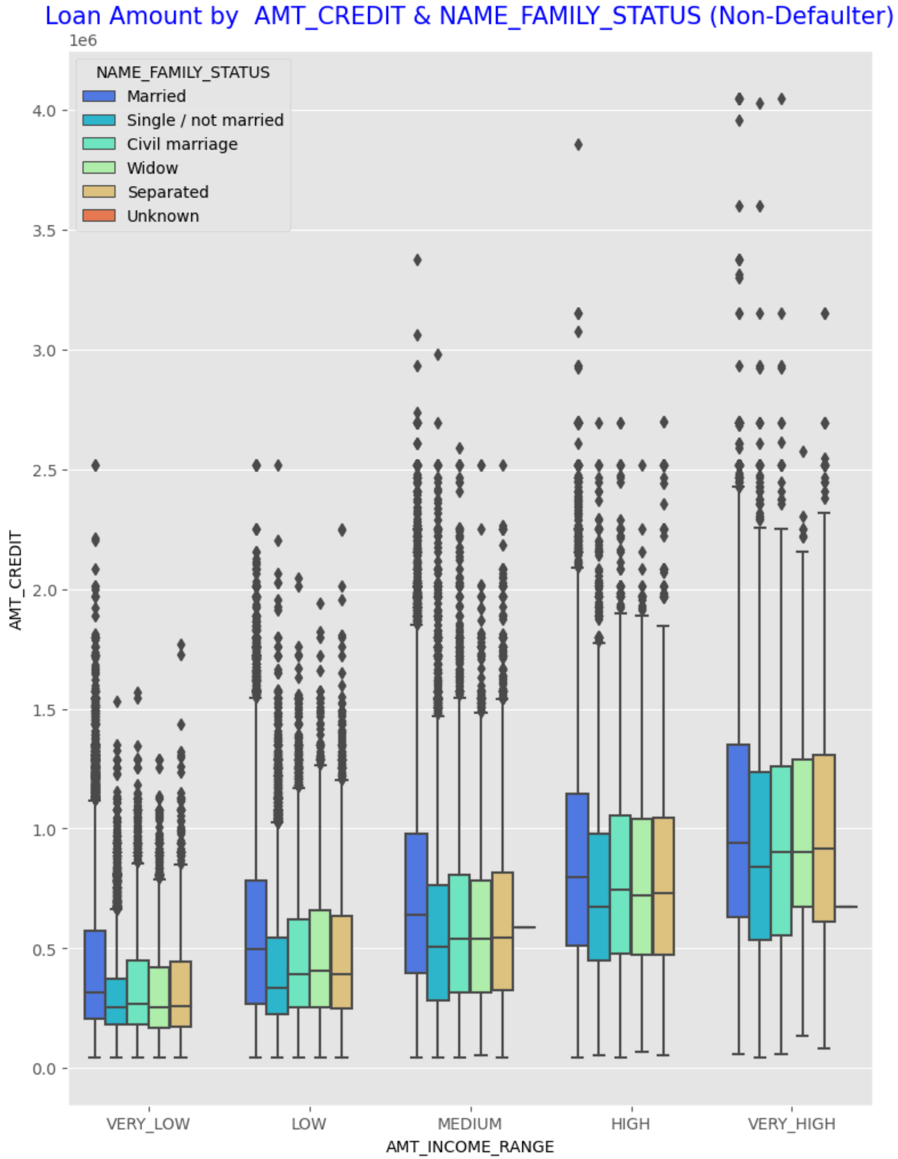
Insights-

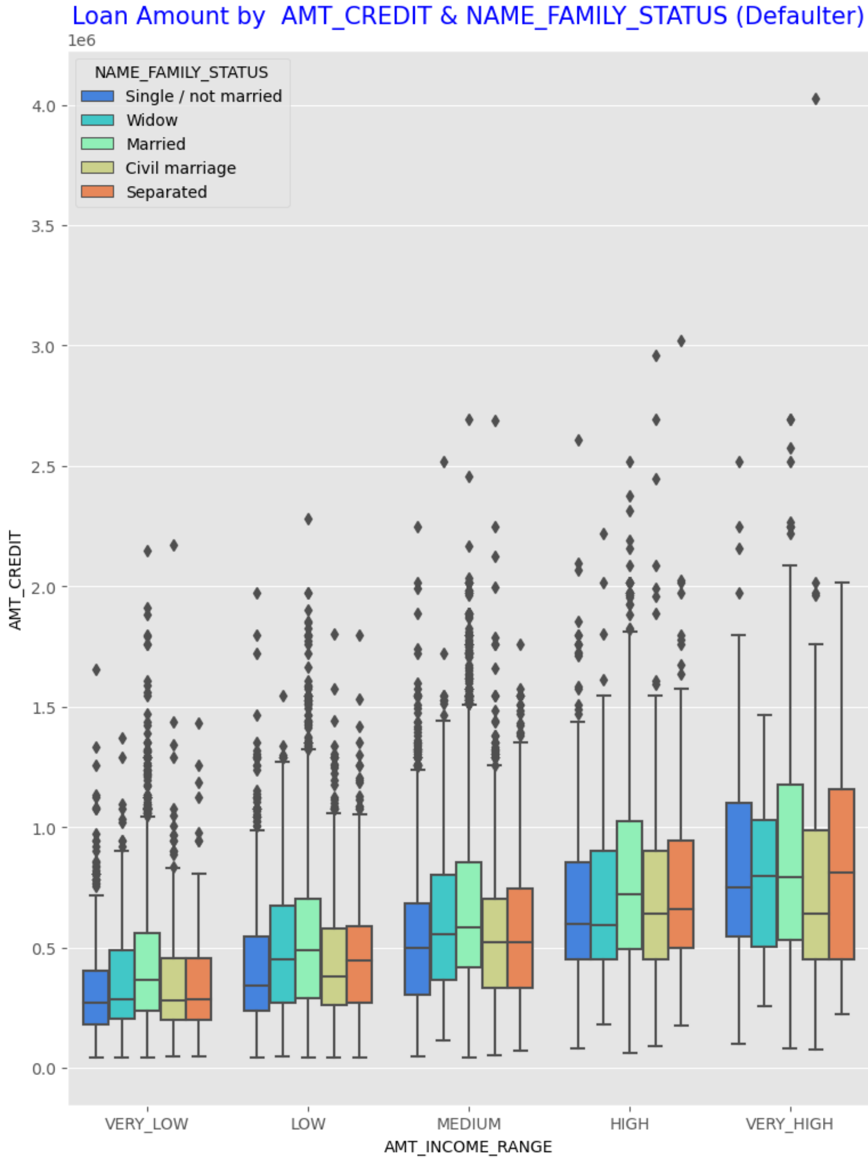
- The distribution are almost unchanged for Defaulters and Non Defaulters, hence we can say that Goods Price doesn't impact the chance of a loan default.

Bivariate & Multivariate Analysis

In [97]:
```
# Function for Multivariate analysis

def multivariate(col1,col2,col3=None):

    fig, axes=plt.subplots(nrows =1,ncols=2,figsize=(20,12))

    axes[0].set_title('Loan Amount by  ' + col2 + ' & ' + col3 + ' (Non-Defaulter)', size=15,color = 'blue')
    sns.boxplot(data=non_defaulter,x=col1, y=col2,palette = 'rainbow', hue= col3,ax=axes[0])

    axes[1].set_title('Loan Amount by  ' + col2 + ' & ' + col3 + ' (Defaulter)', size=15,color = 'blue')
    sns.boxplot(data=defaulter,x=col1, y=col2,palette = 'rainbow', hue= col3,ax=axes[1])
```

In [98]:
```
# Analysis of AMT_INCOME_RANGE, AMT_CREDIT & NAME_FAMILY_STATUS


multivariate('AMT_INCOME_RANGE','AMT_CREDIT','NAME_FAMILY_STATUS')
```

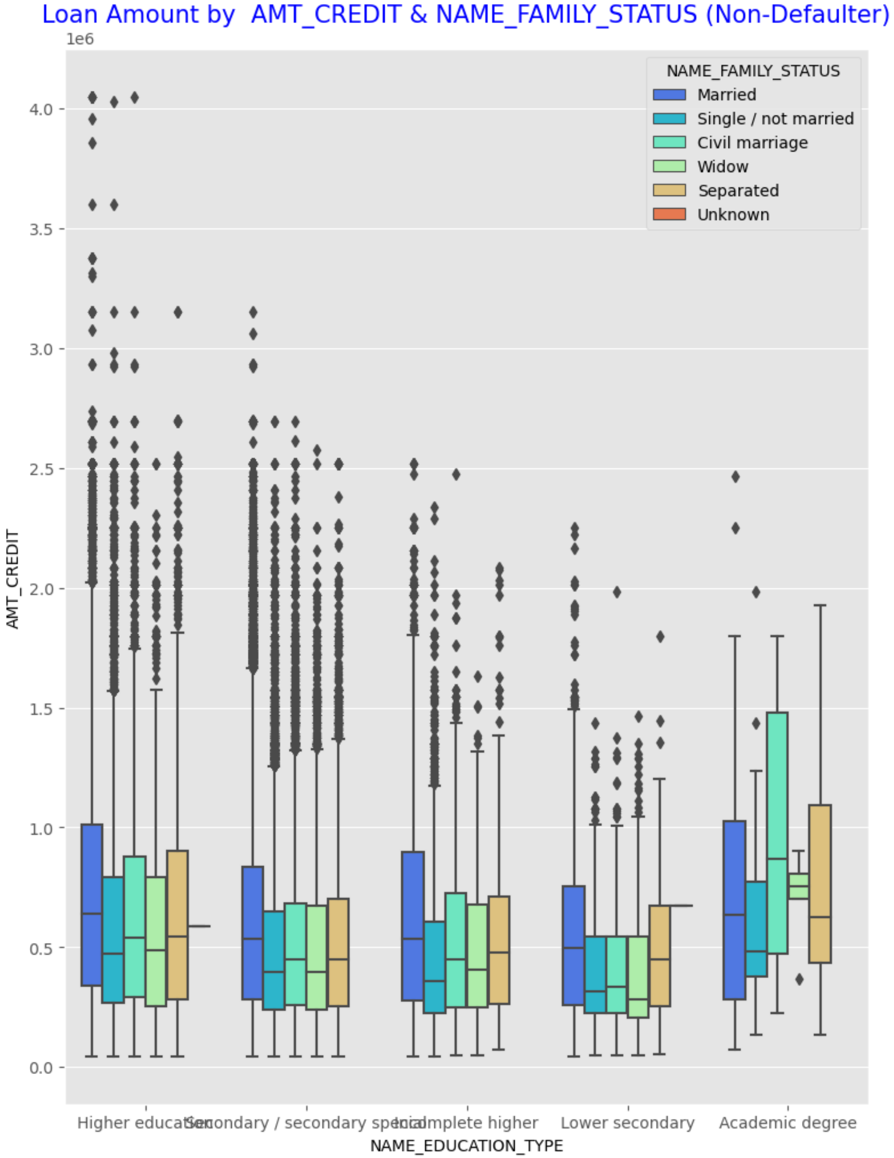


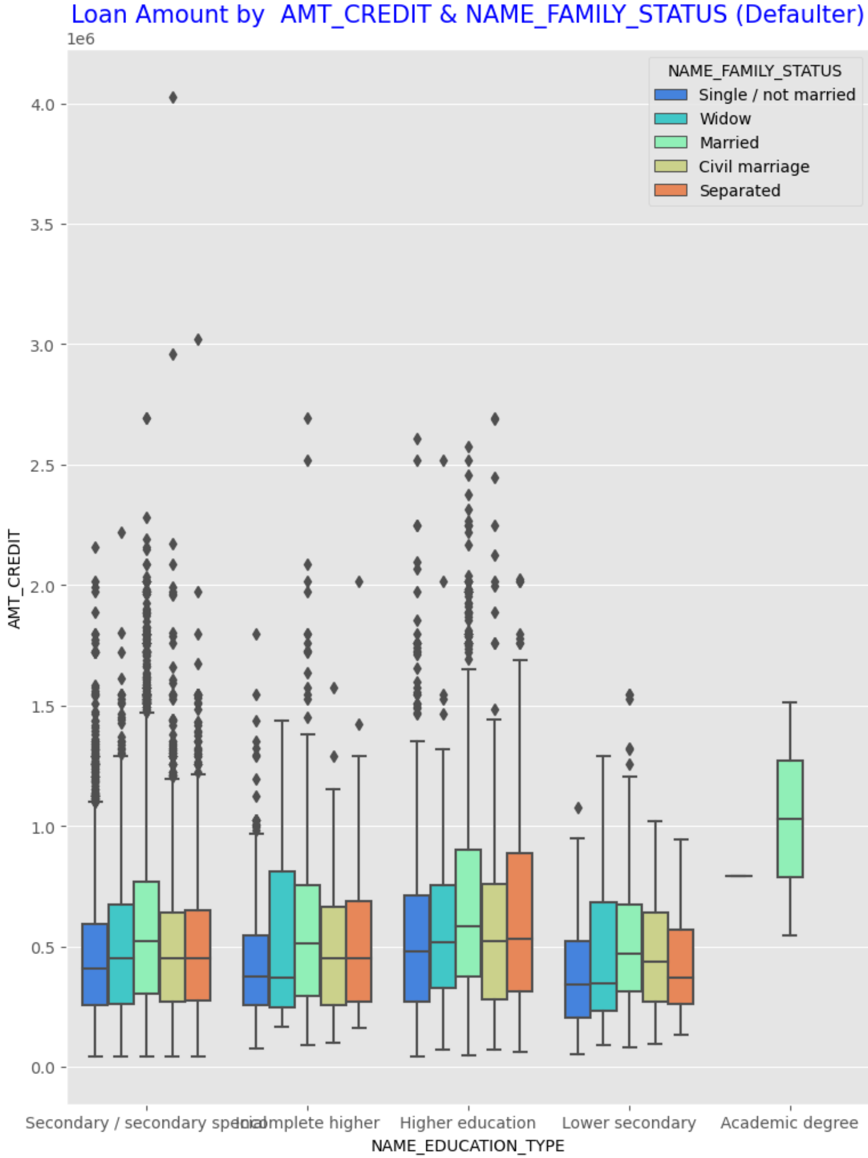


Insights-

- With increase in Income range, the loan amount increases proportionally.
- On family status axis, we observe that Married applicants have higher loan amount than others.

In [99]:
```
# Analysis of NAME_EDUCATION_TYPE, AMT_CREDIT & NAME_FAMILY_STATUS

multivariate('NAME_EDUCATION_TYPE','AMT_CREDIT','NAME_FAMILY_STATUS')
```





Insights-

- Higher the education, lesser is the likelihood of a loan default
- Among different family status, married ones have the highest likelihood of loan default

Drilldown Analysis

Here we'll look for % defaulters within different classes in a particular variable.

In [115…

```
credit_data_2.head()
```

Out[115]:

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

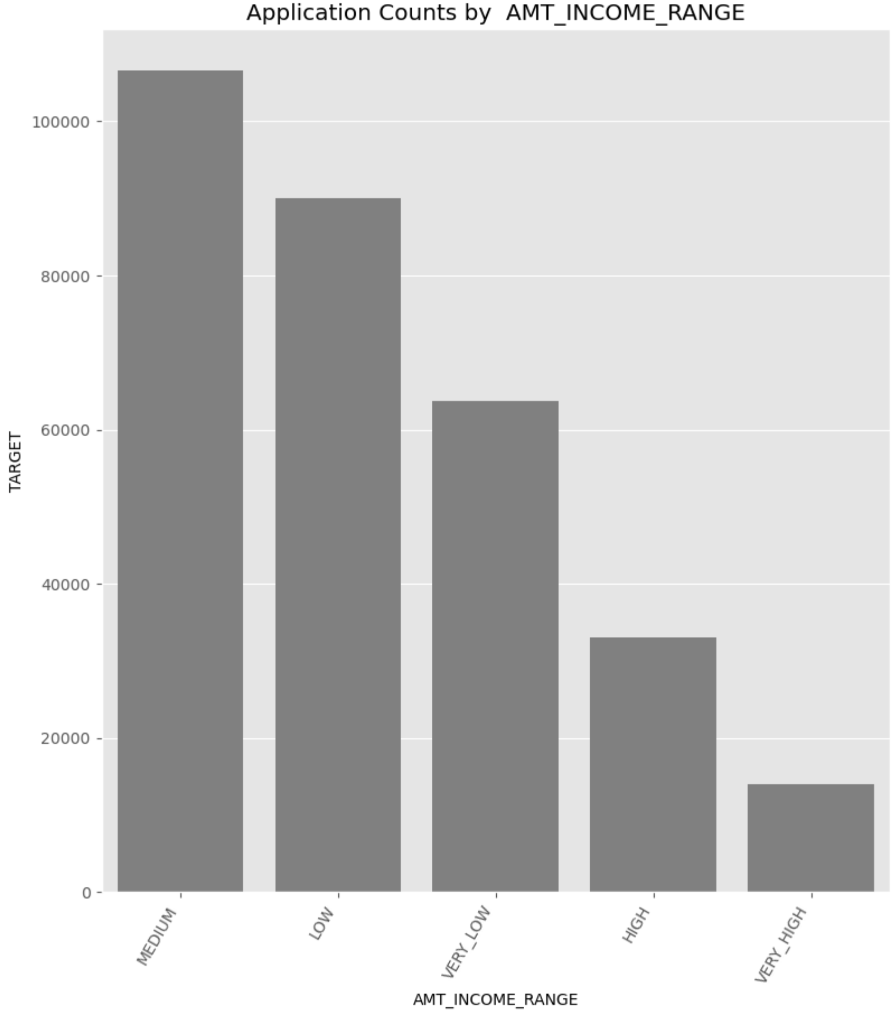
In [109…

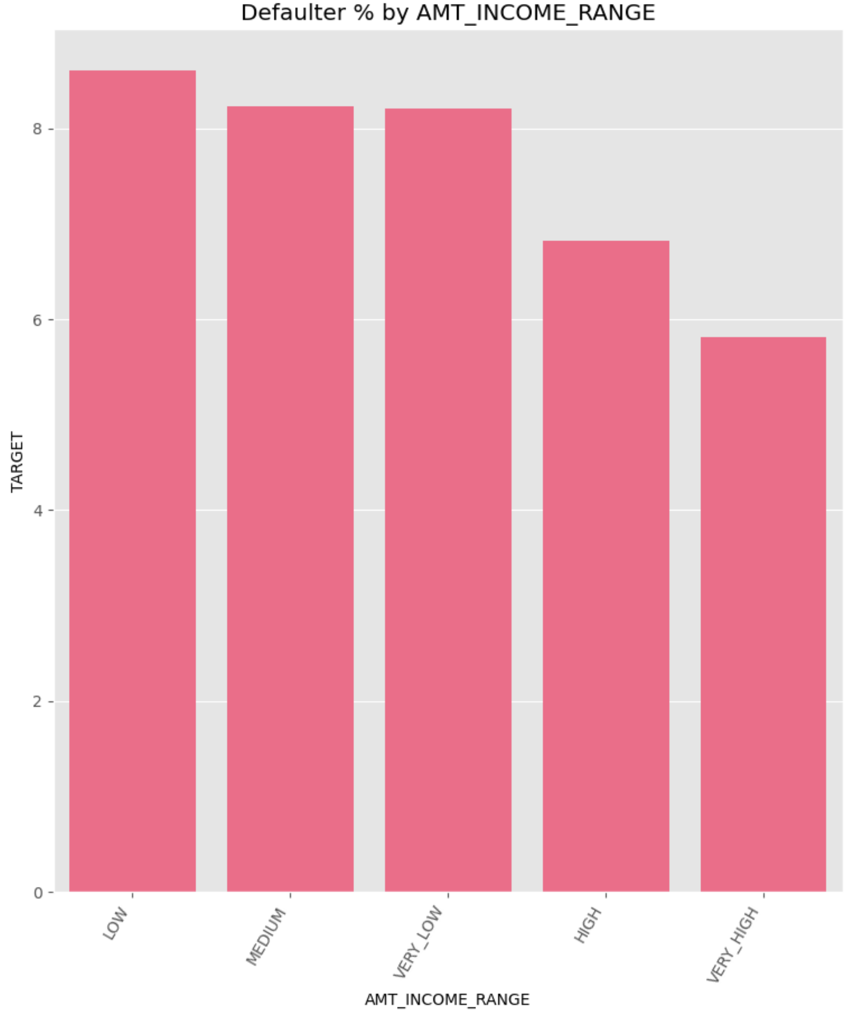
```
# Defining function for drilldown analysis

def perc_defaulters(col):

    fig, axes=plt.subplots(nrows =1,ncols=2,figsize=(20,10))

    total = credit_data_2[[col,'TARGET']].groupby(col).count()
    defaulter_1 = defaulter[[col,'TARGET']].groupby(col).count()
    perc = defaulter_1*100/total

    axes[0].set_title("Application Counts by  "+ col  )
    sns.barplot(x=total.index,y=total.TARGET,color='grey',order=total.sort_values('TARGET',ascending=False).index,ax=axes[0])
    axes[0].set_xticklabels(total.sort_values('TARGET',ascending=False).index,rotation=60, ha='right')

    axes[1].set_title("Defaulter % by " + col  )
```

```python
    sns.barplot(x=perc.index,y=perc.TARGET,color='#ff597d',order=perc.sort_values('TARGET',ascending=False).index,ax=axes[1])
    axes[1].set_xticklabels(perc.sort_values('TARGET',ascending=False).index,rotation=60, ha='right')

    plt.show()
```

In [110…

```python
# Drilldown analysis of AMT_INCOME_RANGE

perc_defaulters('AMT_INCOME_RANGE')
```



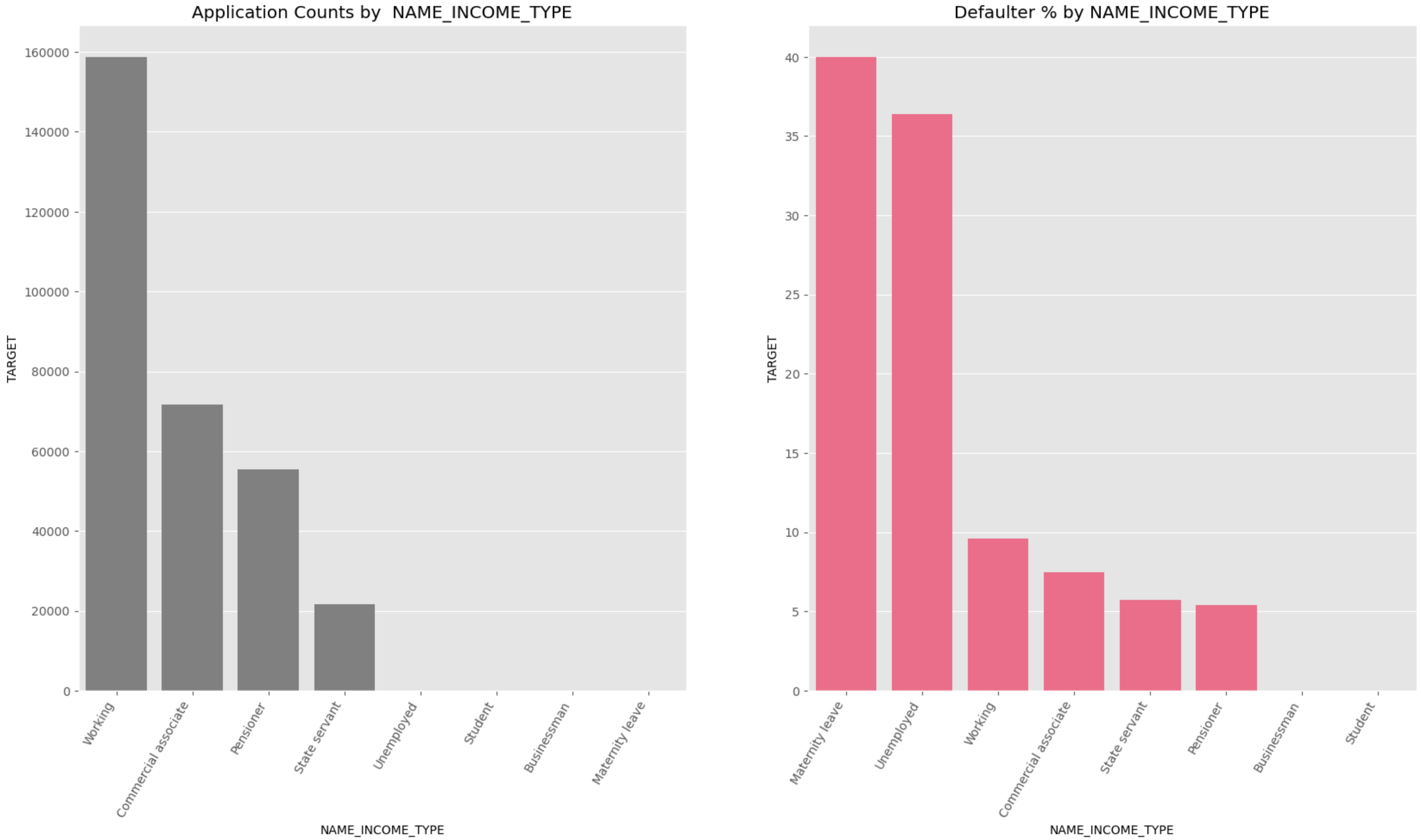


Insights-

- Median income range professionals have maximum applications in the data
- Low Income range have maximum % of loan defaults
- As the Income range increases, loan default probability decreases

In [111…

```
# Drilldown analysis of NAME_INCOME_TYPE

perc_defaulters('NAME_INCOME_TYPE')
```

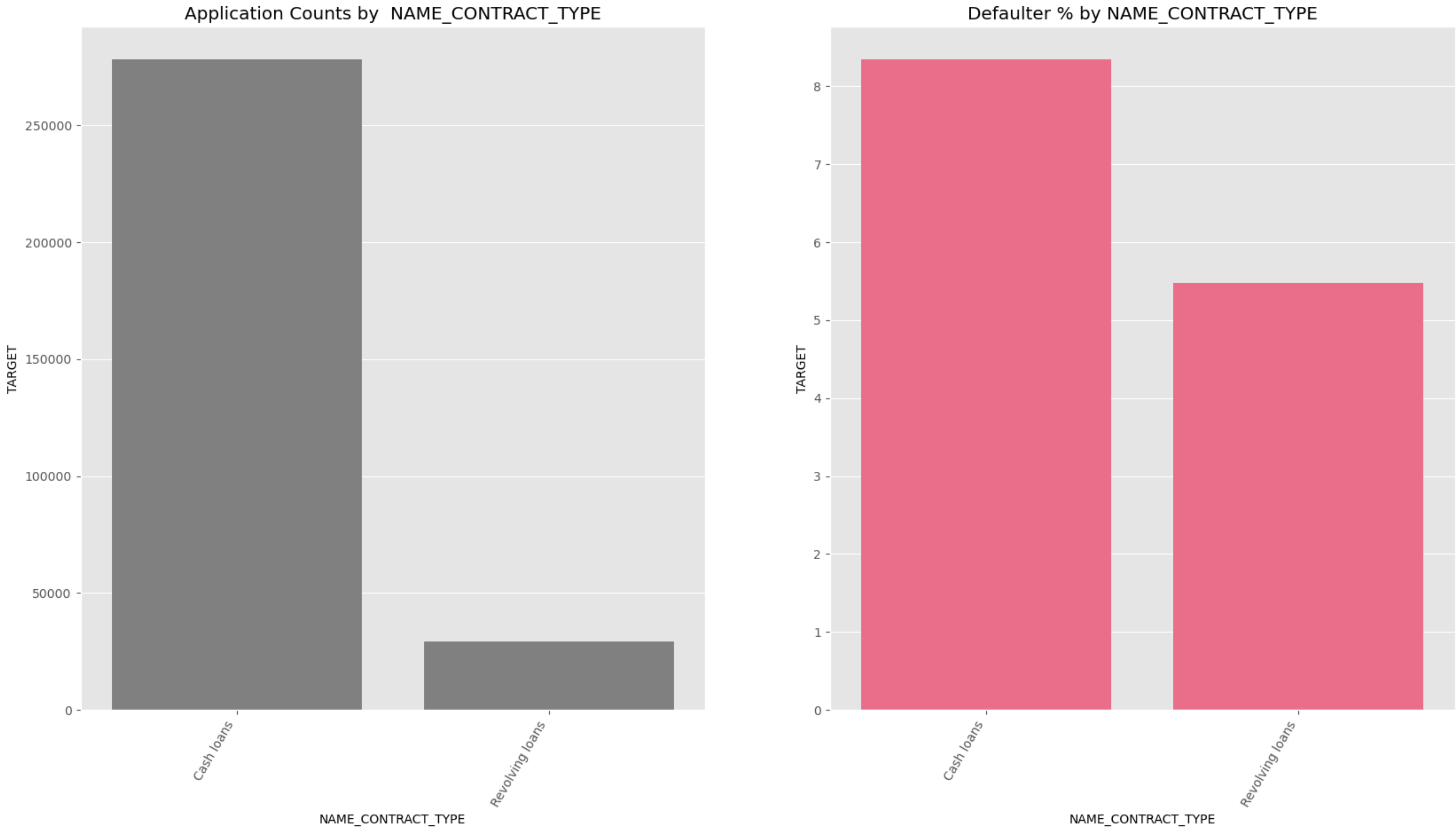


Insights-

- Applicants on Maternity leave have a whopping 40% loan default rate
- The second to the list are Unemployed applicants with 35% loan defaults

In [116…

```
# Drilldown analysis of NAME_CONTRACT_TYPE

perc_defaulters('NAME_CONTRACT_TYPE')
```

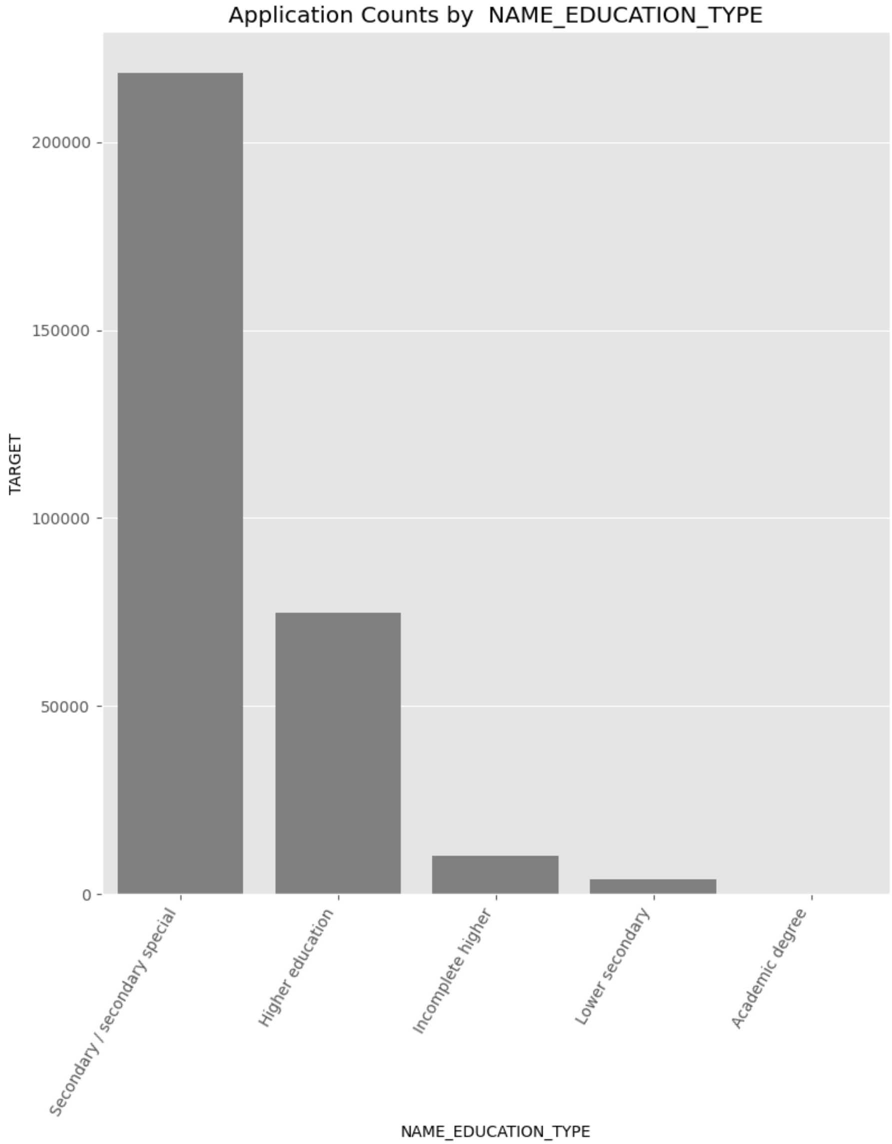


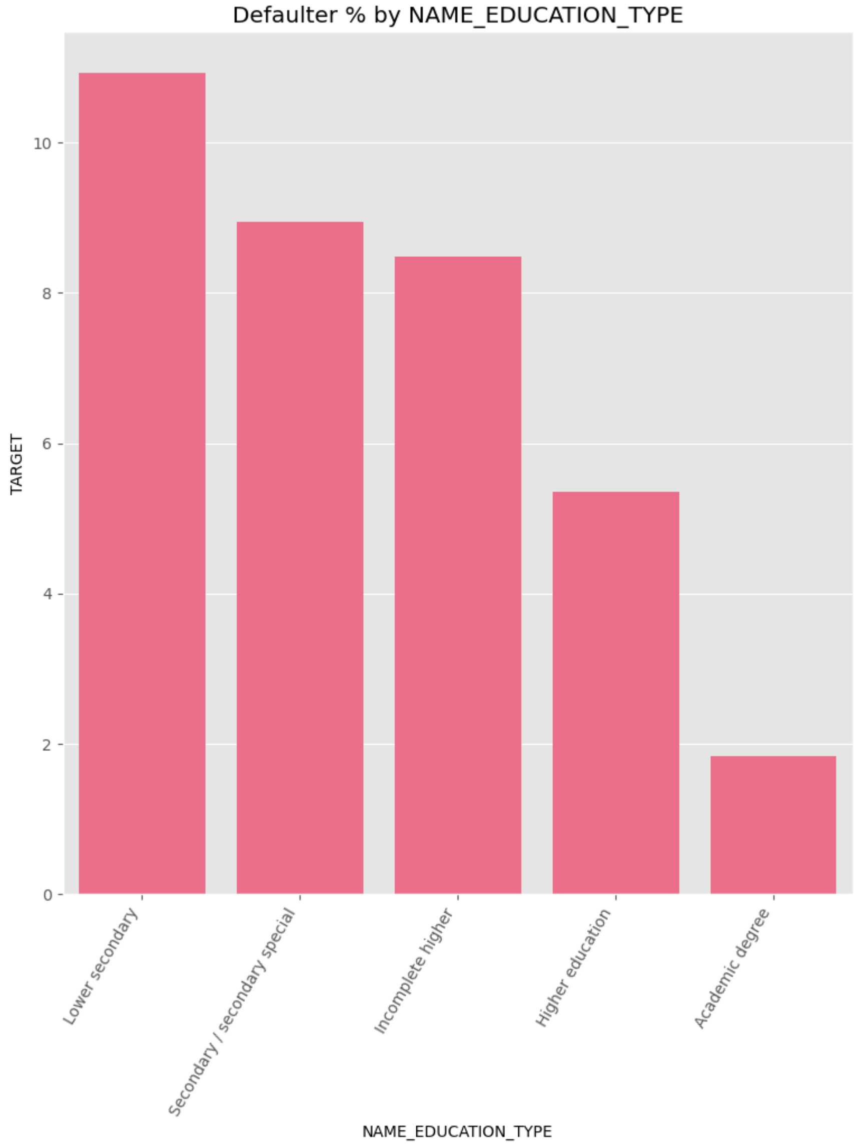
Insights-

- Majority of the loans are cash loans. Cash loans also have almost double probability of a loan default than revolving loans.

In [117…

```
# Drilldown analysis of NAME_EDUCATION_TYPE

perc_defaulters('NAME_EDUCATION_TYPE')
```



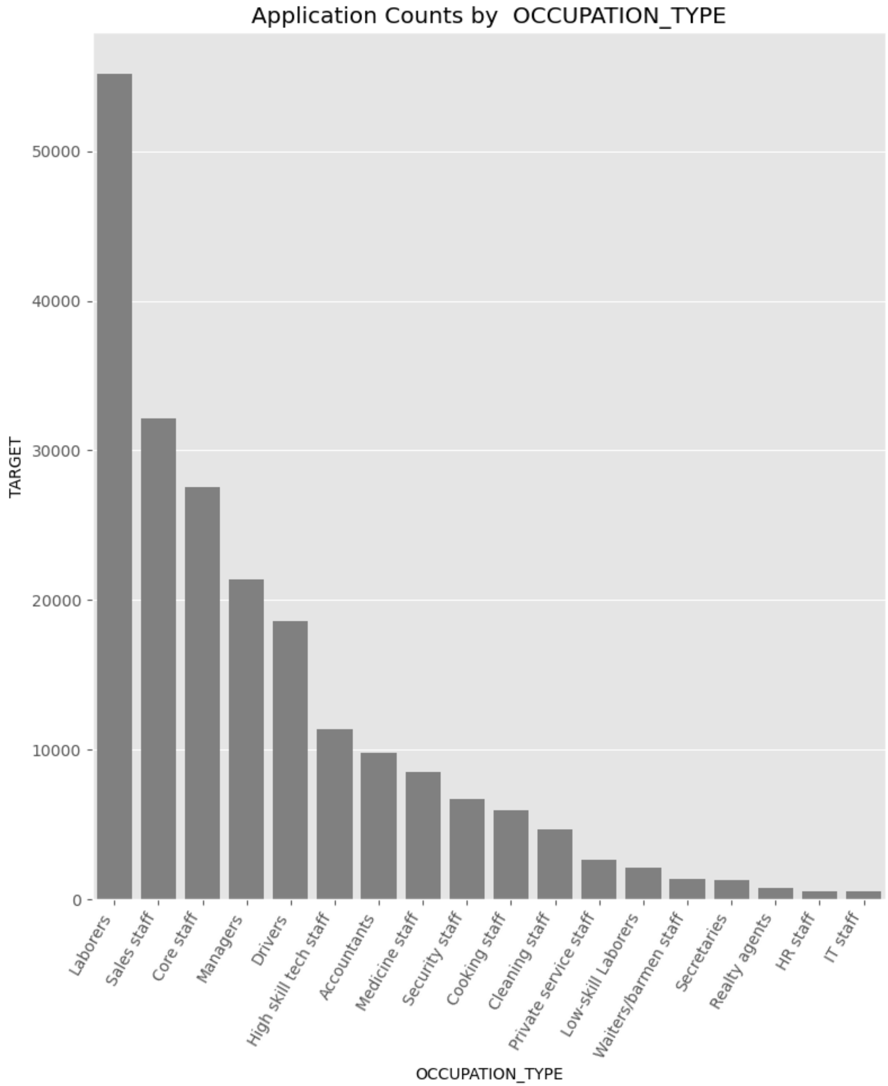


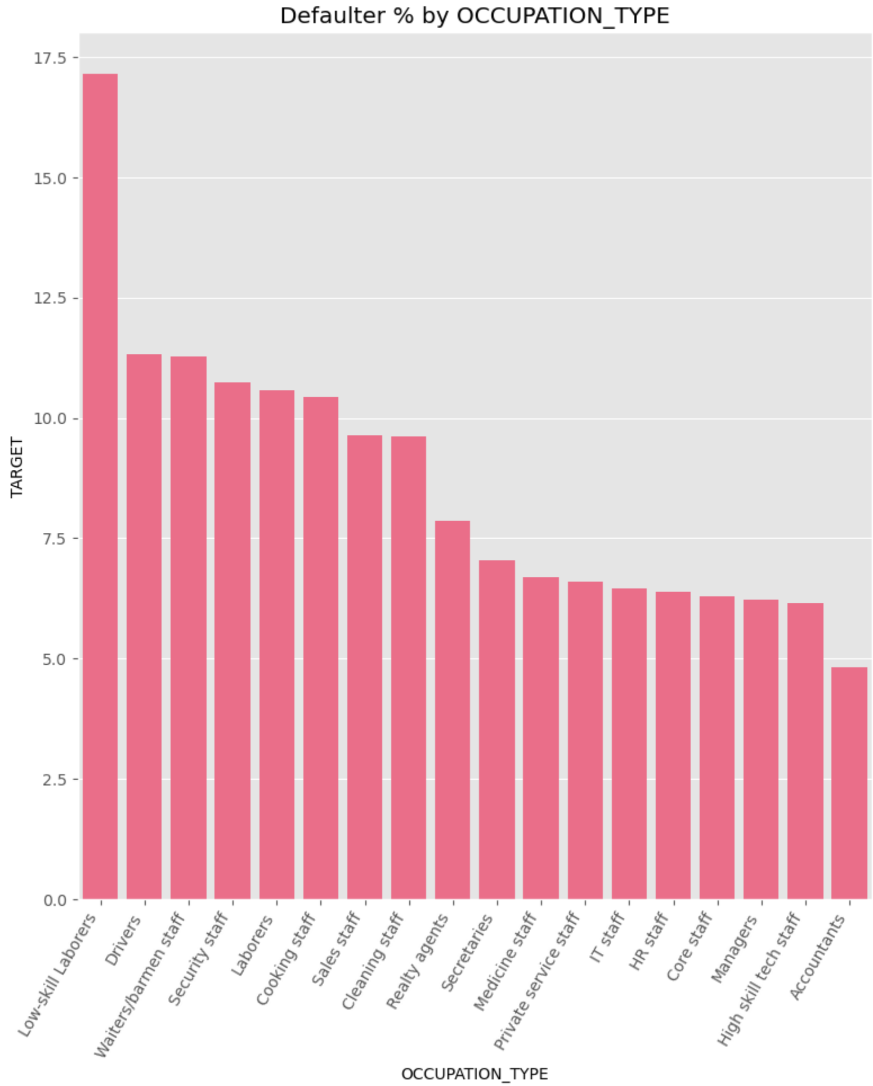
Insights-

- Higher the education of an applicant, lesser the chance of loan default
- Lower secondary applicants have a concerning 11% loan default rate, but the count of applicants is low
- The major concern is of Secondary education applicants. They have highest applicants and a significant 9% loan default rate as well.

In [120…

```
# Drilldown analysis of OCCUPATION_TYPE

perc_defaulters('OCCUPATION_TYPE')
```





Insights-

- Low skill labourers have an alarming 17% loan default rate. The positive here is that they don't have a high applicant count.
- Labourers & Sales staff will be a major area of concern here, with maximum applicants and a significant loan default rate as well.

- Drivers also have an alarming combination of counts and default %.

Pivot table of all loan default %

In [122…

```
perc_defaulters= pd.pivot_table(credit_data_2, values='TARGET',
                      index=['CODE_GENDER','AMT_INCOME_RANGE'],
                      columns=['NAME_EDUCATION_TYPE'], aggfunc=np.mean)
perc_defaulters*100
```

Out[122]:

	NAME_EDUCATION_TYPE	Academic degree	Higher education	Incomplete higher	Lower secondary	Secondary / secondary special
CODE_GENDER	AMT_INCOME_RANGE					
F	VERY_LOW	0.000000	5.606793	8.639863	8.019324	7.677801
	LOW	0.000000	4.902183	8.007537	11.388889	7.952316
	MEDIUM	0.000000	5.025389	7.843137	9.698276	7.569169
	HIGH	10.526316	4.151552	7.431341	3.896104	7.073552
	VERY_HIGH	7.692308	3.728906	8.225108	6.666667	6.593002
M	VERY_LOW	0.000000	8.041061	12.396694	12.500000	11.806626
	LOW	0.000000	7.330468	9.777778	14.285714	12.369265
	MEDIUM	0.000000	7.008598	9.513024	15.051546	11.346642
	HIGH	0.000000	5.591114	7.462687	8.163265	9.348442
	VERY_HIGH	0.000000	4.407996	7.758621	6.451613	8.993853

Insights -

Categories with more than 9% default rate -

- Females, High Income, Academic degree
- Male, Very Low income , Incomplete higher
- Male, Low Income , Incomplete higher
- Male, Medium Income , Incomplete higher
- Female, Low Income, Lower Secondary

- Female, Medium Income, Lower Secondary
- Male, Very Low Income, Lower Secondary
- Male, Low Income, Lower Secondary
- Male, Medium Income, Lower Secondary
- Male, {ALL INCOME RANGES} , Secondary

Final Insights

Following are the driving factors for a loan default -

- Lower the highest education of an applicant, higher the chance of loan default. This is one of the core driving factor in loan defaults.
- Labourers & Sales staff are major area of concern , with maximum applicants and a significant loan default rate. Drivers also have an alarming combination of counts and default %.
- Applicants on Maternity leave have a whopping 40% loan default rate. Unemployed applicants also have 35% loan defaults
- Low Income range have maximum % of loan defaults. As the Income range increases, loan default probability decreases
- Among different family status, married ones have the highest likelihood of loan default
- Applicants with lower Annuity Amount are slightly more likely to default on a loan.
- Young applicants are more expected to default on a loan.
- More Men default loans as compared to Women