Loan Defaulter Dataset

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Load Dataset

In [2]:
```
# application data
data = pd.read_csv('\loan_data\application_data.csv')

# previous applicaiton data
pdata = pd.read_csv('\loan_data\previous_application.csv')
```

Inspecting application data

In [3]:
```
data.shape
```

Out[3]:
```
(307511, 122)
```

122 columns is a lot!! Better start checking the null values.

In [4]:
```
data.isna().sum().sort_values(ascending=False)
```

Out[4]:
```
COMMONAREA_MEDI                 214865
COMMONAREA_AVG                  214865
COMMONAREA_MODE                 214865
NONLIVINGAPARTMENTS_MODE        213514
NONLIVINGAPARTMENTS_MEDI        213514
                                 ...
REG_CITY_NOT_LIVE_CITY               0
LIVE_REGION_NOT_WORK_REGION          0
REG_REGION_NOT_WORK_REGION           0
HOUR_APPR_PROCESS_START              0
SK_ID_CURR                           0
Length: 122, dtype: int64
```

With this many columns, we can clearly see the null values if we convert it to dataframe. Will be useful further.

Handling Missing Values

In [5]:
```
missing = pd.DataFrame(data.isna().sum().sort_values(ascending=False))
missing
```

Out[5]:

	0
COMMONAREA_MEDI	214865
COMMONAREA_AVG	214865
COMMONAREA_MODE	214865
NONLIVINGAPARTMENTS_MODE	213514
NONLIVINGAPARTMENTS_MEDI	213514
...	...
REG_CITY_NOT_LIVE_CITY	0
LIVE_REGION_NOT_WORK_REGION	0
REG_REGION_NOT_WORK_REGION	0
HOUR_APPR_PROCESS_START	0
SK_ID_CURR	0

122 rows × 1 columns

We can see that the index is of col name, so let's reset the index

In [6]:
```
missing.reset_index(inplace=True)
```

In [7]:
```
missing.head()
```

Out[7]:

	index	0
0	COMMONAREA_MEDI	214865
1	COMMONAREA_AVG	214865
2	COMMONAREA_MODE	214865
3	NONLIVINGAPARTMENTS_MODE	213514
4	NONLIVINGAPARTMENTS_MEDI	213514

Now that we have our missing values dataframe, we can start dealing with them.

But before that we need a percentage column to analyze the missing values more accurately

In [8]:
```
missing.rename(columns={'index':'column',0:'null_count'},inplace=True)
missing['percent'] = missing['null_count']/data.shape[0]
```

In [9]:
```
missing.head()
```

Out[9]:

	column	null_count	percent
0	COMMONAREA_MEDI	214865	0.698723
1	COMMONAREA_AVG	214865	0.698723
2	COMMONAREA_MODE	214865	0.698723
3	NONLIVINGAPARTMENTS_MODE	213514	0.694330
4	NONLIVINGAPARTMENTS_MEDI	213514	0.694330

In [10]:
```
missing[missing.percent>0.4].shape[0]
```

Out[10]:
```
49
```

So we see that there are 49 columns with atleast 40 percent of data is missing!! I believe this kind of data will not make much sense even by imputation, so decided to remove those columns.

In [11]:
```
data.drop(missing[missing.percent>0.4]['column'].values,axis=1,inplace=True)
```

In [12]:
```
data.shape
```

Out[12]:
```
(307511, 73)
```

So previously we had 122 columns, and now we removed 40 columns as they atleast 50 percent of data missing, so we are left out with 81 columns.

In [13]:
```
data.columns
```

Out[13]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE',
       'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
       'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH',
       'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'FLAG_MOBIL',
       'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE',
       'FLAG_EMAIL', 'OCCUPATION_TYPE', 'CNT_FAM_MEMBERS',
       'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY',
       'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',
       'ORGANIZATION_TYPE', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
       'DAYS_LAST_PHONE_CHANGE', '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',
       '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'],
      dtype='object')
```

Investigating the columns

At first glance we can see that there are some columns with that starts with FLAG, so we can investigate them first

In [14]:
```
cols_with_flag = data.columns[data.columns.str.startswith('FLAG')]
```

In [15]:
```
flag_cols_data = data[np.concatenate([cols_with_flag,np.array(['TARGET'])])]
```

In [16]:
```
cols_with_flag
```

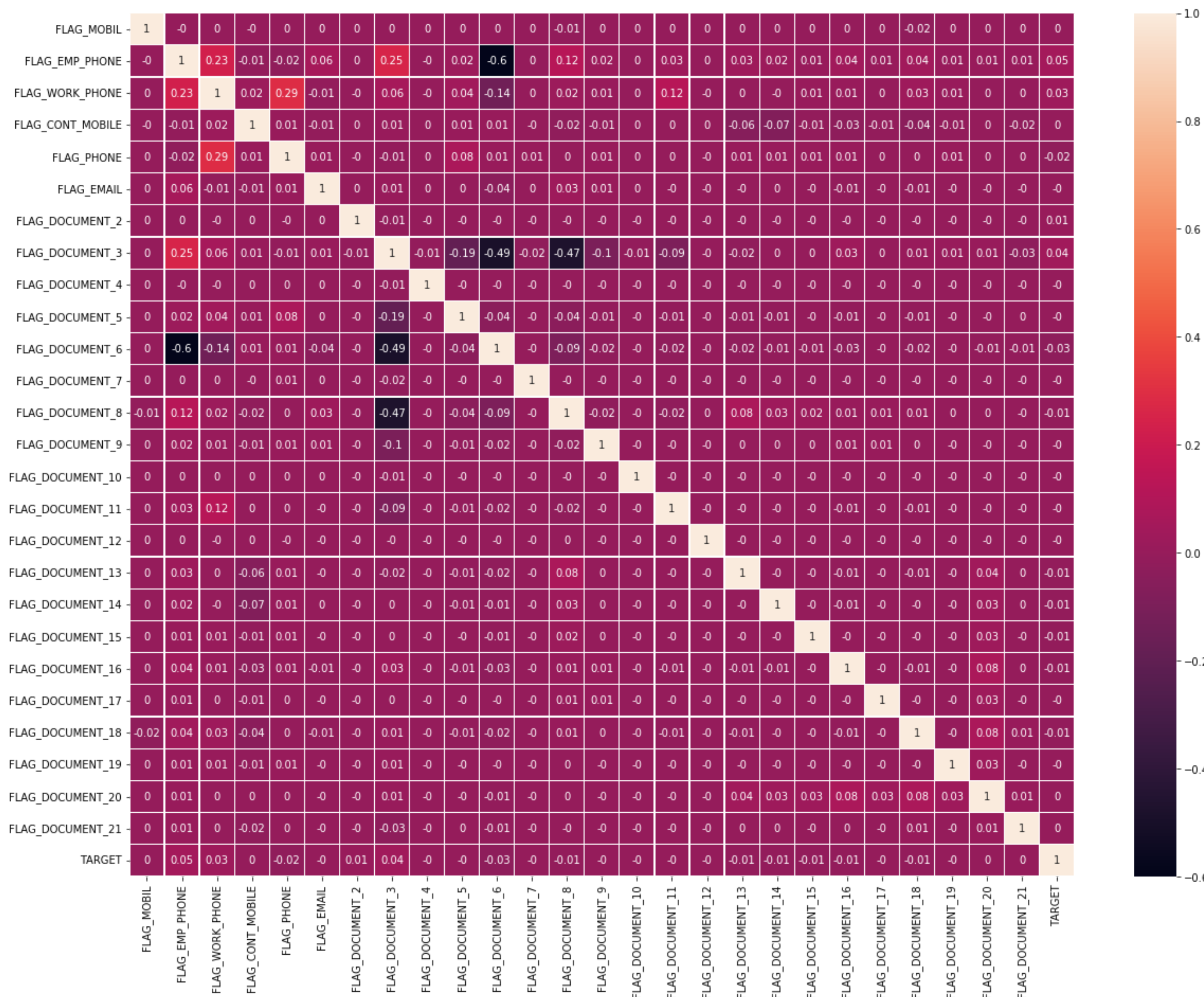
Out[16]:
```
Index(['FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'FLAG_MOBIL', 'FLAG_EMP_PHONE',
       'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE', 'FLAG_PHONE', 'FLAG_EMAIL',
       'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4',
       'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7',
       'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9', 'FLAG_DOCUMENT_10',
       'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12', 'FLAG_DOCUMENT_13',
       'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16',
       'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19',
       'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21'],
      dtype='object')
```

Visualizing how each FLAG Column impact the target

Observing the correlation for these columns

In [17]:
```
plt.figure(figsize=(20,15))
corr_matrix = round(flag_cols_data.corr(),2)
sns.heatmap(corr_matrix,linewidth=0.2,annot=True)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x23889e48ac8>



As we can see that they have very less correlation with the target, which is totally insignificant, hence we can remove them.

In [18]:
```
data.drop(cols_with_flag,axis=1,inplace=True)
```

In [19]:
```
data.shape
```

Out[19]: (307511, 45)

Checking if any other columns can be removed

In [20]:
```
data.head()
```

Out[20]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	CNT_CHILDREN	AMT_INCOME_TOTAL
0	100002	1	Cash loans	M	0	202500.0
1	100003	0	Cash loans	F	0	270000.0
2	100004	0	Revolving loans	M	0	67500.0
3	100006	0	Cash loans	F	0	135000.0
4	100007	0	Cash loans	M	0	121500.0

5 rows × 45 columns

In [21]:
```
data.columns
```

Out[21]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
       'AMT_GOODS_PRICE', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE',
       'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE',
       'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED',
       'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OCCUPATION_TYPE',
       'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
       'REGION_RATING_CLIENT_W_CITY', 'WEEKDAY_APPR_PROCESS_START',
       'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
       'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
       'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY',
       'LIVE_CITY_NOT_WORK_CITY', 'ORGANIZATION_TYPE', 'EXT_SOURCE_2',
       'EXT_SOURCE_3', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',
       'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
       'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object')
```

In [22]:
```
missing = pd.DataFrame(data.isna().sum().sort_values(ascending=False))
missing.reset_index(inplace=True)
missing.rename(columns={'index':'column',0:'null_count'},inplace=True)
missing['percent'] = missing['null_count']/data.shape[0]
missing
```

Out[22]:

	column	null_count	percent
0	OCCUPATION_TYPE	96391	0.313455
1	EXT_SOURCE_3	60965	0.198253
2	AMT_REQ_CREDIT_BUREAU_YEAR	41519	0.135016
3	AMT_REQ_CREDIT_BUREAU_MON	41519	0.135016
4	AMT_REQ_CREDIT_BUREAU_WEEK	41519	0.135016
5	AMT_REQ_CREDIT_BUREAU_DAY	41519	0.135016
6	AMT_REQ_CREDIT_BUREAU_HOUR	41519	0.135016
7	AMT_REQ_CREDIT_BUREAU_QRT	41519	0.135016
8	NAME_TYPE_SUITE	1292	0.004201
9	OBS_30_CNT_SOCIAL_CIRCLE	1021	0.003320
10	DEF_30_CNT_SOCIAL_CIRCLE	1021	0.003320
11	OBS_60_CNT_SOCIAL_CIRCLE	1021	0.003320
12	DEF_60_CNT_SOCIAL_CIRCLE	1021	0.003320
13	EXT_SOURCE_2	660	0.002146
14	AMT_GOODS_PRICE	278	0.000904
15	AMT_ANNUITY	12	0.000039
16	CNT_FAM_MEMBERS	2	0.000007
17	DAYS_LAST_PHONE_CHANGE	1	0.000003
18	NAME_FAMILY_STATUS	0	0.000000
19	NAME_EDUCATION_TYPE	0	0.000000
20	NAME_INCOME_TYPE	0	0.000000
21	NAME_CONTRACT_TYPE	0	0.000000
22	AMT_CREDIT	0	0.000000
23	AMT_INCOME_TOTAL	0	0.000000
24	CNT_CHILDREN	0	0.000000
25	CODE_GENDER	0	0.000000
26	REGION_POPULATION_RELATIVE	0	0.000000
27	TARGET	0	0.000000
28	NAME_HOUSING_TYPE	0	0.000000
29	REGION_RATING_CLIENT_W_CITY	0	0.000000
30	DAYS_BIRTH	0	0.000000
31	DAYS_EMPLOYED	0	0.000000
32	DAYS_REGISTRATION	0	0.000000
33	DAYS_ID_PUBLISH	0	0.000000
34	REGION_RATING_CLIENT	0	0.000000
35	WEEKDAY_APPR_PROCESS_START	0	0.000000
36	HOUR_APPR_PROCESS_START	0	0.000000
37	REG_REGION_NOT_LIVE_REGION	0	0.000000

	column	null_count	percent
38	REG_REGION_NOT_WORK_REGION	0	0.000000
39	LIVE_REGION_NOT_WORK_REGION	0	0.000000
40	REG_CITY_NOT_LIVE_CITY	0	0.000000
41	REG_CITY_NOT_WORK_CITY	0	0.000000
42	LIVE_CITY_NOT_WORK_CITY	0	0.000000
43	ORGANIZATION_TYPE	0	0.000000
44	SK_ID_CURR	0	0.000000

In [23]:
```
missing[missing.percent>0.4]
```

Out[23]:

column	null_count	percent

Still we can see few columns that are almost 50 percent null values, we can remove them as well.

In [24]:
```
data.drop(missing[missing.percent>0.4].column.values,axis=1,inplace=True)
```

In [25]:
```
data.shape
```

Out[25]:
```
(307511, 45)
```

Feature Engineering

In [26]:
```
data.isnull().sum().sort_values(ascending=False)
```

Out[26]:
```
OCCUPATION_TYPE                96391
EXT_SOURCE_3                   60965
AMT_REQ_CREDIT_BUREAU_YEAR     41519
AMT_REQ_CREDIT_BUREAU_MON      41519
AMT_REQ_CREDIT_BUREAU_WEEK     41519
AMT_REQ_CREDIT_BUREAU_DAY      41519
AMT_REQ_CREDIT_BUREAU_HOUR     41519
AMT_REQ_CREDIT_BUREAU_QRT      41519
NAME_TYPE_SUITE                 1292
OBS_30_CNT_SOCIAL_CIRCLE        1021
DEF_30_CNT_SOCIAL_CIRCLE        1021
OBS_60_CNT_SOCIAL_CIRCLE        1021
DEF_60_CNT_SOCIAL_CIRCLE        1021
EXT_SOURCE_2                     660
AMT_GOODS_PRICE                  278
AMT_ANNUITY                       12
CNT_FAM_MEMBERS                    2
DAYS_LAST_PHONE_CHANGE             1
NAME_FAMILY_STATUS                 0
NAME_EDUCATION_TYPE                0
NAME_INCOME_TYPE                   0
NAME_CONTRACT_TYPE                 0
AMT_CREDIT                         0
AMT_INCOME_TOTAL                   0
CNT_CHILDREN                       0
CODE_GENDER                        0
REGION_POPULATION_RELATIVE         0
TARGET                             0
NAME_HOUSING_TYPE                  0
REGION_RATING_CLIENT_W_CITY        0
DAYS_BIRTH                         0
DAYS_EMPLOYED                      0
DAYS_REGISTRATION                  0
DAYS_ID_PUBLISH                    0
REGION_RATING_CLIENT               0
WEEKDAY_APPR_PROCESS_START         0
HOUR_APPR_PROCESS_START            0
REG_REGION_NOT_LIVE_REGION         0
REG_REGION_NOT_WORK_REGION         0
LIVE_REGION_NOT_WORK_REGION        0
REG_CITY_NOT_LIVE_CITY             0
REG_CITY_NOT_WORK_CITY             0
LIVE_CITY_NOT_WORK_CITY            0
ORGANIZATION_TYPE                  0
SK_ID_CURR                         0
dtype: int64
```

Dealing Missing values of Numeric Variables

The mean is used for normal number distributions, which have a low amount of outliers.

If there are more outliers in the data, then median is generally used as it returns the central tendency for skewed number distributions.

we can deal column wise for the rest of missing values, and if we see from the last we have

DAYS_LAST_PHONE_CHANGE

In [27]:
```
data['DAYS_LAST_PHONE_CHANGE'].isna().sum()
```

Out[27]:
```
1
```

In [28]:
```
data.dropna(subset=['DAYS_LAST_PHONE_CHANGE'],inplace=True)
```

CNT_FAM_MEMBERS Column

As there is only one row with null value, decided to remove it.

In [29]:
```
data['CNT_FAM_MEMBERS'] = data['CNT_FAM_MEMBERS'].fillna((data['CNT_FAM_MEMBERS'].mode()
[0]))
```

In [30]:
```
data['CNT_FAM_MEMBERS'].isnull().sum()
```

Out[30]:
```
0
```

AMT_Annuity Column

In [31]:
```
data['AMT_ANNUITY']
```

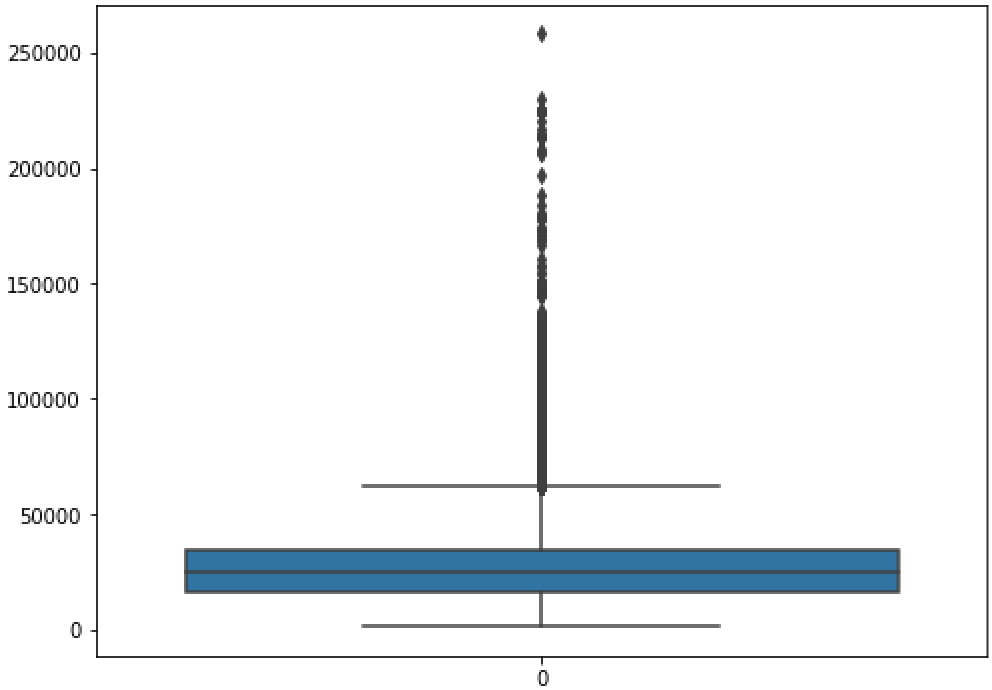
Out[31]:
```
0         24700.5
1         35698.5
2          6750.0
3         29686.5
4         21865.5
           ...
307506    27558.0
307507    12001.5
307508    29979.0
307509    20205.0
307510    49117.5
Name: AMT_ANNUITY, Length: 307510, dtype: float64
```

In [32]:
```
data['AMT_ANNUITY'].isna().sum()
```

Out[32]:
```
12
```

In [33]:
```
plt.figure(figsize=(8,6))
sns.boxplot(data['AMT_ANNUITY'])
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x2388d438f08>



Observing that it has significant amount of outliers, decided to impute with median

In [34]:
```
data['AMT_ANNUITY'] = data['AMT_ANNUITY'].fillna((data['AMT_ANNUITY'].median()))
```

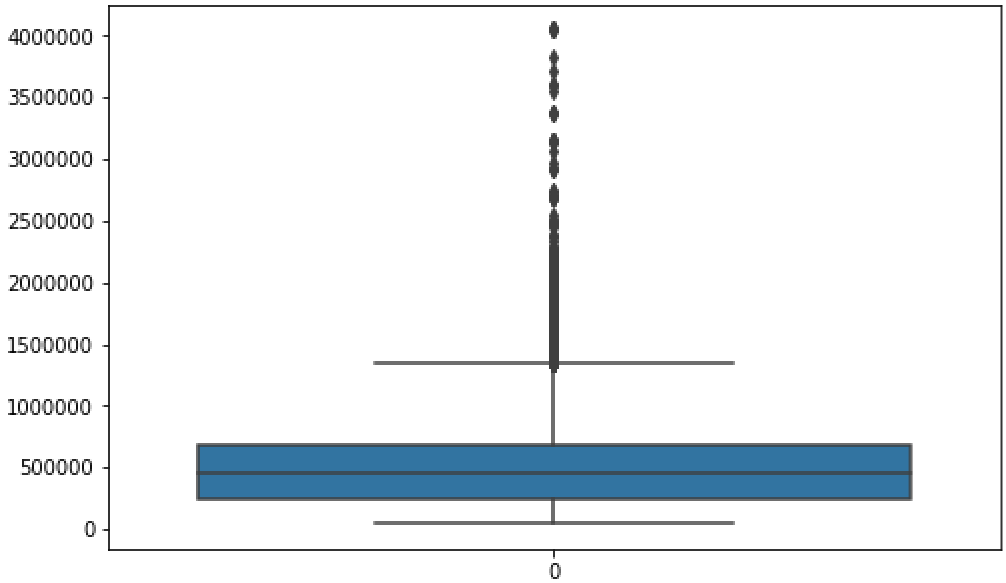
In [35]:
```
data['AMT_ANNUITY'].isna().sum()
```

Out[35]: 0

AMT_GOODS_PRICE Column

In [36]:
```
plt.figure(figsize=(8,5))
sns.boxplot(data['AMT_GOODS_PRICE'])
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2388d418a48>



Observing that it has significant amount of outliers, decided to impute with median

In [37]:
```
data['AMT_GOODS_PRICE'] = data['AMT_GOODS_PRICE'].fillna((data['AMT_GOODS_PRICE'].median
()))
```

In [38]:
```
data['AMT_GOODS_PRICE'].isna().sum()
```

Out[38]: 0

In [39]:
```
# Fill with median value
data['AMT_GOODS_PRICE'] = data['AMT_GOODS_PRICE'].fillna((data['AMT_GOODS_PRICE'].median
()))
```

Dealing Missing Values of Categorical Variables

In [40]:
```
# Fill missing values with a new class 'Unknown'
data['OCCUPATION_TYPE'] = data['OCCUPATION_TYPE'].fillna('Unknown')
```

In [41]:
```
# Fill the missing values with mode
data['DEF_60_CNT_SOCIAL_CIRCLE'] = data['DEF_60_CNT_SOCIAL_CIRCLE'].fillna((data['DEF_60
_CNT_SOCIAL_CIRCLE'].mode()[0]))
data['OBS_30_CNT_SOCIAL_CIRCLE'] = data['OBS_30_CNT_SOCIAL_CIRCLE'].fillna((data['OBS_30
_CNT_SOCIAL_CIRCLE'].mode()[0]))
data['DEF_30_CNT_SOCIAL_CIRCLE'] = data['DEF_30_CNT_SOCIAL_CIRCLE'].fillna((data['DEF_30
_CNT_SOCIAL_CIRCLE'].mode()[0]))
data['OBS_60_CNT_SOCIAL_CIRCLE'] = data['OBS_60_CNT_SOCIAL_CIRCLE'].fillna((data['OBS_60
_CNT_SOCIAL_CIRCLE'].mode()[0]))
```

In [42]:
```python
# NAME_TYPE_SUITE
data['NAME_TYPE_SUITE'].value_counts()

# 'Unaccompanied' class is purely dominating the distribution. So, we use it to fill the missing values
data['NAME_TYPE_SUITE'] = data['NAME_TYPE_SUITE'].fillna((data['NAME_TYPE_SUITE'].mode()[0]))
```

In [43]:
```python
data.isna().sum().sort_values(ascending=False).head(20)
```

Out[43]:
```
EXT_SOURCE_3                  60964
AMT_REQ_CREDIT_BUREAU_YEAR    41518
AMT_REQ_CREDIT_BUREAU_MON     41518
AMT_REQ_CREDIT_BUREAU_WEEK    41518
AMT_REQ_CREDIT_BUREAU_DAY     41518
AMT_REQ_CREDIT_BUREAU_HOUR    41518
AMT_REQ_CREDIT_BUREAU_QRT     41518
EXT_SOURCE_2                    659
NAME_TYPE_SUITE                   0
DAYS_EMPLOYED                     0
DAYS_BIRTH                        0
REGION_POPULATION_RELATIVE        0
NAME_HOUSING_TYPE                 0
NAME_FAMILY_STATUS                0
NAME_EDUCATION_TYPE               0
NAME_INCOME_TYPE                  0
AMT_CREDIT                        0
AMT_GOODS_PRICE                   0
AMT_ANNUITY                       0
DAYS_ID_PUBLISH                   0
dtype: int64
```

Dealing with columns related to date

In [44]:
```python
data[data['AMT_REQ_CREDIT_BUREAU_DAY'].isna()].head()
```

Out[44]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	CNT_CHILDREN	AMT_INCOME_TOTAL
3	100006	0	Cash loans	F	0	135000.0
9	100012	0	Revolving loans	M	0	135000.0
14	100018	0	Cash loans	F	0	189000.0
17	100021	0	Revolving loans	F	1	81000.0
20	100024	0	Revolving loans	M	0	135000.0

5 rows × 45 columns

In [45]:
```
# Fetching the columns
amt_req = []

for k in data.columns:
    if k.startswith('AMT_REQ_CREDIT_BUREAU_'):
        amt_req.append(k)  # Add features to list

amt_req
```

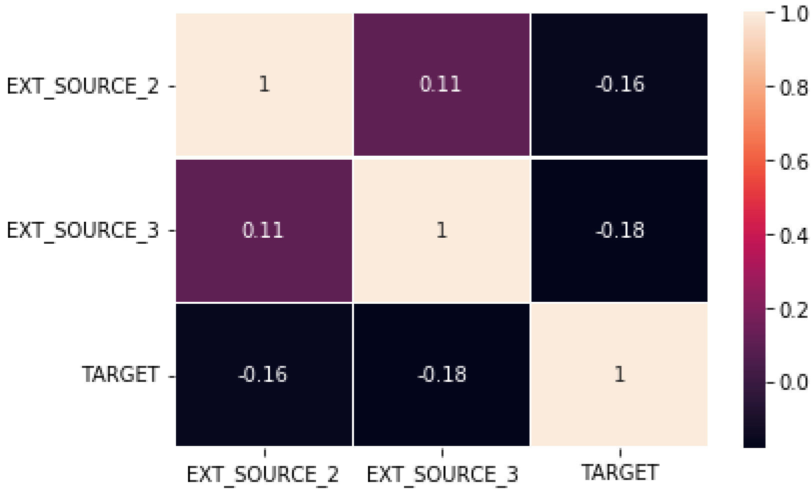
Out[45]:
```
['AMT_REQ_CREDIT_BUREAU_HOUR',
 'AMT_REQ_CREDIT_BUREAU_DAY',
 'AMT_REQ_CREDIT_BUREAU_WEEK',
 'AMT_REQ_CREDIT_BUREAU_MON',
 'AMT_REQ_CREDIT_BUREAU_QRT',
 'AMT_REQ_CREDIT_BUREAU_YEAR']
```

In [46]:
```
# Impute missing values with median
for col in amt_req:
    data[col] = data[col].fillna((data[col].median()))
```

In [47]:
```
data.isna().sum().sort_values(ascending=False).head(20)
```

Out[47]:
```
EXT_SOURCE_3                  60964
EXT_SOURCE_2                    659
DAYS_ID_PUBLISH                   0
DAYS_REGISTRATION                 0
DAYS_EMPLOYED                     0
DAYS_BIRTH                        0
REGION_POPULATION_RELATIVE        0
NAME_HOUSING_TYPE                 0
NAME_FAMILY_STATUS                0
NAME_EDUCATION_TYPE               0
NAME_INCOME_TYPE                  0
AMT_REQ_CREDIT_BUREAU_YEAR        0
CNT_FAM_MEMBERS                   0
NAME_TYPE_SUITE                   0
AMT_GOODS_PRICE                   0
AMT_ANNUITY                       0
AMT_CREDIT                        0
AMT_INCOME_TOTAL                  0
CNT_CHILDREN                      0
CODE_GENDER                       0
dtype: int64
```

In [48]:
```python
# Correlation matrix
plt.figure(figsize=(6,4))
sns.heatmap(round(data[['EXT_SOURCE_2', 'EXT_SOURCE_3', 'TARGET']].corr(),2),
            linewidths=0.5, annot=True)
plt.show()
```



In [49]:
```python
# Drop features
data = data.drop(columns=['EXT_SOURCE_2','EXT_SOURCE_3'])
```

In [50]:
```python
data.isna().sum().sort_values(ascending=False).head(20)
```

Out[50]:
```
AMT_REQ_CREDIT_BUREAU_YEAR    0
NAME_INCOME_TYPE              0
DAYS_ID_PUBLISH               0
DAYS_REGISTRATION             0
DAYS_EMPLOYED                 0
DAYS_BIRTH                    0
REGION_POPULATION_RELATIVE    0
NAME_HOUSING_TYPE             0
NAME_FAMILY_STATUS            0
NAME_EDUCATION_TYPE           0
NAME_TYPE_SUITE               0
CNT_FAM_MEMBERS               0
AMT_GOODS_PRICE               0
AMT_ANNUITY                   0
AMT_CREDIT                    0
AMT_INCOME_TOTAL              0
CNT_CHILDREN                  0
CODE_GENDER                   0
NAME_CONTRACT_TYPE            0
TARGET                        0
dtype: int64
```

Numerical Variables Binning for Data Visualization

In [51]:
```
data.select_dtypes(include='float')
```

Out[51]:

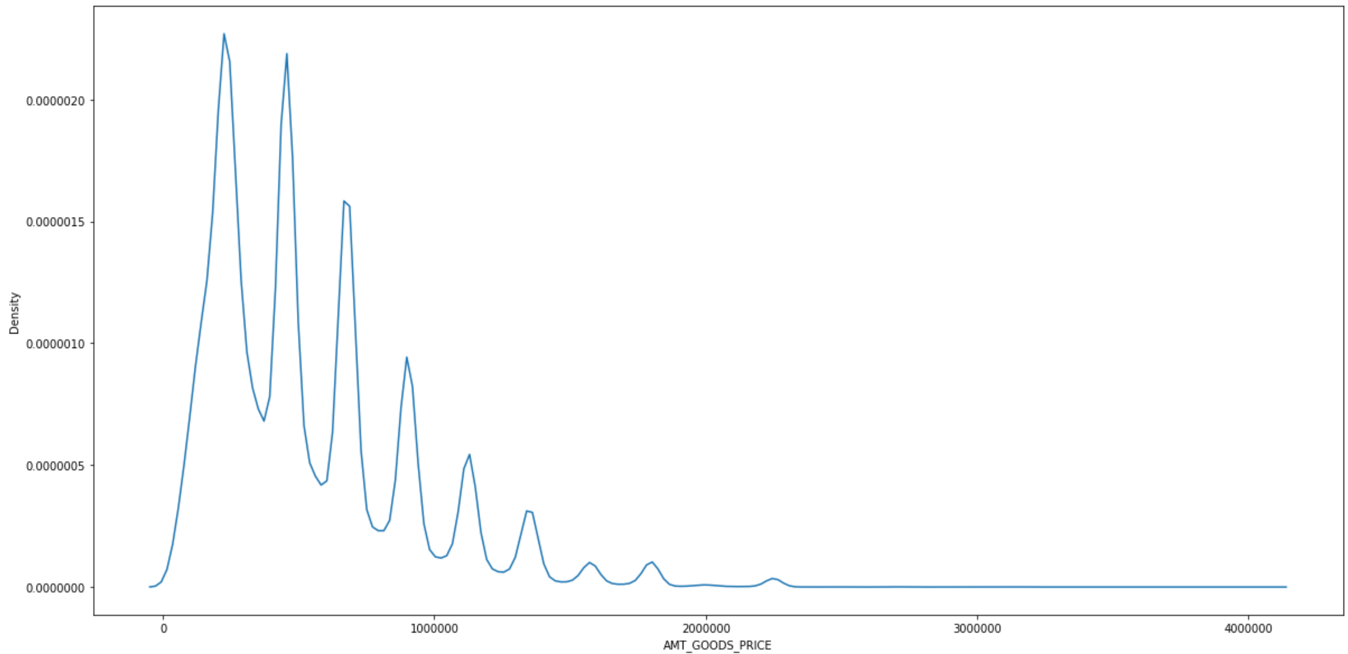
	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	REGION_POPULATION_REL
0	202500.0	406597.5	24700.5	351000.0	0.0
1	270000.0	1293502.5	35698.5	1129500.0	0.0
2	67500.0	135000.0	6750.0	135000.0	0.0
3	135000.0	312682.5	29686.5	297000.0	0.0
4	121500.0	513000.0	21865.5	513000.0	0.0
...	...	...	...	...	
307506	157500.0	254700.0	27558.0	225000.0	0.0
307507	72000.0	269550.0	12001.5	225000.0	0.0
307508	153000.0	677664.0	29979.0	585000.0	0.0
307509	171000.0	370107.0	20205.0	319500.0	0.0
307510	157500.0	675000.0	49117.5	675000.0	0.0

307510 rows × 18 columns

In [52]:
```python
# Number of unique values
data.nunique().sort_values(ascending=False)
```

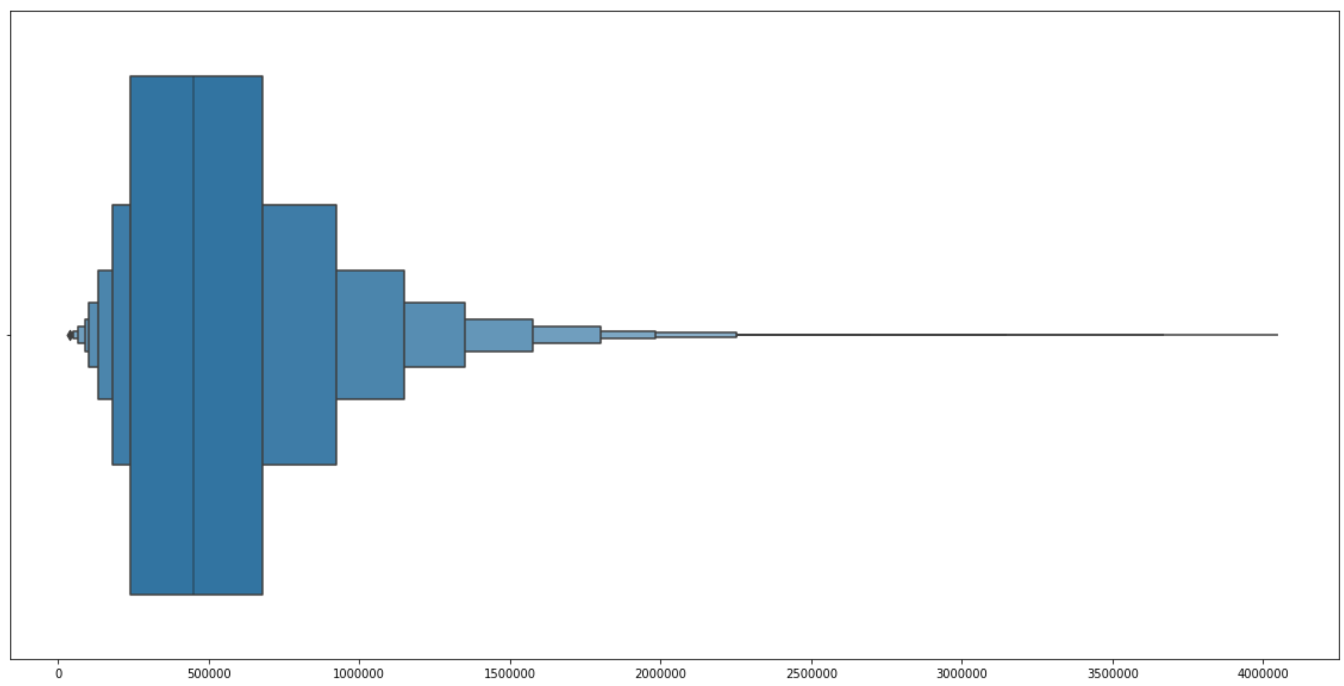
Out[52]:
```
SK_ID_CURR                     307510
DAYS_BIRTH                      17460
DAYS_REGISTRATION               15688
AMT_ANNUITY                     13672
DAYS_EMPLOYED                   12574
DAYS_ID_PUBLISH                  6168
AMT_CREDIT                       5603
DAYS_LAST_PHONE_CHANGE           3773
AMT_INCOME_TOTAL                 2548
AMT_GOODS_PRICE                  1002
REGION_POPULATION_RELATIVE         81
ORGANIZATION_TYPE                  58
OBS_60_CNT_SOCIAL_CIRCLE           33
OBS_30_CNT_SOCIAL_CIRCLE           33
AMT_REQ_CREDIT_BUREAU_YEAR         25
AMT_REQ_CREDIT_BUREAU_MON          24
HOUR_APPR_PROCESS_START            24
OCCUPATION_TYPE                    19
CNT_FAM_MEMBERS                    17
CNT_CHILDREN                       15
AMT_REQ_CREDIT_BUREAU_QRT          11
DEF_30_CNT_SOCIAL_CIRCLE           10
AMT_REQ_CREDIT_BUREAU_WEEK          9
DEF_60_CNT_SOCIAL_CIRCLE            9
AMT_REQ_CREDIT_BUREAU_DAY           9
NAME_INCOME_TYPE                    8
NAME_TYPE_SUITE                     7
WEEKDAY_APPR_PROCESS_START          7
NAME_FAMILY_STATUS                  6
NAME_HOUSING_TYPE                   6
AMT_REQ_CREDIT_BUREAU_HOUR          5
NAME_EDUCATION_TYPE                 5
CODE_GENDER                         3
REGION_RATING_CLIENT                3
REGION_RATING_CLIENT_W_CITY         3
REG_REGION_NOT_WORK_REGION          2
LIVE_CITY_NOT_WORK_CITY             2
REG_CITY_NOT_WORK_CITY              2
REG_CITY_NOT_LIVE_CITY              2
REG_REGION_NOT_LIVE_REGION          2
NAME_CONTRACT_TYPE                  2
TARGET                              2
LIVE_REGION_NOT_WORK_REGION         2
dtype: int64
```

In [53]:
```
# KDE-plot
plt.figure(figsize=(20,10))
sns.kdeplot(data=data, x='AMT_GOODS_PRICE')
plt.show()
```



In [54]:
```
plt.figure(figsize=(20,10))
sns.boxenplot(data=data, x='AMT_GOODS_PRICE')
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x2388b6de608>

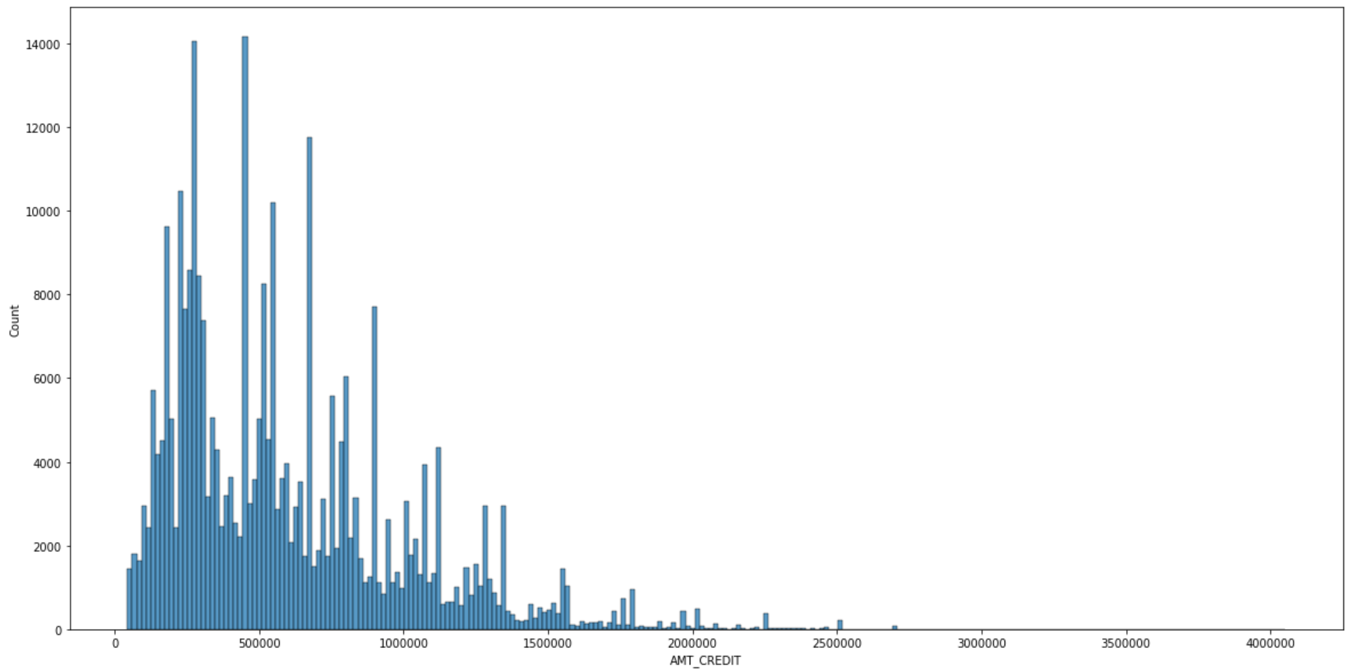


In [55]:
```python
# AMT_GOODS_PRICE
data['AMT_GOODS_PRICE'].quantile([0.1,0.25,0.50,0.75,0.90])
```

Out[55]:
```
0.10     180000.0
0.25     238500.0
0.50     450000.0
0.75     679500.0
0.90    1093500.0
Name: AMT_GOODS_PRICE, dtype: float64
```

In [56]:
```python
plt.figure(figsize=(20,10))
sns.histplot(data['AMT_CREDIT'])
```

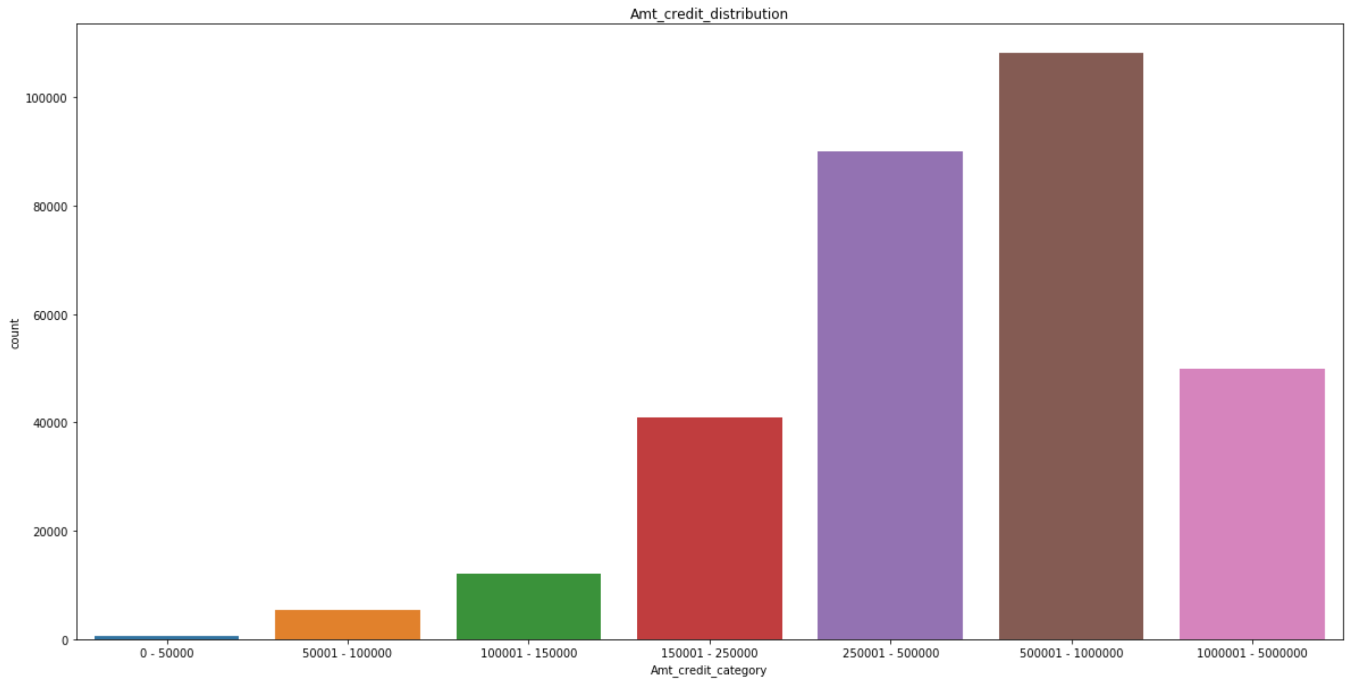
Out[56]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2388b777e88>
```



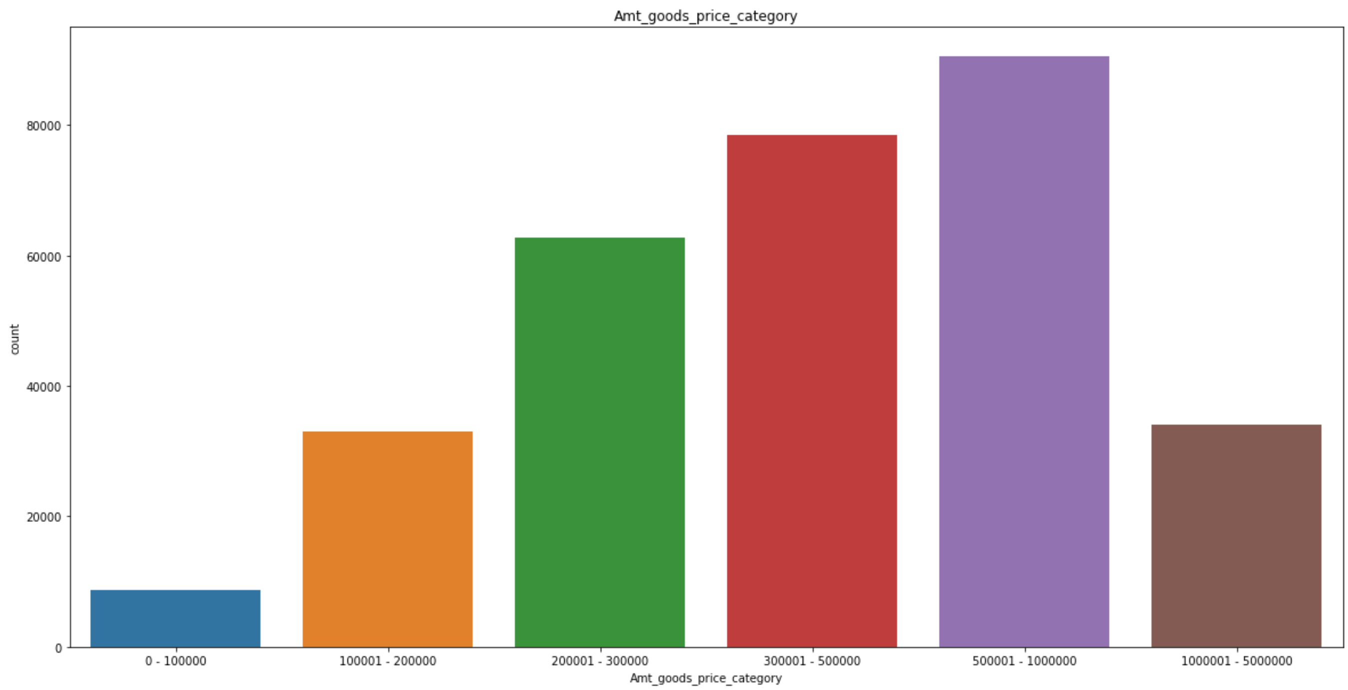
In [57]:
```python
data['AMT_CREDIT'].describe().loc[['min','max']]
```

Out[57]:
```
min      45000.0
max    4050000.0
Name: AMT_CREDIT, dtype: float64
```

In [58]:
```
# Amt_Credit
labels= ['0 - 50000','50001 - 100000','100001 - 150000','150001 - 250000','250001 - 500000','500001 - 1000000', '1000001 - 5000000']
data['Amt_credit_category'] = pd.cut(data['AMT_CREDIT'], bins=[0,50000,100000,150000,250000,500000,1000000,5000000], labels=labels)

plt.figure(figsize=(20,10))
sns.countplot(x=data['Amt_credit_category'])
plt.title('Amt_credit_distribution')
plt.show()
```

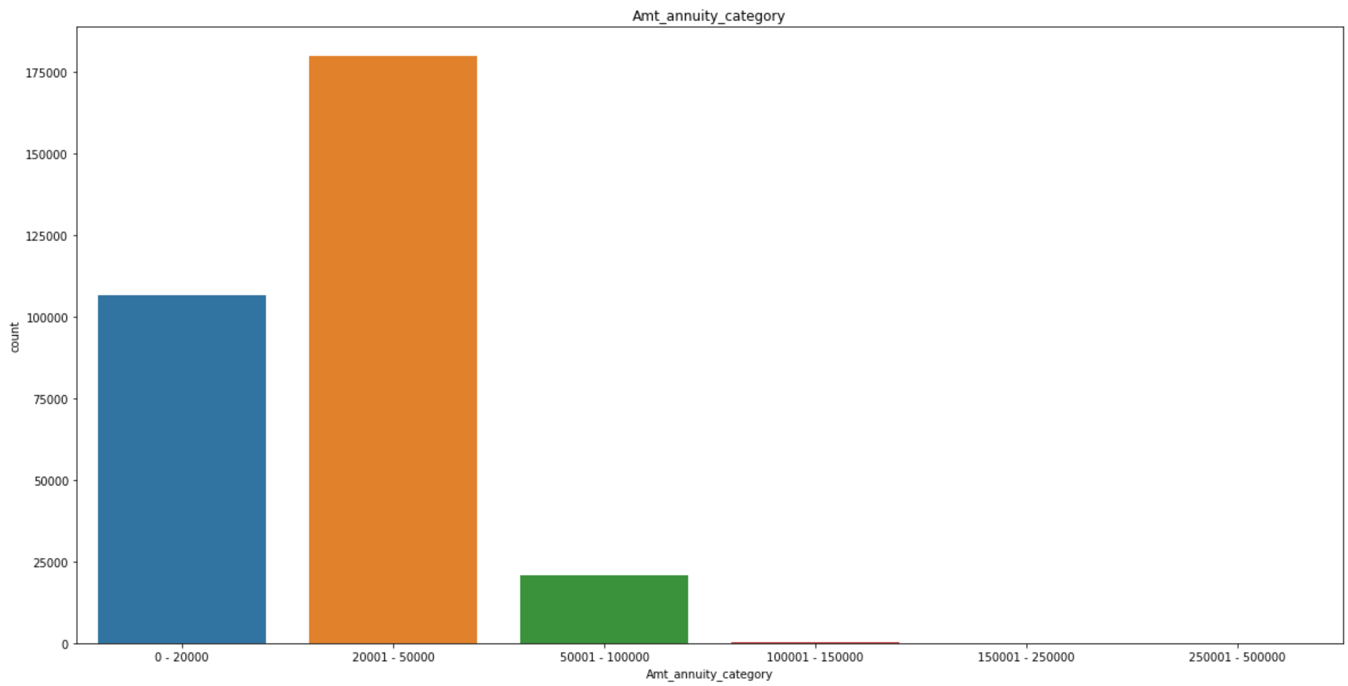


In [59]:
```
# AMT_GOODS_PRICE
labels= ['0 - 100000','100001 - 200000','200001 - 300000','300001 - 500000','500001 - 1000000','1000001 - 5000000']
data['Amt_goods_price_category'] = pd.cut(data['AMT_GOODS_PRICE'], bins=[0,100000,200000,300000,500000,1000000,5000000], labels=labels)

plt.figure(figsize=(20,10))
sns.countplot(x=data['Amt_goods_price_category'])
plt.title('Amt_goods_price_category')
plt.show()
```

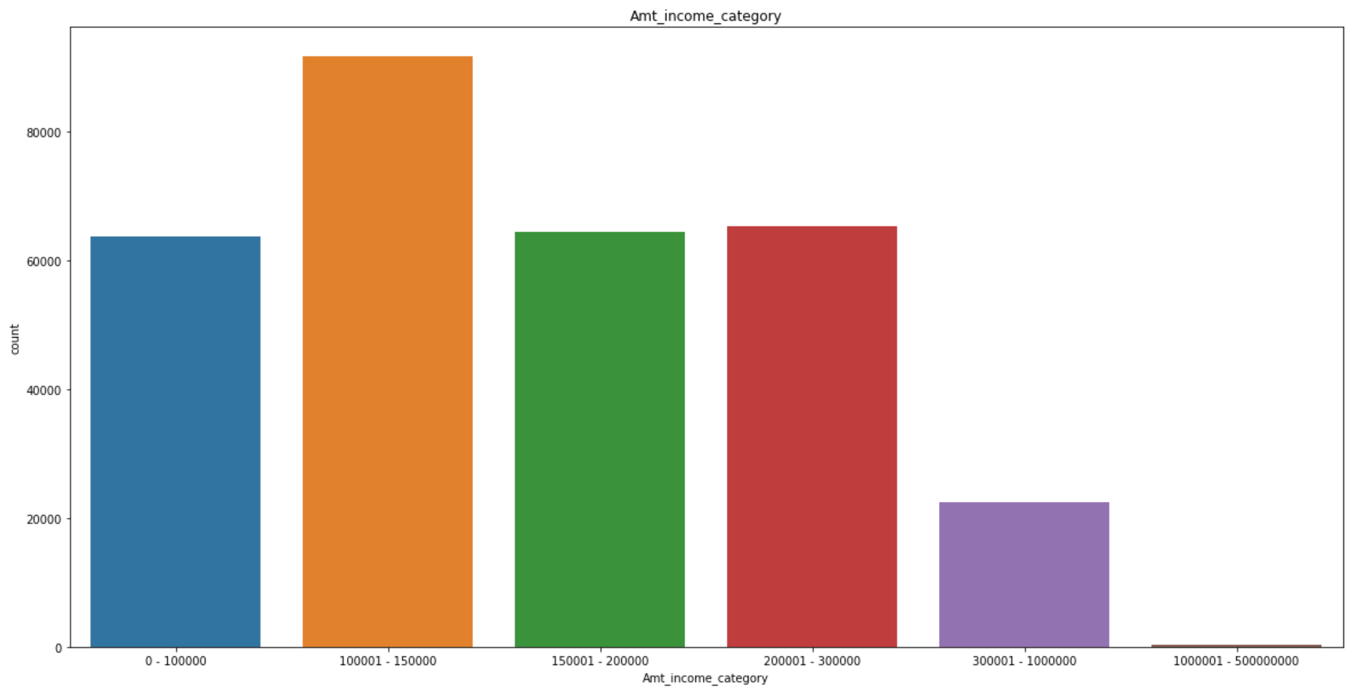


In [60]:

```
# AMT_ANNUITY
labels= ['0 - 20000','20001 - 50000','50001 - 100000','100001 - 150000','150001 - 25000
0','250001 - 500000']
data['Amt_annuity_category'] = pd.cut(data['AMT_ANNUITY'], bins=[0,20000,50000,100000,15
0000,250000,300000], labels=labels)

plt.figure(figsize=(20,10))
sns.countplot(x=data['Amt_annuity_category'])
plt.title('Amt_annuity_category')
plt.show()
```



In [61]:
```
# AMT_INCOME_TOTAL
labels= ['0 - 100000','100001 - 150000','150001 - 200000','200001 - 300000','300001 - 1000000','1000001 - 500000000']
data['Amt_income_category'] = pd.cut(data['AMT_INCOME_TOTAL'], bins=[0,100000,150000,200000,300000,1000000,500000000], labels=labels)

plt.figure(figsize=(20,10))
sns.countplot(x=data['Amt_income_category'])
plt.title('Amt_income_category')
plt.show()
```

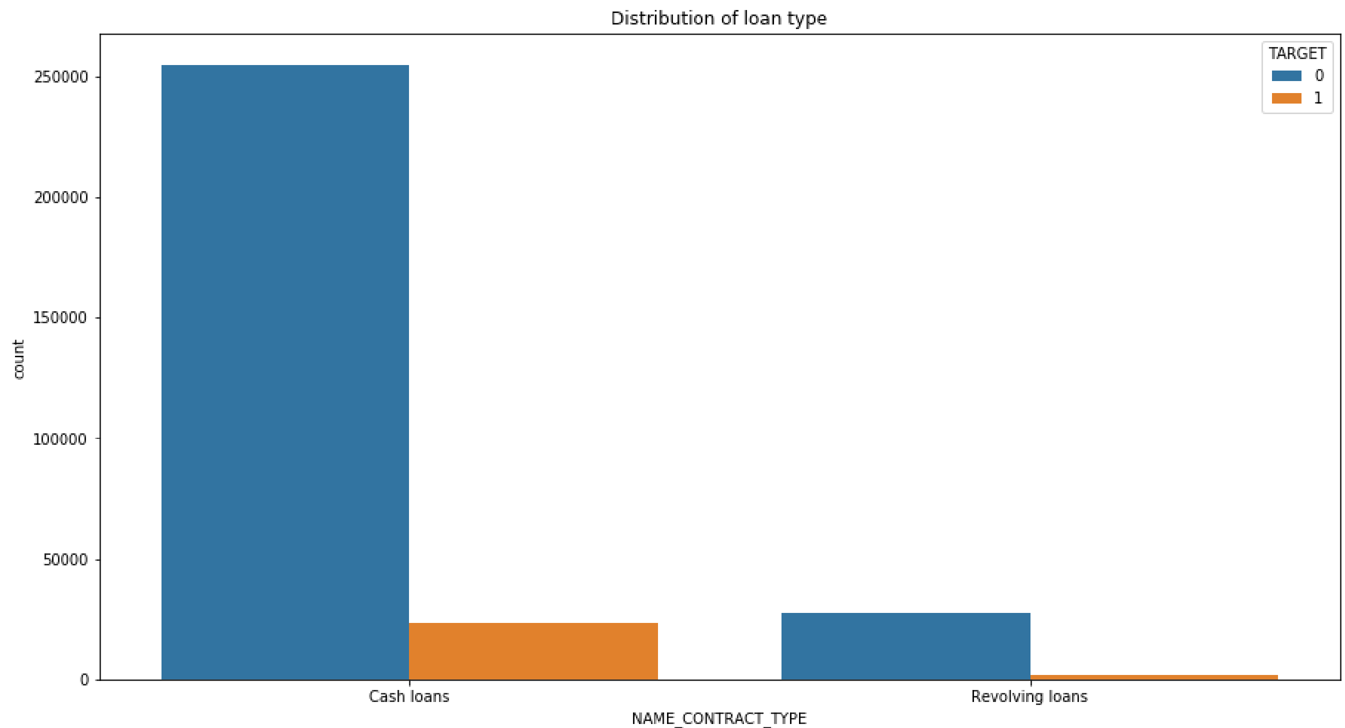


Categorical variables data visualization

In [62]:
```
# NAME_CONTRACT_TYPE
data['NAME_CONTRACT_TYPE'].value_counts()
```

Out[62]:
```
Cash loans         278231
Revolving loans     29279
Name: NAME_CONTRACT_TYPE, dtype: int64
```

In [63]:
```
# Countplot
plt.figure(figsize=(15,8))
sns.countplot(x='NAME_CONTRACT_TYPE', data=data, hue='TARGET')
plt.title("Distribution of loan type")
plt.show()
```



By observation we can say that those who have taken cash loan defaulted the loan most.

In [64]:
```
# NAME_CONTRACT_TYPE
data['NAME_CONTRACT_TYPE'].value_counts()
```

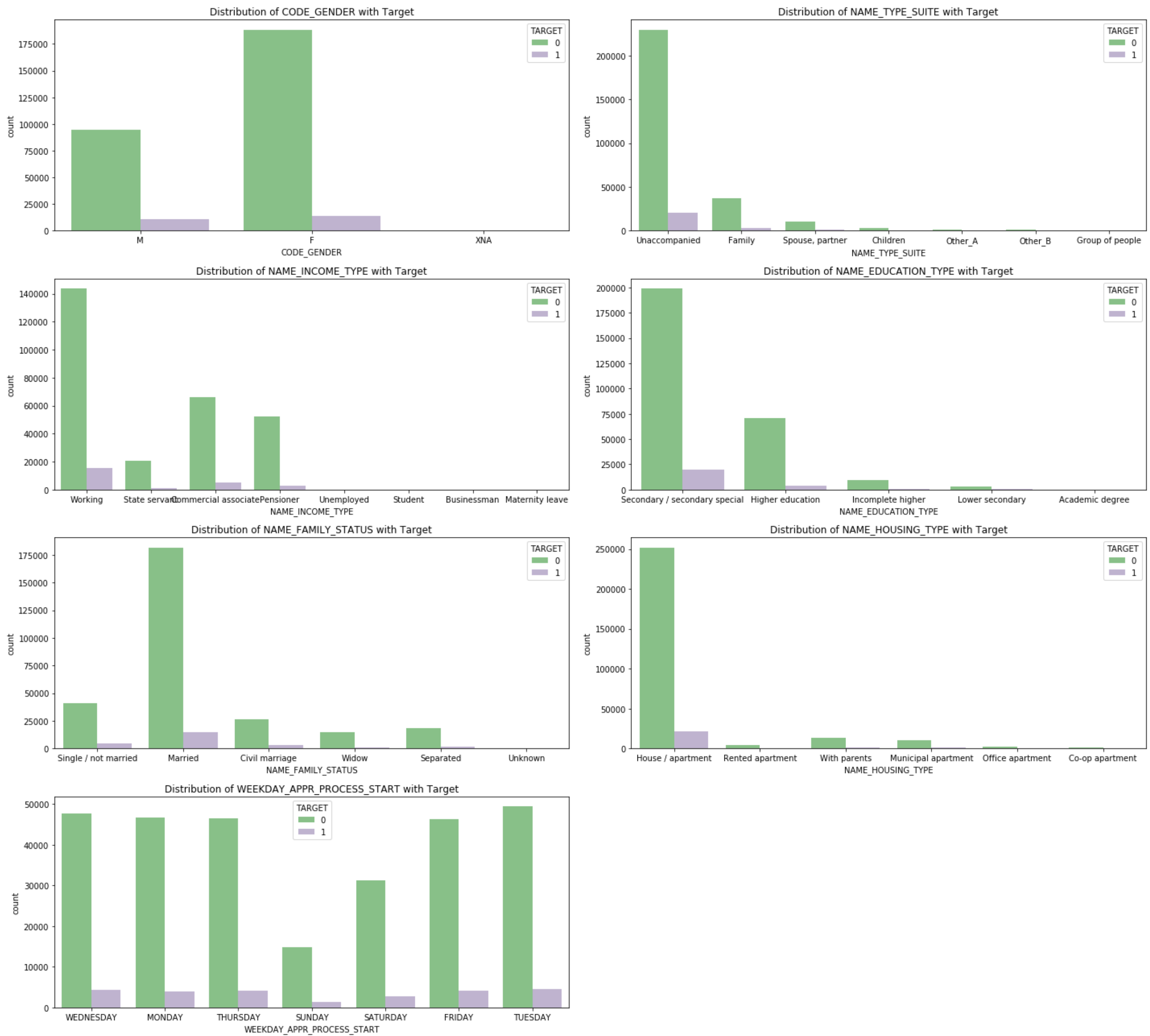
Out[64]:
```
Cash loans         278231
Revolving loans     29279
Name: NAME_CONTRACT_TYPE, dtype: int64
```

In [65]:
```
# Dataframe for Loan type with target
loan_with_target = data.groupby(['NAME_CONTRACT_TYPE', 'TARGET']).size().reset_index(nam
e='count')

loan_with_target['Percentage'] = round((loan_with_target['count']/len(data['NAME_CONTRAC
T_TYPE']))*100,2)
loan_with_target
```

Out[65]:

	NAME_CONTRACT_TYPE	TARGET	count	Percentage
0	Cash loans	0	255010	82.93
1	Cash loans	1	23221	7.55
2	Revolving loans	0	27675	9.00
3	Revolving loans	1	1604	0.52

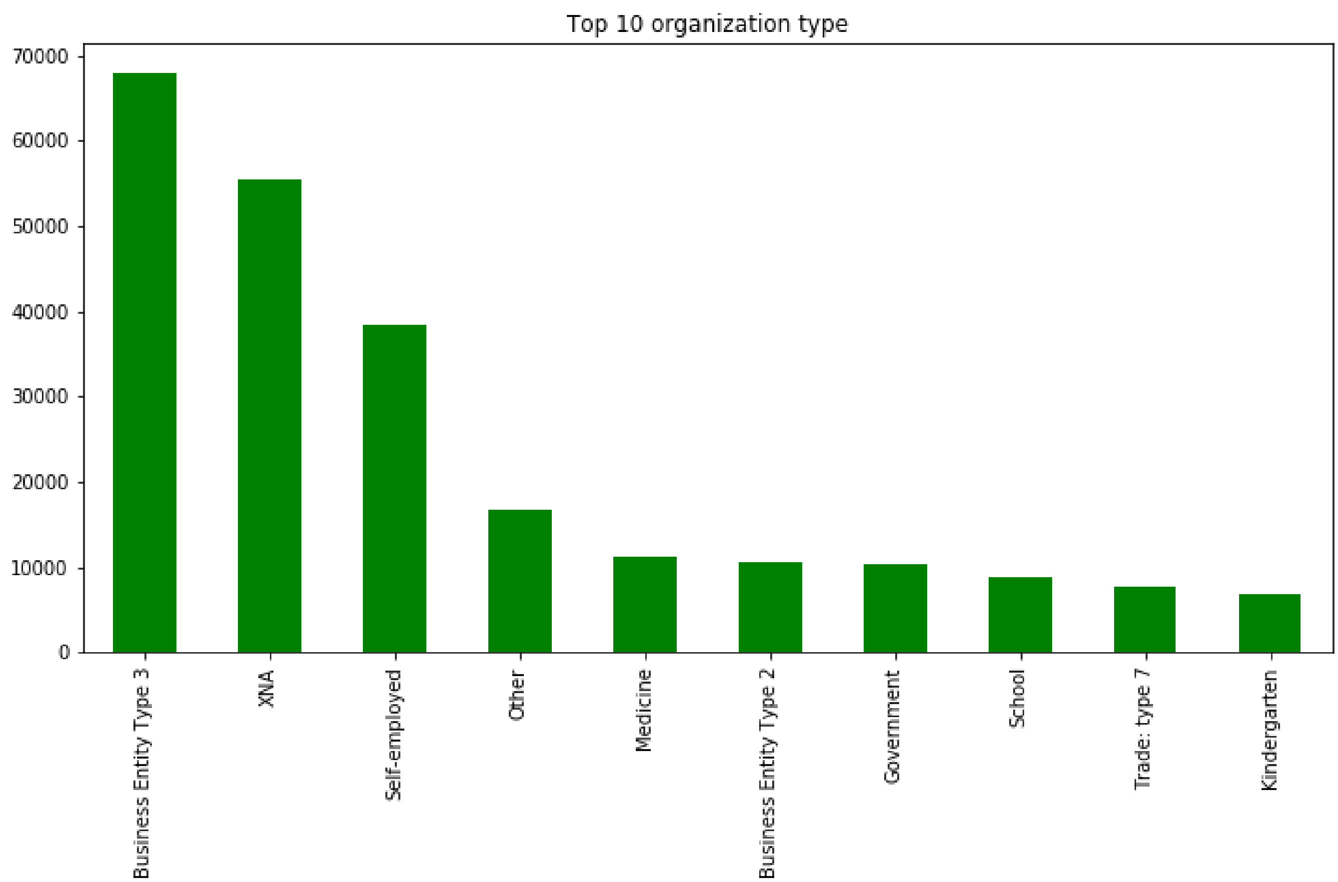
In [66]:
```python
cols = ['CODE_GENDER', 'NAME_TYPE_SUITE','NAME_INCOME_TYPE','NAME_EDUCATION_TYPE','NAME_FAMILY_STATUS',
        'NAME_HOUSING_TYPE', 'WEEKDAY_APPR_PROCESS_START']

# Countplot
plt.figure(figsize=(20,18))
for index, c in enumerate(cols):
    plt.subplot(4,2, index+1)
    sns.countplot(x=c, data=data, hue='TARGET', palette='Accent')
    plt.title(f"Distribution of {c} with Target")

plt.tight_layout()
```



By Close observation of each bar chart, we can come to following conclusions:

1. Females are less likely to default the loan than male.
2. Working client, Commercial associate and Pensioner have taken more loans.
3. Unaccompanied has taken most number of loans.
4. Married client has received more number of credits.
5. Most of the clients have their house apartment.
6. All days have equal number of application received, except sunday.

In [67]:
```
# Organization type
plt.figure(figsize=(12,6))
data['ORGANIZATION_TYPE'].value_counts().sort_values(ascending=False)[:10].plot(kind='ba
r', color='green')
plt.title("Top 10 organization type")
plt.show()
```



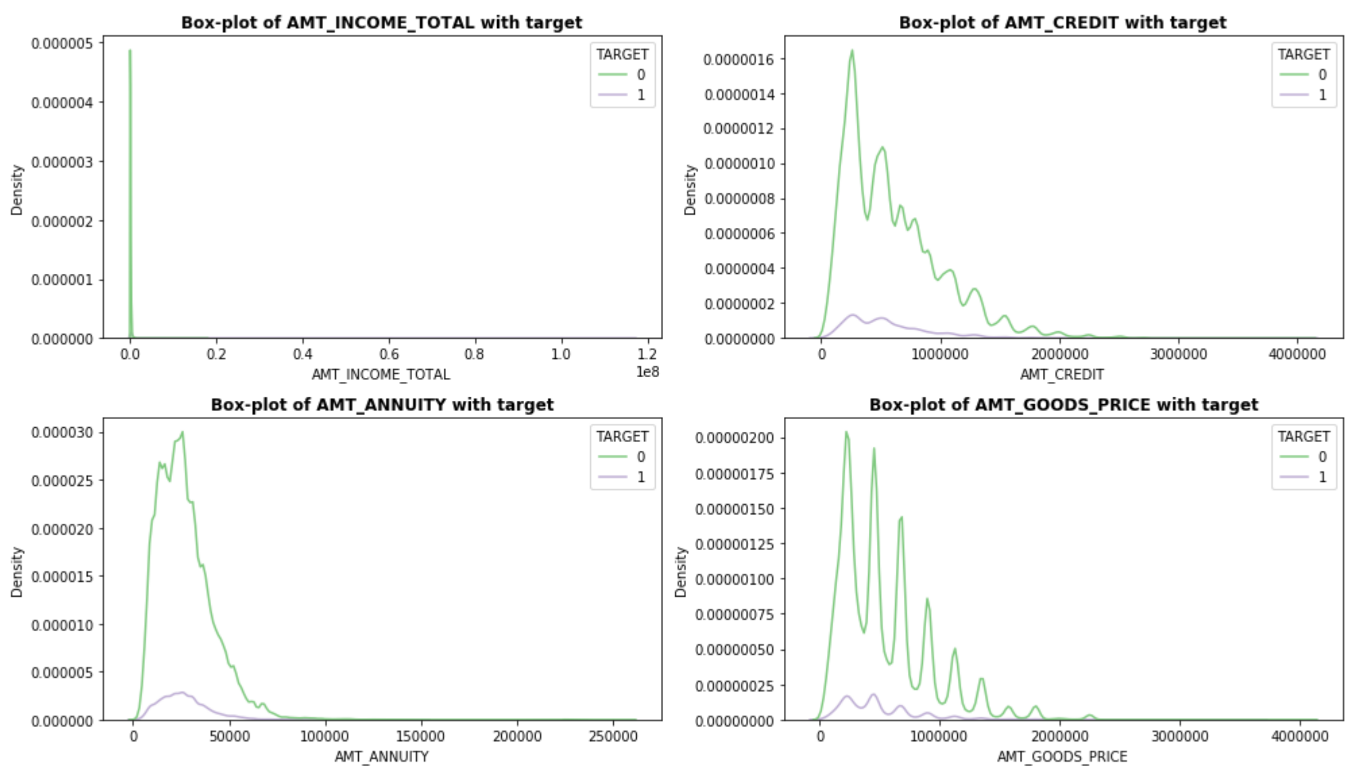
In [68]:
```
# Numeric features and categorical features
num_features = data.select_dtypes(include=['int', 'float']).columns
num_cat_features = data.select_dtypes(include=['int', 'float', 'category']).columns
```

In [69]:
```
data['TARGET']
```

Out[69]:
```
0         1
1         0
2         0
3         0
4         0
         ..
307506    0
307507    0
307508    0
307509    1
307510    0
Name: TARGET, Length: 307510, dtype: int64
```

In [70]:
```
# Numeric dataframe
num_data = data[np.concatenate([num_features,np.array(['TARGET'])])]

defaulters = num_data[num_data['TARGET']==1]  # Dataframe for defaulters
repayers = num_data[num_data['TARGET']==0]   # Dataframe for non-defaulters
```

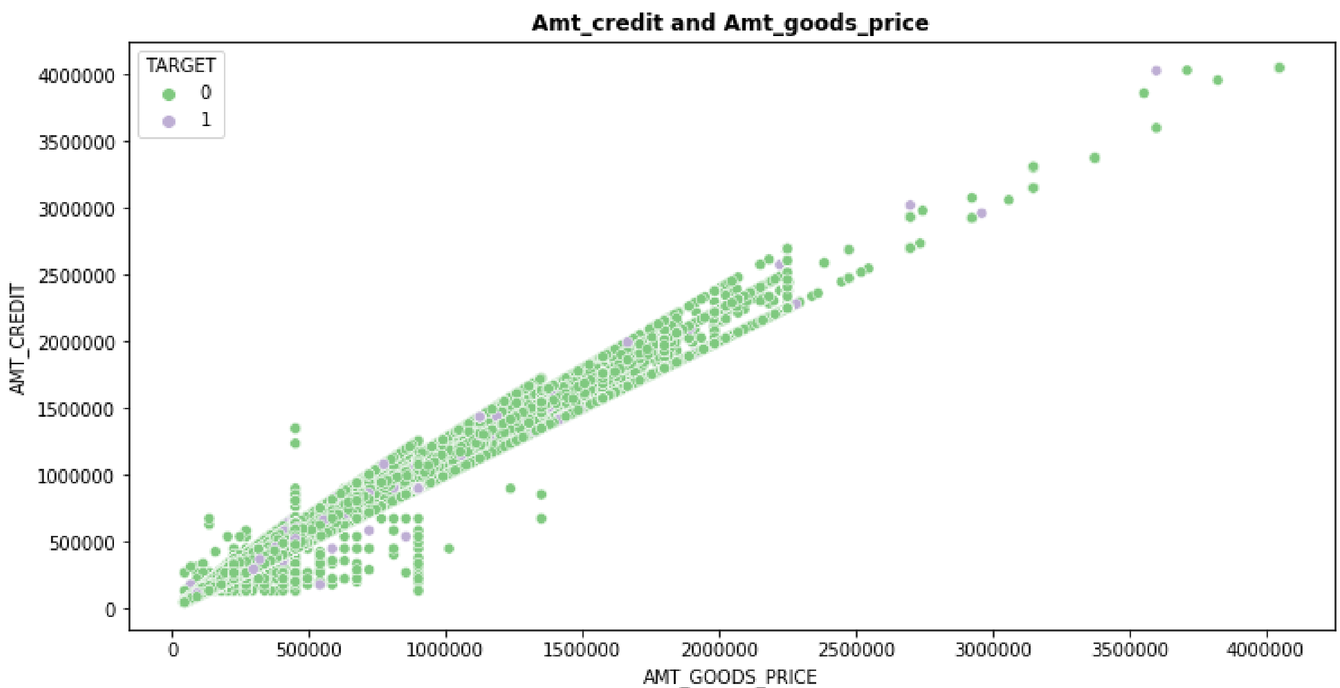
In [72]:
```
# Amt_features
amt_var = ['AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AMT_GOODS_PRICE']

plt.figure(figsize=(14,8))
for index, k in enumerate(amt_var):
    plt.subplot(2,2, index+1)
    sns.kdeplot(x=k, data=num_data, hue='TARGET', palette='Accent')
    plt.title(f"Box-plot of {k} with target", fontweight='bold')

plt.tight_layout()
```



Observations:

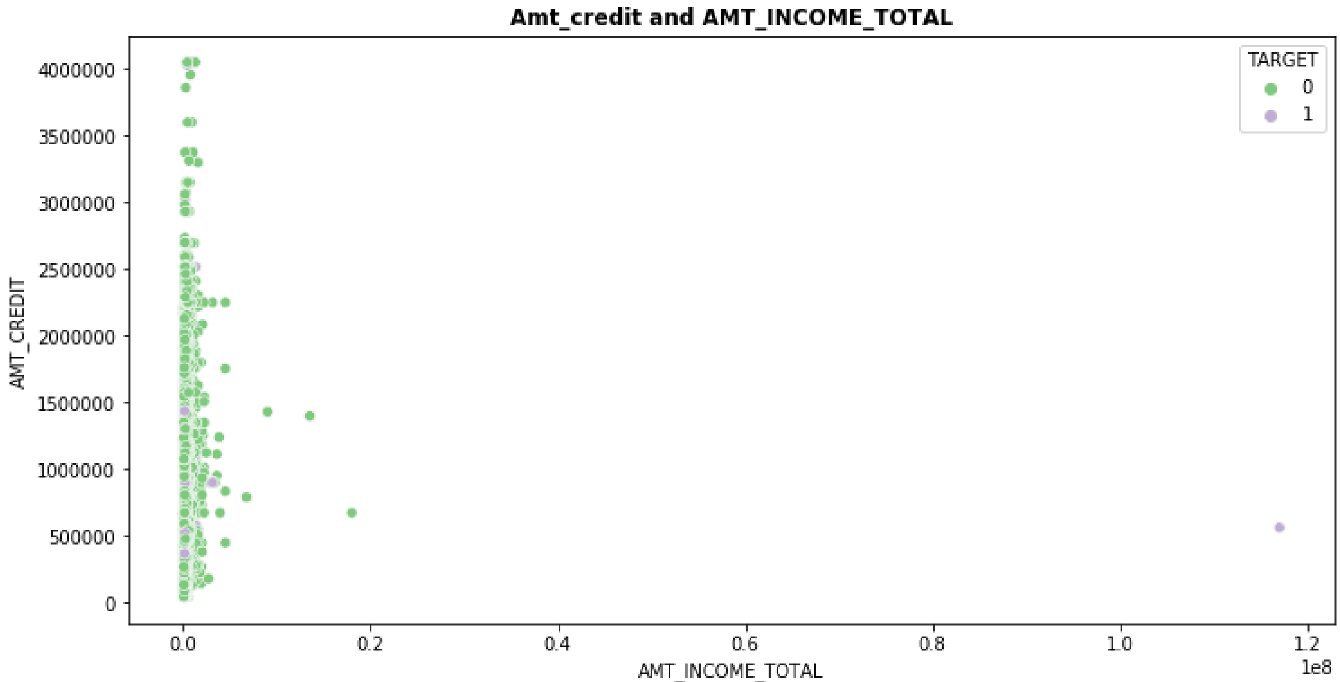
1. Most of the defaulters are from high-income groups.
2. Most defaulters fall under the category of amt_credit between 0 to 1 million.
3. Annuity payment of 0 to 50000 have more number of defaults.
4. Amount goods price between o to 1 million have more number of defaults.

In [73]:
```
# Scatter plot
plt.figure(figsize=(12,6))
sns.scatterplot(data=num_data, x='AMT_GOODS_PRICE', y='AMT_CREDIT', palette='Accent', hu
e='TARGET')
plt.title("Amt_credit and Amt_goods_price", fontweight='bold')
plt.show()
```



Here we can observe that Amt_goods_price and Amt_credit have linear relation. And, most of the defaulters are under 1 million level.

In [74]:
```
plt.figure(figsize=(12,6))
sns.scatterplot(data=num_data, x='AMT_INCOME_TOTAL', y='AMT_CREDIT', palette='Accent', h
ue='TARGET')
plt.title("Amt_credit and AMT_INCOME_TOTAL", fontweight='bold')
plt.show()
```



People with income less than 1 million is taking more number of loans. And, people who got credit/loans less than 150,000 are more likely to default.

Final Observations:

1. Female loan has less default rate. So, the bank should give a little bit priority to females.
2. Those clients who do not have any accompany should be focused.
3. Safest segementation of employment are workers, commercial associates and pensioners.
4. Client who have the higher education should be given more loans.
5. Married clients are safer than unmarried.
6. People having house/apartment are safer to provide loans.
7. Low-skill laborers and drivers should be given less priority as they have high probability of making defaults.
8. People having income less than 1 million and taking loans near to 1 million have higher chance of defaults. So, should not be given focus.
9. Married couples having children less than five are safe for providng loans.
10. Client having annuity less than 100K are safer side for the bank.

In [ ]: