Part 1 with Current Applicants

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import os
import warnings
warnings.simplefilter(action='ignore')
%matplotlib inline
```

In [2]:
```
os.chdir("D:\Lohith\DA\Handson\Risk_Analytics")
```

In [3]:
```
Client_Data = pd.read_csv("application_data.csv")    #Reading the Client data
Description = pd.read_csv(r"columns_description.csv",encoding='cp1252')
```

By Default it will show only 20 columns,Since we have more then 20 column, this function is used

In [4]:
```
pd.set_option("display.max_columns",None,"display.max_rows",None)
```

In [5]:
```
Description.drop(columns="Unnamed: 0", axis =1, inplace = True)   # Description of our Columns
Description[:122]
```

Out[5]:

	Table	Row	Description	Special
0	application_data	SK_ID_CURR	ID of loan in our sample	NaN
1	application_data	TARGET	Target variable (1 - client with payment diffi...	NaN
2	application_data	NAME_CONTRACT_TYPE	Identification if loan is cash or revolving	NaN
3	application_data	CODE_GENDER	Gender of the client	NaN
4	application_data	FLAG_OWN_CAR	Flag if the client owns a car	NaN
5	application_data	FLAG_OWN_REALTY	Flag if client owns a house or flat	NaN
6	application_data	CNT_CHILDREN	Number of children the client has	NaN
7	application_data	AMT_INCOME_TOTAL	Income of the client	NaN
8	application_data	AMT_CREDIT	Credit amount of the loan	NaN
9	application_data	AMT_ANNUITY	Loan annuity	NaN
10	application_data	AMT_GOODS_PRICE	For consumer loans it is the price of the good...	NaN
11	application_data	NAME_TYPE_SUITE	Who was accompanying client when he was applyi...	NaN
12	application_data	NAME_INCOME_TYPE	Clients income type (businessman, working, mat...	NaN
13	application_data	NAME_EDUCATION_TYPE	Level of highest education the client achieved	NaN
14	application_data	NAME_FAMILY_STATUS	Family status of the client	NaN
15	application_data	NAME_HOUSING_TYPE	What is the housing situation of the client (r...	NaN
16	application_data	REGION_POPULATION_RELATIVE	Normalized population of region where client l...	normalized
17	application_data	DAYS_BIRTH	Client's age in days at the time of application	time only relative to the application
18	application_data	DAYS_EMPLOYED	How many days before the application the perso...	time only relative to the application
19	application_data	DAYS_REGISTRATION	How many days before the application did clien...	time only relative to the application
20	application_data	DAYS_ID_PUBLISH	How many days before the application did clien...	time only relative to the application
21	application_data	OWN_CAR_AGE	Age of client's car	NaN
22	application_data	FLAG_MOBIL	Did client provide mobile phone (1=YES, 0=NO)	NaN
23	application_data	FLAG_EMP_PHONE	Did client provide work phone (1=YES, 0=NO)	NaN
24	application_data	FLAG_WORK_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
25	application_data	FLAG_CONT_MOBILE	Was mobile phone reachable (1=YES, 0=NO)	NaN
26	application_data	FLAG_PHONE	Did client provide home phone (1=YES, 0=NO)	NaN
27	application_data	FLAG_EMAIL	Did client provide email (1=YES, 0=NO)	NaN
28	application_data	OCCUPATION_TYPE	What kind of occupation does the client have	NaN
29	application_data	CNT_FAM_MEMBERS	How many family members does client have	NaN
30	application_data	REGION_RATING_CLIENT	Our rating of the region where client lives (1...	NaN
31	application_data	REGION_RATING_CLIENT_W_CITY	Our rating of the region where client lives wi...	NaN
32	application_data	WEEKDAY_APPR_PROCESS_START	On which day of the week did the client apply ...	NaN
33	application_data	HOUR_APPR_PROCESS_START	Approximately at what hour did the client appl...	rounded
34	application_data	REG_REGION_NOT_LIVE_REGION	Flag if client's permanent address does not ma...	NaN
35	application_data	REG_REGION_NOT_WORK_REGION	Flag if client's permanent address does not ma...	NaN
36	application_data	LIVE_REGION_NOT_WORK_REGION	Flag if client's contact address does not matc...	NaN
37	application_data	REG_CITY_NOT_LIVE_CITY	Flag if client's permanent address does not ma...	NaN
38	application_data	REG_CITY_NOT_WORK_CITY	Flag if client's permanent address does not ma...	NaN
39	application_data	LIVE_CITY_NOT_WORK_CITY	Flag if client's contact address does not matc...	NaN
40	application_data	ORGANIZATION_TYPE	Type of organization where client works	NaN
41	application_data	EXT_SOURCE_1	Normalized score from external data source	normalized
42	application_data	EXT_SOURCE_2	Normalized score from external data source	normalized
43	application_data	EXT_SOURCE_3	Normalized score from external data source	normalized
44	application_data	APARTMENTS_AVG	Normalized information about building where th...	normalized
45	application_data	BASEMENTAREA_AVG	Normalized information about building where th...	normalized
46	application_data	YEARS_BEGINEXPLUATATION_AVG	Normalized information about building where th...	normalized
47	application_data	YEARS_BUILD_AVG	Normalized information about building where th...	normalized
48	application_data	COMMONAREA_AVG	Normalized information about building where th...	normalized
49	application_data	ELEVATORS_AVG	Normalized information about building where th...	normalized
50	application_data	ENTRANCES_AVG	Normalized information about building where th...	normalized
51	application_data	FLOORSMAX_AVG	Normalized information about building where th...	normalized
52	application_data	FLOORSMIN_AVG	Normalized information about building where th...	normalized
53	application_data	LANDAREA_AVG	Normalized information about building where th...	normalized
54	application_data	LIVINGAPARTMENTS_AVG	Normalized information about building where th...	normalized
55	application_data	LIVINGAREA_AVG	Normalized information about building where th...	normalized
56	application_data	NONLIVINGAPARTMENTS_AVG	Normalized information about building where th...	normalized
57	application_data	NONLIVINGAREA_AVG	Normalized information about building where th...	normalized
58	application_data	APARTMENTS_MODE	Normalized information about building where th...	normalized
59	application_data	BASEMENTAREA_MODE	Normalized information about building where th...	normalized
60	application_data	YEARS_BEGINEXPLUATATION_MODE	Normalized information about building where th...	normalized
61	application_data	YEARS_BUILD_MODE	Normalized information about building where th...	normalized
62	application_data	COMMONAREA_MODE	Normalized information about building where th...	normalized
63	application_data	ELEVATORS_MODE	Normalized information about building where th...	normalized
64	application_data	ENTRANCES_MODE	Normalized information about building where th...	normalized
65	application_data	FLOORSMAX_MODE	Normalized information about building where th...	normalized
66	application_data	FLOORSMIN_MODE	Normalized information about building where th...	normalized
67	application_data	LANDAREA_MODE	Normalized information about building where th...	normalized
68	application_data	LIVINGAPARTMENTS_MODE	Normalized information about building where th...	normalized
69	application_data	LIVINGAREA_MODE	Normalized information about building where th...	normalized
70	application_data	NONLIVINGAPARTMENTS_MODE	Normalized information about building where th...	normalized
71	application_data	NONLIVINGAREA_MODE	Normalized information about building where th...	normalized
72	application_data	APARTMENTS_MEDI	Normalized information about building where th...	normalized
73	application_data	BASEMENTAREA_MEDI	Normalized information about building where th...	normalized
74	application_data	YEARS_BEGINEXPLUATATION_MEDI	Normalized information about building where th...	normalized
75	application_data	YEARS_BUILD_MEDI	Normalized information about building where th...	normalized
76	application_data	COMMONAREA_MEDI	Normalized information about building where th...	normalized
77	application_data	ELEVATORS_MEDI	Normalized information about building where th...	normalized
78	application_data	ENTRANCES_MEDI	Normalized information about building where th...	normalized
79	application_data	FLOORSMAX_MEDI	Normalized information about building where th...	normalized
80	application_data	FLOORSMIN_MEDI	Normalized information about building where th...	normalized
81	application_data	LANDAREA_MEDI	Normalized information about building where th...	normalized
82	application_data	LIVINGAPARTMENTS_MEDI	Normalized information about building where th...	normalized
83	application_data	LIVINGAREA_MEDI	Normalized information about building where th...	normalized
84	application_data	NONLIVINGAPARTMENTS_MEDI	Normalized information about building where th...	normalized
85	application_data	NONLIVINGAREA_MEDI	Normalized information about building where th...	normalized
86	application_data	FONDKAPREMONT_MODE	Normalized information about building where th...	normalized
87	application_data	HOUSETYPE_MODE	Normalized information about building where th...	normalized
88	application_data	TOTALAREA_MODE	Normalized information about building where th...	normalized
89	application_data	WALLSMATERIAL_MODE	Normalized information about building where th...	normalized
90	application_data	EMERGENCYSTATE_MODE	Normalized information about building where th...	normalized
91	application_data	OBS_30_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
92	application_data	DEF_30_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
93	application_data	OBS_60_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
94	application_data	DEF_60_CNT_SOCIAL_CIRCLE	How many observation of client's social surrou...	NaN
95	application_data	DAYS_LAST_PHONE_CHANGE	How many days before application did client ch...	NaN
96	application_data	FLAG_DOCUMENT_2	Did client provide document 2	NaN
97	application_data	FLAG_DOCUMENT_3	Did client provide document 3	NaN
98	application_data	FLAG_DOCUMENT_4	Did client provide document 4	NaN
99	application_data	FLAG_DOCUMENT_5	Did client provide document 5	NaN
100	application_data	FLAG_DOCUMENT_6	Did client provide document 6	NaN
101	application_data	FLAG_DOCUMENT_7	Did client provide document 7	NaN
102	application_data	FLAG_DOCUMENT_8	Did client provide document 8	NaN
103	application_data	FLAG_DOCUMENT_9	Did client provide document 9	NaN
104	application_data	FLAG_DOCUMENT_10	Did client provide document 10	NaN
105	application_data	FLAG_DOCUMENT_11	Did client provide document 11	NaN
106	application_data	FLAG_DOCUMENT_12	Did client provide document 12	NaN
107	application_data	FLAG_DOCUMENT_13	Did client provide document 13	NaN
108	application_data	FLAG_DOCUMENT_14	Did client provide document 14	NaN
109	application_data	FLAG_DOCUMENT_15	Did client provide document 15	NaN
110	application_data	FLAG_DOCUMENT_16	Did client provide document 16	NaN
111	application_data	FLAG_DOCUMENT_17	Did client provide document 17	NaN
112	application_data	FLAG_DOCUMENT_18	Did client provide document 18	NaN
113	application_data	FLAG_DOCUMENT_19	Did client provide document 19	NaN
114	application_data	FLAG_DOCUMENT_20	Did client provide document 20	NaN
115	application_data	FLAG_DOCUMENT_21	Did client provide document 21	NaN
116	application_data	AMT_REQ_CREDIT_BUREAU_HOUR	Number of enquiries to Credit Bureau about the...	NaN
117	application_data	AMT_REQ_CREDIT_BUREAU_DAY	Number of enquiries to Credit Bureau about the...	NaN
118	application_data	AMT_REQ_CREDIT_BUREAU_WEEK	Number of enquiries to Credit Bureau about the...	NaN
119	application_data	AMT_REQ_CREDIT_BUREAU_MON	Number of enquiries to Credit Bureau about the...	NaN
120	application_data	AMT_REQ_CREDIT_BUREAU_QRT	Number of enquiries to Credit Bureau about the...	NaN
121	application_data	AMT_REQ_CREDIT_BUREAU_YEAR	Number of enquiries to Credit Bureau about the...	NaN

In [6]:
```
Client_Data.head(5) # Checking the top 5 records
```

Out[6]:

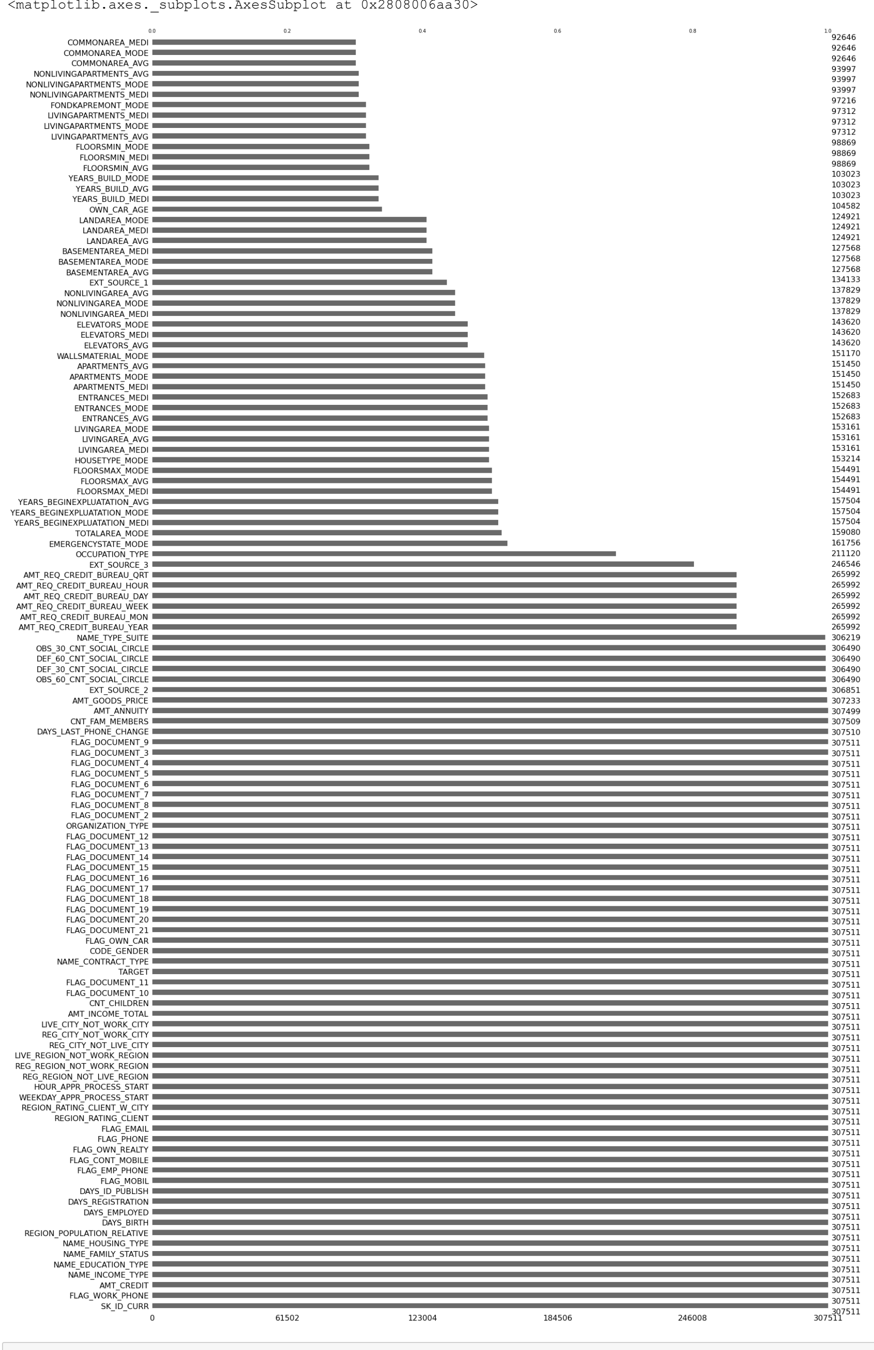
	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN
0	100002	1	Cash loans	M	N	Y	0
1	100003	0	Cash loans	F	N	N	0
2	100004	0	Revolving loans	M	Y	Y	0
3	100006	0	Cash loans	F	N	Y	0
4	100007	0	Cash loans	M	N	Y	0

In [7]:
```
print("Client_Data: ",Client_Data.shape)
```

```
Client_Data:  (307511, 122)
```

In [8]:
```
msno.bar(Client_Data,sort = "descending")
```

Out[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2808006aa30>
```



In [9]:
```
Client_Data.drop(Client_Data.columns[41:91],axis = 1, inplace =True)
```

In [10]:
```
Client_Data.drop(columns=["DAYS_REGISTRATION","REGION_POPULATION_RELATIVE","FLAG_PHONE","REG_REGION_NOT_LIVE_REGION","REG_REGION_NOT_WORK_REGION","LIVE_REGION_NOT_WORK_REGION","OCCUPATION_TYPE","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"],axis =1, inplace =True)
```

In [11]:
```
Client_Data.dropna(thresh=round(len(Client_Data)*0.4),axis=1,inplace =True)
```

The reason for dropping columns is few are redundant and few has missing values more than 60 %

- In few columns we can infer data by comparing with with other columns,"OCCUPATION_TYPE" can be filled by comparing data at "NAME_INCOME_TYPE".
- But as we can get insights directly from "NAME_INCOME_TYPE" which is higly depedant,we have dropped "OCCUPATION_TYPE".

In [12]:
```
print("Client_Data: ",Client_Data.shape)
```

```
Client_Data:  (307511, 58)
```

In [13]:
```
Client_Data.isnull().sum()
```

Out[13]:
```
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                     12
AMT_GOODS_PRICE                278
NAME_TYPE_SUITE               1292
NAME_INCOME_TYPE                 0
NAME_EDUCATION_TYPE              0
NAME_FAMILY_STATUS               0
NAME_HOUSING_TYPE                0
DAYS_BIRTH                       0
DAYS_EMPLOYED                    0
DAYS_ID_PUBLISH                  0
FLAG_MOBIL                       0
FLAG_EMP_PHONE                   0
FLAG_WORK_PHONE                  0
FLAG_CONT_MOBILE                 0
FLAG_EMAIL                       0
CNT_FAM_MEMBERS                  2
REGION_RATING_CLIENT             0
REGION_RATING_CLIENT_W_CITY      0
WEEKDAY_APPR_PROCESS_START       0
HOUR_APPR_PROCESS_START          0
REG_CITY_NOT_LIVE_CITY           0
REG_CITY_NOT_WORK_CITY           0
LIVE_CITY_NOT_WORK_CITY          0
ORGANIZATION_TYPE                0
OBS_30_CNT_SOCIAL_CIRCLE      1021
DEF_30_CNT_SOCIAL_CIRCLE      1021
OBS_60_CNT_SOCIAL_CIRCLE      1021
DEF_60_CNT_SOCIAL_CIRCLE      1021
DAYS_LAST_PHONE_CHANGE           1
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
dtype: int64
```

In [14]:
```
Client_Data.dropna(how ="any",inplace =True)
```

In [15]:
```
Client_Data.shape
```

Out[15]:
```
(305185, 58)
```

In [16]:
```
Client_Data.dtypes
```

Out[16]:
```
SK_ID_CURR                       int64
TARGET                           int64
NAME_CONTRACT_TYPE              object
CODE_GENDER                     object
FLAG_OWN_CAR                    object
FLAG_OWN_REALTY                 object
CNT_CHILDREN                     int64
AMT_INCOME_TOTAL               float64
AMT_CREDIT                     float64
AMT_ANNUITY                    float64
AMT_GOODS_PRICE                float64
NAME_TYPE_SUITE                 object
NAME_INCOME_TYPE                object
NAME_EDUCATION_TYPE             object
NAME_FAMILY_STATUS              object
NAME_HOUSING_TYPE               object
DAYS_BIRTH                       int64
DAYS_EMPLOYED                    int64
DAYS_ID_PUBLISH                  int64
FLAG_MOBIL                       int64
FLAG_EMP_PHONE                   int64
FLAG_WORK_PHONE                  int64
FLAG_CONT_MOBILE                 int64
FLAG_EMAIL                       int64
CNT_FAM_MEMBERS                float64
REGION_RATING_CLIENT             int64
REGION_RATING_CLIENT_W_CITY      int64
WEEKDAY_APPR_PROCESS_START      object
HOUR_APPR_PROCESS_START          int64
REG_CITY_NOT_LIVE_CITY           int64
REG_CITY_NOT_WORK_CITY           int64
LIVE_CITY_NOT_WORK_CITY          int64
ORGANIZATION_TYPE               object
OBS_30_CNT_SOCIAL_CIRCLE       float64
DEF_30_CNT_SOCIAL_CIRCLE       float64
OBS_60_CNT_SOCIAL_CIRCLE       float64
DEF_60_CNT_SOCIAL_CIRCLE       float64
DAYS_LAST_PHONE_CHANGE         float64
FLAG_DOCUMENT_2                  int64
FLAG_DOCUMENT_3                  int64
FLAG_DOCUMENT_4                  int64
FLAG_DOCUMENT_5                  int64
FLAG_DOCUMENT_6                  int64
FLAG_DOCUMENT_7                  int64
FLAG_DOCUMENT_8                  int64
FLAG_DOCUMENT_9                  int64
FLAG_DOCUMENT_10                 int64
FLAG_DOCUMENT_11                 int64
FLAG_DOCUMENT_12                 int64
FLAG_DOCUMENT_13                 int64
FLAG_DOCUMENT_14                 int64
FLAG_DOCUMENT_15                 int64
FLAG_DOCUMENT_16                 int64
FLAG_DOCUMENT_17                 int64
FLAG_DOCUMENT_18                 int64
FLAG_DOCUMENT_19                 int64
FLAG_DOCUMENT_20                 int64
FLAG_DOCUMENT_21                 int64
dtype: object
```

Converting the below columns to Absolute values

In [17]:
```
Client_Data["CODE_GENDER"]=Client_Data["CODE_GENDER"].replace("XNA","Others")
Client_Data["DAYS_LAST_PHONE_CHANGE"] = Client_Data["DAYS_LAST_PHONE_CHANGE"].abs()
Client_Data["DAYS_BIRTH"] = Client_Data["DAYS_BIRTH"].abs()
Client_Data["DAYS_EMPLOYED"] = Client_Data["DAYS_EMPLOYED"].abs()
Client_Data["DAYS_ID_PUBLISH"] = Client_Data["DAYS_ID_PUBLISH"].abs()
Client_Data["AMT_INCOME_TOTAL"] = Client_Data["AMT_INCOME_TOTAL"].abs()
Client_Data["AMT_CREDIT"] = Client_Data["AMT_CREDIT"].abs()
Client_Data["AMT_ANNUITY"] = Client_Data["AMT_ANNUITY"].abs()
Client_Data["AMT_GOODS_PRICE"] = Client_Data["AMT_GOODS_PRICE"].abs()
```

In [18]:
```
Client_Data[["CODE_GENDER","DAYS_LAST_PHONE_CHANGE","DAYS_BIRTH","DAYS_EMPLOYED","DAYS_ID_PUBLISH","AMT_INCOME_TOTAL"]].head(5)
```

Out[18]:

	CODE_GENDER	DAYS_LAST_PHONE_CHANGE	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_ID_PUBLISH	AMT_INCOME_TOTAL
0	M	1134.0	9461	637	2120	202500.0
1	F	828.0	16765	1188	291	270000.0
2	M	815.0	19046	225	2531	67500.0
3	F	617.0	19005	3039	2437	135000.0
4	M	1106.0	19932	3038	3458	121500.0

Converting number of Days to Years

In [19]:
```
Client_Data.insert(loc=12,column="Age",value=(Client_Data[["DAYS_BIRTH"]]/365.25).astype(int))
Client_Data[["DAYS_EMPLOYED"]] = round(Client_Data[["DAYS_EMPLOYED"]]/365.25,1)
Client_Data[["DAYS_ID_PUBLISH"]] = round(Client_Data[["DAYS_ID_PUBLISH"]]/365.25,1)
Client_Data.drop("DAYS_BIRTH",axis =1,inplace= True)
```

In [20]:
```
Client_Data[["Age","DAYS_EMPLOYED","DAYS_ID_PUBLISH"]].describe()
```

Out[20]:

	Age	DAYS_EMPLOYED	DAYS_ID_PUBLISH
count	305185.000000	305185.000000	305185.000000
mean	43.417825	185.592190	8.198860
std	11.941714	381.919921	4.132549
min	20.000000	0.000000	0.000000
25%	34.000000	2.600000	4.700000
50%	43.000000	6.100000	8.900000
75%	53.000000	15.700000	11.800000
max	69.000000	1000.000000	19.700000

- If we take 70 years as a standard bar

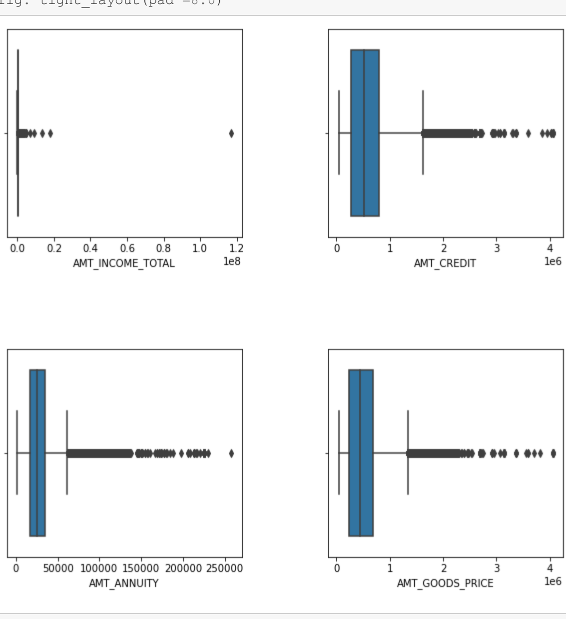
  Age Falls in our assumption but not the Days_Employed.

  Imputing the Days_Employed > 70 with our standard assumption value(70).

In [21]:
```
Client_Data["DAYS_EMPLOYED"].loc[Client_Data["DAYS_EMPLOYED"]<=0] =0.1
Client_Data["DAYS_ID_PUBLISH"].replace(to_replace=0,value=0.1,inplace=True)
Client_Data["DAYS_EMPLOYED"].replace(to_replace=1000,value=70,inplace=True)
```

Cheking Outlier on our main parameters using Box plot

In [22]:
```
fig,axes =plt.subplots(2,2,figsize=(10,10))
sns.boxplot("AMT_INCOME_TOTAL",data =Client_Data,ax=axes[0,0])
sns.boxplot("AMT_CREDIT",data =Client_Data,ax=axes[0,1])
sns.boxplot("AMT_ANNUITY",data =Client_Data,ax=axes[1,0])
sns.boxplot("AMT_GOODS_PRICE",data =Client_Data,ax=axes[1,1])
fig. tight_layout(pad =8.0)
```



In [23]:
```
Client_Data[["AMT_INCOME_TOTAL","AMT_CREDIT"]].describe()
```

Out[23]:

	AMT_INCOME_TOTAL	AMT_CREDIT
count	3.051850e+05	3.051850e+05
mean	1.686140e+05	5.992816e+05
std	2.376652e+05	4.020170e+05
min	2.565000e+04	4.500000e+04
25%	1.125000e+05	2.700000e+05
50%	1.458000e+05	5.147775e+05
75%	2.025000e+05	8.086500e+05
max	1.170000e+08	4.050000e+06

In [24]:
```
Client_Data.loc[Client_Data["AMT_INCOME_TOTAL"]>6000000,["TARGET","AMT_INCOME_TOTAL","AMT_CREDIT"]].head(10)
```

Out[24]:

	TARGET	AMT_INCOME_TOTAL	AMT_CREDIT
12840	1	117000000.0	562491.0
77768	0	9000000.0	1431531.0
131127	0	6750000.0	790830.0
203693	0	18000090.0	675000.0
246858	0	13500000.0	1400503.5

- Income Data has an outlier between 6 and 120 Millions,But the "Amt_Credit"(Loan amount provided) has 1Million Maximum and "Amt_Annuity" has 2.5 Lakhs maximum.
- As our Anlaysis gets effeted with values between 6 and 120 millions, it is better to drop rather to impute because there may be chances of person earning such huge amount but probability getting ~5% of income as loan is very low.

In [25]:
```
Client_Data.drop(Client_Data[Client_Data["AMT_INCOME_TOTAL"]>6000000].index,inplace=True)
```

In [26]:
```
Client_Data.loc[Client_Data["AMT_INCOME_TOTAL"]>6000000,["TARGET","AMT_INCOME_TOTAL","AMT_CREDIT"]].head(10)
```

Out[26]:

TARGET	AMT_INCOME_TOTAL	AMT_CREDIT

In [27]:
```
Client_Data.describe()
```

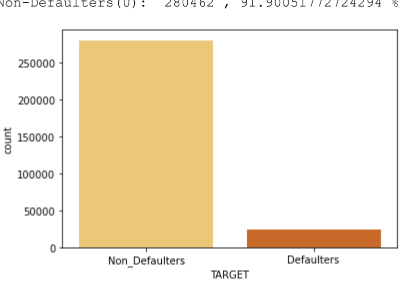
Out[27]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	
count	305180.000000	305180.000000	305180.000000	3.051800e+05	3.051800e+05	305180.000000	3.051800e+05	305180.0
mean	278164.564955	0.080995	0.417147	1.680786e+05	5.992755e+05	27135.854142	5.382210e+05	43.4
std	102784.567591	0.272828	0.722266	9.867711e+04	4.020147e+05	14473.432700	3.689252e+05	11.9
min	100002.000000	0.000000	0.000000	2.565000e+04	4.500000e+04	1615.500000	4.050000e+04	20.0
25%	189128.750000	0.000000	0.000000	1.125000e+05	2.700000e+05	16573.500000	2.385000e+05	34.0
50%	278189.500000	0.000000	0.000000	1.455008e+05	5.147775e+05	24939.000000	4.500000e+05	43.0
75%	367120.250000	0.000000	1.000000	2.025000e+05	8.086500e+05	34614.000000	6.795000e+05	53.0
max	456255.000000	1.000000	19.000000	4.500000e+06	4.050000e+06	258025.500000	4.050000e+06	69.0

Univariate Analysis

In [28]:
```
sns.countplot(Client_Data["TARGET"],palette="YlOrBr").set(xticklabels=["Non_Defaulters","Defaulters"])
print("Defaulters(1): ",Client_Data["TARGET"].value_counts()[1],",",(Client_Data["TARGET"].value_counts()[1]/len(Client_Data["TARGET"]))*100,"%")
print("Non-Defaulters(0): ",Client_Data["TARGET"].value_counts()[0],",",(Client_Data["TARGET"].value_counts()[0]/len(Client_Data["TARGET"]))*100,"%")
```

```
Defaulters(1):  24718 , 8.099482272757061 %
Non-Defaulters(0):  280462 , 91.90051772724294 %
```

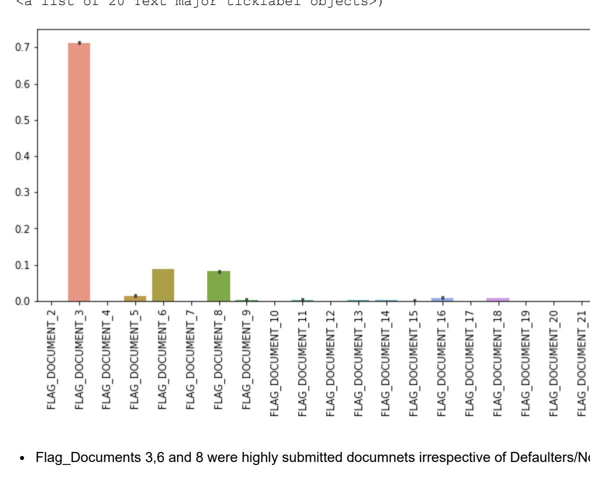


- Only 8% were Defaulters, we have to focus on this category

Documents Status

In [29]:
```
Document_Status =Client_Data[["FLAG_DOCUMENT_2","FLAG_DOCUMENT_3","FLAG_DOCUMENT_4","FLAG_DOCUMENT_5","FLAG_DOCUMENT_6","FLAG_DOCUMENT_7","FLAG_DOCUMENT_8","FLAG_DOCUMENT_9","FLAG_DOCUMENT_10","FLAG_DOCUMENT_11","FLAG_DOCUMENT_12","FLAG_DOCUMENT_13","FLAG_DOCUMENT_14","FLAG_DOCUMENT_15","FLAG_DOCUMENT_16","FLAG_DOCUMENT_17","FLAG_DOCUMENT_18","FLAG_DOCUMENT_19","FLAG_DOCUMENT_20","FLAG_DOCUMENT_21"]]
#Document_Status.head(10)
plt.figure(figsize = (10,5))
sns.barplot(data = Document_Status)
plt.xticks(rotation =90)
```

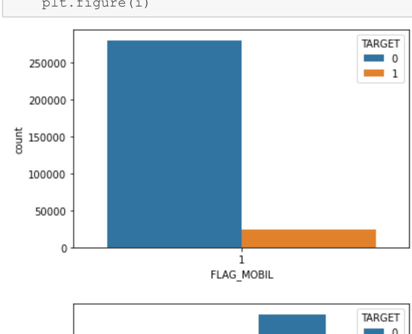
Out[29]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19]),
 <a list of 20 Text major ticklabel objects>)
```

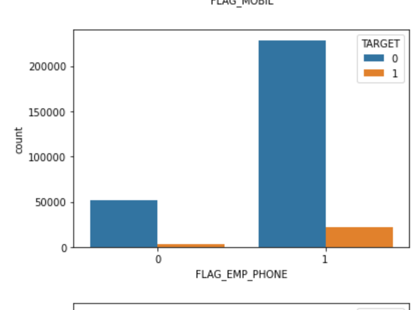


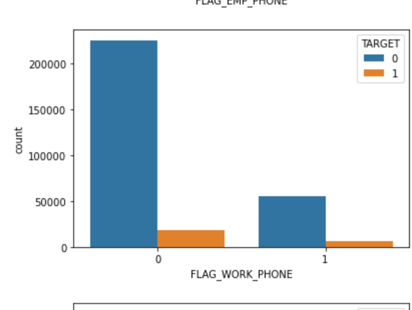
- Flag_Documents 3,6 and 8 were highly submitted documnets irrespective of Defaulters/Non-Defaulters

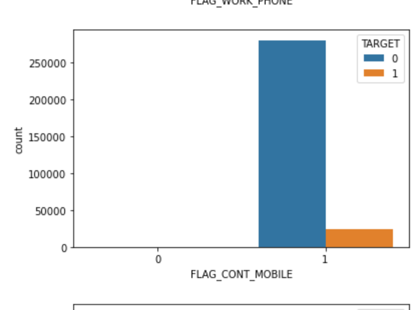
Contact Status

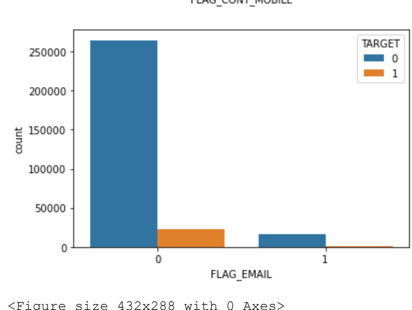
In [30]:
```
for i in Client_Data[["FLAG_MOBIL","FLAG_EMP_PHONE","FLAG_WORK_PHONE","FLAG_CONT_MOBILE","FLAG_EMAIL"]]:
    sns.countplot(data = Client_Data,x= i, hue="TARGET")
    plt.figure(i)
```











```
<Figure size 432x288 with 0 Axes>
```

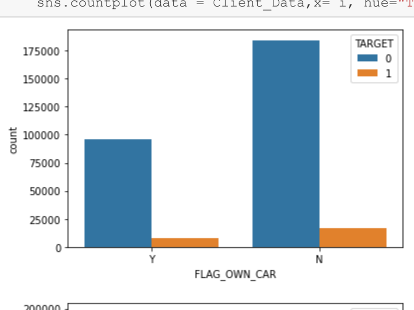
In [31]:
```
for i in Client_Data[["FLAG_MOBIL","FLAG_EMP_PHONE","FLAG_WORK_PHONE","FLAG_CONT_MOBILE","FLAG_EMAIL"]]:
    defaulters = Client_Data[(Client_Data[i]==0) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":  ",round((len(defaulters)/Total)*100,3))
```

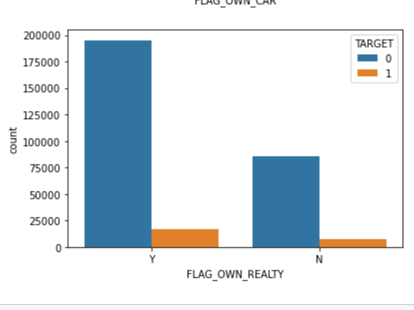
```
FLAG_MOBIL :   0.0
FLAG_EMP_PHONE :   12.036
FLAG_WORK_PHONE :   76.208
FLAG_CONT_MOBILE :   0.182
FLAG_EMAIL :   94.453
```

- 76% home phone data Missing with Defaulters.
- Email Category was higly neglected in all Applications.

Asset Status

In [32]:
```python
for i in Client_Data[["FLAG_OWN_CAR","FLAG_OWN_REALTY"]]:
    plt.figure(i)
    sns.countplot(data = Client_Data,x= i, hue="TARGET",order=("Y","N"))
```





In [33]:
```python
for i in Client_Data[["FLAG_OWN_CAR","FLAG_OWN_REALTY"]]:
    defaulters1 = Client_Data[(Client_Data[i]=="Y") & (Client_Data["TARGET"] ==1)]
    defaulters2 = Client_Data[(Client_Data[i]=="N") & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,"(H/C)",":   ",round((len(defaulters1)/Total)*100,3))
    print(i,"(NH/NC)",":   ",round((len(defaulters2)/Total)*100,3))
```

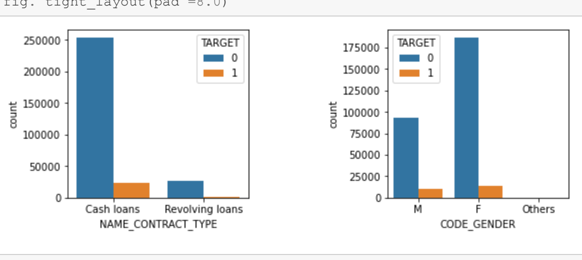
```
FLAG_OWN_CAR (H/C) :   30.532
FLAG_OWN_CAR (NH/NC) :   69.468
FLAG_OWN_REALTY (H/C) :   68.452
FLAG_OWN_REALTY (NH/NC) :   31.548
```

- 70% of Defaulters dont have own car but had Own house which is a Risk factor

Family Details

In [34]:
```python
Fam_Details = Client_Data[["NAME_CONTRACT_TYPE","CODE_GENDER","CNT_FAM_MEMBERS","CNT_CHILDREN","NAME_IN
COME_TYPE","NAME_EDUCATION_TYPE","NAME_FAMILY_STATUS","NAME_TYPE_SUITE","NAME_HOUSING_TYPE"]]
```

In [35]:
```python
fig,axes =plt.subplots(1,2,figsize=(10,5),)
sns.countplot(data =Client_Data,x="NAME_CONTRACT_TYPE",hue="TARGET",ax=axes[0])
sns.countplot(x="CODE_GENDER",hue="TARGET",data =Client_Data,ax=axes[1])
fig. tight_layout(pad =8.0)
```

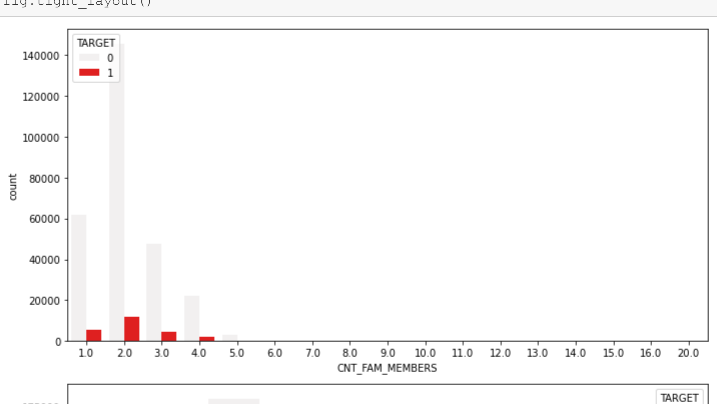


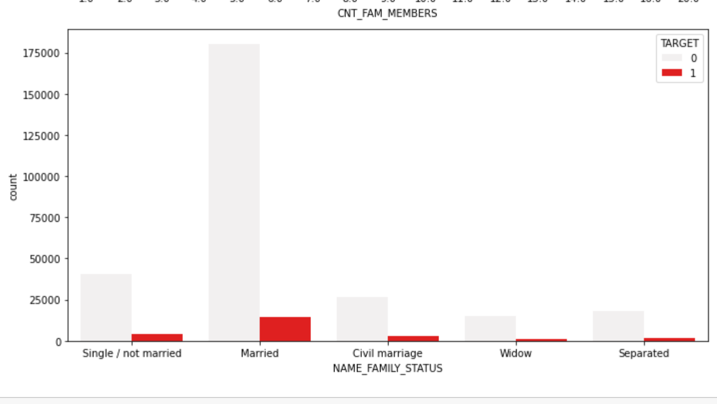
In [36]:
```python
for i in Fam_Details["NAME_CONTRACT_TYPE"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_CONTRACT_TYPE"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",(len(defaulters1)/Total)*100)
```

```
Cash loans :   93.7454486608949
Revolving loans :   6.254551339105105
```

- Highest Applicants and Defaulters are Female and of Cash loans
- But when compared to total Male Applicants, the deafulters were quite high in Male

In [37]:
```python
fig,axes =plt.subplots(2,1,figsize=(10,10))
sns.countplot(data =Client_Data,x="CNT_FAM_MEMBERS",hue="TARGET",ax=axes[0],color="red")
sns.countplot(data =Client_Data,x="NAME_FAMILY_STATUS",hue="TARGET",ax=axes[1],color="red")
fig.tight_layout()
```





In [38]:
```python
for i in Fam_Details["NAME_FAMILY_STATUS"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_FAMILY_STATUS"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

```
Single / not married :   17.967
Married :   59.815
Civil marriage :   11.922
Widow :   3.779
Separated :   6.518
```

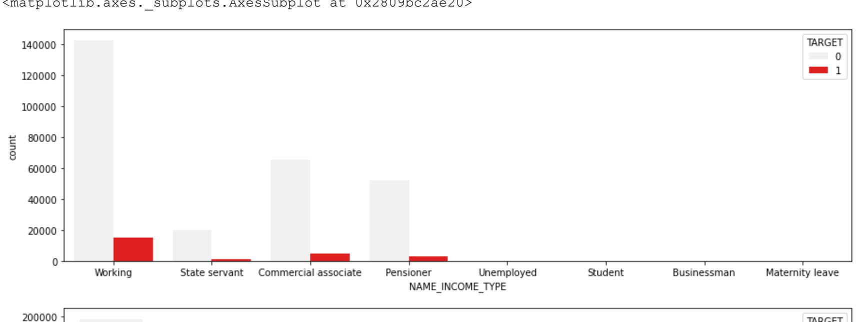
In [39]:
```python
for i in Fam_Details["CNT_FAM_MEMBERS"].unique():
    defaulters1 = Fam_Details[(Fam_Details["CNT_FAM_MEMBERS"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

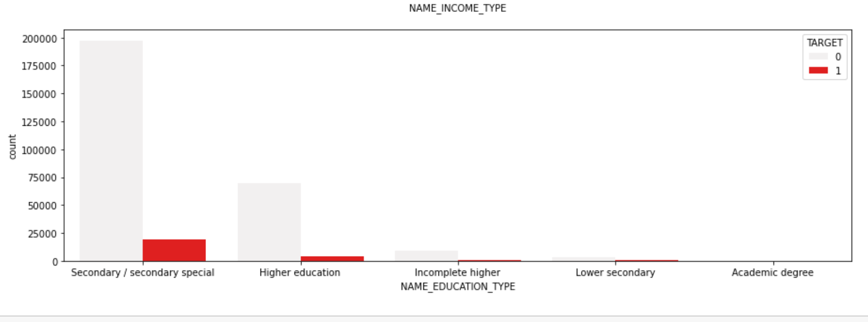
```
1.0 :   22.87
2.0 :   48.357
3.0 :   18.557
4.0 :   8.609
5.0 :   1.323
6.0 :   0.223
9.0 :   0.0
7.0 :   0.024
8.0 :   0.024
10.0 :   0.004
13.0 :   0.004
14.0 :   0.0
12.0 :   0.0
20.0 :   0.0
15.0 :   0.0
16.0 :   0.0
11.0 :   0.004
```

- Eventhough highest Defaulters lie around Married, but risk factor is high with ~5 - ~10% Single,Civil marriages and Seperated
- Highest Defaulters with Family members less than 5

In [40]:
```python
fig,axes =plt.subplots(2,1,figsize=(15,10))
sns.countplot(data =Client_Data,x="NAME_INCOME_TYPE",hue="TARGET",ax=axes[0],color="red")
sns.countplot(data =Client_Data,x="NAME_EDUCATION_TYPE",hue="TARGET",ax=axes[1],color="red")
```

Out[40]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2809bc2ae20>
```





In [41]:
```python
for i in Fam_Details["NAME_EDUCATION_TYPE"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_EDUCATION_TYPE"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

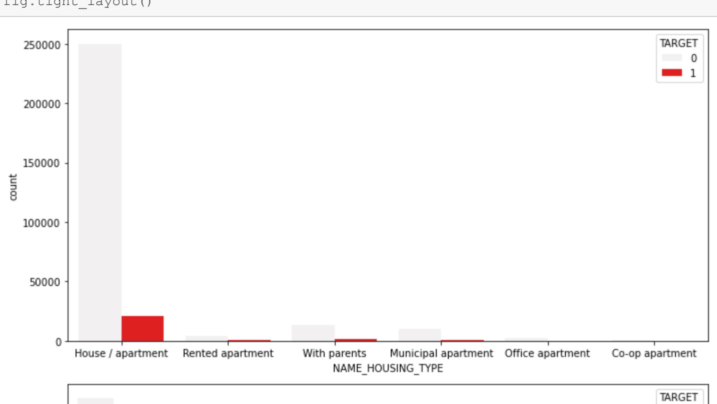
```
Secondary / secondary special :   78.684
Higher education :   16.118
Incomplete higher :   3.508
Lower secondary :   1.679
Academic degree :   0.012
```

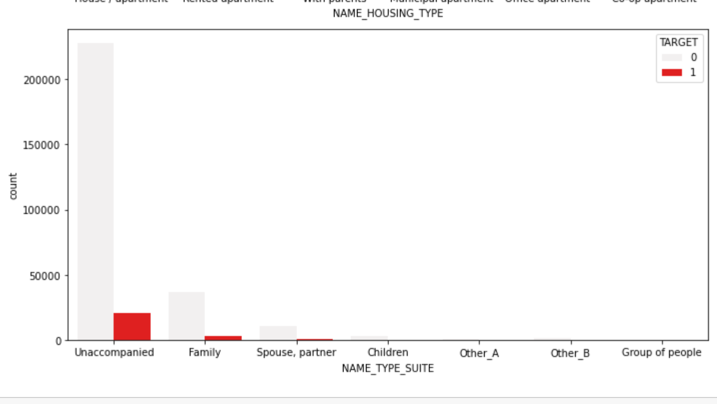
In [42]:
```python
for i in Fam_Details["NAME_INCOME_TYPE"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_INCOME_TYPE"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

```
Working :   61.372
State servant :   5.021
Commercial associate :   21.567
Pensioner :   11.999
Unemployed :   0.032
Student :   0.0
Businessman :   0.0
Maternity leave :   0.008
```

- Highest Defaulters were Working and Commercial associate, but the risk to be assesed on 11% Pensioner based on their asset value.

In [43]:
```python
fig,axes =plt.subplots(2,1,figsize=(10,10))
sns.countplot(data =Client_Data,x="NAME_HOUSING_TYPE",hue="TARGET",ax=axes[0],color="red")
sns.countplot(data =Client_Data,x="NAME_TYPE_SUITE",hue="TARGET",ax=axes[1],color="red")
fig.tight_layout()
```





In [44]:
```python
for i in Fam_Details["NAME_HOUSING_TYPE"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_HOUSING_TYPE"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

```
House / apartment :   85.691
Rented apartment :   2.415
With parents :   7.007
Municipal apartment :   3.843
Office apartment :   0.688
Co-op apartment :   0.356
```

In [45]:
```python
for i in Fam_Details["NAME_TYPE_SUITE"].unique():
    defaulters1 = Fam_Details[(Fam_Details["NAME_TYPE_SUITE"] == i) & (Client_Data["TARGET"] ==1)]
    Total = len(Client_Data[Client_Data["TARGET"] ==1])
    print(i,":   ",round((len(defaulters1)/Total)*100,3))
```

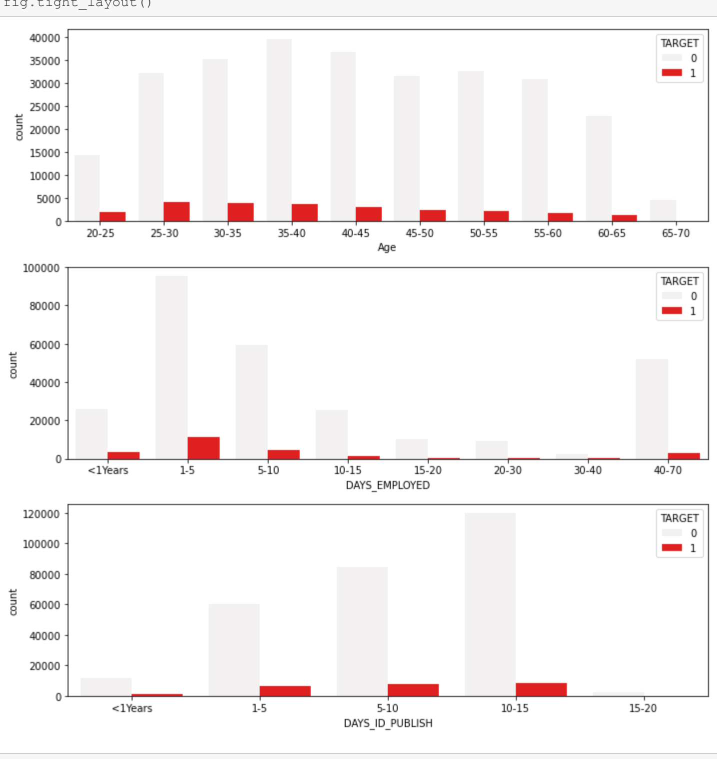
```
Unaccompanied :   82.13
Family :   12.169
Spouse, partner :   3.621
Children :   0.975
Other_A :   0.307
Other_B :   0.704
Group of people :   0.093
```

- 82% Defaulters were Unaccompanied while submiting loan Application, but cannot be considered as primary risk factor
- 2% Defaulters live in Rented Apartments a concern factor.

In [46]:
```python
Client_Data1=Client_Data.copy()
```

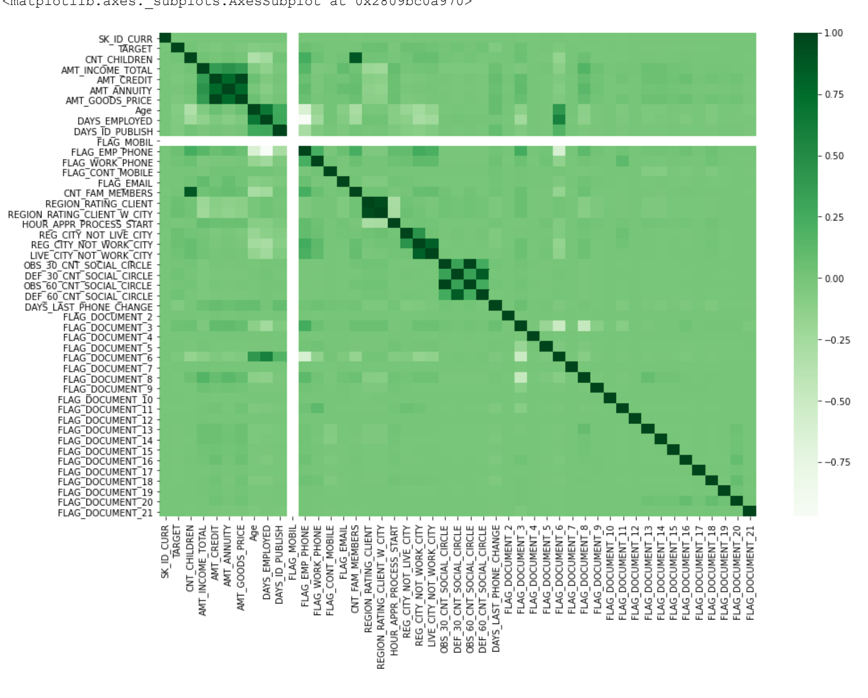
In [47]:
```python
Client_Data1["Age"] = pd.cut(x= Client_Data1["Age"],bins = [20,25,30,35,40,45,50,55,60,65,70],labels =
['20-25','25-30','30-35','35-40','40-45','45-50','50-55','55-60','60-65','65-70'])
Client_Data1["DAYS_EMPLOYED"] = pd.cut(x= Client_Data1["DAYS_EMPLOYED"],bins = [0.1,1.0,5.0,10.0,15.0,2
0.0,30.0,40.0,70.0],labels = ['<1Years','1-5','5-10','10-15','15-20','20-30','30-40','40-70'])
Client_Data1["DAYS_ID_PUBLISH"] = pd.cut(x= Client_Data1["DAYS_ID_PUBLISH"],bins = [0.1,1.0,5.0,10.0,1
5.0,20.0],labels = ['<1Years','1-5','5-10','10-15','15-20'])
```

In [48]:
```python
fig,axes =plt.subplots(3,1,figsize=(10,10))
sns.countplot(data =Client_Data1,x="Age",hue="TARGET",ax=axes[0],color="red")
sns.countplot(data =Client_Data1,x="DAYS_EMPLOYED",hue="TARGET",ax=axes[1],color="red")
sns.countplot(data =Client_Data1,x="DAYS_ID_PUBLISH",hue="TARGET",ax=axes[2],color="red")
fig.tight_layout()
```



In [49]:
```python
plt.figure(figsize=(15,10))
sns.heatmap(Client_Data.corr(), cmap="Greens")
```

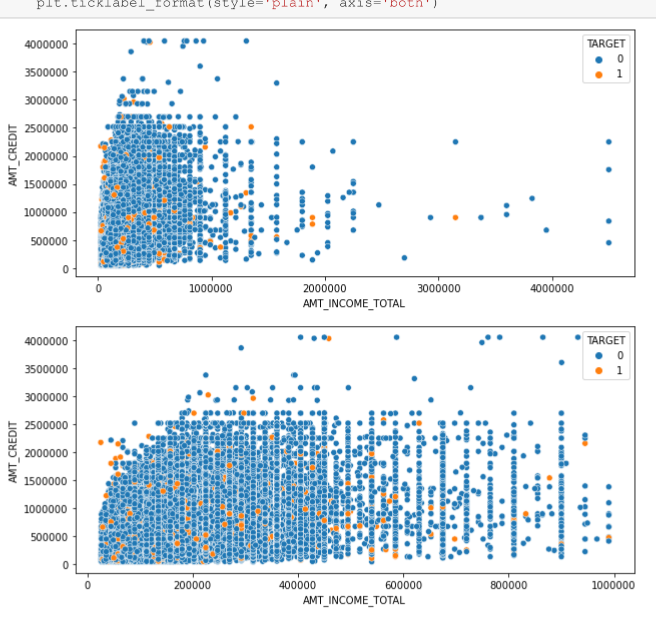
Out[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2809bc0a970>
```



- Amt_Goods Price is highly correlated with Amt_Credit.
- From our Document Status plot, we didnt got much insights, but we could see correlation exists between Age,Days_Employed with Flag document6.

Bi-Variate Analysis

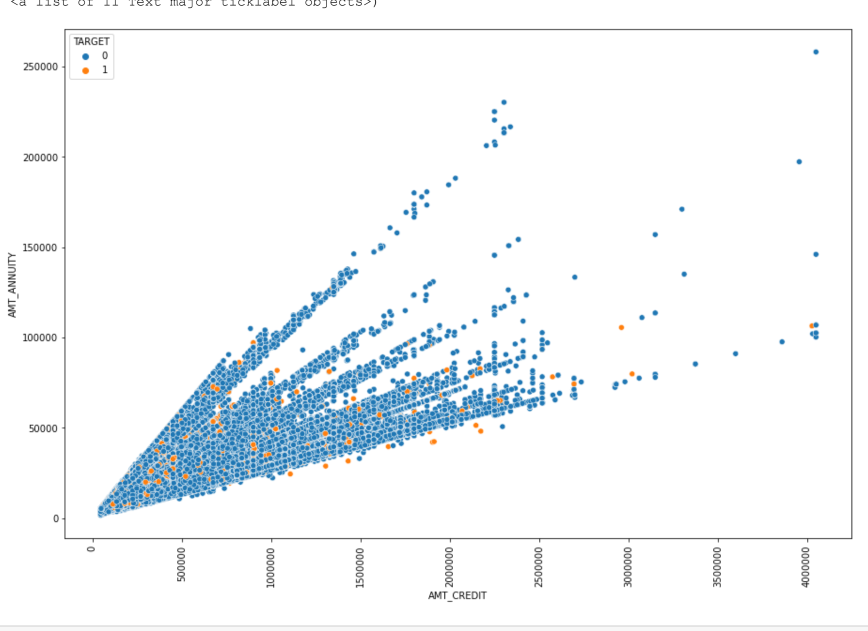
In [50]:
```python
fig,ax =plt.subplots(2,1,figsize=(10,10))
sns.scatterplot(data=Client_Data, x="AMT_INCOME_TOTAL", y="AMT_CREDIT",hue ="TARGET",ax=ax[0])
Inc =Client_Data.loc[Client_Data["AMT_INCOME_TOTAL"]<1000000,["AMT_INCOME_TOTAL","TARGET","AMT_CREDIT"
]]
sns.scatterplot(data=Inc, x="AMT_INCOME_TOTAL", y="AMT_CREDIT",hue ="TARGET",ax=ax[1])

for ax in fig.axes:
    plt.sca(ax)
    plt.ticklabel_format(style='plain', axis='both')
```



- Majority of Applicants has Income <1Millions and Credited loan amount is < 2.5 Millions
- More Defaulters fall under Income range of 0.4 Millions

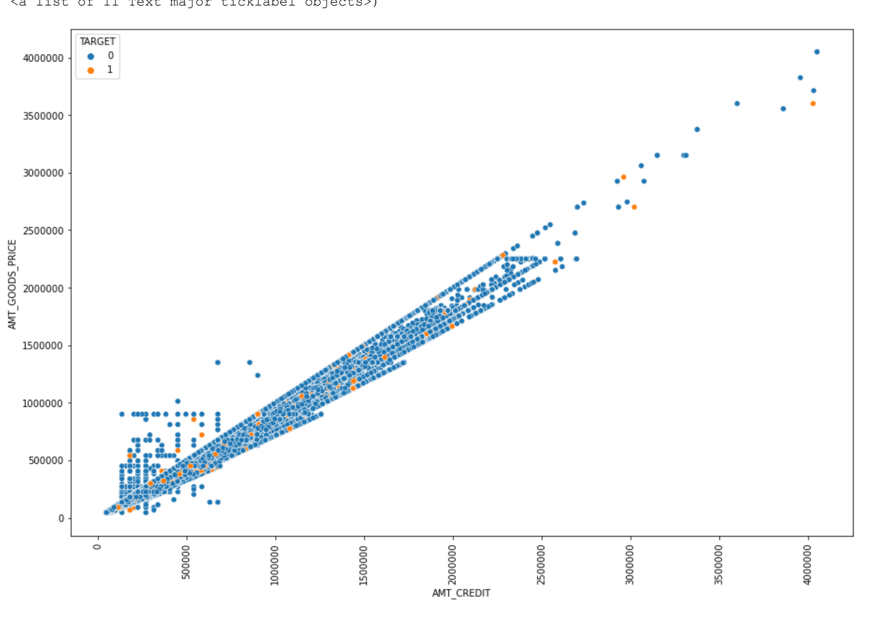
In [51]:
```python
plt.figure(figsize=(15,10),)
sns.scatterplot(data=Client_Data, x="AMT_CREDIT", y="AMT_ANNUITY",hue ="TARGET")
plt.ticklabel_format(style='plain', axis='both')
plt.xticks(rotation =90)
```

Out[51]:
```
(array([-500000.,       0.,  500000., 1000000., 1500000., 2000000.,
        2500000., 3000000., 3500000., 4000000., 4500000.]),
 <a list of 11 Text major ticklabel objects>)
```



In [52]:
```python
plt.figure(figsize=(15,10),)
sns.scatterplot(data=Client_Data, x="AMT_CREDIT", y="AMT_GOODS_PRICE",hue ="TARGET")
plt.ticklabel_format(style='plain', axis='both')
plt.xticks(rotation =90)
```

Out[52]:
```
(array([-500000.,       0.,  500000., 1000000., 1500000., 2000000.,
        2500000., 3000000., 3500000., 4000000., 4500000.]),
 <a list of 11 Text major ticklabel objects>)
```



Conclusion:

8% were Defaulters out of 3Lakh Applicants.

Data_Discrepancies:

- AMT_INCOME column has income ranging from 6-120 Millions, but the credit amount 5% which is concern factor.
- Few Records in Days Employeed has crossed max 70 years, they were imputed with 70.

Findings:

- Maximum loans sanctioned were Cash loans.
- Highest Applicants are female, but deafuters were high in Male.
- Risk is less with applicants who are having either car or Own House.
- Applicants in Rented houses and Pensioners are of high risk.
- Risk is high with Single parent applicants
- Maximum Defaulters lie in Age group of 25-30.
- Maximum Defaulters has employee experince < 5years, but the risk lies with <1 year Experience Employees.
- Most Applicants and defaulters fall under Income range of 40K and 2.5 Lakhs.

In [53]:
```python
Client_Data.to_csv("Client_data.csv",index=False)
```

In [ ]: