

```

# Importing all the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import random
pd.set_option("max_rows", None)
pd.set_option('display.max_columns', 500)

```

```

# Supress Warnings
import warnings
warnings.filterwarnings('ignore')

```

```

# Read data from file 'application_data.csv'
df= pd.read_csv("application_data.csv")

```

```

# Preview the first 5 lines of the loaded data
df.head()

```

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

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	\
0	Y	0	202500.0	406597.5	24700.5	
1	N	0	270000.0	1293502.5	35698.5	
2	Y	0	67500.0	135000.0	6750.0	
3	Y	0	135000.0	312682.5	29686.5	
4	Y	0	121500.0	513000.0	21865.5	

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	351000.0	Unaccompanied	Working	
1	1129500.0	Family	State servant	
2	135000.0	Unaccompanied	Working	
3	297000.0	Unaccompanied	Working	
4	513000.0	Unaccompanied	Working	

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	\
0	Secondary / secondary special	Single / not married	House /	

apartment				
1	Higher education		Married	House /
apartment				
2	Secondary / secondary special	Single / not married		House /
apartment				
3	Secondary / secondary special		Civil marriage	House /
apartment				
4	Secondary / secondary special	Single / not married		House /
apartment				

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	
DAYS_REGISTRATION \				
0	0.018801	-9461	-637	-
3648.0				
1	0.003541	-16765	-1188	-
1186.0				
2	0.010032	-19046	-225	-
4260.0				
3	0.008019	-19005	-3039	-
9833.0				
4	0.028663	-19932	-3038	-
4311.0				

	DAYS_ID_PUBLISH	OWN_CAR_AGE	FLAG_MOBIL	FLAG_EMP_PHONE
FLAG_WORK_PHONE \				
0	-2120	NaN	1	1
0				
1	-291	NaN	1	1
0				
2	-2531	26.0	1	1
1				
3	-2437	NaN	1	1
0				
4	-3458	NaN	1	1
0				

	FLAG_CONT_MOBILE	FLAG_PHONE	FLAG_EMAIL	OCCUPATION_TYPE
CNT_FAM_MEMBERS \				
0	1	1	0	Laborers
1.0				
1	1	1	0	Core staff
2.0				
2	1	1	0	Laborers
1.0				
3	1	0	0	Laborers
2.0				
4	1	0	0	Core staff
1.0				

REGION_RATING_CLIENT	REGION_RATING_CLIENT_W_CITY \
----------------------	-------------------------------

0	2	2
1	1	1
2	2	2
3	2	2
4	2	2

WEEKDAY_APPR_PROCESS_START	HOUR_APPR_PROCESS_START	\
0	WEDNESDAY	10
1	MONDAY	11
2	MONDAY	9
3	WEDNESDAY	17
4	THURSDAY	11

REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION	\
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

LIVE_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY	\
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	
ORGANIZATION_TYPE	\	
0	0	0 Business Entity
Type 3		
1	0	0
School		
2	0	0
Government		
3	0	0 Business Entity
Type 3		
4	1	1
Religion		

EXT_SOURCE_1	EXT_SOURCE_2	EXT_SOURCE_3	APARTMENTS_AVG
BASEMENTAREA_AVG	\		
0	0.083037	0.262949	0.139376
0.0369			0.0247
1	0.311267	0.622246	NaN
0.0529			0.0959
2	NaN	0.555912	0.729567
NaN			NaN
3	NaN	0.650442	NaN
NaN			NaN

4	NaN	0.322738	NaN	NaN
NaN				

	YEARS_BEGINEXPLUATATION_AVG	YEARS_BUILD_AVG	COMMONAREA_AVG	\
0	0.9722	0.6192	0.0143	
1	0.9851	0.7960	0.0605	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	ELEVATORS_AVG	ENTRANCES_AVG	FLOORSMAX_AVG	FLOORSMIN_AVG
LANDAREA_AVG	\			
0	0.00	0.0690	0.0833	0.1250
0.0369				
1	0.08	0.0345	0.2917	0.3333
0.0130				
2	NaN	NaN	NaN	NaN
NaN				
3	NaN	NaN	NaN	NaN
NaN				
4	NaN	NaN	NaN	NaN
NaN				

	LIVINGAPARTMENTS_AVG	LIVINGAREA_AVG	NONLIVINGAPARTMENTS_AVG	\
0	0.0202	0.0190	0.0000	
1	0.0773	0.0549	0.0039	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	NONLIVINGAREA_AVG	APARTMENTS_MODE	BASEMENTAREA_MODE	\
0	0.0000	0.0252	0.0383	
1	0.0098	0.0924	0.0538	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	YEARS_BEGINEXPLUATATION_MODE	YEARS_BUILD_MODE	COMMONAREA_MODE	\
0	0.9722	0.6341	0.0144	
1	0.9851	0.8040	0.0497	
2	NaN	NaN	NaN	
3	NaN	NaN	NaN	
4	NaN	NaN	NaN	

	ELEVATORS_MODE	ENTRANCES_MODE	FLOORSMAX_MODE	FLOORSMIN_MODE	\
0	0.0000	0.0690	0.0833	0.1250	
1	0.0806	0.0345	0.2917	0.3333	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

	LANDAREA_MODE	LIVINGAPARTMENTS_MODE	LIVINGAREA_MODE \
0	0.0377	0.022	0.0198
1	0.0128	0.079	0.0554
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE	APARTMENTS_MEDI \
0	0.0	0.0	0.0250
1	0.0	0.0	0.0968
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	BASEMENTAREA_MEDI YEARS_BUILD_MEDI \	YEARS_BEGINEXPLUATATION_MEDI	
0	0.0369	0.9722	0.6243
1	0.0529	0.9851	0.7987
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	NaN	NaN	NaN

	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	FLOORSMAX_MEDI \
0	0.0144	0.00	0.0690	0.0833
1	0.0608	0.08	0.0345	0.2917
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN

	FLOORSMIN_MEDI LIVINGAREA_MEDI \	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI
0	0.1250	0.0375	0.0205
0.0193			
1	0.3333	0.0132	0.0787
0.0558			
2	NaN	NaN	NaN
NaN			
3	NaN	NaN	NaN
NaN			
4	NaN	NaN	NaN
NaN			

	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	FONDKAPREMONT_MODE \
--	--------------------------	--------------------	----------------------

0	0.0000	0.00	reg	oper	account
1	0.0039	0.01	reg	oper	account
2	NaN	NaN			NaN
3	NaN	NaN			NaN
4	NaN	NaN			NaN

HOUSETYPE_MODE	TOTALAREA_MODE	WALLSMATERIAL_MODE
EMERGENCYSTATE_MODE \		
0 block of flats	0.0149	Stone, brick
No		
1 block of flats	0.0714	Block
No		
2 NaN	NaN	NaN
NaN		
3 NaN	NaN	NaN
NaN		
4 NaN	NaN	NaN
NaN		

OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE \
0 2.0	2.0
1 1.0	0.0
2 0.0	0.0
3 2.0	0.0
4 0.0	0.0

OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE
DAYS_LAST_PHONE_CHANGE \	
0 2.0	2.0
-1134.0	
1 1.0	0.0
-828.0	
2 0.0	0.0
-815.0	
3 2.0	0.0
-617.0	
4 0.0	0.0
-1106.0	

FLAG_DOCUMENT_2	FLAG_DOCUMENT_3	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5
\			
0 0	1	0	0
1 0	1	0	0
2 0	0	0	0
3 0	1	0	0

4	0	0	0	0
---	---	---	---	---

	FLAG_DOCUMENT_6	FLAG_DOCUMENT_7	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9
\				
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	1	0

	FLAG_DOCUMENT_10	FLAG_DOCUMENT_11	FLAG_DOCUMENT_12
FLAG_DOCUMENT_13 \			
0	0	0	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	FLAG_DOCUMENT_14	FLAG_DOCUMENT_15	FLAG_DOCUMENT_16
FLAG_DOCUMENT_17 \			
0	0	0	0
0			
1	0	0	0
0			
2	0	0	0
0			
3	0	0	0
0			
4	0	0	0
0			

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20
FLAG_DOCUMENT_21 \			
0	0	0	0
0			
1	0	0	0
0			
2	0	0	0

```

0
3          0          0          0
0
4          0          0          0
0

```

```

    AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
0                               0.0                        0.0
1                               0.0                        0.0
2                               0.0                        0.0
3                               NaN                        NaN
4                               0.0                        0.0

```

```

    AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                               0.0                        0.0
1                               0.0                        0.0
2                               0.0                        0.0
3                               NaN                        NaN
4                               0.0                        0.0

```

```

    AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                               0.0                        1.0
1                               0.0                        0.0
2                               0.0                        0.0
3                               NaN                        NaN
4                               0.0                        0.0

```

#Determining the number of rows and columns

```
df.shape
```

```
(307511, 122)
```

#summary of all the numeric columns in the dataset

```
df.describe()
```

	SK_ID_CURR	TARGET	CNT_CHILDREN	
AMT_INCOME_TOTAL \				
count	307511.000000	307511.000000	307511.000000	3.075110e+05
mean	278180.518577	0.080729	0.417052	1.687979e+05
std	102790.175348	0.272419	0.722121	2.371231e+05
min	100002.000000	0.000000	0.000000	2.565000e+04
25%	189145.500000	0.000000	0.000000	1.125000e+05
50%	278202.000000	0.000000	0.000000	1.471500e+05
75%	367142.500000	0.000000	1.000000	2.025000e+05

max	456255.000000	1.000000	19.000000	1.170000e+08
-----	---------------	----------	-----------	--------------

	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE \
count	3.075110e+05	307499.000000	3.072330e+05
mean	5.990260e+05	27108.573909	5.383962e+05
std	4.024908e+05	14493.737315	3.694465e+05
min	4.500000e+04	1615.500000	4.050000e+04
25%	2.700000e+05	16524.000000	2.385000e+05
50%	5.135310e+05	24903.000000	4.500000e+05
75%	8.086500e+05	34596.000000	6.795000e+05
max	4.050000e+06	258025.500000	4.050000e+06

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED \
count	307511.000000	307511.000000	307511.000000
mean	0.020868	-16036.995067	63815.045904
std	0.013831	4363.988632	141275.766519
min	0.000290	-25229.000000	-17912.000000
25%	0.010006	-19682.000000	-2760.000000
50%	0.018850	-15750.000000	-1213.000000
75%	0.028663	-12413.000000	-289.000000
max	0.072508	-7489.000000	365243.000000

	DAYS_REGISTRATION	DAYS_ID_PUBLISH	OWN_CAR_AGE
count	307511.000000	307511.000000	104582.000000
mean	-4986.120328	-2994.202373	12.061091
std	3522.886321	1509.450419	11.944812
min	-24672.000000	-7197.000000	0.000000
25%	-7479.500000	-4299.000000	5.000000
50%	-4504.000000	-3254.000000	9.000000
75%	-2010.000000	-1720.000000	15.000000
max	0.000000	0.000000	91.000000

	FLAG_EMP_PHONE	FLAG_WORK_PHONE	FLAG_CONT_MOBILE
count	307511.000000	307511.000000	307511.000000
mean	0.819889	0.199368	0.998133
std	0.384280	0.399526	0.043164

0.449521			
min	0.000000	0.000000	0.000000
0.000000			
25%	1.000000	0.000000	1.000000
0.000000			
50%	1.000000	0.000000	1.000000
0.000000			
75%	1.000000	0.000000	1.000000
1.000000			
max	1.000000	1.000000	1.000000
1.000000			

	FLAG_EMAIL	CNT_FAM_MEMBERS	REGION_RATING_CLIENT \
count	307511.000000	307509.000000	307511.000000
mean	0.056720	2.152665	2.052463
std	0.231307	0.910682	0.509034
min	0.000000	1.000000	1.000000
25%	0.000000	2.000000	2.000000
50%	0.000000	2.000000	2.000000
75%	0.000000	3.000000	2.000000
max	1.000000	20.000000	3.000000

	REGION_RATING_CLIENT_W_CITY	hour_APPR_PROCESS_START \
count	307511.000000	307511.000000
mean	2.031521	12.063419
std	0.502737	3.265832
min	1.000000	0.000000
25%	2.000000	10.000000
50%	2.000000	12.000000
75%	2.000000	14.000000
max	3.000000	23.000000

	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION \
count	307511.000000	307511.000000
mean	0.015144	0.050769
std	0.122126	0.219526
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	LIVE_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY \
count	307511.000000	307511.000000
mean	0.040659	0.078173
std	0.197499	0.268444
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000

max	1.000000	1.000000	
	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	EXT_SOURCE_1
\			
count	307511.000000	307511.000000	134133.000000
mean	0.230454	0.179555	0.502130
std	0.421124	0.383817	0.211062
min	0.000000	0.000000	0.014568
25%	0.000000	0.000000	0.334007
50%	0.000000	0.000000	0.505998
75%	0.000000	0.000000	0.675053
max	1.000000	1.000000	0.962693

	EXT_SOURCE_2	EXT_SOURCE_3	APARTMENTS_AVG	
BASEMENTAREA_AVG				
\				
count	3.068510e+05	246546.000000	151450.00000	127568.000000
mean	5.143927e-01	0.510853	0.11744	0.088442
std	1.910602e-01	0.194844	0.10824	0.082438
min	8.173617e-08	0.000527	0.00000	0.000000
25%	3.924574e-01	0.370650	0.05770	0.044200
50%	5.659614e-01	0.535276	0.08760	0.076300
75%	6.636171e-01	0.669057	0.14850	0.112200
max	8.549997e-01	0.896010	1.00000	1.000000

	YEARS_BEGINEXPLUATATION_AVG	YEARS_BUILD_AVG	COMMONAREA_AVG	\
count	157504.000000	103023.000000	92646.000000	
mean	0.977735	0.752471	0.044621	
std	0.059223	0.113280	0.076036	
min	0.000000	0.000000	0.000000	
25%	0.976700	0.687200	0.007800	
50%	0.981600	0.755200	0.021100	
75%	0.986600	0.823200	0.051500	

max	1.000000	1.000000	1.000000
-----	----------	----------	----------

	ELEVATORS_AVG	ENTRANCES_AVG	FLOORSMAX_AVG	FLOORSMIN_AVG \
count	143620.000000	152683.000000	154491.000000	98869.000000
mean	0.078942	0.149725	0.226282	0.231894
std	0.134576	0.100049	0.144641	0.161380
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.069000	0.166700	0.083300
50%	0.000000	0.137900	0.166700	0.208300
75%	0.120000	0.206900	0.333300	0.375000
max	1.000000	1.000000	1.000000	1.000000

	LANDAREA_AVG	LIVINGAPARTMENTS_AVG	LIVINGAREA_AVG \
count	124921.000000	97312.000000	153161.000000
mean	0.066333	0.100775	0.107399
std	0.081184	0.092576	0.110565
min	0.000000	0.000000	0.000000
25%	0.018700	0.050400	0.045300
50%	0.048100	0.075600	0.074500
75%	0.085600	0.121000	0.129900
max	1.000000	1.000000	1.000000

	NONLIVINGAPARTMENTS_AVG	NONLIVINGAREA_AVG	APARTMENTS_MODE \
count	93997.000000	137829.000000	151450.000000
mean	0.008809	0.028358	0.114231
std	0.047732	0.069523	0.107936
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.052500
50%	0.000000	0.003600	0.084000
75%	0.003900	0.027700	0.143900
max	1.000000	1.000000	1.000000

	BASEMENTAREA_MODE	YEARS_BEGINEXPLUATATION_MODE
YEARS_BUILD_MODE \		
count	127568.000000	157504.000000
103023.000000		
mean	0.087543	0.977065
0.759637		
std	0.084307	0.064575
0.110111		
min	0.000000	0.000000
0.000000		
25%	0.040700	0.976700
0.699400		
50%	0.074600	0.981600
0.764800		
75%	0.112400	0.986600
0.823600		
max	1.000000	1.000000
1.000000		

	COMMONAREA_MODE	ELEVATORS_MODE	ENTRANCES_MODE	FLOORSMAX_MODE
\count	92646.000000	143620.000000	152683.000000	154491.000000
mean	0.042553	0.074490	0.145193	0.222315
std	0.074445	0.132256	0.100977	0.143709
min	0.000000	0.000000	0.000000	0.000000
25%	0.007200	0.000000	0.069000	0.166700
50%	0.019000	0.000000	0.137900	0.166700
75%	0.049000	0.120800	0.206900	0.333300
max	1.000000	1.000000	1.000000	1.000000

	FLOORSMIN_MODE	LANDAREA_MODE	LIVINGAPARTMENTS_MODE
LIVINGAREA_MODE \count	98869.000000	124921.000000	97312.000000
153161.000000			
mean	0.228058	0.064958	0.105645
0.105975			
std	0.161160	0.081750	0.097880
0.111845			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.083300	0.016600	0.054200
0.042700			
50%	0.208300	0.045800	0.077100
0.073100			
75%	0.375000	0.084100	0.131300
0.125200			
max	1.000000	1.000000	1.000000
1.000000			

	NONLIVINGAPARTMENTS_MODE	NONLIVINGAREA_MODE
APARTMENTS_MEDI \count	93997.000000	137829.000000
		151450.000000
mean	0.008076	0.027022
		0.117850
std	0.046276	0.070254
		0.109076
min	0.000000	0.000000
		0.000000

25%	0.000000	0.000000	0.058300
50%	0.000000	0.001100	0.086400
75%	0.003900	0.023100	0.148900
max	1.000000	1.000000	1.000000

	BASEMENTAREA_MEDI	YEARS_BEGINEXPLUATATION_MEDI
YEARS_BUILD_MEDI \		
count	127568.000000	157504.000000
103023.000000		
mean	0.087955	0.977752
0.755746		
std	0.082179	0.059897
0.112066		
min	0.000000	0.000000
0.000000		
25%	0.043700	0.976700
0.691400		
50%	0.075800	0.981600
0.758500		
75%	0.111600	0.986600
0.825600		
max	1.000000	1.000000
1.000000		

	COMMONAREA_MEDI	ELEVATORS_MEDI	ENTRANCES_MEDI	FLOORSMAX_MEDI
\				
count	92646.000000	143620.000000	152683.000000	154491.000000
mean	0.044595	0.078078	0.149213	0.225897
std	0.076144	0.134467	0.100368	0.145067
min	0.000000	0.000000	0.000000	0.000000
25%	0.007900	0.000000	0.069000	0.166700
50%	0.020800	0.000000	0.137900	0.166700
75%	0.051300	0.120000	0.206900	0.333300
max	1.000000	1.000000	1.000000	1.000000

	FLOORSMIN_MEDI	LANDAREA_MEDI	LIVINGAPARTMENTS_MEDI
LIVINGAREA_MEDI \			

count	98869.000000	124921.000000	97312.000000
153161.000000			
mean	0.231625	0.067169	0.101954
0.108607			
std	0.161934	0.082167	0.093642
0.112260			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.083300	0.018700	0.051300
0.045700			
50%	0.208300	0.048700	0.076100
0.074900			
75%	0.375000	0.086800	0.123100
0.130300			
max	1.000000	1.000000	1.000000
1.000000			

	NONLIVINGAPARTMENTS_MEDI	NONLIVINGAREA_MEDI	TOTALAREA_MODE \
count	93997.000000	137829.000000	159080.000000
mean	0.008651	0.028236	0.102547
std	0.047415	0.070166	0.107462
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.041200
50%	0.000000	0.003100	0.068800
75%	0.003900	0.026600	0.127600
max	1.000000	1.000000	1.000000

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE \
count	306490.000000	306490.000000
mean	1.422245	0.143421
std	2.400989	0.446698
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	2.000000	0.000000
max	348.000000	34.000000

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE \
count	306490.000000	306490.000000
mean	1.405292	0.100049
std	2.379803	0.362291
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	2.000000	0.000000
max	344.000000	24.000000

	DAYS_LAST_PHONE_CHANGE	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3 \
count	307510.000000	307511.000000	307511.000000
mean	-962.858788	0.000042	0.710023

std	826.808487	0.006502	0.453752
min	-4292.000000	0.000000	0.000000
25%	-1570.000000	0.000000	0.000000
50%	-757.000000	0.000000	1.000000
75%	-274.000000	0.000000	1.000000
max	0.000000	1.000000	1.000000

	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5	FLAG_DOCUMENT_6
FLAG_DOCUMENT_7 \			
count	307511.000000	307511.000000	307511.000000
307511.000000			
mean	0.000081	0.015115	0.088055
0.000192			
std	0.009016	0.122010	0.283376
0.013850			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.000000	0.000000	0.000000
0.000000			
50%	0.000000	0.000000	0.000000
0.000000			
75%	0.000000	0.000000	0.000000
0.000000			
max	1.000000	1.000000	1.000000
1.000000			

	FLAG_DOCUMENT_8	FLAG_DOCUMENT_9	FLAG_DOCUMENT_10
FLAG_DOCUMENT_11 \			
count	307511.000000	307511.000000	307511.000000
307511.000000			
mean	0.081376	0.003896	0.000023
0.003912			
std	0.273412	0.062295	0.004771
0.062424			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.000000	0.000000	0.000000
0.000000			
50%	0.000000	0.000000	0.000000
0.000000			
75%	0.000000	0.000000	0.000000
0.000000			
max	1.000000	1.000000	1.000000
1.000000			

	FLAG_DOCUMENT_12	FLAG_DOCUMENT_13	FLAG_DOCUMENT_14
FLAG_DOCUMENT_15 \			
count	307511.000000	307511.000000	307511.000000
307511.000000			
mean	0.000007	0.003525	0.002936

0.00121			
std	0.002550	0.059268	0.054110
0.03476			
min	0.000000	0.000000	0.000000
0.00000			
25%	0.000000	0.000000	0.000000
0.00000			
50%	0.000000	0.000000	0.000000
0.00000			
75%	0.000000	0.000000	0.000000
0.00000			
max	1.000000	1.000000	1.000000
1.00000			

	FLAG_DOCUMENT_16	FLAG_DOCUMENT_17	FLAG_DOCUMENT_18
FLAG_DOCUMENT_19 \			
count	307511.000000	307511.000000	307511.000000
307511.000000			
mean	0.009928	0.000267	0.008130
0.000595			
std	0.099144	0.016327	0.089798
0.024387			
min	0.000000	0.000000	0.000000
0.000000			
25%	0.000000	0.000000	0.000000
0.000000			
50%	0.000000	0.000000	0.000000
0.000000			
75%	0.000000	0.000000	0.000000
0.000000			
max	1.000000	1.000000	1.000000
1.000000			

	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	AMT_REQ_CREDIT_BUREAU_HOUR
\			
count	307511.000000	307511.000000	265992.000000
mean	0.000507	0.000335	0.006402
std	0.022518	0.018299	0.083849
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000

max	1.000000	1.000000	4.000000
-----	----------	----------	----------

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK	\
count	265992.000000	265992.000000	
mean	0.007000	0.034362	
std	0.110757	0.204685	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	0.000000	
max	9.000000	8.000000	

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT	\
count	265992.000000	265992.000000	
mean	0.267395	0.265474	
std	0.916002	0.794056	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	0.000000	
max	27.000000	261.000000	

	AMT_REQ_CREDIT_BUREAU_YEAR
count	265992.000000
mean	1.899974
std	1.869295
min	0.000000
25%	0.000000
50%	1.000000
75%	3.000000
max	25.000000

#Datatypes of each column

df.info(verbose=True)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 122 columns):
#      Column                                Dtype
---  -
0      SK_ID_CURR                             int64
1      TARGET                                int64
2      NAME_CONTRACT_TYPE                     object
3      CODE_GENDER                           object
4      FLAG_OWN_CAR                           object
5      FLAG_OWN_REALTY                       object
6      CNT_CHILDREN                           int64
7      AMT_INCOME_TOTAL                       float64
8      AMT_CREDIT                             float64
```

9	AMT_ANNUITY	float64
10	AMT_GOODS_PRICE	float64
11	NAME_TYPE_SUITE	object
12	NAME_INCOME_TYPE	object
13	NAME_EDUCATION_TYPE	object
14	NAME_FAMILY_STATUS	object
15	NAME_HOUSING_TYPE	object
16	REGION_POPULATION_RELATIVE	float64
17	DAYS_BIRTH	int64
18	DAYS_EMPLOYED	int64
19	DAYS_REGISTRATION	float64
20	DAYS_ID_PUBLISH	int64
21	OWN_CAR_AGE	float64
22	FLAG_MOBIL	int64
23	FLAG_EMP_PHONE	int64
24	FLAG_WORK_PHONE	int64
25	FLAG_CONT_MOBILE	int64
26	FLAG_PHONE	int64
27	FLAG_EMAIL	int64
28	OCCUPATION_TYPE	object
29	CNT_FAM_MEMBERS	float64
30	REGION_RATING_CLIENT	int64
31	REGION_RATING_CLIENT_W_CITY	int64
32	WEEKDAY_APPR_PROCESS_START	object
33	HOURL_APPR_PROCESS_START	int64
34	REG_REGION_NOT_LIVE_REGION	int64
35	REG_REGION_NOT_WORK_REGION	int64
36	LIVE_REGION_NOT_WORK_REGION	int64
37	REG_CITY_NOT_LIVE_CITY	int64
38	REG_CITY_NOT_WORK_CITY	int64
39	LIVE_CITY_NOT_WORK_CITY	int64
40	ORGANIZATION_TYPE	object
41	EXT_SOURCE_1	float64
42	EXT_SOURCE_2	float64
43	EXT_SOURCE_3	float64
44	APARTMENTS_AVG	float64
45	BASEMENTAREA_AVG	float64
46	YEARS_BEGINEXPLUATATION_AVG	float64
47	YEARS_BUILD_AVG	float64
48	COMMONAREA_AVG	float64
49	ELEVATORS_AVG	float64
50	ENTRANCES_AVG	float64
51	FLOORSMAX_AVG	float64
52	FLOORSMIN_AVG	float64
53	LANDAREA_AVG	float64
54	LIVINGAPARTMENTS_AVG	float64
55	LIVINGAREA_AVG	float64
56	NONLIVINGAPARTMENTS_AVG	float64
57	NONLIVINGAREA_AVG	float64
58	APARTMENTS_MODE	float64

59	BASEMENTAREA_MODE	float64
60	YEARS_BEGINEXPLUATATION_MODE	float64
61	YEARS_BUILD_MODE	float64
62	COMMONAREA_MODE	float64
63	ELEVATORS_MODE	float64
64	ENTRANCES_MODE	float64
65	FLOORSMAX_MODE	float64
66	FLOORSMIN_MODE	float64
67	LANDAREA_MODE	float64
68	LIVINGAPARTMENTS_MODE	float64
69	LIVINGAREA_MODE	float64
70	NONLIVINGAPARTMENTS_MODE	float64
71	NONLIVINGAREA_MODE	float64
72	APARTMENTS_MEDI	float64
73	BASEMENTAREA_MEDI	float64
74	YEARS_BEGINEXPLUATATION_MEDI	float64
75	YEARS_BUILD_MEDI	float64
76	COMMONAREA_MEDI	float64
77	ELEVATORS_MEDI	float64
78	ENTRANCES_MEDI	float64
79	FLOORSMAX_MEDI	float64
80	FLOORSMIN_MEDI	float64
81	LANDAREA_MEDI	float64
82	LIVINGAPARTMENTS_MEDI	float64
83	LIVINGAREA_MEDI	float64
84	NONLIVINGAPARTMENTS_MEDI	float64
85	NONLIVINGAREA_MEDI	float64
86	FONDKAPREMONT_MODE	object
87	HOUSETYPE_MODE	object
88	TOTALAREA_MODE	float64
89	WALLSMATERIAL_MODE	object
90	EMERGENCYSTATE_MODE	object
91	OBS_30_CNT_SOCIAL_CIRCLE	float64
92	DEF_30_CNT_SOCIAL_CIRCLE	float64
93	OBS_60_CNT_SOCIAL_CIRCLE	float64
94	DEF_60_CNT_SOCIAL_CIRCLE	float64
95	DAYS_LAST_PHONE_CHANGE	float64
96	FLAG_DOCUMENT_2	int64
97	FLAG_DOCUMENT_3	int64
98	FLAG_DOCUMENT_4	int64
99	FLAG_DOCUMENT_5	int64
100	FLAG_DOCUMENT_6	int64
101	FLAG_DOCUMENT_7	int64
102	FLAG_DOCUMENT_8	int64
103	FLAG_DOCUMENT_9	int64
104	FLAG_DOCUMENT_10	int64
105	FLAG_DOCUMENT_11	int64
106	FLAG_DOCUMENT_12	int64
107	FLAG_DOCUMENT_13	int64
108	FLAG_DOCUMENT_14	int64

```

109 FLAG_DOCUMENT_15          int64
110 FLAG_DOCUMENT_16          int64
111 FLAG_DOCUMENT_17          int64
112 FLAG_DOCUMENT_18          int64
113 FLAG_DOCUMENT_19          int64
114 FLAG_DOCUMENT_20          int64
115 FLAG_DOCUMENT_21          int64
116 AMT_REQ_CREDIT_BUREAU_HOUR float64
117 AMT_REQ_CREDIT_BUREAU_DAY  float64
118 AMT_REQ_CREDIT_BUREAU_WEEK float64
119 AMT_REQ_CREDIT_BUREAU_MON  float64
120 AMT_REQ_CREDIT_BUREAU_QRT  float64
121 AMT_REQ_CREDIT_BUREAU_YEAR float64
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB

```

Checking missing values

#Column-wise null count

```
df.isnull().sum()
```

```

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
REGION_POPULATION_RELATIVE 0
DAYS_BIRTH          0
DAYS_EMPLOYED       0
DAYS_REGISTRATION   0
DAYS_ID_PUBLISH     0
OWN_CAR_AGE         202929
FLAG_MOBIL          0
FLAG_EMP_PHONE       0
FLAG_WORK_PHONE      0
FLAG_CONT_MOBILE     0
FLAG_PHONE           0
FLAG_EMAIL           0
OCCUPATION_TYPE     96391

```

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_REGION_NOT_LIVE_REGION	0
REG_REGION_NOT_WORK_REGION	0
LIVE_REGION_NOT_WORK_REGION	0
REG_CITY_NOT_LIVE_CITY	0
REG_CITY_NOT_WORK_CITY	0
LIVE_CITY_NOT_WORK_CITY	0
ORGANIZATION_TYPE	0
EXT_SOURCE_1	173378
EXT_SOURCE_2	660
EXT_SOURCE_3	60965
APARTMENTS_AVG	156061
BASEMENTAREA_AVG	179943
YEARS_BEGINEXPLUATATION_AVG	150007
YEARS_BUILD_AVG	204488
COMMONAREA_AVG	214865
ELEVATORS_AVG	163891
ENTRANCES_AVG	154828
FLOORSMAX_AVG	153020
FLOORSMIN_AVG	208642
LANDAREA_AVG	182590
LIVINGAPARTMENTS_AVG	210199
LIVINGAREA_AVG	154350
NONLIVINGAPARTMENTS_AVG	213514
NONLIVINGAREA_AVG	169682
APARTMENTS_MODE	156061
BASEMENTAREA_MODE	179943
YEARS_BEGINEXPLUATATION_MODE	150007
YEARS_BUILD_MODE	204488
COMMONAREA_MODE	214865
ELEVATORS_MODE	163891
ENTRANCES_MODE	154828
FLOORSMAX_MODE	153020
FLOORSMIN_MODE	208642
LANDAREA_MODE	182590
LIVINGAPARTMENTS_MODE	210199
LIVINGAREA_MODE	154350
NONLIVINGAPARTMENTS_MODE	213514
NONLIVINGAREA_MODE	169682
APARTMENTS_MEDI	156061
BASEMENTAREA_MEDI	179943
YEARS_BEGINEXPLUATATION_MEDI	150007
YEARS_BUILD_MEDI	204488
COMMONAREA_MEDI	214865
ELEVATORS_MEDI	163891
ENTRANCES_MEDI	154828

FLOORSMAX_MEDI	153020
FLOORSMIN_MEDI	208642
LANDAREA_MEDI	182590
LIVINGAPARTMENTS_MEDI	210199
LIVINGAREA_MEDI	154350
NONLIVINGAPARTMENTS_MEDI	213514
NONLIVINGAREA_MEDI	169682
FONDKAPREMONT_MODE	210295
HOUSETYPE_MODE	154297
TOTALAREA_MODE	148431
WALLSMATERIAL_MODE	156341
EMERGENCYSTATE_MODE	145755
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
AMT_REQ_CREDIT_BUREAU_HOUR	41519
AMT_REQ_CREDIT_BUREAU_DAY	41519
AMT_REQ_CREDIT_BUREAU_WEEK	41519
AMT_REQ_CREDIT_BUREAU_MON	41519
AMT_REQ_CREDIT_BUREAU_QRT	41519
AMT_REQ_CREDIT_BUREAU_YEAR	41519

dtype: int64

#Percentage of missing values for all columns

```
null_count=round(100*(df.isnull().sum()/len(df.index)),2)
null_count
```

SK_ID_CURR	0.00
TARGET	0.00

NAME_CONTRACT_TYPE	0.00
CODE_GENDER	0.00
FLAG_OWN_CAR	0.00
FLAG_OWN_REALTY	0.00
CNT_CHILDREN	0.00
AMT_INCOME_TOTAL	0.00
AMT_CREDIT	0.00
AMT_ANNUITY	0.00
AMT_GOODS_PRICE	0.09
NAME_TYPE_SUITE	0.42
NAME_INCOME_TYPE	0.00
NAME_EDUCATION_TYPE	0.00
NAME_FAMILY_STATUS	0.00
NAME_HOUSING_TYPE	0.00
REGION_POPULATION_RELATIVE	0.00
DAYS_BIRTH	0.00
DAYS_EMPLOYED	0.00
DAYS_REGISTRATION	0.00
DAYS_ID_PUBLISH	0.00
OWN_CAR_AGE	65.99
FLAG_MOBIL	0.00
FLAG_EMP_PHONE	0.00
FLAG_WORK_PHONE	0.00
FLAG_CONT_MOBILE	0.00
FLAG_PHONE	0.00
FLAG_EMAIL	0.00
OCCUPATION_TYPE	31.35
CNT_FAM_MEMBERS	0.00
REGION_RATING_CLIENT	0.00
REGION_RATING_CLIENT_W_CITY	0.00
WEEKDAY_APPR_PROCESS_START	0.00
HOURL_APPR_PROCESS_START	0.00
REG_REGION_NOT_LIVE_REGION	0.00
REG_REGION_NOT_WORK_REGION	0.00
LIVE_REGION_NOT_WORK_REGION	0.00
REG_CITY_NOT_LIVE_CITY	0.00
REG_CITY_NOT_WORK_CITY	0.00
LIVE_CITY_NOT_WORK_CITY	0.00
ORGANIZATION_TYPE	0.00
EXT_SOURCE_1	56.38
EXT_SOURCE_2	0.21
EXT_SOURCE_3	19.83
APARTMENTS_AVG	50.75
BASEMENTAREA_AVG	58.52
YEARS_BEGINEXPLUATATION_AVG	48.78
YEARS_BUILD_AVG	66.50
COMMONAREA_AVG	69.87
ELEVATORS_AVG	53.30
ENTRANCES_AVG	50.35
FLOORSMAX_AVG	49.76

FLOORSMIN_AVG	67.85
LANDAREA_AVG	59.38
LIVINGAPARTMENTS_AVG	68.35
LIVINGAREA_AVG	50.19
NONLIVINGAPARTMENTS_AVG	69.43
NONLIVINGAREA_AVG	55.18
APARTMENTS_MODE	50.75
BASEMENTAREA_MODE	58.52
YEARS_BEGINEXPLUATATION_MODE	48.78
YEARS_BUILD_MODE	66.50
COMMONAREA_MODE	69.87
ELEVATORS_MODE	53.30
ENTRANCES_MODE	50.35
FLOORSMAX_MODE	49.76
FLOORSMIN_MODE	67.85
LANDAREA_MODE	59.38
LIVINGAPARTMENTS_MODE	68.35
LIVINGAREA_MODE	50.19
NONLIVINGAPARTMENTS_MODE	69.43
NONLIVINGAREA_MODE	55.18
APARTMENTS_MEDI	50.75
BASEMENTAREA_MEDI	58.52
YEARS_BEGINEXPLUATATION_MEDI	48.78
YEARS_BUILD_MEDI	66.50
COMMONAREA_MEDI	69.87
ELEVATORS_MEDI	53.30
ENTRANCES_MEDI	50.35
FLOORSMAX_MEDI	49.76
FLOORSMIN_MEDI	67.85
LANDAREA_MEDI	59.38
LIVINGAPARTMENTS_MEDI	68.35
LIVINGAREA_MEDI	50.19
NONLIVINGAPARTMENTS_MEDI	69.43
NONLIVINGAREA_MEDI	55.18
FONDKAPREMONT_MODE	68.39
HOUSETYPE_MODE	50.18
TOTALAREA_MODE	48.27
WALLSMATERIAL_MODE	50.84
EMERGENCYSTATE_MODE	47.40
OBS_30_CNT_SOCIAL_CIRCLE	0.33
DEF_30_CNT_SOCIAL_CIRCLE	0.33
OBS_60_CNT_SOCIAL_CIRCLE	0.33
DEF_60_CNT_SOCIAL_CIRCLE	0.33
DAYS_LAST_PHONE_CHANGE	0.00
FLAG_DOCUMENT_2	0.00
FLAG_DOCUMENT_3	0.00
FLAG_DOCUMENT_4	0.00
FLAG_DOCUMENT_5	0.00
FLAG_DOCUMENT_6	0.00
FLAG_DOCUMENT_7	0.00

FLAG_DOCUMENT_8	0.00
FLAG_DOCUMENT_9	0.00
FLAG_DOCUMENT_10	0.00
FLAG_DOCUMENT_11	0.00
FLAG_DOCUMENT_12	0.00
FLAG_DOCUMENT_13	0.00
FLAG_DOCUMENT_14	0.00
FLAG_DOCUMENT_15	0.00
FLAG_DOCUMENT_16	0.00
FLAG_DOCUMENT_17	0.00
FLAG_DOCUMENT_18	0.00
FLAG_DOCUMENT_19	0.00
FLAG_DOCUMENT_20	0.00
FLAG_DOCUMENT_21	0.00
AMT_REQ_CREDIT_BUREAU_HOUR	13.50
AMT_REQ_CREDIT_BUREAU_DAY	13.50
AMT_REQ_CREDIT_BUREAU_WEEK	13.50
AMT_REQ_CREDIT_BUREAU_MON	13.50
AMT_REQ_CREDIT_BUREAU_QRT	13.50
AMT_REQ_CREDIT_BUREAU_YEAR	13.50

dtype: float64

#Columns with high missing percentage >=50%

```
null_count=null_count[null_count>=50]
null_count
```

OWN_CAR_AGE	65.99
EXT_SOURCE_1	56.38
APARTMENTS_AVG	50.75
BASEMENTAREA_AVG	58.52
YEARS_BUILD_AVG	66.50
COMMONAREA_AVG	69.87
ELEVATORS_AVG	53.30
ENTRANCES_AVG	50.35
FLOORSMIN_AVG	67.85
LANDAREA_AVG	59.38
LIVINGAPARTMENTS_AVG	68.35
LIVINGAREA_AVG	50.19
NONLIVINGAPARTMENTS_AVG	69.43
NONLIVINGAREA_AVG	55.18
APARTMENTS_MODE	50.75
BASEMENTAREA_MODE	58.52
YEARS_BUILD_MODE	66.50
COMMONAREA_MODE	69.87
ELEVATORS_MODE	53.30
ENTRANCES_MODE	50.35
FLOORSMIN_MODE	67.85
LANDAREA_MODE	59.38
LIVINGAPARTMENTS_MODE	68.35
LIVINGAREA_MODE	50.19
NONLIVINGAPARTMENTS_MODE	69.43

```

NONLIVINGAREA_MODE      55.18
APARTMENTS_MEDI         50.75
BASEMENTAREA_MEDI       58.52
YEARS_BUILD_MEDI        66.50
COMMONAREA_MEDI         69.87
ELEVATORS_MEDI          53.30
ENTRANCES_MEDI          50.35
FLOORSMIN_MEDI          67.85
LANDAREA_MEDI           59.38
LIVINGAPARTMENTS_MEDI   68.35
LIVINGAREA_MEDI         50.19
NONLIVINGAPARTMENTS_MEDI 69.43
NONLIVINGAREA_MEDI      55.18
FONDKAPREMONT_MODE      68.39
HOUSETYPE_MODE          50.18
WALLSMATERIAL_MODE      50.84
dtype: float64

```

```
len(null_count)
```

```
41
```

Thus, here we can see that there are 41 columns having the highest missing percentage ($\geq 50\%$) So here we remove those columns

Remove missing values

#Removing those 41 columns which have missing values more than 50%

```

cols_dropped=([null_count[null_count >=50.00].index])
df.drop(labels=cols_dropped[0],axis=1,inplace=True)

```

#Rows and Columns after removing columns with high missing percentage

```
df.shape
```

```
(307511, 81)
```

Checking the columns after removing high missing values($\geq 50\%$)

```
100*(df.isnull().sum()/len(df.index))
```

```

SK_ID_CURR      0.000000
TARGET          0.000000
NAME_CONTRACT_TYPE 0.000000
CODE_GENDER     0.000000
FLAG_OWN_CAR    0.000000
FLAG_OWN_REALTY 0.000000
CNT_CHILDREN    0.000000
AMT_INCOME_TOTAL 0.000000
AMT_CREDIT      0.000000
AMT_ANNUITY     0.003902
AMT_GOODS_PRICE 0.090403
NAME_TYPE_SUITE 0.420148

```

NAME_INCOME_TYPE	0.000000
NAME_EDUCATION_TYPE	0.000000
NAME_FAMILY_STATUS	0.000000
NAME_HOUSING_TYPE	0.000000
REGION_POPULATION_RELATIVE	0.000000
DAYS_BIRTH	0.000000
DAYS_EMPLOYED	0.000000
DAYS_REGISTRATION	0.000000
DAYS_ID_PUBLISH	0.000000
FLAG_MOBIL	0.000000
FLAG_EMP_PHONE	0.000000
FLAG_WORK_PHONE	0.000000
FLAG_CONT_MOBILE	0.000000
FLAG_PHONE	0.000000
FLAG_EMAIL	0.000000
OCCUPATION_TYPE	31.345545
CNT_FAM_MEMBERS	0.000650
REGION_RATING_CLIENT	0.000000
REGION_RATING_CLIENT_W_CITY	0.000000
WEEKDAY_APPR_PROCESS_START	0.000000
HOURL_APPR_PROCESS_START	0.000000
REG_REGION_NOT_LIVE_REGION	0.000000
REG_REGION_NOT_WORK_REGION	0.000000
LIVE_REGION_NOT_WORK_REGION	0.000000
REG_CITY_NOT_LIVE_CITY	0.000000
REG_CITY_NOT_WORK_CITY	0.000000
LIVE_CITY_NOT_WORK_CITY	0.000000
ORGANIZATION_TYPE	0.000000
EXT_SOURCE_2	0.214626
EXT_SOURCE_3	19.825307
YEARS_BEGINEXPLUATATION_AVG	48.781019
FLOORSMAX_AVG	49.760822
YEARS_BEGINEXPLUATATION_MODE	48.781019
FLOORSMAX_MODE	49.760822
YEARS_BEGINEXPLUATATION_MEDI	48.781019
FLOORSMAX_MEDI	49.760822
TOTALAREA_MODE	48.268517
EMERGENCYSTATE_MODE	47.398304
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
DAYS_LAST_PHONE_CHANGE	0.000325
FLAG_DOCUMENT_2	0.000000
FLAG_DOCUMENT_3	0.000000
FLAG_DOCUMENT_4	0.000000
FLAG_DOCUMENT_5	0.000000
FLAG_DOCUMENT_6	0.000000
FLAG_DOCUMENT_7	0.000000
FLAG_DOCUMENT_8	0.000000

```

FLAG_DOCUMENT_9          0.000000
FLAG_DOCUMENT_10         0.000000
FLAG_DOCUMENT_11         0.000000
FLAG_DOCUMENT_12         0.000000
FLAG_DOCUMENT_13         0.000000
FLAG_DOCUMENT_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_21         0.000000
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
dtype: float64

```

Drop unnecessary columns from the dataset

```

Drop_col=['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',
'FLAG_CONT_MOBILE', 'YEARS_BEGINEXPLUATATION_MODE', 'FLOORSMAX_MODE', 'TO
TALAREA_MODE', 'EMERGENCYSTATE_MODE',
'FLAG_PHONE',
'FLAG_EMAIL', 'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY', 'FLA
G_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',
'REGION_RATING_CLIENT_W_CITY', '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', 'EXT_SOURCE_3', 'YEARS_BEGINEXPLUATATION_AVG', 'FLOOR
SMAX_AVG', 'YEARS_BEGINEXPLUATATION_MEDI', 'FLOORSMAX_MEDI']

```

```
df.drop(labels=Drop_col,axis=1,inplace=True)
```

Checking the columns after dropping unnecessary columns

```
100*(df.isnull().sum()/len(df.index))
```

```

SK_ID_CURR          0.000000
TARGET              0.000000

```

NAME_CONTRACT_TYPE	0.000000
CODE_GENDER	0.000000
FLAG_OWN_CAR	0.000000
FLAG_OWN_REALTY	0.000000
CNT_CHILDREN	0.000000
AMT_INCOME_TOTAL	0.000000
AMT_CREDIT	0.000000
AMT_ANNUITY	0.003902
AMT_GOODS_PRICE	0.090403
NAME_TYPE_SUITE	0.420148
NAME_INCOME_TYPE	0.000000
NAME_EDUCATION_TYPE	0.000000
NAME_FAMILY_STATUS	0.000000
NAME_HOUSING_TYPE	0.000000
REGION_POPULATION_RELATIVE	0.000000
DAYS_BIRTH	0.000000
DAYS_EMPLOYED	0.000000
DAYS_REGISTRATION	0.000000
DAYS_ID_PUBLISH	0.000000
OCCUPATION_TYPE	31.345545
WEEKDAY_APPR_PROCESS_START	0.000000
HOUR_APPR_PROCESS_START	0.000000
REG_REGION_NOT_LIVE_REGION	0.000000
REG_REGION_NOT_WORK_REGION	0.000000
LIVE_REGION_NOT_WORK_REGION	0.000000
REG_CITY_NOT_LIVE_CITY	0.000000
REG_CITY_NOT_WORK_CITY	0.000000
LIVE_CITY_NOT_WORK_CITY	0.000000
ORGANIZATION_TYPE	0.000000
EXT_SOURCE_2	0.214626
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
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

dtype: float64

AMT_ANNUITY Variable

```
#Missing values in "AMT_ANNUITY" column
df.AMT_ANNUITY.isnull().sum()
```

12

```
#Percentage of missing values in "AMT_ANNUITY" column
float(100*(12/307511))
```

```
0.003902299429939092
```

We can see that 'AMT_ANNUITY' column is having very less percentage of null values and is also a numeric data. These values can be imputed by the mean of the complete cases of the variable. Since this column is also having an outlier which is very large we can impute missing values with Median.

AMT GOODS PRICE variable

```
#Missing values in "AMT_GOODS_PRICE" column
```

```
df.AMT_GOODS_PRICE.isnull().sum()
```

```
278
```

```
#Percentage of missing values in "AMT_GOODS_PRICE" column
```

```
float(100*(278/307511))
```

```
0.09040327012692229
```

AMT_GOODS_PRICE has less percentage of missing values. And also has outliers. These missing values can be imputed with median

EXT SOURCE 2 variable

```
df.EXT_SOURCE_2.isnull().sum()
```

```
660
```

```
float(100*(660/307511))
```

```
0.21462646864665005
```

EXT_SOURCE_2 column has less percentage of missing values. Here we can impute the missing values with 0

NAME TYPE SUITE Variable

```
#Missing values in "NAME_TYPE_SUITE" column
```

```
df.NAME_TYPE_SUITE.isnull().sum()
```

```
1292
```

```
#Percentage of missing values in "NAME_TYPE_SUITE" column
```

```
100*(1292/307511)
```

```
0.42014757195677555
```

```
#print the percentage of each NAME_TYPE_SUITE in the data frame df.
```

```
df.NAME_TYPE_SUITE.value_counts(normalize= True)
```

```

Unaccompanied      0.811596
Family              0.131112
Spouse, partner    0.037130
Children           0.010669
Other_B            0.005780
Other_A            0.002828
Group of people    0.000885
Name: NAME_TYPE_SUITE, dtype: float64

```

#find the mode of NAME_TYPE_SUITE in df, check which category is most repeated

```

name_mode=df.NAME_TYPE_SUITE.mode()[0]
name_mode

```

```
'Unaccompanied'
```

Hence here 'NAME_TYPE_SUITE' being a categorical variable, has about 0.42% of missing values. So here we can impute the missing values with the most popular category which is "Unaccompanied"

OCCUPATION TYPE variable

#Missing values in "OCCUPATION_TYPE" column

```
df.OCCUPATION_TYPE.isnull().sum()
```

```
96391
```

#Percentage of missing values in "OCCUPATION_TYPE" column

```
100*(96391/307511)
```

```
31.345545362604916
```

#print the percentage of each OCCUPATION TYPES in the data frame df

```
df.OCCUPATION_TYPE .value_counts(normalize=True)
```

```

Laborers           0.261396
Sales staff        0.152056
Core staff         0.130589
Managers           0.101227
Drivers            0.088116
High skill tech staff 0.053903
Accountants        0.046481
Medicine staff     0.040437
Security staff     0.031835
Cooking staff      0.028164
Cleaning staff     0.022040
Private service staff 0.012562
Low-skill Laborers 0.009914
Waiters/barmen staff 0.006385
Secretaries        0.006181
Realty agents      0.003557

```



```
HR staff          0.002667
IT staff          0.002491
Name: OCCUPATION_TYPE, dtype: float64
```

```
#find the mode of NAME_TYPE_SUITE in df, check which category is most repeated
```

```
occ_mode=df.OCCUPATION_TYPE.mode()[0]
occ_mode
```

```
'Laborers'
```

Here 'OCCUPATION_TYPE' is also a categorical variable, has about 31.3% of missing values. So here we can impute the missing values with the most popular category which is "Laborers"

Checking Datatypes

```
#Preview the first 5 lines of the data
```

```
df.head()
```

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

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
0	Y	0	202500.0	406597.5
1	N	0	270000.0	1293502.5
2	Y	0	67500.0	135000.0
3	Y	0	135000.0	312682.5
4	Y	0	121500.0	513000.0

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	351000.0	Unaccompanied	Working	
1	1129500.0	Family	State servant	
2	135000.0	Unaccompanied	Working	
3	297000.0	Unaccompanied	Working	
4	513000.0	Unaccompanied	Working	

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS
0	Secondary / secondary special	Single / not married

apartment				
1	Higher education	Married	House /	
apartment				
2	Secondary / secondary special	Single / not married	House /	
apartment				
3	Secondary / secondary special	Civil marriage	House /	
apartment				
4	Secondary / secondary special	Single / not married	House /	
apartment				

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	
DAYS_REGISTRATION \				
0	0.018801	-9461	-637	-
3648.0				
1	0.003541	-16765	-1188	-
1186.0				
2	0.010032	-19046	-225	-
4260.0				
3	0.008019	-19005	-3039	-
9833.0				
4	0.028663	-19932	-3038	-
4311.0				

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START	\
0	-2120	Laborers	WEDNESDAY	
1	-291	Core staff	MONDAY	
2	-2531	Laborers	MONDAY	
3	-2437	Laborers	WEDNESDAY	
4	-3458	Core staff	THURSDAY	

	HOOR_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
0	10	0	
1	11	0	
2	9	0	
3	17	0	
4	11	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY
LIVE_CITY_NOT_WORK_CITY \		
0	0	0
0		
1	0	0
0		

2	0	0
0		
3	0	0
0		
4	0	1
1		

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE \
0	Business Entity Type 3	0.262949	2.0
1	School	0.622246	1.0
2	Government	0.555912	0.0
3	Business Entity Type 3	0.650442	2.0
4	Religion	0.322738	0.0

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE \
0	2.0	2.0
1	0.0	1.0
2	0.0	0.0
3	0.0	2.0
4	0.0	0.0

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR \
0	2.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR
0	1.0
1	0.0
2	0.0
3	NaN
4	0.0

```
# I can check the number of unique values is a column
# If the number of unique values <=40: Categorical column
# If the number of unique values in a columns> 50: Continuous
```

```
df.nunique().sort_values()
```

LIVE_REGION_NOT_WORK_REGION	2
TARGET	2
NAME_CONTRACT_TYPE	2
FLAG_OWN_CAR	2
FLAG_OWN_REALTY	2
REG_REGION_NOT_LIVE_REGION	2
LIVE_CITY_NOT_WORK_CITY	2
REG_CITY_NOT_LIVE_CITY	2
REG_CITY_NOT_WORK_CITY	2
REG_REGION_NOT_WORK_REGION	2
CODE_GENDER	3
AMT_REQ_CREDIT_BUREAU_HOUR	5
NAME_EDUCATION_TYPE	5
NAME_FAMILY_STATUS	6
NAME_HOUSING_TYPE	6
NAME_TYPE_SUITE	7
WEEKDAY_APPR_PROCESS_START	7
NAME_INCOME_TYPE	8
AMT_REQ_CREDIT_BUREAU_DAY	9
DEF_60_CNT_SOCIAL_CIRCLE	9
AMT_REQ_CREDIT_BUREAU_WEEK	9
DEF_30_CNT_SOCIAL_CIRCLE	10
AMT_REQ_CREDIT_BUREAU_QRT	11
CNT_CHILDREN	15
OCCUPATION_TYPE	18
AMT_REQ_CREDIT_BUREAU_MON	24
HOUR_APPR_PROCESS_START	24
AMT_REQ_CREDIT_BUREAU_YEAR	25
OBS_30_CNT_SOCIAL_CIRCLE	33
OBS_60_CNT_SOCIAL_CIRCLE	33
ORGANIZATION_TYPE	58
REGION_POPULATION_RELATIVE	81
AMT_GOODS_PRICE	1002
AMT_INCOME_TOTAL	2548
AMT_CREDIT	5603
DAYS_ID_PUBLISH	6168
DAYS_EMPLOYED	12574
AMT_ANNUITY	13672
DAYS_REGISTRATION	15688
DAYS_BIRTH	17460
EXT_SOURCE_2	119831
SK_ID_CURR	307511

dtype: int64

Now it is clear that which are Continuous and Categorical variables in the dataset given.
Now we can consider some continuous and categorical variables and change the datatypes if needed

#changing negative ages to positive ages.

```
df['DAYS_BIRTH']=abs(df['DAYS_BIRTH'])  
df['DAYS_BIRTH'].describe()
```

```
count      307511.000000  
mean       16036.995067  
std        4363.988632  
min        7489.000000  
25%       12413.000000  
50%       15750.000000  
75%       19682.000000  
max       25229.000000  
Name: DAYS_BIRTH, dtype: float64
```

#changing negative values in days to positive days

```
df['DAYS_EMPLOYED']=abs(df['DAYS_EMPLOYED'])  
df['DAYS_EMPLOYED'].describe()
```

```
count      307511.000000  
mean       67724.742149  
std       139443.751806  
min         0.000000  
25%        933.000000  
50%       2219.000000  
75%       5707.000000  
max      365243.000000  
Name: DAYS_EMPLOYED, dtype: float64
```

#changing negative days to positive days.

```
df['DAYS_REGISTRATION']=abs(df['DAYS_REGISTRATION'])  
df['DAYS_REGISTRATION'].describe()
```

```
count      307511.000000  
mean       4986.120328  
std       3522.886321  
min         0.000000  
25%       2010.000000  
50%       4504.000000  
75%       7479.500000  
max      24672.000000  
Name: DAYS_REGISTRATION, dtype: float64
```

#changing negative days to positive

```
df['DAYS_ID_PUBLISH']=abs(df['DAYS_ID_PUBLISH'])  
df['DAYS_ID_PUBLISH'].describe()
```

```
count      307511.000000  
mean       2994.202373
```

```

std          1509.450419
min           0.000000
25%          1720.000000
50%          3254.000000
75%          4299.000000
max           7197.000000
Name: DAYS_ID_PUBLISH, dtype: float64

```

```

#converting the data type of categorical column
df['REG_REGION_NOT_LIVE_REGION'] =
df['REG_REGION_NOT_LIVE_REGION'].astype(object)
df.dtypes

```

```

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
REGION_POPULATION_RELATIVE float64
DAYS_BIRTH          int64
DAYS_EMPLOYED       int64
DAYS_REGISTRATION   float64
DAYS_ID_PUBLISH     int64
OCCUPATION_TYPE     object
WEEKDAY_APPR_PROCESS_START object
HOUR_APPR_PROCESS_START int64
REG_REGION_NOT_LIVE_REGION object
REG_REGION_NOT_WORK_REGION int64
LIVE_REGION_NOT_WORK_REGION int64
REG_CITY_NOT_LIVE_CITY int64
REG_CITY_NOT_WORK_CITY int64
LIVE_CITY_NOT_WORK_CITY int64
ORGANIZATION_TYPE   object
EXT_SOURCE_2        float64
OBS_30_CNT_SOCIAL_CIRCLE float64
DEF_30_CNT_SOCIAL_CIRCLE float64
OBS_60_CNT_SOCIAL_CIRCLE float64
DEF_60_CNT_SOCIAL_CIRCLE float64
AMT_REQ_CREDIT_BUREAU_HOUR float64
AMT_REQ_CREDIT_BUREAU_DAY float64

```

```

AMT_REQ_CREDIT_BUREAU_WEEK    float64
AMT_REQ_CREDIT_BUREAU_MON     float64
AMT_REQ_CREDIT_BUREAU_QRT     float64
AMT_REQ_CREDIT_BUREAU_YEAR    float64
dtype: object

```

```
#Changing region from int to object
```

```
df['REG_REGION_NOT_WORK_REGION'] =
df['REG_REGION_NOT_WORK_REGION'].astype(object)
```

```
#Changing region from int to object
```

```
df['LIVE_REGION_NOT_WORK_REGION'] =
df['LIVE_REGION_NOT_WORK_REGION'].astype(object)
```

```
#Changing city from int to object
```

```
df['REG_CITY_NOT_LIVE_CITY'] =
df['REG_CITY_NOT_LIVE_CITY'].astype(object)
```

```
#Changing city from int to object
```

```
df['REG_CITY_NOT_WORK_CITY'] =
df['REG_CITY_NOT_WORK_CITY'].astype(object)
```

```
#Changing city from int to object
```

```
df['LIVE_CITY_NOT_WORK_CITY']=df['LIVE_CITY_NOT_WORK_CITY'].astype(object)
```

```
df.head()
```

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

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	\
0	Y	0	202500.0	406597.5	24700.5	
1	N	0	270000.0	1293502.5	35698.5	
2	Y	0	67500.0	135000.0	6750.0	
3	Y	0	135000.0	312682.5	29686.5	
4	Y	0	121500.0	513000.0	21865.5	

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	351000.0	Unaccompanied	Working	
1	1129500.0	Family	State servant	

2	135000.0	Unaccompanied	Working
3	297000.0	Unaccompanied	Working
4	513000.0	Unaccompanied	Working

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE \
0	Secondary / secondary special	Single / not married	House / apartment
1	Higher education	Married	House / apartment
2	Secondary / secondary special	Single / not married	House / apartment
3	Secondary / secondary special	Civil marriage	House / apartment
4	Secondary / secondary special	Single / not married	House / apartment

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED
0	0.018801	9461	637
3648.0			
1	0.003541	16765	1188
1186.0			
2	0.010032	19046	225
4260.0			
3	0.008019	19005	3039
9833.0			
4	0.028663	19932	3038
4311.0			

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START \
0	2120	Laborers	WEDNESDAY
1	291	Core staff	MONDAY
2	2531	Laborers	MONDAY
3	2437	Laborers	WEDNESDAY
4	3458	Core staff	THURSDAY

	HOUR_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION \
0	10	0
1	11	0
2	9	0
3	17	0
4	11	0

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

	REG_CITY_NOT_LIVE_CITY LIVE_CITY_NOT_WORK_CITY \	REG_CITY_NOT_WORK_CITY
--	---	------------------------

0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	1
1		

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE \
0	Business Entity Type 3	0.262949	2.0
1	School	0.622246	1.0
2	Government	0.555912	0.0
3	Business Entity Type 3	0.650442	2.0
4	Religion	0.322738	0.0

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE \
0	2.0	2.0
1	0.0	1.0
2	0.0	0.0
3	0.0	2.0
4	0.0	0.0

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR \
0	2.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR
0	1.0
1	0.0
2	0.0
3	NaN
4	0.0

Handling Outliers

Major approaches to the treat outliers:

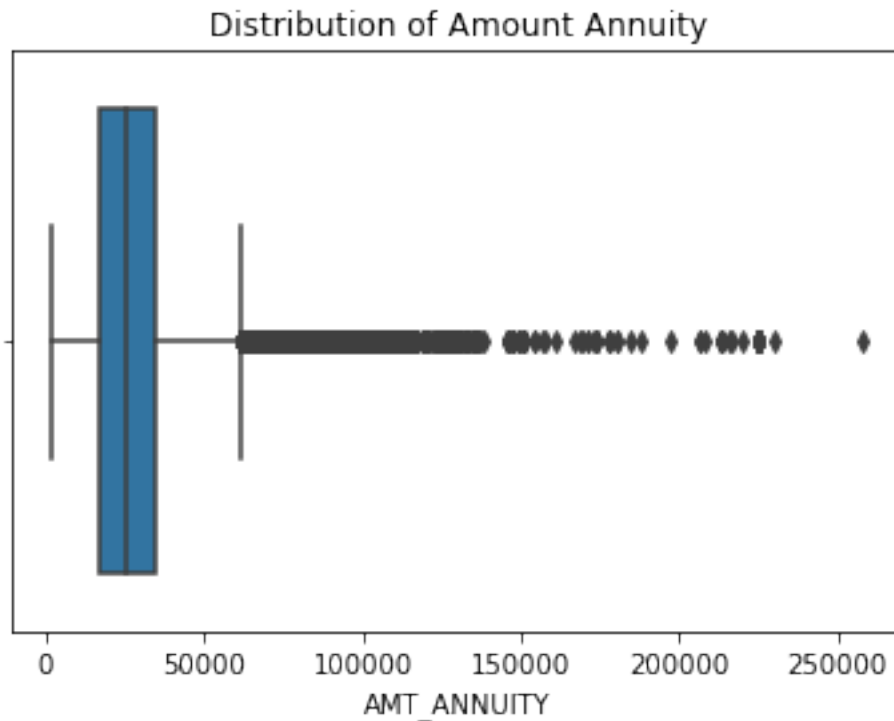
a)Imputation b)Deletion of outliers c)Binning of values d)Cap the outlier

#describe the AMT_ANNUIITY variable of df

```
df.AMT_ANNUIITY.describe()
```

```
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_ANNUIITY, dtype: float64
```

```
sns.boxplot(df.AMT_ANNUIITY)
plt.title('Distribution of Amount Annuity')
plt.show()
```

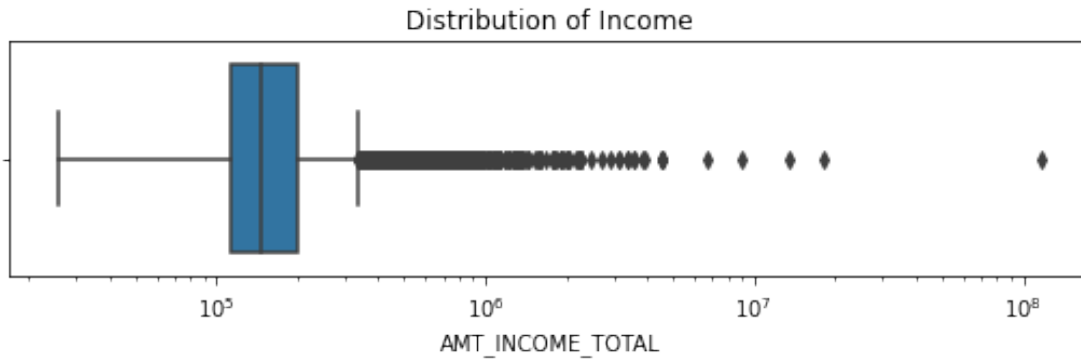


As we take a look at AMT_ANNUIITY column we can see that there are outliers at 258025. But there is no much difference between the mean and median, We can impute the outliers with Median here

```
df.AMT_INCOME_TOTAL.describe()

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

plt.figure(figsize=(9,2))
sns.boxplot(df.AMT_INCOME_TOTAL)
plt.xscale('log')
plt.title('Distribution of Income')
plt.show()
```



```
df.AMT_INCOME_TOTAL.quantile([0.5, 0.7, 0.9,0.95,0.99])
```

```
0.50    147150.0
```

```
0.70    180000.0
```

```
0.90    270000.0
```

```
0.95    337500.0
```

```
0.99    472500.0
```

```
Name: AMT_INCOME_TOTAL, dtype: float64
```

In 'AMT_INCOME_TOTAL' column, We can see that there are outlier values at 1.17×10^8 . Sometimes, it is beneficial to look into the quantiles instead of the box plot, mean or median. Quantile may give you a fair idea about the outliers. If there is a huge difference between the maximum value and the 95th or 99th quantiles, then there are outliers in the data set.

Total income will definitely vary from person to person. We can cap the outliers here

```
df.AMT_CREDIT.describe()
```

```
count    3.075110e+05
```

```
mean     5.990260e+05
```

```
std      4.024908e+05
```

```
min      4.500000e+04
```

```
25%      2.700000e+05
```

```
50%      5.135310e+05
```

```
75%      8.086500e+05
```

```
max      4.050000e+06
```

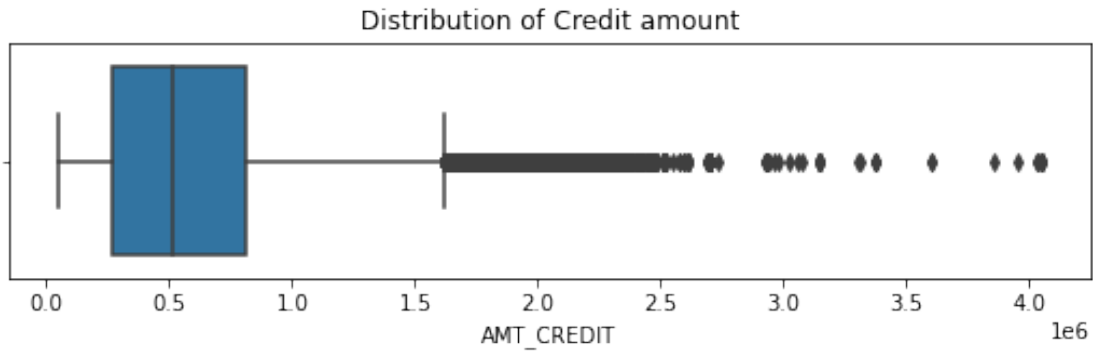
```
Name: AMT_CREDIT, dtype: float64
```

```
plt.figure(figsize=(9,2))
```

```
sns.boxplot(df.AMT_CREDIT)
```

```
plt.title('Distribution of Credit amount')
```

```
plt.show()
```



```
df.AMT_CREDIT.quantile([0.5, 0.7, 0.9,0.95,0.99])
```

```
0.50    513531.0
0.70    755190.0
0.90   1133748.0
0.95   1350000.0
0.99   1854000.0
```

```
Name: AMT_CREDIT, dtype: float64
```

In this AMT_CREDIT column we can see the outliers after 99th quantile at 4.05×10^6 Amount credited also varies from person to person.

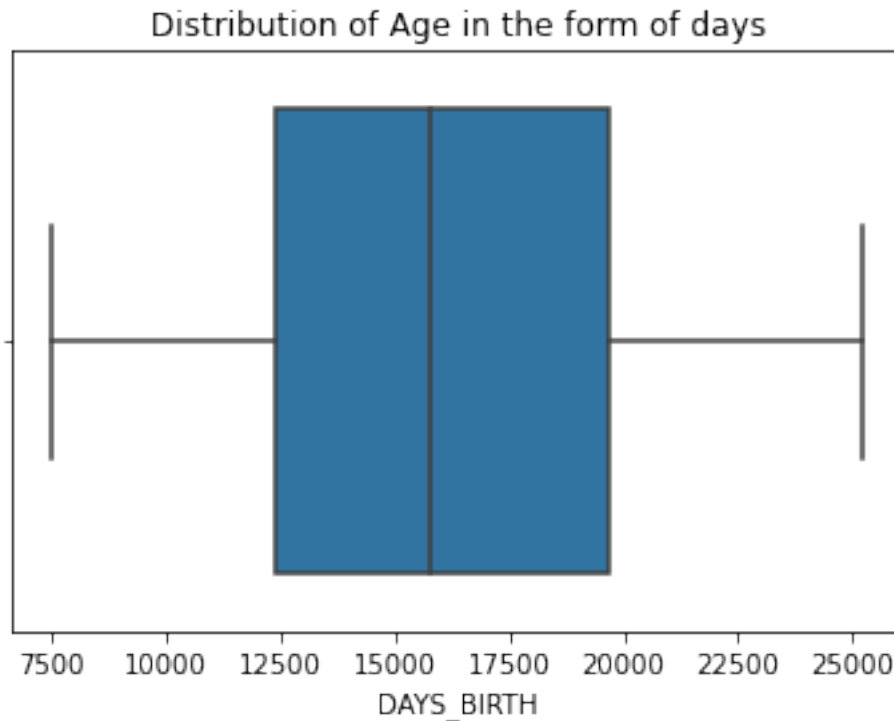
DAYS_BIRTH variable

```
df.DAYS_BIRTH.describe()
```

```
count    307511.000000
mean     16036.995067
std       4363.988632
min       7489.000000
25%      12413.000000
50%      15750.000000
75%      19682.000000
max      25229.000000
```

```
Name: DAYS_BIRTH, dtype: float64
```

```
sns.boxplot(df.DAYS_BIRTH)
plt.title('Distribution of Age in the form of days')
plt.show()
```



DAYS_BIRTH column we can see from box plot that there are no outliers. There is no much difference between mean and median. Which means that all the applications received from the customers are of almost same age.

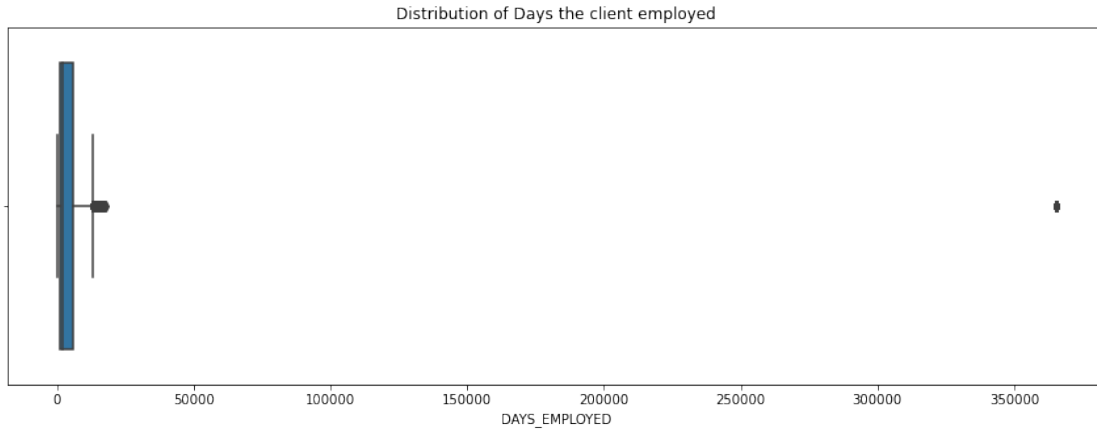
DAYS EMPLOYED variable

```
df.DAYS_EMPLOYED.describe()
```

```
count    307511.000000
mean      67724.742149
std       139443.751806
min         0.000000
25%        933.000000
50%       2219.000000
75%       5707.000000
max      365243.000000
Name: DAYS_EMPLOYED, dtype: float64
```

```
plt.figure(figsize=(15,5))
sns.boxplot(df.DAYS_EMPLOYED)
#plt.yscale('log')
plt.title('Distribution of Days the client employed')

plt.show()
```



DAYS_EMPLOYED column has outliers at 365243. Number of days the person was employed varies from person to person

Binning Continuous Variable

#Creating bins for Credit amount

```
bins = [0,350000,700000,10000000000]
slots = ['Low','Medium','High']
```

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

Creating bins for income amount

```
bins = [0,200000,400000,100000000000]
slot = ['Low','Medium','High']
```

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

Creating bins for days_birth

```
bins = [0,7300,10950,14600,18250,21900,25500]
slot = ['0-20','20-30','30-40','40-50','50-60','60-70']
```

```
df['AGE_RANGE']=pd.cut(df['DAYS_BIRTH'],bins,labels=slot)
```

#Checking bin columns created in df.

```
df.head()
```

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

FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
0	Y	0	202500.0
24700.5			406597.5
1	N	0	270000.0
35698.5			1293502.5
2	Y	0	67500.0
6750.0			135000.0
3	Y	0	135000.0
29686.5			312682.5
4	Y	0	121500.0
21865.5			513000.0

AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE
0	351000.0	Unaccompanied
		Working
1	1129500.0	Family
		State servant
2	135000.0	Unaccompanied
		Working
3	297000.0	Unaccompanied
		Working
4	513000.0	Unaccompanied
		Working

NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS
0	Secondary / secondary special
	Single / not married
	House / apartment
1	Higher education
	Married
	House / apartment
2	Secondary / secondary special
	Single / not married
	House / apartment
3	Secondary / secondary special
	Civil marriage
	House / apartment
4	Secondary / secondary special
	Single / not married
	House / apartment

REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED
0	0.018801	9461
3648.0		637
1	0.003541	16765
1186.0		1188
2	0.010032	19046
4260.0		225
3	0.008019	19005
9833.0		3039
4	0.028663	19932
4311.0		3038

DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START
0	2120	Laborers
		WEDNESDAY
1	291	Core staff
		MONDAY
2	2531	Laborers
		MONDAY

3	2437	Laborers	WEDNESDAY
4	3458	Core staff	THURSDAY

	HOUR_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
0	10	0	
1	11	0	
2	9	0	
3	17	0	
4	11	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	\
0	0	0		
0				
1	0	0		
0				
2	0	0		
0				
3	0	0		
0				
4	0	1		
1				

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
0	Business Entity Type 3	0.262949	2.0	
1	School	0.622246	1.0	
2	Government	0.555912	0.0	
3	Business Entity Type 3	0.650442	2.0	
4	Religion	0.322738	0.0	

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	\
0	2.0	2.0	
1	0.0	1.0	
2	0.0	0.0	
3	0.0	2.0	
4	0.0	0.0	

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR	\
0	2.0	0.0	
1	0.0	0.0	
2	0.0	0.0	
3	0.0	NaN	
4	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	NaN	NaN
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR	AMT_CREDIT_RANGE	AMT_INCOME_RANGE
0	1.0	Medium	Medium
20-30			
1	0.0	High	Medium
40-50			
2	0.0	Low	Low
50-60			
3	NaN	Low	Low
50-60			
4	0.0	Medium	Low
50-60			

Analysis

Calculating Imbalance percentage

```
100*(df.TARGET.value_counts())/ (len(df))
```

```
0    91.927118
```

```
1     8.072882
```

```
Name: TARGET, dtype: float64
```

So TARGET column has 8.07% of 1's which means 8% clients have payment difficulties and 91.92% are having no difficulties

Dividing the dataset into two dataset of target=1(client with payment difficulties) and target=0(all other)

```
target_1 = df[df['TARGET']==1]
```

```
target_0 = df[df['TARGET']==0]
```

#Dataframe having target values 0

```
target_0.head()
```

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR \
1	100003	0	Cash loans	F	N

2	100004	0	Revolving loans	M	Y
3	100006	0	Cash loans	F	N
4	100007	0	Cash loans	M	N
5	100008	0	Cash loans	M	N

FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
AMT_ANNUITY \			
1 N	0	270000.0	1293502.5
35698.5			
2 Y	0	67500.0	135000.0
6750.0			
3 Y	0	135000.0	312682.5
29686.5			
4 Y	0	121500.0	513000.0
21865.5			
5 Y	0	99000.0	490495.5
27517.5			

AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE
1 1129500.0	Family	State servant
2 135000.0	Unaccompanied	Working
3 297000.0	Unaccompanied	Working
4 513000.0	Unaccompanied	Working
5 454500.0	Spouse, partner	State servant

NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS
NAME_HOUSING_TYPE \	
1 Higher education	Married House / apartment
2 Secondary / secondary special	Single / not married House / apartment
3 Secondary / secondary special	Civil marriage House / apartment
4 Secondary / secondary special	Single / not married House / apartment
5 Secondary / secondary special	Married House / apartment

REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED
DAYS_REGISTRATION \		
1 0.003541	16765	1188
1186.0		
2 0.010032	19046	225
4260.0		
3 0.008019	19005	3039
9833.0		
4 0.028663	19932	3038
4311.0		
5 0.035792	16941	1588
4970.0		

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START	\
1	291	Core staff	MONDAY	
2	2531	Laborers	MONDAY	
3	2437	Laborers	WEDNESDAY	
4	3458	Core staff	THURSDAY	
5	477	Laborers	WEDNESDAY	

	HOUR_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
1	11	0	
2	9	0	
3	17	0	
4	11	0	
5	16	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
1	0	0	
2	0	0	
3	0	0	
4	0	0	
5	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	\
1	0	0		
0				
2	0	0		
0				
3	0	0		
0				
4	0	1		
1				
5	0	0		
0				

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
1	School	0.622246	1.0	
2	Government	0.555912	0.0	
3	Business Entity Type 3	0.650442	2.0	
4	Religion	0.322738	0.0	
5	Other	0.354225	0.0	

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	\
1	0.0	1.0	
2	0.0	0.0	
3	0.0	2.0	
4	0.0	0.0	
5	0.0	0.0	

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR	\
1	0.0	0.0	
2	0.0	0.0	
3	0.0	NaN	
4	0.0	0.0	
5	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK	\
1	0.0	0.0	
2	0.0	0.0	
3	NaN	NaN	
4	0.0	0.0	
5	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT	\
1	0.0	0.0	
2	0.0	0.0	
3	NaN	NaN	
4	0.0	0.0	
5	0.0	1.0	

	AMT_REQ_CREDIT_BUREAU_YEAR	AMT_CREDIT_RANGE	AMT_INCOME_RANGE
AGE_RANGE			
1	0.0	High	Medium
40-50			
2	0.0	Low	Low
50-60			
3	NaN	Low	Low
50-60			
4	0.0	Medium	Low
50-60			
5	1.0	Medium	Low
40-50			

#Dataframe having target values 1
target_1.head()

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	\
0	100002	1	Cash loans	M	N	
26	100031	1	Cash loans	F	N	
40	100047	1	Cash loans	M	N	
42	100049	1	Cash loans	F	N	
81	100096	1	Cash loans	F	N	

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
AMT_ANNUITY				
0	Y	0	202500.0	406597.5
24700.5				
26	Y	0	112500.0	979992.0
27076.5				

40	Y	0	202500.0	1193580.0
35028.0				
42	N	0	135000.0	288873.0
16258.5				
81	Y	0	81000.0	252000.0
14593.5				

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	351000.0	Unaccompanied	Working	
26	702000.0	Unaccompanied	Working	
40	855000.0	Unaccompanied	Commercial associate	
42	238500.0	Unaccompanied	Working	
81	252000.0	Unaccompanied	Pensioner	

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	\
0	Secondary / secondary special	Single / not married	House / apartment	
26	Secondary / secondary special	Widow	House / apartment	
40	Secondary / secondary special	Married	House / apartment	
42	Secondary / secondary special	Civil marriage	House / apartment	
81	Secondary / secondary special	Married	House / apartment	

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	\
0	0.018801	9461	637	3648.0	
26	0.018029	18724	2628	6573.0	
40	0.025164	17482	1262	1182.0	
42	0.007305	13384	3597	45.0	
81	0.028663	24794	365243	5391.0	

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START	\
0	2120	Laborers	WEDNESDAY	
26	1827	Cooking staff	MONDAY	
40	1029	Laborers	TUESDAY	
42	4409	Sales staff	THURSDAY	
81	4199	NaN	THURSDAY	

	HOUR_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
0	10	0	
26	9	0	

40	9	0
42	11	0
81	10	0

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
26	0	0	
40	0	0	
42	0	0	
81	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	\
0	0	0		
0				
26	0	0		
0				
40	0	0		
0				
42	0	0		
0				
81	0	0		
0				

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
0	Business Entity Type 3	0.262949	2.0	
26	Business Entity Type 3	0.548477	10.0	
40	Business Entity Type 3	0.306841	0.0	
42	Self-employed	0.674203	1.0	
81	XNA	0.023952	1.0	

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	\
0	2.0	2.0	
26	1.0	10.0	
40	0.0	0.0	
42	0.0	1.0	
81	1.0	1.0	

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR	\
0	2.0	0.0	
26	0.0	0.0	
40	0.0	0.0	
42	0.0	0.0	
81	1.0	0.0	

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK	\
0	0.0	0.0	
26	0.0	0.0	
40	0.0	0.0	
42	0.0	0.0	

81	0.0	0.0
----	-----	-----

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	0.0	0.0
26	0.0	2.0
40	2.0	0.0
42	0.0	0.0
81	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR	AMT_CREDIT_RANGE	AMT_INCOME_RANGE
AGE_RANGE			
0	1.0	Medium	Medium
20-30			
26	2.0	High	Low
50-60			
40	4.0	High	Medium
40-50			
42	2.0	Low	Low
30-40			
81	0.0	Low	Low
60-70			

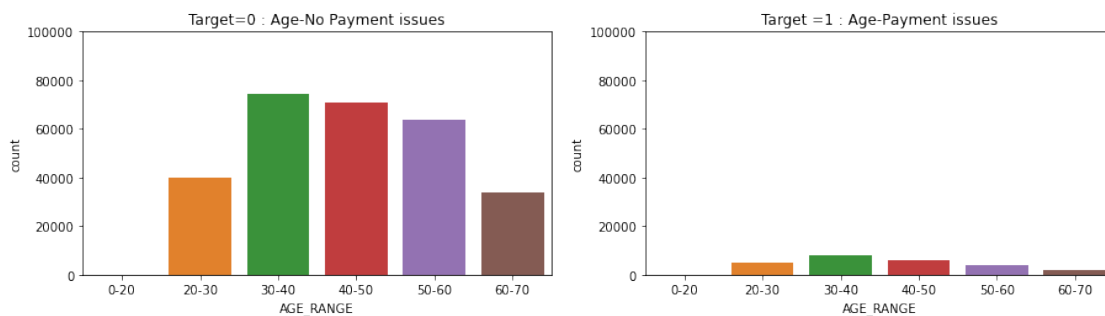
Univariate Analysis for target =0 and target=1

Numeric variable analysis for target_0 & target_1 dataframe

```
plt.figure(figsize = (15, 8))
plt.subplot(2, 2, 1)
plt.ylim(0,100000)
plt.title('Target=0 : Age-No Payment issues')
sns.countplot(target_0['AGE_RANGE'])
```

subplot 2

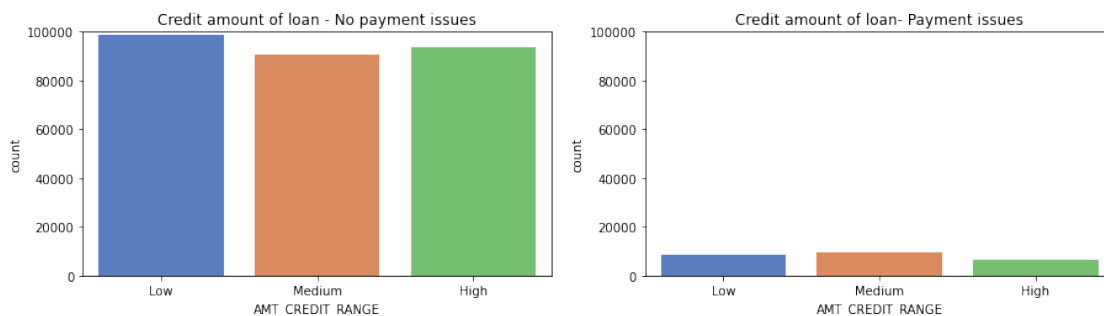
```
plt.subplot(2, 2, 2)
plt.title('Target =1 : Age-Payment issues')
plt.ylim(0,100000)
sns.countplot(target_1['AGE_RANGE'])
plt.show()
```



We can observe that customers belonging to age group 30-40 are able to make payment on time and can be considered while lending loan. The customers from 40 to 60 age are also can be considered.

```
# Numeric variable analysis for target_0 & target_1 dataframe
plt.figure(figsize = (15, 8))
plt.subplot(2, 2, 1)
plt.ylim(0,100000)
plt.title('Credit amount of loan - No payment issues')
sns.countplot(target_0['AMT_CREDIT_RANGE'],palette='muted')
```

```
# subplot 2
plt.subplot(2, 2, 2)
plt.title('Credit amount of loan- Payment issues')
plt.ylim(0,100000)
sns.countplot(target_1['AMT_CREDIT_RANGE'], palette='muted')
plt.show()
```



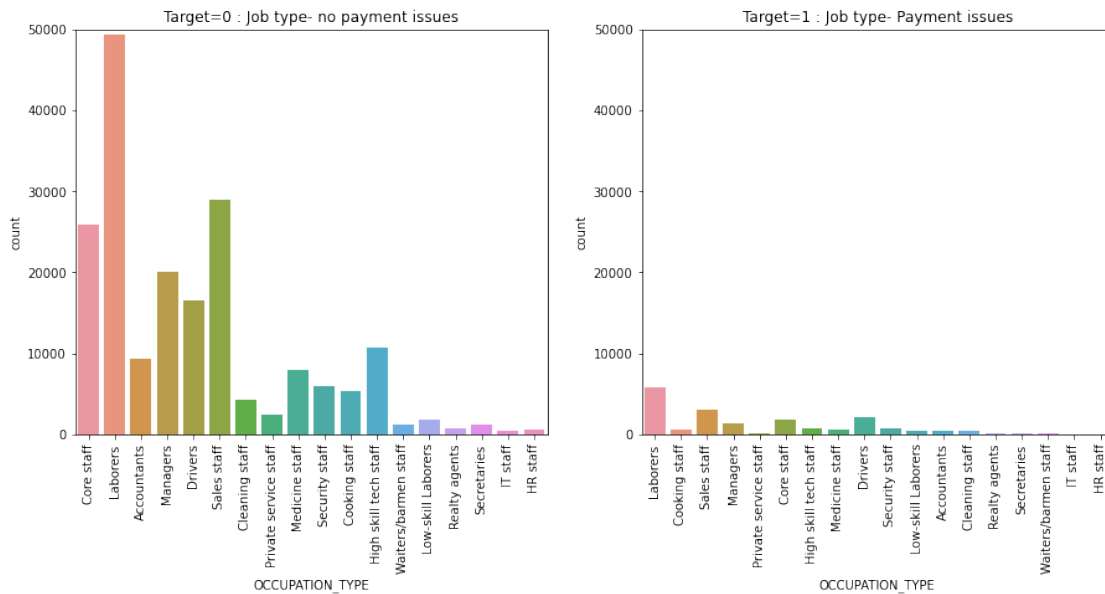
Customers with less credit and most likely to make payment. Customers having medium and high credit can also be considered while lending the loan

```
# Categorical variable analysis for target_0 & target_1 dataframe
plt.figure(figsize = (15,6))
plt.subplot(1, 2, 1)
#plt.subplots_adjust(wspace=0.5)
```

```
sns.countplot(target_0['OCCUPATION_TYPE'])
plt.title('Target=0 : Job type- no payment issues')
plt.ylim(0,50000)
plt.xticks(rotation = 90)
```

```
# subplot 2
plt.subplot(1, 2, 2)
```

```
sns.countplot(target_1['OCCUPATION_TYPE'])
plt.title('Target=1 : Job type- Payment issues')
plt.ylim(0,50000)
plt.xticks(rotation = 90)
plt.show()
```

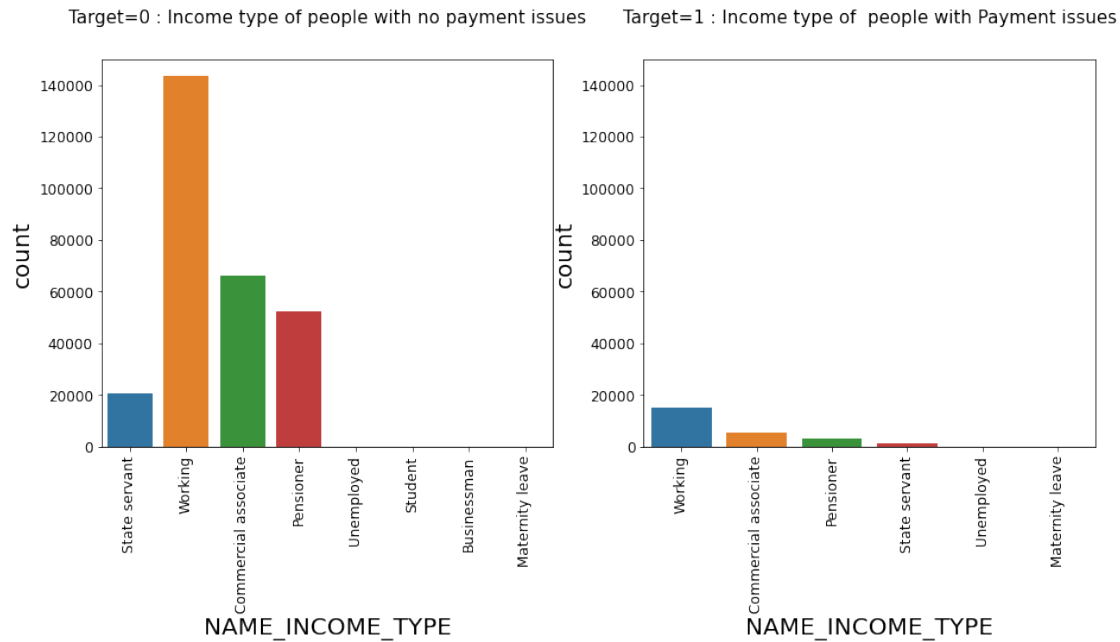


The plot clearly shows that labourers are most likely to make payment on time whereas HR staff are less likely to make payment on time

```
# Categorical variable analysis for target_0 & target_1 dataframe
plt.figure(figsize = (15,6))
plt.rcParams['axes.titlesize'] = 15
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlepad'] = 30
plt.rc('xtick',labelsize=12)
plt.rc('ytick',labelsize=12)
plt.subplot(1, 2, 1)
#plt.title()
sns.countplot(target_0['NAME_INCOME_TYPE'].dropna())
plt.title('Target=0 : Income type of people with no payment issues')
plt.ylim(0,150000)
plt.xticks(rotation = 90)

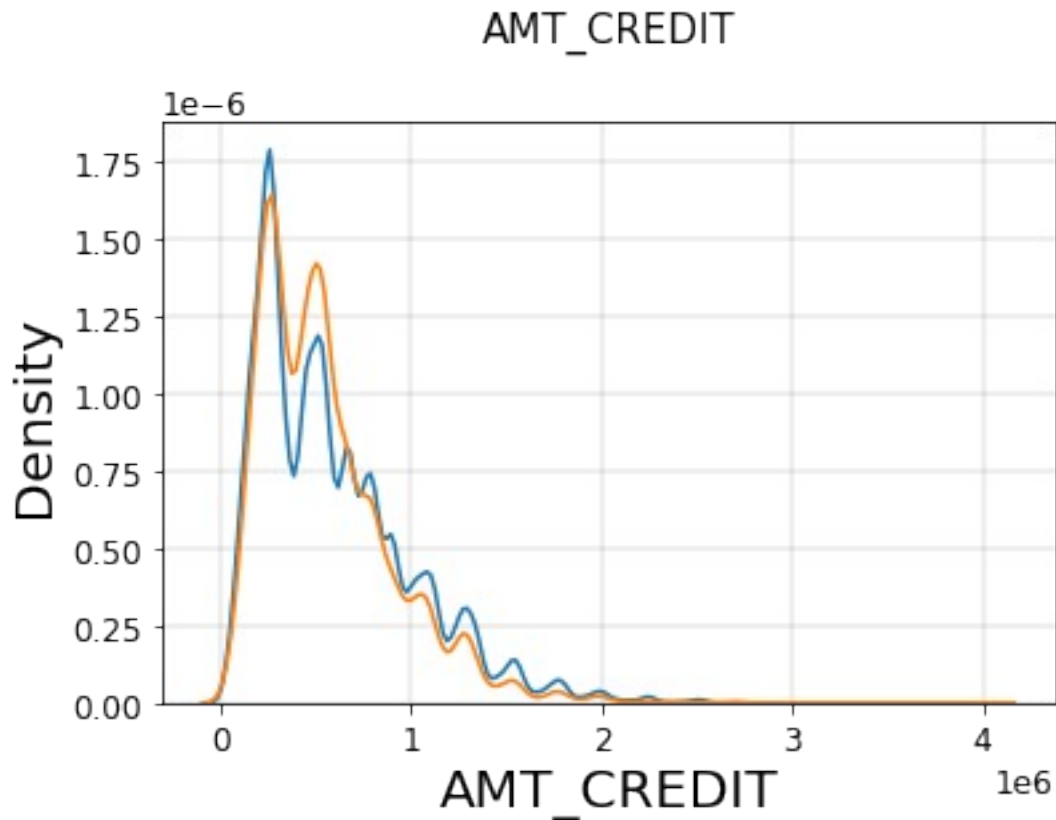
# subplot 2
plt.subplot(1, 2, 2)

sns.countplot(target_1['NAME_INCOME_TYPE'].dropna())
plt.title('Target=1 : Income type of people with Payment issues')
plt.ylim(0,150000)
plt.xticks(rotation = 90)
plt.show()
```

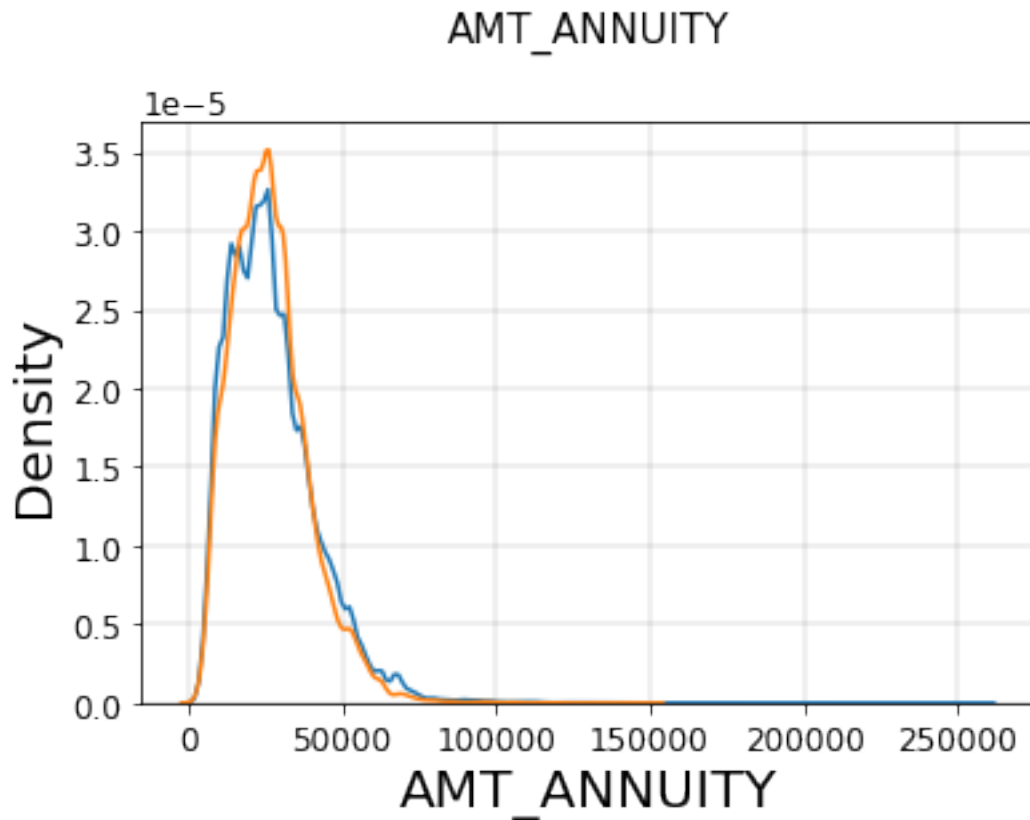


The plot clearly shows that labourers are most likely to make payment on time whereas HR staff are less likely to make payment on time

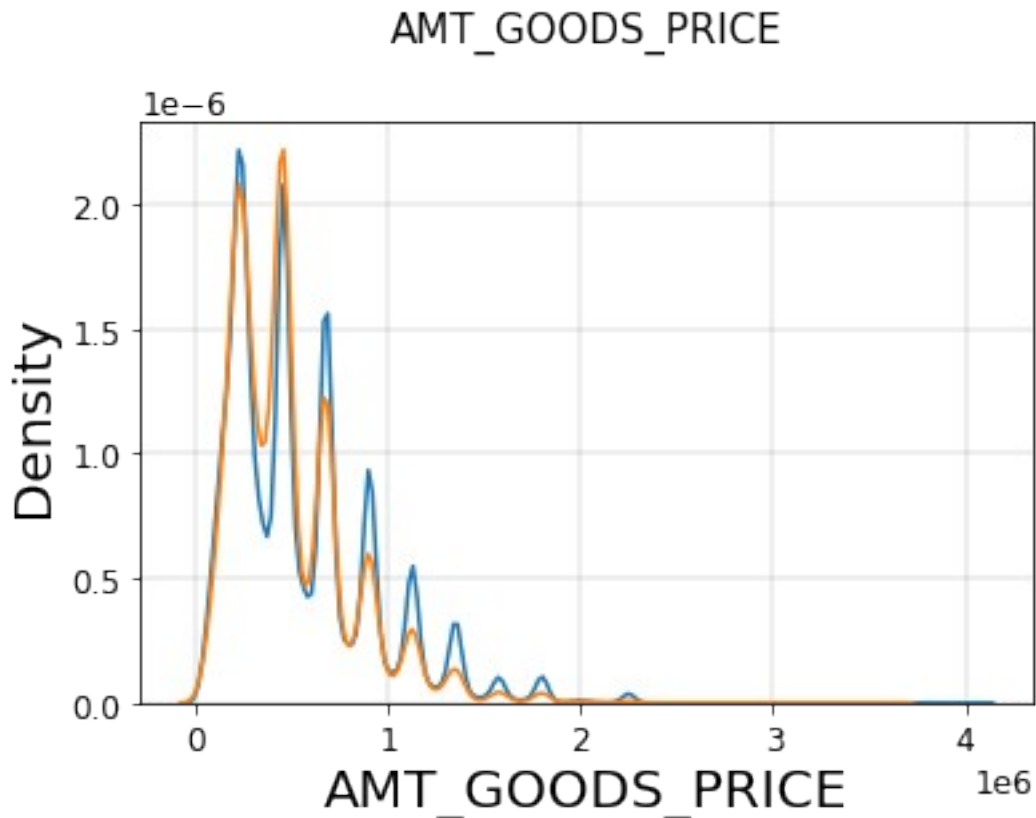
```
#Analyse continuous column with respect to the target column
sns.distplot(target_0['AMT_CREDIT'], hist = False, label="Good")#
Target = 0
sns.distplot(target_1['AMT_CREDIT'], hist = False, label='Bad')# Target
= 1
plt.title('AMT_CREDIT')
plt.grid(color='black', linestyle='--', linewidth=0.25, alpha=0.5)
plt.show()
```



```
#Analyse continuous column with respect to the target column
sns.distplot(target_0['AMT_ANNUIITY'], hist = False, label="Good")#
Target = 0
sns.distplot(target_1['AMT_ANNUIITY'], hist = False, label="Bad")#
Target = 1
plt.title('AMT_ANNUIITY')
plt.grid(color='black', linestyle='--', linewidth=0.25, alpha=0.5)
plt.show()
```



```
#Analyse continuous column with respect to the target column
sns.distplot(target_0['AMT_GOODS_PRICE'], hist = False, label= "good")#
Target = 0
sns.distplot(target_1['AMT_GOODS_PRICE'], hist = False, label="bad")#
Target = 1
plt.title('AMT_GOODS_PRICE')
plt.grid(color='black', linestyle='--', linewidth=0.25, alpha=0.5)
plt.show()
```

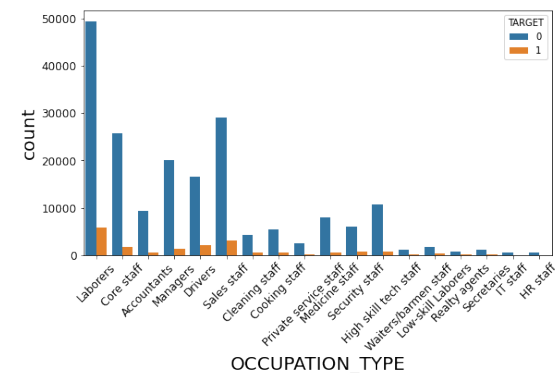
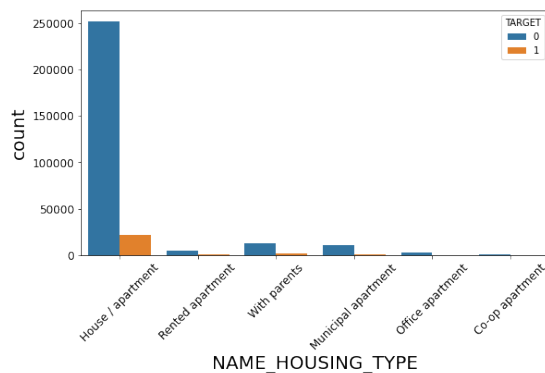
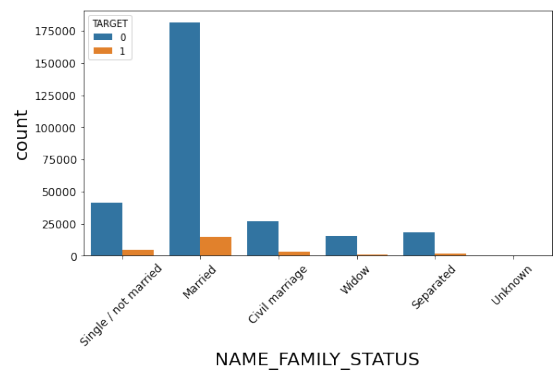
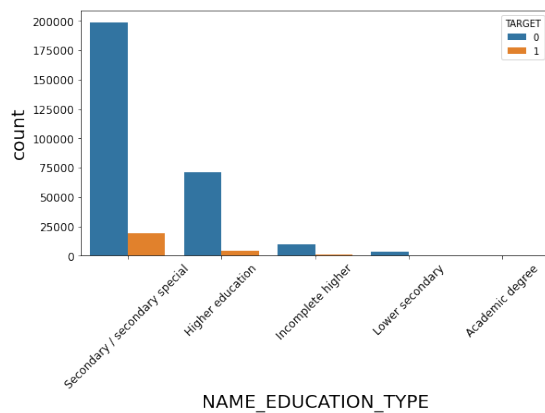
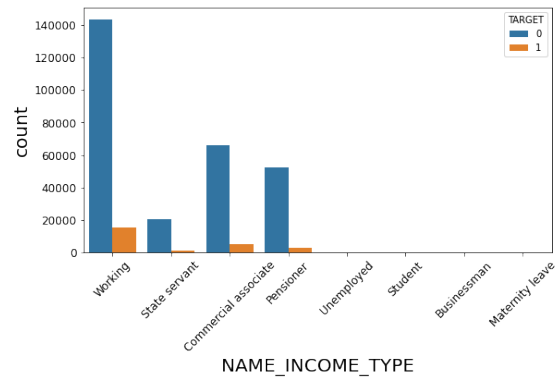
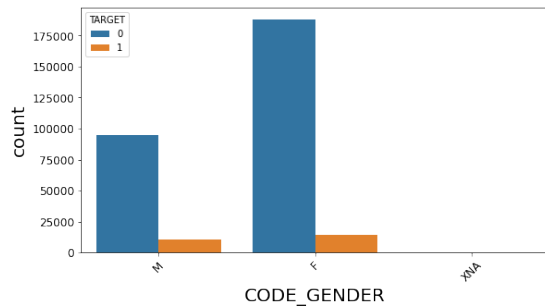


```
#Plot mutiple categorical columns with respect to Target column:
Subplot
features = ['CODE_GENDER', 'NAME_INCOME_TYPE',
'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPA
TION_TYPE']
list(enumerate(features))

[(0, 'CODE_GENDER'),
 (1, 'NAME_INCOME_TYPE'),
 (2, 'NAME_EDUCATION_TYPE'),
 (3, 'NAME_FAMILY_STATUS'),
 (4, 'NAME_HOUSING_TYPE'),
 (5, 'OCCUPATION_TYPE')]

features = ['CODE_GENDER', 'NAME_INCOME_TYPE',
'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPA
TION_TYPE']
plt.figure(figsize = (20, 40))

plt.subplots_adjust(hspace=0.8)
for i in enumerate(features):
    plt.subplot(5, 2, i[0]+1)
    sns.countplot(x = i[1], hue = 'TARGET', data = df)
    plt.xticks(rotation = 45)
```



From the above plot we can see that,

- Female customers pay loan amount on time and banks can target more female customers for lending loan.
- Working customers can be targetted to lend loans as they have higher percentage of making payments on time.
- Customers with secondary education are most likely to make payments when compared to customers with academic degree.
- Married customers have paid loan amount on time when compared to widows.

e) Customers owning House/apartment are most likely to make payments on time compared to those living in CO-OP apartment.

f) Labourers have high repayment percentage. Hence banks can think of lending small amount loans to them.

Correlation Matrix

#correlation matrix for all numerical columns

corr=target_0.corr()

corr

	SK_ID_CURR	TARGET	CNT_CHILDREN	\
SK_ID_CURR	1.000000	NaN	-0.000716	
TARGET	NaN	NaN	NaN	
CNT_CHILDREN	-0.000716	NaN	1.000000	
AMT_INCOME_TOTAL	0.001739	NaN	0.027397	
AMT_CREDIT	-0.000342	NaN	0.003081	
AMT_ANNUITY	0.000068	NaN	0.020905	
AMT_GOODS_PRICE	-0.000205	NaN	-0.000525	
REGION_POPULATION_RELATIVE	0.000360	NaN	-0.024363	
DAYS_BIRTH	0.001346	NaN	-0.336966	
DAYS_EMPLOYED	0.001744	NaN	-0.245174	
DAYS_REGISTRATION	0.001475	NaN	-0.185792	
DAYS_ID_PUBLISH	0.000077	NaN	0.028751	
HOUR_APPR_PROCESS_START	-0.000115	NaN	-0.005244	
EXT_SOURCE_2	0.001589	NaN	-0.015455	
OBS_30_CNT_SOCIAL_CIRCLE	-0.000695	NaN	0.014471	
DEF_30_CNT_SOCIAL_CIRCLE	0.000556	NaN	-0.002246	
OBS_60_CNT_SOCIAL_CIRCLE	-0.000741	NaN	0.014137	
DEF_60_CNT_SOCIAL_CIRCLE	0.002382	NaN	-0.002172	
AMT_REQ_CREDIT_BUREAU_HOUR	-0.001879	NaN	-0.000432	
AMT_REQ_CREDIT_BUREAU_DAY	-0.001725	NaN	0.000648	
AMT_REQ_CREDIT_BUREAU_WEEK	0.002524	NaN	-0.001632	
AMT_REQ_CREDIT_BUREAU_MON	0.000054	NaN	-0.010455	
AMT_REQ_CREDIT_BUREAU_QRT	0.001148	NaN	-0.007087	
AMT_REQ_CREDIT_BUREAU_YEAR	0.004349	NaN	-0.042547	
	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	\
SK_ID_CURR	0.001739	-0.000342	0.000068	
TARGET	NaN	NaN	NaN	
CNT_CHILDREN	0.027397	0.003081	0.020905	
AMT_INCOME_TOTAL	1.000000	0.342799	0.418953	
AMT_CREDIT	0.342799	1.000000	0.771309	

AMT_ANNUITY	0.418953	0.771309	1.000000
AMT_GOODS_PRICE	0.349462	0.987250	0.776686
REGION_POPULATION_RELATIVE	0.167851	0.100604	0.120988
DAYS_BIRTH	-0.062609	0.047378	-0.012263
DAYS_EMPLOYED	-0.140392	-0.070104	-0.104978
DAYS_REGISTRATION	-0.064937	-0.013477	-0.039436
DAYS_ID_PUBLISH	-0.022896	0.001464	-0.014113
HOURL_APPR_PROCESS_START	0.076743	0.053619	0.053589
EXT_SOURCE_2	0.139598	0.129140	0.126615
OBS_30_CNT_SOCIAL_CIRCLE	-0.027828	-0.000914	-0.013091
DEF_30_CNT_SOCIAL_CIRCLE	-0.027621	-0.019851	-0.022535
OBS_60_CNT_SOCIAL_CIRCLE	-0.027690	-0.000892	-0.012893
DEF_60_CNT_SOCIAL_CIRCLE	-0.027593	-0.022225	-0.023385
AMT_REQ_CREDIT_BUREAU_HOUR	0.001417	-0.003734	0.003148
AMT_REQ_CREDIT_BUREAU_DAY	0.007862	0.004409	0.002392
AMT_REQ_CREDIT_BUREAU_WEEK	0.006234	-0.001883	0.012681
AMT_REQ_CREDIT_BUREAU_MON	0.061470	0.054071	0.038181
AMT_REQ_CREDIT_BUREAU_QRT	0.013128	0.017767	0.011248
AMT_REQ_CREDIT_BUREAU_YEAR	0.029536	-0.048866	-0.010882

REGION_POPULATION_RELATIVE	AMT_GOODS_PRICE
SK_ID_CURR	\
0.000360	-0.000205
TARGET	NaN
NaN	
CNT_CHILDREN	-0.000525
0.024363	-

AMT_INCOME_TOTAL	0.349462	
0.167851		
AMT_CREDIT	0.987250	
0.100604		
AMT_ANNUITY	0.776686	
0.120988		
AMT_GOODS_PRICE	1.000000	
0.103827		
REGION_POPULATION_RELATIVE	0.103827	
1.000000		
DAYS_BIRTH	0.044565	
0.025244		
DAYS_EMPLOYED	-0.068609	-
0.007198		
DAYS_REGISTRATION	-0.015916	
0.052083		
DAYS_ID_PUBLISH	0.003649	
0.001071		
HOUR_APPR_PROCESS_START	0.062766	
0.172814		
EXT_SOURCE_2	0.135694	
0.198493		
OBS_30_CNT_SOCIAL_CIRCLE	-0.000707	-
0.012107		
DEF_30_CNT_SOCIAL_CIRCLE	-0.021025	
0.005941		
OBS_60_CNT_SOCIAL_CIRCLE	-0.000723	-
0.011591		
DEF_60_CNT_SOCIAL_CIRCLE	-0.023171	
0.002255		
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003116	-
0.002265		
AMT_REQ_CREDIT_BUREAU_DAY	0.004820	
0.001969		
AMT_REQ_CREDIT_BUREAU_WEEK	-0.001597	-
0.002480		
AMT_REQ_CREDIT_BUREAU_MON	0.055850	
0.078629		
AMT_REQ_CREDIT_BUREAU_QRT	0.018163	-
0.001013		
AMT_REQ_CREDIT_BUREAU_YEAR	-0.051266	
0.001775		

	DAYS_BIRTH	DAYS_EMPLOYED	
DAYS_REGISTRATION \			
SK_ID_CURR	0.001346	0.001744	
0.001475			
TARGET	NaN	NaN	
NaN			
CNT_CHILDREN	-0.336966	-0.245174	-

0.185792			
AMT_INCOME_TOTAL	-0.062609	-0.140392	-
0.064937			
AMT_CREDIT	0.047378	-0.070104	-
0.013477			
AMT_ANNUITY	-0.012263	-0.104978	-
0.039436			
AMT_GOODS_PRICE	0.044565	-0.068609	-
0.015916			
REGION_POPULATION_RELATIVE	0.025244	-0.007198	
0.052083			
DAYS_BIRTH	1.000000	0.626114	
0.333151			
DAYS_EMPLOYED	0.626114	1.000000	
0.214511			
DAYS_REGISTRATION	0.333151	0.214511	
1.000000			
DAYS_ID_PUBLISH	0.271314	0.276663	
0.100236			
HOUR_APPR_PROCESS_START	-0.095916	-0.095455	
0.008044			
EXT_SOURCE_2	0.078158	-0.028530	
0.052503			
OBS_30_CNT_SOCIAL_CIRCLE	-0.007726	0.007272	-
0.008315			
DEF_30_CNT_SOCIAL_CIRCLE	0.003057	0.019379	-
0.001213			
OBS_60_CNT_SOCIAL_CIRCLE	-0.007316	0.007453	-
0.008247			
DEF_60_CNT_SOCIAL_CIRCLE	0.000990	0.016383	-
0.002652			
AMT_REQ_CREDIT_BUREAU_HOUR	-0.004461	-0.004460	
0.002730			
AMT_REQ_CREDIT_BUREAU_DAY	-0.002772	-0.000874	
0.000035			
AMT_REQ_CREDIT_BUREAU_WEEK	0.001069	0.002223	
0.001431			
AMT_REQ_CREDIT_BUREAU_MON	-0.002855	-0.034890	
0.011857			
AMT_REQ_CREDIT_BUREAU_QRT	0.011335	0.015116	
0.000527			
AMT_REQ_CREDIT_BUREAU_YEAR	0.072886	0.052169	
0.026639			
	DAYS_ID_PUBLISH		
HOUR_APPR_PROCESS_START \			
SK_ID_CURR	0.000077		-0.000115
TARGET	NaN		NaN

CNT_CHILDREN	0.028751	-0.005244
AMT_INCOME_TOTAL	-0.022896	0.076743
AMT_CREDIT	0.001464	0.053619
AMT_ANNUITY	-0.014113	0.053589
AMT_GOODS_PRICE	0.003649	0.062766
REGION_POPULATION_RELATIVE	0.001071	0.172814
DAYS_BIRTH	0.271314	-0.095916
DAYS_EMPLOYED	0.276663	-0.095455
DAYS_REGISTRATION	0.100236	0.008044
DAYS_ID_PUBLISH	1.000000	-0.033980
HOUR_APPR_PROCESS_START	-0.033980	1.000000
EXT_SOURCE_2	0.041703	0.157221
OBS_30_CNT_SOCIAL_CIRCLE	0.012326	-0.008013
DEF_30_CNT_SOCIAL_CIRCLE	-0.000403	-0.005718
OBS_60_CNT_SOCIAL_CIRCLE	0.012810	-0.007956
DEF_60_CNT_SOCIAL_CIRCLE	-0.002491	-0.008826
AMT_REQ_CREDIT_BUREAU_HOUR	-0.004797	-0.015832
AMT_REQ_CREDIT_BUREAU_DAY	0.000198	0.003847
AMT_REQ_CREDIT_BUREAU_WEEK	0.001655	-0.002652
AMT_REQ_CREDIT_BUREAU_MON	0.008728	0.037332
AMT_REQ_CREDIT_BUREAU_QRT	0.007071	-0.000671
AMT_REQ_CREDIT_BUREAU_YEAR	0.035639	-0.030330

SK_ID_CURR	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
TARGET	0.001589	-0.000695	
	NaN	NaN	

CNT_CHILDREN	-0.015455	0.014471
AMT_INCOME_TOTAL	0.139598	-0.027828
AMT_CREDIT	0.129140	-0.000914
AMT_ANNUITY	0.126615	-0.013091
AMT_GOODS_PRICE	0.135694	-0.000707
REGION_POPULATION_RELATIVE	0.198493	-0.012107
DAYS_BIRTH	0.078158	-0.007726
DAYS_EMPLOYED	-0.028530	0.007272
DAYS_REGISTRATION	0.052503	-0.008315
DAYS_ID_PUBLISH	0.041703	0.012326
HOURL_APPR_PROCESS_START	0.157221	-0.008013
EXT_SOURCE_2	1.000000	-0.021569
OBS_30_CNT_SOCIAL_CIRCLE	-0.021569	1.000000
DEF_30_CNT_SOCIAL_CIRCLE	-0.027427	0.329206
OBS_60_CNT_SOCIAL_CIRCLE	-0.021224	0.998508
DEF_60_CNT_SOCIAL_CIRCLE	-0.029722	0.253000
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003918	0.000420
AMT_REQ_CREDIT_BUREAU_DAY	0.001597	-0.001940
AMT_REQ_CREDIT_BUREAU_WEEK	0.001420	0.000383
AMT_REQ_CREDIT_BUREAU_MON	0.050993	0.001574
AMT_REQ_CREDIT_BUREAU_QRT	-0.002961	0.003966
AMT_REQ_CREDIT_BUREAU_YEAR	-0.021168	0.031884

	DEF_30_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	0.000556
TARGET	NaN
CNT_CHILDREN	-0.002246
AMT_INCOME_TOTAL	-0.027621
AMT_CREDIT	-0.019851
AMT_ANNUITY	-0.022535
AMT_GOODS_PRICE	-0.021025
REGION_POPULATION_RELATIVE	0.005941
DAYS_BIRTH	0.003057
DAYS_EMPLOYED	0.019379
DAYS_REGISTRATION	-0.001213
DAYS_ID_PUBLISH	-0.000403
HOURL_APPR_PROCESS_START	-0.005718
EXT_SOURCE_2	-0.027427
OBS_30_CNT_SOCIAL_CIRCLE	0.329206
DEF_30_CNT_SOCIAL_CIRCLE	1.000000
OBS_60_CNT_SOCIAL_CIRCLE	0.331336
DEF_60_CNT_SOCIAL_CIRCLE	0.859332
AMT_REQ_CREDIT_BUREAU_HOUR	-0.001472
AMT_REQ_CREDIT_BUREAU_DAY	-0.001712
AMT_REQ_CREDIT_BUREAU_WEEK	-0.001882
AMT_REQ_CREDIT_BUREAU_MON	0.000817
AMT_REQ_CREDIT_BUREAU_QRT	-0.000960
AMT_REQ_CREDIT_BUREAU_YEAR	0.018606

OBS_60_CNT_SOCIAL_CIRCLE \

SK_ID_CURR	-0.000741
TARGET	NaN
CNT_CHILDREN	0.014137
AMT_INCOME_TOTAL	-0.027690
AMT_CREDIT	-0.000892
AMT_ANNUITY	-0.012893
AMT_GOODS_PRICE	-0.000723
REGION_POPULATION_RELATIVE	-0.011591
DAYS_BIRTH	-0.007316
DAYS_EMPLOYED	0.007453
DAYS_REGISTRATION	-0.008247
DAYS_ID_PUBLISH	0.012810
HOURL_APPR_PROCESS_START	-0.007956
EXT_SOURCE_2	-0.021224
OBS_30_CNT_SOCIAL_CIRCLE	0.998508
DEF_30_CNT_SOCIAL_CIRCLE	0.331336
OBS_60_CNT_SOCIAL_CIRCLE	1.000000
DEF_60_CNT_SOCIAL_CIRCLE	0.254970
AMT_REQ_CREDIT_BUREAU_HOUR	0.000328
AMT_REQ_CREDIT_BUREAU_DAY	-0.002024
AMT_REQ_CREDIT_BUREAU_WEEK	0.000468
AMT_REQ_CREDIT_BUREAU_MON	0.001598
AMT_REQ_CREDIT_BUREAU_QRT	0.003793
AMT_REQ_CREDIT_BUREAU_YEAR	0.032291

	DEF_60_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	0.002382
TARGET	NaN
CNT_CHILDREN	-0.002172
AMT_INCOME_TOTAL	-0.027593
AMT_CREDIT	-0.022225
AMT_ANNUITY	-0.023385
AMT_GOODS_PRICE	-0.023171
REGION_POPULATION_RELATIVE	0.002255
DAYS_BIRTH	0.000990
DAYS_EMPLOYED	0.016383
DAYS_REGISTRATION	-0.002652
DAYS_ID_PUBLISH	-0.002491
HOURL_APPR_PROCESS_START	-0.008826
EXT_SOURCE_2	-0.029722
OBS_30_CNT_SOCIAL_CIRCLE	0.253000
DEF_30_CNT_SOCIAL_CIRCLE	0.859332
OBS_60_CNT_SOCIAL_CIRCLE	0.254970
DEF_60_CNT_SOCIAL_CIRCLE	1.000000
AMT_REQ_CREDIT_BUREAU_HOUR	-0.002132
AMT_REQ_CREDIT_BUREAU_DAY	-0.001742
AMT_REQ_CREDIT_BUREAU_WEEK	-0.002374
AMT_REQ_CREDIT_BUREAU_MON	-0.001396
AMT_REQ_CREDIT_BUREAU_QRT	-0.000274
AMT_REQ_CREDIT_BUREAU_YEAR	0.018088

	AMT_REQ_CREDIT_BUREAU_HOUR \
SK_ID_CURR	-0.001879
TARGET	NaN
CNT_CHILDREN	-0.000432
AMT_INCOME_TOTAL	0.001417
AMT_CREDIT	-0.003734
AMT_ANNUITY	0.003148
AMT_GOODS_PRICE	-0.003116
REGION_POPULATION_RELATIVE	-0.002265
DAYS_BIRTH	-0.004461
DAYS_EMPLOYED	-0.004460
DAYS_REGISTRATION	0.002730
DAYS_ID_PUBLISH	-0.004797
HOUR_APPR_PROCESS_START	-0.015832
EXT_SOURCE_2	-0.003918
OBS_30_CNT_SOCIAL_CIRCLE	0.000420
DEF_30_CNT_SOCIAL_CIRCLE	-0.001472
OBS_60_CNT_SOCIAL_CIRCLE	0.000328
DEF_60_CNT_SOCIAL_CIRCLE	-0.002132
AMT_REQ_CREDIT_BUREAU_HOUR	1.000000
AMT_REQ_CREDIT_BUREAU_DAY	0.229065
AMT_REQ_CREDIT_BUREAU_WEEK	0.004576
AMT_REQ_CREDIT_BUREAU_MON	0.000528
AMT_REQ_CREDIT_BUREAU_QRT	-0.003350
AMT_REQ_CREDIT_BUREAU_YEAR	-0.004790

	AMT_REQ_CREDIT_BUREAU_DAY \
SK_ID_CURR	-0.001725
TARGET	NaN
CNT_CHILDREN	0.000648
AMT_INCOME_TOTAL	0.007862
AMT_CREDIT	0.004409
AMT_ANNUITY	0.002392
AMT_GOODS_PRICE	0.004820
REGION_POPULATION_RELATIVE	0.001969
DAYS_BIRTH	-0.002772
DAYS_EMPLOYED	-0.000874
DAYS_REGISTRATION	0.000035
DAYS_ID_PUBLISH	0.000198
HOUR_APPR_PROCESS_START	0.003847
EXT_SOURCE_2	0.001597
OBS_30_CNT_SOCIAL_CIRCLE	-0.001940
DEF_30_CNT_SOCIAL_CIRCLE	-0.001712
OBS_60_CNT_SOCIAL_CIRCLE	-0.002024
DEF_60_CNT_SOCIAL_CIRCLE	-0.001742
AMT_REQ_CREDIT_BUREAU_HOUR	0.229065
AMT_REQ_CREDIT_BUREAU_DAY	1.000000
AMT_REQ_CREDIT_BUREAU_WEEK	0.220087
AMT_REQ_CREDIT_BUREAU_MON	-0.004753

AMT_REQ_CREDIT_BUREAU_QRT	-0.004749
AMT_REQ_CREDIT_BUREAU_YEAR	-0.003798

	AMT_REQ_CREDIT_BUREAU_WEEK \
SK_ID_CURR	0.002524
TARGET	NaN
CNT_CHILDREN	-0.001632
AMT_INCOME_TOTAL	0.006234
AMT_CREDIT	-0.001883
AMT_ANNUITY	0.012681
AMT_GOODS_PRICE	-0.001597
REGION_POPULATION_RELATIVE	-0.002480
DAYS_BIRTH	0.001069
DAYS_EMPLOYED	0.002223
DAYS_REGISTRATION	0.001431
DAYS_ID_PUBLISH	0.001655
HOUR_APPR_PROCESS_START	-0.002652
EXT_SOURCE_2	0.001420
OBS_30_CNT_SOCIAL_CIRCLE	0.000383
DEF_30_CNT_SOCIAL_CIRCLE	-0.001882
OBS_60_CNT_SOCIAL_CIRCLE	0.000468
DEF_60_CNT_SOCIAL_CIRCLE	-0.002374
AMT_REQ_CREDIT_BUREAU_HOUR	0.004576
AMT_REQ_CREDIT_BUREAU_DAY	0.220087
AMT_REQ_CREDIT_BUREAU_WEEK	1.000000
AMT_REQ_CREDIT_BUREAU_MON	-0.014248
AMT_REQ_CREDIT_BUREAU_QRT	-0.015466
AMT_REQ_CREDIT_BUREAU_YEAR	0.019085

	AMT_REQ_CREDIT_BUREAU_MON \
SK_ID_CURR	0.000054
TARGET	NaN
CNT_CHILDREN	-0.010455
AMT_INCOME_TOTAL	0.061470
AMT_CREDIT	0.054071
AMT_ANNUITY	0.038181
AMT_GOODS_PRICE	0.055850
REGION_POPULATION_RELATIVE	0.078629
DAYS_BIRTH	-0.002855
DAYS_EMPLOYED	-0.034890
DAYS_REGISTRATION	0.011857
DAYS_ID_PUBLISH	0.008728
HOUR_APPR_PROCESS_START	0.037332
EXT_SOURCE_2	0.050993
OBS_30_CNT_SOCIAL_CIRCLE	0.001574
DEF_30_CNT_SOCIAL_CIRCLE	0.000817
OBS_60_CNT_SOCIAL_CIRCLE	0.001598
DEF_60_CNT_SOCIAL_CIRCLE	-0.001396
AMT_REQ_CREDIT_BUREAU_HOUR	0.000528
AMT_REQ_CREDIT_BUREAU_DAY	-0.004753

AMT_REQ_CREDIT_BUREAU_WEEK	-0.014248
AMT_REQ_CREDIT_BUREAU_MON	1.000000
AMT_REQ_CREDIT_BUREAU_QRT	-0.008160
AMT_REQ_CREDIT_BUREAU_YEAR	-0.004889

	AMT_REQ_CREDIT_BUREAU_QRT \
SK_ID_CURR	0.001148
TARGET	NaN
CNT_CHILDREN	-0.007087
AMT_INCOME_TOTAL	0.013128
AMT_CREDIT	0.017767
AMT_ANNUITY	0.011248
AMT_GOODS_PRICE	0.018163
REGION_POPULATION_RELATIVE	-0.001013
DAYS_BIRTH	0.011335
DAYS_EMPLOYED	0.015116
DAYS_REGISTRATION	0.000527
DAYS_ID_PUBLISH	0.007071
HOUR_APPR_PROCESS_START	-0.000671
EXT_SOURCE_2	-0.002961
OBS_30_CNT_SOCIAL_CIRCLE	0.003966
DEF_30_CNT_SOCIAL_CIRCLE	-0.000960
OBS_60_CNT_SOCIAL_CIRCLE	0.003793
DEF_60_CNT_SOCIAL_CIRCLE	-0.000274
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003350
AMT_REQ_CREDIT_BUREAU_DAY	-0.004749
AMT_REQ_CREDIT_BUREAU_WEEK	-0.015466
AMT_REQ_CREDIT_BUREAU_MON	-0.008160
AMT_REQ_CREDIT_BUREAU_QRT	1.000000
AMT_REQ_CREDIT_BUREAU_YEAR	0.074664

	AMT_REQ_CREDIT_BUREAU_YEAR
SK_ID_CURR	0.004349
TARGET	NaN
CNT_CHILDREN	-0.042547
AMT_INCOME_TOTAL	0.029536
AMT_CREDIT	-0.048866
AMT_ANNUITY	-0.010882
AMT_GOODS_PRICE	-0.051266
REGION_POPULATION_RELATIVE	0.001775
DAYS_BIRTH	0.072886
DAYS_EMPLOYED	0.052169
DAYS_REGISTRATION	0.026639
DAYS_ID_PUBLISH	0.035639
HOUR_APPR_PROCESS_START	-0.030330
EXT_SOURCE_2	-0.021168
OBS_30_CNT_SOCIAL_CIRCLE	0.031884
DEF_30_CNT_SOCIAL_CIRCLE	0.018606
OBS_60_CNT_SOCIAL_CIRCLE	0.032291
DEF_60_CNT_SOCIAL_CIRCLE	0.018088

AMT_REQ_CREDIT_BUREAU_HOUR	-0.004790
AMT_REQ_CREDIT_BUREAU_DAY	-0.003798
AMT_REQ_CREDIT_BUREAU_WEEK	0.019085
AMT_REQ_CREDIT_BUREAU_MON	-0.004889
AMT_REQ_CREDIT_BUREAU_QRT	0.074664
AMT_REQ_CREDIT_BUREAU_YEAR	1.000000

*#Convert the diagonal and below diagonal values of matrix to False,
Wherever False is there is replaced with NaN on execution*

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

	SK_ID_CURR	TARGET	CNT_CHILDREN	\
SK_ID_CURR	NaN	NaN	-0.000716	
TARGET	NaN	NaN	NaN	
CNT_CHILDREN	NaN	NaN	NaN	
AMT_INCOME_TOTAL	NaN	NaN	NaN	
AMT_CREDIT	NaN	NaN	NaN	
AMT_ANNUITY	NaN	NaN	NaN	
AMT_GOODS_PRICE	NaN	NaN	NaN	
REGION_POPULATION_RELATIVE	NaN	NaN	NaN	
DAYS_BIRTH	NaN	NaN	NaN	
DAYS_EMPLOYED	NaN	NaN	NaN	
DAYS_REGISTRATION	NaN	NaN	NaN	
DAYS_ID_PUBLISH	NaN	NaN	NaN	
HOUR_APPR_PROCESS_START	NaN	NaN	NaN	
EXT_SOURCE_2	NaN	NaN	NaN	
OBS_30_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN	
DEF_30_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN	
OBS_60_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN	
DEF_60_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_HOUR	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_DAY	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_WEEK	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_MON	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_QRT	NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_YEAR	NaN	NaN	NaN	

\	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
SK_ID_CURR	0.001739	-0.000342	0.000068
TARGET	NaN	NaN	NaN
CNT_CHILDREN	0.027397	0.003081	0.020905
AMT_INCOME_TOTAL	NaN	0.342799	0.418953
AMT_CREDIT	NaN	NaN	0.771309

AMT_ANNUITY	NaN	NaN	NaN
AMT_GOODS_PRICE	NaN	NaN	NaN
REGION_POPULATION_RELATIVE	NaN	NaN	NaN
DAYS_BIRTH	NaN	NaN	NaN
DAYS_EMPLOYED	NaN	NaN	NaN
DAYS_REGISTRATION	NaN	NaN	NaN
DAYS_ID_PUBLISH	NaN	NaN	NaN
HOURL_APPR_PROCESS_START	NaN	NaN	NaN
EXT_SOURCE_2	NaN	NaN	NaN
OBS_30_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN
DEF_30_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN
OBS_60_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN
DEF_60_CNT_SOCIAL_CIRCLE	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN	NaN	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN	NaN	NaN

REGION_POPULATION_RELATIVE	AMT_GOODS_PRICE	
SK_ID_CURR	\	
0.000360	-0.000205	
TARGET	NaN	
NaN		
CNT_CHILDREN	-0.000525	-
0.024363		
AMT_INCOME_TOTAL	0.349462	

0.167851		
AMT_CREDIT	0.987250	
0.100604		
AMT_ANNUITY	0.776686	
0.120988		
AMT_GOODS_PRICE	NaN	
0.103827		
REGION_POPULATION_RELATIVE	NaN	
NaN		
DAYS_BIRTH	NaN	
NaN		
DAYS_EMPLOYED	NaN	
NaN		
DAYS_REGISTRATION	NaN	
NaN		
DAYS_ID_PUBLISH	NaN	
NaN		
HOUR_APPR_PROCESS_START	NaN	
NaN		
EXT_SOURCE_2	NaN	
NaN		
OBS_30_CNT_SOCIAL_CIRCLE	NaN	
NaN		
DEF_30_CNT_SOCIAL_CIRCLE	NaN	
NaN		
OBS_60_CNT_SOCIAL_CIRCLE	NaN	
NaN		
DEF_60_CNT_SOCIAL_CIRCLE	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_HOUR	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_DAY	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_WEEK	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_MON	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_QRT	NaN	
NaN		
AMT_REQ_CREDIT_BUREAU_YEAR	NaN	
NaN		

	DAYS_BIRTH	DAYS_EMPLOYED
DAYS_REGISTRATION \		
SK_ID_CURR	0.001346	0.001744
0.001475		
TARGET	NaN	NaN
NaN		
CNT_CHILDREN	-0.336966	-0.245174
0.185792		

-

AMT_INCOME_TOTAL 0.064937	-0.062609	-0.140392	-
AMT_CREDIT 0.013477	0.047378	-0.070104	-
AMT_ANNUITY 0.039436	-0.012263	-0.104978	-
AMT_GOODS_PRICE 0.015916	0.044565	-0.068609	-
REGION_POPULATION_RELATIVE 0.052083	0.025244	-0.007198	
DAYS_BIRTH 0.333151	NaN	0.626114	
DAYS_EMPLOYED 0.214511	NaN	NaN	
DAYS_REGISTRATION NaN	NaN	NaN	
DAYS_ID_PUBLISH NaN	NaN	NaN	
HOUR_APPR_PROCESS_START NaN	NaN	NaN	
EXT_SOURCE_2 NaN	NaN	NaN	
OBS_30_CNT_SOCIAL_CIRCLE NaN	NaN	NaN	
DEF_30_CNT_SOCIAL_CIRCLE NaN	NaN	NaN	
OBS_60_CNT_SOCIAL_CIRCLE NaN	NaN	NaN	
DEF_60_CNT_SOCIAL_CIRCLE NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_HOUR NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_DAY NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_WEEK NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_MON NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_QRT NaN	NaN	NaN	
AMT_REQ_CREDIT_BUREAU_YEAR NaN	NaN	NaN	
	DAYS_ID_PUBLISH		
HOUR_APPR_PROCESS_START \ SK_ID_CURR	0.000077		-0.000115
TARGET	NaN		NaN
CNT_CHILDREN	0.028751		-0.005244

AMT_INCOME_TOTAL	-0.022896	0.076743
AMT_CREDIT	0.001464	0.053619
AMT_ANNUITY	-0.014113	0.053589
AMT_GOODS_PRICE	0.003649	0.062766
REGION_POPULATION_RELATIVE	0.001071	0.172814
DAYS_BIRTH	0.271314	-0.095916
DAYS_EMPLOYED	0.276663	-0.095455
DAYS_REGISTRATION	0.100236	0.008044
DAYS_ID_PUBLISH	NaN	-0.033980
HOURL_APPR_PROCESS_START	NaN	NaN
EXT_SOURCE_2	NaN	NaN
OBS_30_CNT_SOCIAL_CIRCLE	NaN	NaN
DEF_30_CNT_SOCIAL_CIRCLE	NaN	NaN
OBS_60_CNT_SOCIAL_CIRCLE	NaN	NaN
DEF_60_CNT_SOCIAL_CIRCLE	NaN	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN	NaN

SK_ID_CURR	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
TARGET	0.001589	-0.000695	
CNT_CHILDREN	NaN	NaN	
	-0.015455	0.014471	

AMT_INCOME_TOTAL	0.139598	-0.027828
AMT_CREDIT	0.129140	-0.000914
AMT_ANNUITY	0.126615	-0.013091
AMT_GOODS_PRICE	0.135694	-0.000707
REGION_POPULATION_RELATIVE	0.198493	-0.012107
DAYS_BIRTH	0.078158	-0.007726
DAYS_EMPLOYED	-0.028530	0.007272
DAYS_REGISTRATION	0.052503	-0.008315
DAYS_ID_PUBLISH	0.041703	0.012326
HOURL_APPR_PROCESS_START	0.157221	-0.008013
EXT_SOURCE_2	NaN	-0.021569
OBS_30_CNT_SOCIAL_CIRCLE	NaN	NaN
DEF_30_CNT_SOCIAL_CIRCLE	NaN	NaN
OBS_60_CNT_SOCIAL_CIRCLE	NaN	NaN
DEF_60_CNT_SOCIAL_CIRCLE	NaN	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN	NaN

	DEF_30_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	0.000556
TARGET	NaN
CNT_CHILDREN	-0.002246
AMT_INCOME_TOTAL	-0.027621
AMT_CREDIT	-0.019851
AMT_ANNUITY	-0.022535
AMT_GOODS_PRICE	-0.021025
REGION_POPULATION_RELATIVE	0.005941
DAYS_BIRTH	0.003057
DAYS_EMPLOYED	0.019379
DAYS_REGISTRATION	-0.001213
DAYS_ID_PUBLISH	-0.000403
HOURL_APPR_PROCESS_START	-0.005718
EXT_SOURCE_2	-0.027427
OBS_30_CNT_SOCIAL_CIRCLE	0.329206
DEF_30_CNT_SOCIAL_CIRCLE	NaN
OBS_60_CNT_SOCIAL_CIRCLE	NaN
DEF_60_CNT_SOCIAL_CIRCLE	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	OBS_60_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	-0.000741

TARGET	NaN
CNT_CHILDREN	0.014137
AMT_INCOME_TOTAL	-0.027690
AMT_CREDIT	-0.000892
AMT_ANNUITY	-0.012893
AMT_GOODS_PRICE	-0.000723
REGION_POPULATION_RELATIVE	-0.011591
DAYS_BIRTH	-0.007316
DAYS_EMPLOYED	0.007453
DAYS_REGISTRATION	-0.008247
DAYS_ID_PUBLISH	0.012810
HOURL_APPR_PROCESS_START	-0.007956
EXT_SOURCE_2	-0.021224
OBS_30_CNT_SOCIAL_CIRCLE	0.998508
DEF_30_CNT_SOCIAL_CIRCLE	0.331336
OBS_60_CNT_SOCIAL_CIRCLE	NaN
DEF_60_CNT_SOCIAL_CIRCLE	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	DEF_60_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	0.002382
TARGET	NaN
CNT_CHILDREN	-0.002172
AMT_INCOME_TOTAL	-0.027593
AMT_CREDIT	-0.022225
AMT_ANNUITY	-0.023385
AMT_GOODS_PRICE	-0.023171
REGION_POPULATION_RELATIVE	0.002255
DAYS_BIRTH	0.000990
DAYS_EMPLOYED	0.016383
DAYS_REGISTRATION	-0.002652
DAYS_ID_PUBLISH	-0.002491
HOURL_APPR_PROCESS_START	-0.008826
EXT_SOURCE_2	-0.029722
OBS_30_CNT_SOCIAL_CIRCLE	0.253000
DEF_30_CNT_SOCIAL_CIRCLE	0.859332
OBS_60_CNT_SOCIAL_CIRCLE	0.254970
DEF_60_CNT_SOCIAL_CIRCLE	NaN
AMT_REQ_CREDIT_BUREAU_HOUR	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	AMT_REQ_CREDIT_BUREAU_HOUR \
SK_ID_CURR	-0.001879
TARGET	NaN
CNT_CHILDREN	-0.000432
AMT_INCOME_TOTAL	0.001417
AMT_CREDIT	-0.003734
AMT_ANNUITY	0.003148
AMT_GOODS_PRICE	-0.003116
REGION_POPULATION_RELATIVE	-0.002265
DAYS_BIRTH	-0.004461
DAYS_EMPLOYED	-0.004460
DAYS_REGISTRATION	0.002730
DAYS_ID_PUBLISH	-0.004797
HOURL_APPR_PROCESS_START	-0.015832
EXT_SOURCE_2	-0.003918
OBS_30_CNT_SOCIAL_CIRCLE	0.000420
DEF_30_CNT_SOCIAL_CIRCLE	-0.001472
OBS_60_CNT_SOCIAL_CIRCLE	0.000328
DEF_60_CNT_SOCIAL_CIRCLE	-0.002132
AMT_REQ_CREDIT_BUREAU_HOUR	NaN
AMT_REQ_CREDIT_BUREAU_DAY	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	AMT_REQ_CREDIT_BUREAU_DAY \
SK_ID_CURR	-0.001725
TARGET	NaN
CNT_CHILDREN	0.000648
AMT_INCOME_TOTAL	0.007862
AMT_CREDIT	0.004409
AMT_ANNUITY	0.002392
AMT_GOODS_PRICE	0.004820
REGION_POPULATION_RELATIVE	0.001969
DAYS_BIRTH	-0.002772
DAYS_EMPLOYED	-0.000874
DAYS_REGISTRATION	0.000035
DAYS_ID_PUBLISH	0.000198
HOURL_APPR_PROCESS_START	0.003847
EXT_SOURCE_2	0.001597
OBS_30_CNT_SOCIAL_CIRCLE	-0.001940
DEF_30_CNT_SOCIAL_CIRCLE	-0.001712
OBS_60_CNT_SOCIAL_CIRCLE	-0.002024
DEF_60_CNT_SOCIAL_CIRCLE	-0.001742
AMT_REQ_CREDIT_BUREAU_HOUR	0.229065
AMT_REQ_CREDIT_BUREAU_DAY	NaN
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN

AMT_REQ_CREDIT_BUREAU_YEAR	NaN
----------------------------	-----

	AMT_REQ_CREDIT_BUREAU_WEEK \
SK_ID_CURR	0.002524
TARGET	NaN
CNT_CHILDREN	-0.001632
AMT_INCOME_TOTAL	0.006234
AMT_CREDIT	-0.001883
AMT_ANNUITY	0.012681
AMT_GOODS_PRICE	-0.001597
REGION_POPULATION_RELATIVE	-0.002480
DAYS_BIRTH	0.001069
DAYS_EMPLOYED	0.002223
DAYS_REGISTRATION	0.001431
DAYS_ID_PUBLISH	0.001655
HOUR_APPR_PROCESS_START	-0.002652
EXT_SOURCE_2	0.001420
OBS_30_CNT_SOCIAL_CIRCLE	0.000383
DEF_30_CNT_SOCIAL_CIRCLE	-0.001882
OBS_60_CNT_SOCIAL_CIRCLE	0.000468
DEF_60_CNT_SOCIAL_CIRCLE	-0.002374
AMT_REQ_CREDIT_BUREAU_HOUR	0.004576
AMT_REQ_CREDIT_BUREAU_DAY	0.220087
AMT_REQ_CREDIT_BUREAU_WEEK	NaN
AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	AMT_REQ_CREDIT_BUREAU_MON \
SK_ID_CURR	0.000054
TARGET	NaN
CNT_CHILDREN	-0.010455
AMT_INCOME_TOTAL	0.061470
AMT_CREDIT	0.054071
AMT_ANNUITY	0.038181
AMT_GOODS_PRICE	0.055850
REGION_POPULATION_RELATIVE	0.078629
DAYS_BIRTH	-0.002855
DAYS_EMPLOYED	-0.034890
DAYS_REGISTRATION	0.011857
DAYS_ID_PUBLISH	0.008728
HOUR_APPR_PROCESS_START	0.037332
EXT_SOURCE_2	0.050993
OBS_30_CNT_SOCIAL_CIRCLE	0.001574
DEF_30_CNT_SOCIAL_CIRCLE	0.000817
OBS_60_CNT_SOCIAL_CIRCLE	0.001598
DEF_60_CNT_SOCIAL_CIRCLE	-0.001396
AMT_REQ_CREDIT_BUREAU_HOUR	0.000528
AMT_REQ_CREDIT_BUREAU_DAY	-0.004753
AMT_REQ_CREDIT_BUREAU_WEEK	-0.014248

AMT_REQ_CREDIT_BUREAU_MON	NaN
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	AMT_REQ_CREDIT_BUREAU_QRT \
SK_ID_CURR	0.001148
TARGET	NaN
CNT_CHILDREN	-0.007087
AMT_INCOME_TOTAL	0.013128
AMT_CREDIT	0.017767
AMT_ANNUITY	0.011248
AMT_GOODS_PRICE	0.018163
REGION_POPULATION_RELATIVE	-0.001013
DAYS_BIRTH	0.011335
DAYS_EMPLOYED	0.015116
DAYS_REGISTRATION	0.000527
DAYS_ID_PUBLISH	0.007071
HOUR_APPR_PROCESS_START	-0.000671
EXT_SOURCE_2	-0.002961
OBS_30_CNT_SOCIAL_CIRCLE	0.003966
DEF_30_CNT_SOCIAL_CIRCLE	-0.000960
OBS_60_CNT_SOCIAL_CIRCLE	0.003793
DEF_60_CNT_SOCIAL_CIRCLE	-0.000274
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003350
AMT_REQ_CREDIT_BUREAU_DAY	-0.004749
AMT_REQ_CREDIT_BUREAU_WEEK	-0.015466
AMT_REQ_CREDIT_BUREAU_MON	-0.008160
AMT_REQ_CREDIT_BUREAU_QRT	NaN
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

	AMT_REQ_CREDIT_BUREAU_YEAR
SK_ID_CURR	0.004349
TARGET	NaN
CNT_CHILDREN	-0.042547
AMT_INCOME_TOTAL	0.029536
AMT_CREDIT	-0.048866
AMT_ANNUITY	-0.010882
AMT_GOODS_PRICE	-0.051266
REGION_POPULATION_RELATIVE	0.001775
DAYS_BIRTH	0.072886
DAYS_EMPLOYED	0.052169
DAYS_REGISTRATION	0.026639
DAYS_ID_PUBLISH	0.035639
HOUR_APPR_PROCESS_START	-0.030330
EXT_SOURCE_2	-0.021168
OBS_30_CNT_SOCIAL_CIRCLE	0.031884
DEF_30_CNT_SOCIAL_CIRCLE	0.018606
OBS_60_CNT_SOCIAL_CIRCLE	0.032291
DEF_60_CNT_SOCIAL_CIRCLE	0.018088
AMT_REQ_CREDIT_BUREAU_HOUR	-0.004790

AMT_REQ_CREDIT_BUREAU_DAY	-0.003798
AMT_REQ_CREDIT_BUREAU_WEEK	0.019085
AMT_REQ_CREDIT_BUREAU_MON	-0.004889
AMT_REQ_CREDIT_BUREAU_QRT	0.074664
AMT_REQ_CREDIT_BUREAU_YEAR	NaN

#convert it to dataframe

```
corrdf = corr.unstack().reset_index()
corrdf.head()
```

	level_0	level_1	0
0	SK_ID_CURR	SK_ID_CURR	NaN
1	SK_ID_CURR	TARGET	NaN
2	SK_ID_CURR	CNT_CHILDREN	NaN
3	SK_ID_CURR	AMT_INCOME_TOTAL	NaN
4	SK_ID_CURR	AMT_CREDIT	NaN

#Changing the names of columns

```
corrdf.columns=['VAR1', 'VAR2', 'Correlation']
corrdf.head()
```

	VAR1	VAR2	Correlation
0	SK_ID_CURR	SK_ID_CURR	NaN
1	SK_ID_CURR	TARGET	NaN
2	SK_ID_CURR	CNT_CHILDREN	NaN
3	SK_ID_CURR	AMT_INCOME_TOTAL	NaN
4	SK_ID_CURR	AMT_CREDIT	NaN

#Drop the columns having the missing data

```
corrdf.dropna(subset = ['Correlation'], inplace = True)
corrdf.head()
```

	VAR1	VAR2	Correlation
48	CNT_CHILDREN	SK_ID_CURR	-0.000716
72	AMT_INCOME_TOTAL	SK_ID_CURR	0.001739
74	AMT_INCOME_TOTAL	CNT_CHILDREN	0.027397
96	AMT_CREDIT	SK_ID_CURR	-0.000342
98	AMT_CREDIT	CNT_CHILDREN	0.003081

#Rounding off the values

```
corrdf['Correlation'] = round(corrdf['Correlation'], 2)
corrdf.head()
```

	VAR1	VAR2	Correlation
48	CNT_CHILDREN	SK_ID_CURR	-0.00
72	AMT_INCOME_TOTAL	SK_ID_CURR	0.00
74	AMT_INCOME_TOTAL	CNT_CHILDREN	0.03
96	AMT_CREDIT	SK_ID_CURR	-0.00
98	AMT_CREDIT	CNT_CHILDREN	0.00

Since we see correlation as an absolute value, we are converting it into absolute value

```
corrdf['Correlation'] = corrdf['Correlation'].abs()
corrdf.head()
```

	VAR1	VAR2	Correlation
48	CNT_CHILDREN	SK_ID_CURR	0.00
72	AMT_INCOME_TOTAL	SK_ID_CURR	0.00
74	AMT_INCOME_TOTAL	CNT_CHILDREN	0.03
96	AMT_CREDIT	SK_ID_CURR	0.00
98	AMT_CREDIT	CNT_CHILDREN	0.00

#Sorting the correlation values

```
corrdf.sort_values(by = 'Correlation', ascending = False).head(10)
```

	VAR1	VAR2	Correlation
398	OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	1.00
148	AMT_GOODS_PRICE	AMT_CREDIT	0.99
423	DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.86
149	AMT_GOODS_PRICE	AMT_ANNUITY	0.78
124	AMT_ANNUITY	AMT_CREDIT	0.77
224	DAYS_EMPLOYED	DAYS_BIRTH	0.63
123	AMT_ANNUITY	AMT_INCOME_TOTAL	0.42
147	AMT_GOODS_PRICE	AMT_INCOME_TOTAL	0.35
194	DAYS_BIRTH	CNT_CHILDREN	0.34
99	AMT_CREDIT	AMT_INCOME_TOTAL	0.34

We can see that for Target_0 dataframe, Social circle for 30 days and 60 days are most correlated and Goods price and Loan amount credit are highly correlated. Then we have Goods price and amount annuity on 4th place

#For target_1 dataframe we perform the same operations to find correlation

```
corr = target_1.corr()
```

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

```
corrdf = corr.unstack().reset_index()
```

```
corrdf.columns = ['VAR1', 'VAR2', 'Correlation']
```

```
corrdf.dropna(subset = ['Correlation'], inplace = True)
```

```
corrdf['Correlation'] = round(corrdf['Correlation'], 2)
```

Since we see correlation as an absolute value, we are converting it into absolute value

```
corrdf['Correlation_abs'] =
```

```
corrdf['Correlation'].abs()
```

```
corrdf.sort_values(by = 'Correlation', ascending = False).head(10)
```

	VAR1	VAR2	Correlation
398	OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	1.00
148	AMT_GOODS_PRICE	AMT_CREDIT	0.98
423	DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.87
124	AMT_ANNUITY	AMT_CREDIT	0.75
149	AMT_GOODS_PRICE	AMT_ANNUITY	0.75
224	DAYS_EMPLOYED	DAYS_BIRTH	0.58
399	OBS_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.34

374	DEF_30_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.33
248	DAYS_REGISTRATION	DAYS_BIRTH	0.29
422	DEF_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.26

From the observation above we can say that for target_1 dataframe Goods price and loan credit amount are most correlated next to social circle observations for different days. So the variables correlated in target_0 dataframe and target_1 dataframe are same with slightly varying correlation values

Bivariate Analysis for target 0 and target 1

Income vs Credit, Goods price vs Credit

#Scatter plot for numeric columns

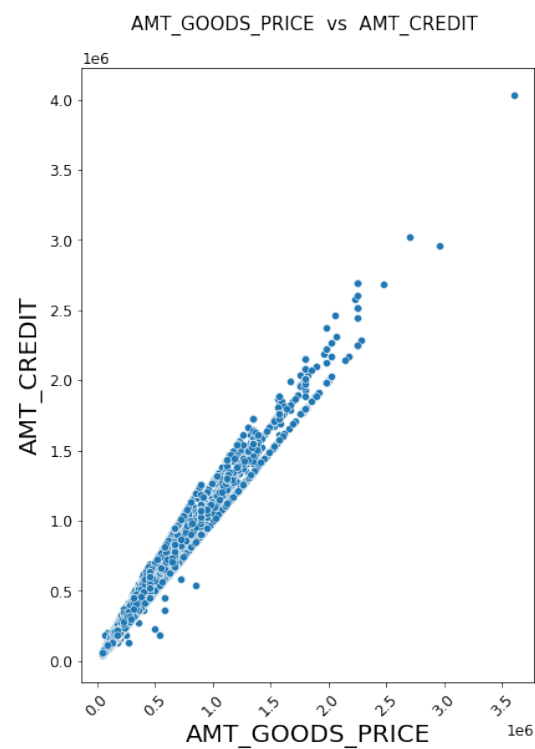
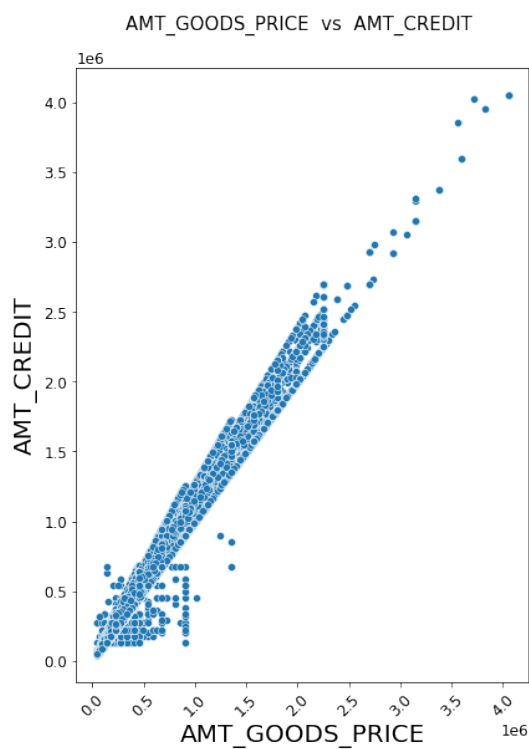
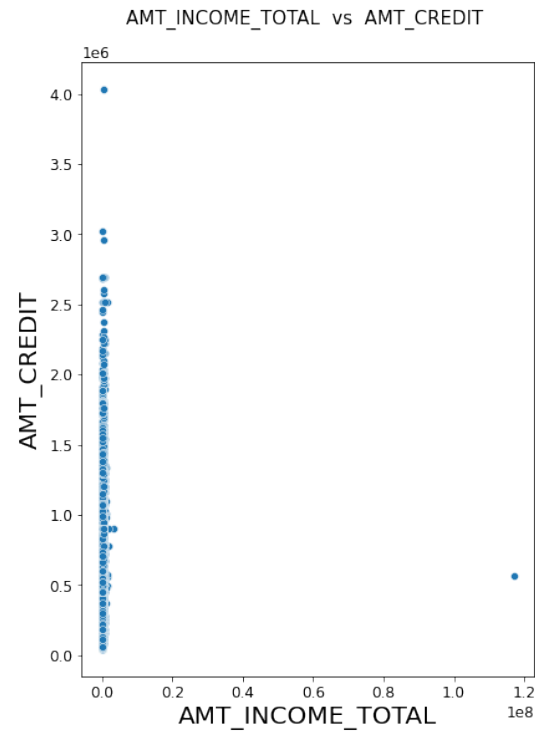
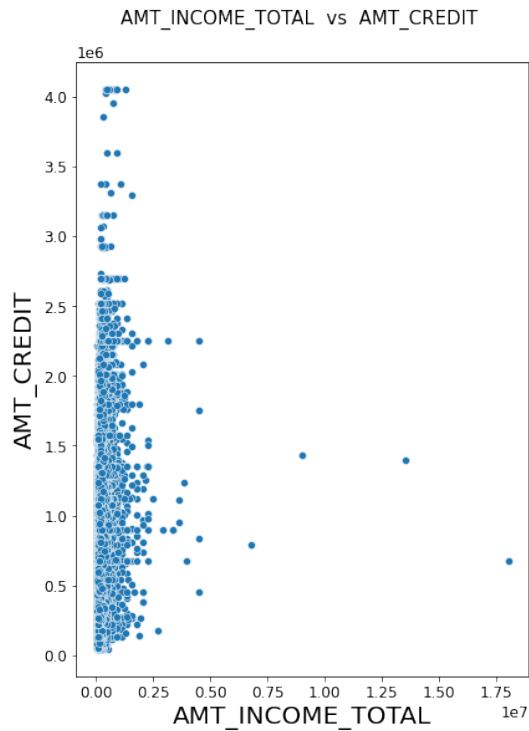
```
plt.figure(figsize = (15, 20))
plt.subplots_adjust(wspace=0.3)
```

```
plt.subplot(2,2,1)
sns.scatterplot(target_0.AMT_INCOME_TOTAL,target_0.AMT_CREDIT)
plt.xlabel('AMT_INCOME_TOTAL')
plt.ylabel('AMT_CREDIT')
plt.title('AMT_INCOME_TOTAL vs AMT_CREDIT ')
```

```
plt.subplot(2,2,2)
sns.scatterplot(target_1.AMT_INCOME_TOTAL,target_1.AMT_CREDIT)
plt.xlabel('AMT_INCOME_TOTAL')
plt.ylabel('AMT_CREDIT')
plt.title('AMT_INCOME_TOTAL vs AMT_CREDIT ')
```

```
plt.subplot(2,2,3)
sns.scatterplot(target_0.AMT_GOODS_PRICE,target_0.AMT_CREDIT)
plt.xlabel('AMT_GOODS_PRICE')
plt.ylabel('AMT_CREDIT')
plt.title('AMT_GOODS_PRICE vs AMT_CREDIT ')
plt.xticks(rotation = 45)
```

```
plt.subplot(2,2,4)
sns.scatterplot(target_1.AMT_GOODS_PRICE,target_1.AMT_CREDIT)
plt.xlabel('AMT_GOODS_PRICE')
plt.ylabel('AMT_CREDIT')
plt.title('AMT_GOODS_PRICE vs AMT_CREDIT ')
plt.xticks(rotation = 45)
plt.show()
```



Those who have paid the loan amount on/within time are more likely to get higher credits than those who didn't pay/did late payments. People who have higher goods price and have made payments on time have higher credits than those with higher goods price but didn't pay loan.

Numerical categorical analysis

Income range- Gender

```
# Numeric variable analysis for target_0 & target_1 dataframe
```

```
plt.figure(figsize = (15, 8))
```

```
plt.subplot(2, 2, 1)
```

```
plt.title('Target_0:Income Range b/w Male and Female')
```

```
sns.countplot(x='AMT_INCOME_RANGE', hue='CODE_GENDER', data=target_0,  
palette='rocket')
```

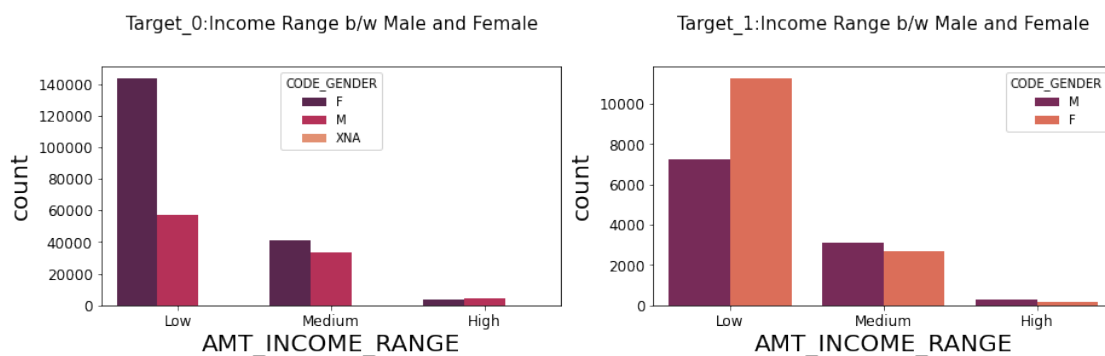
```
# subplot 2
```

```
plt.subplot(2, 2, 2)
```

```
plt.title('Target_1:Income Range b/w Male and Female')
```

```
sns.countplot(x='AMT_INCOME_RANGE', hue='CODE_GENDER',  
data=target_1,palette='rocket')
```

```
plt.show()
```



We can see that Females with low income don't have any payment issues.

Credit amount vs Education Status

```
# Box plotting for Credit amount
```

```
plt.figure(figsize=(15,10))
```

```
plt.subplots_adjust(wspace=0.3)
```

```
plt.subplot(121)
```

```
sns.boxplot(data =target_0, x='NAME_EDUCATION_TYPE',y='AMT_CREDIT',  
hue ='NAME_FAMILY_STATUS',orient='v']')
```

```
plt.title('Credit amount vs Education Status')
```

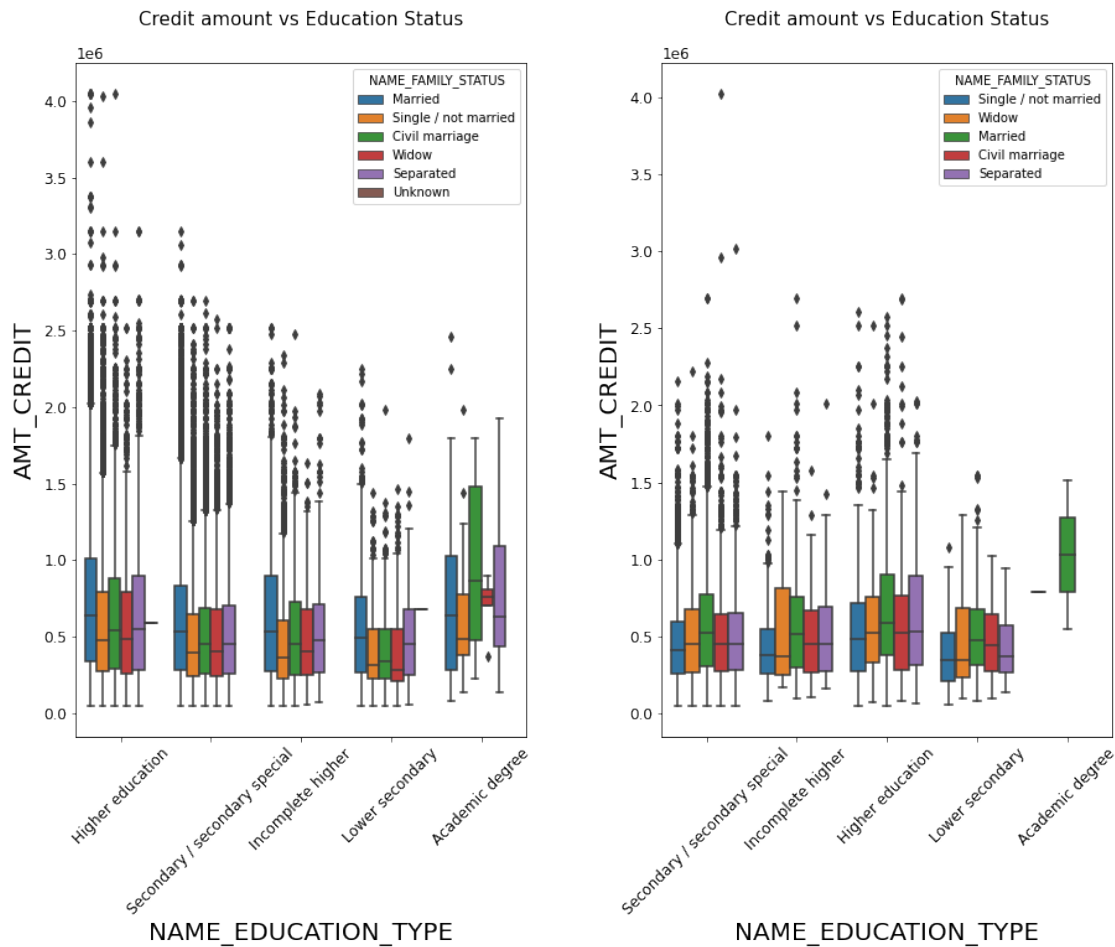
```
plt.xticks(rotation=45)
```

```
plt.subplot(122)
```

```
sns.boxplot(data =target_1, x='NAME_EDUCATION_TYPE',y='AMT_CREDIT',  
hue ='NAME_FAMILY_STATUS',orient='v']')
```



```
plt.title('Credit amount vs Education Status')
plt.xticks(rotation=45)
plt.show()
```



From the above plot, we can see that

1. Some of the highly educated, married persons are having credits higher than those who have done lower secondary education.
2. Those with higher education have higher credits and are more likely to make payments on time.
3. More number of outliers are seen in higher education.
4. The people with secondary and secondary special education are less likely to make payments on time.

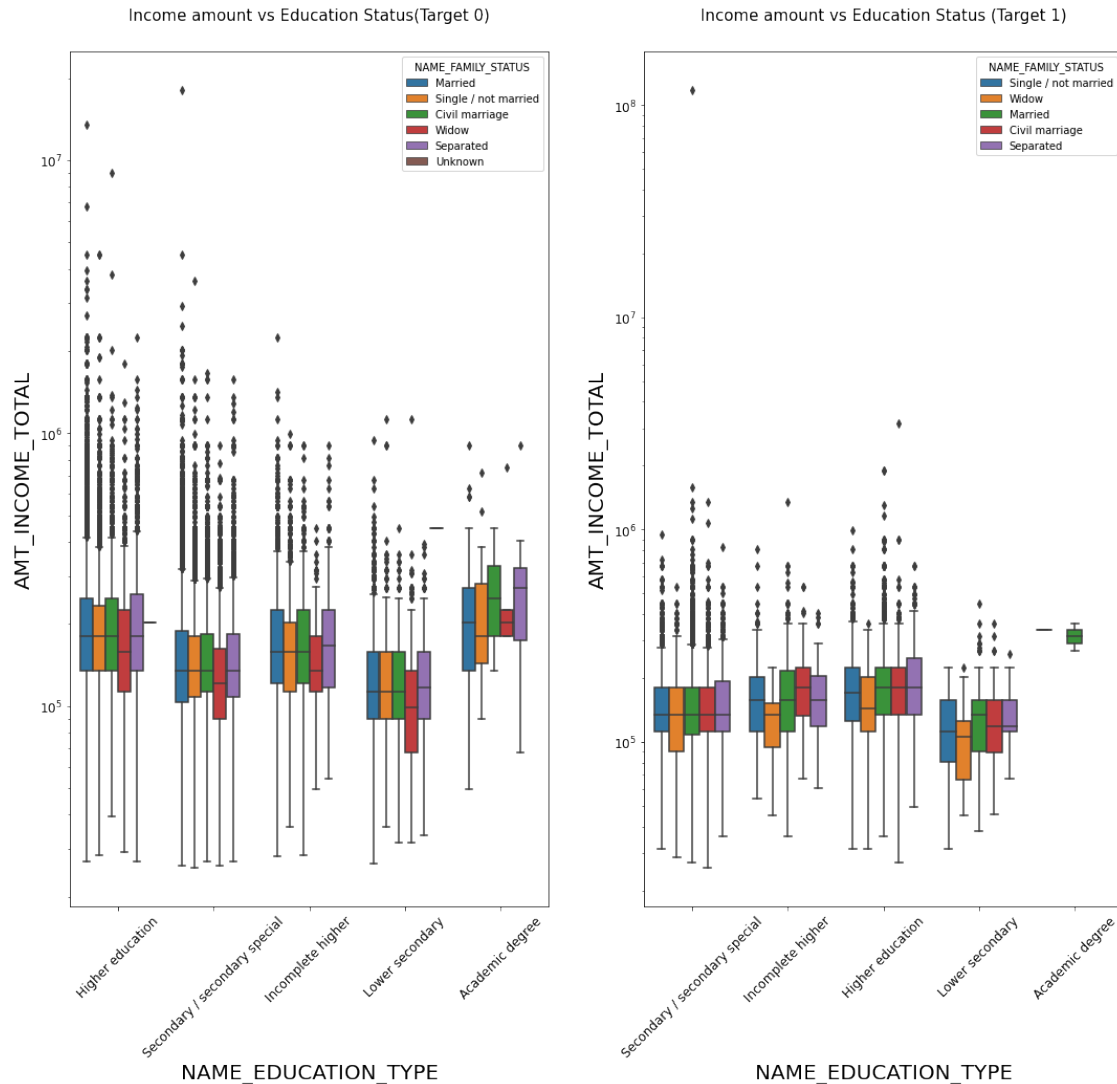
Income vs Education Status

Box plotting for Income amount in logarithmic scale

```
plt.figure(figsize=(18,15))
```

```
plt.subplot(1,2,1)
plt.yscale('log')
sns.boxplot(data =target_0,
x='NAME_EDUCATION_TYPE',y='AMT_INCOME_TOTAL', hue
='NAME_FAMILY_STATUS',orient='v')
plt.title('Income amount vs Education Status(Target 0)')
plt.xticks(rotation=45)
```

```
plt.subplot(1,2,2)
plt.yscale('log')
sns.boxplot(data =target_1,
x='NAME_EDUCATION_TYPE',y='AMT_INCOME_TOTAL', hue
='NAME_FAMILY_STATUS',orient='v')
plt.title('Income amount vs Education Status (Target 1)')
plt.xticks(rotation=45)
plt.show()
```



From the above plots,

1. we can see that Higher education has many outliers.
2. People with higher education have higher income and don't have difficulties in making loan payment.
3. People with higher education who have lesser income are unable to pay the loan.

Hence we can conclude that, people with Higher income are most likely to make payments.

Reading the previous application

```
#Reading the data from file previous_application
df1=pd.read_csv("previous_application.csv")
df1.head()
```

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

	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE
WEEKDAY_APPR_PROCESS_START \			
0	17145.0	0.0	17145.0
SATURDAY			
1	679671.0	NaN	607500.0
THURSDAY			
2	136444.5	NaN	112500.0
TUESDAY			
3	470790.0	NaN	450000.0
MONDAY			
4	404055.0	NaN	337500.0
THURSDAY			

	HOUR_APPR_PROCESS_START	FLAG_LAST_APPL_PER_CONTRACT	\
0	15	Y	
1	11	Y	
2	11	Y	
3	7	Y	
4	9	Y	

	NFLAG_LAST_APPL_IN_DAY	RATE_DOWN_PAYMENT	RATE_INTEREST_PRIMARY	\
0	1	0.0	0.182832	
1	1	NaN	NaN	
2	1	NaN	NaN	
3	1	NaN	NaN	
4	1	NaN	NaN	

	RATE_INTEREST_PRIVILEGED	NAME_CASH_LOAN_PURPOSE
NAME_CONTRACT_STATUS \		
0	0.867336	XAP
Approved		
1	NaN	XNA
Approved		
2	NaN	XNA
Approved		
3	NaN	XNA
Approved		

4	NaN	Repairs
Refused		

DAYS_DECISION	NAME_PAYMENT_TYPE	CODE_REJECT_REASON
NAME_TYPE_SUITE \		
0	-73 Cash through the bank	XAP
NaN		
1	-164 XNA	XAP
Unaccompanied		
2	-301 Cash through the bank	XAP Spouse,
partner		
3	-512 Cash through the bank	XAP
NaN		
4	-781 Cash through the bank	HC
NaN		

NAME_CLIENT_TYPE	NAME_GOODS_CATEGORY	NAME_PORTFOLIO
NAME_PRODUCT_TYPE \		
0	Repeater Mobile	POS
XNA		
1	Repeater XNA	Cash x-
sell		
2	Repeater XNA	Cash x-
sell		
3	Repeater XNA	Cash x-
sell		
4	Repeater XNA	Cash walk-
in		

CHANNEL_TYPE	SELLERPLACE_AREA	NAME_SELLER_INDUSTRY \
0	Country-wide	35 Connectivity
1	Contact center	-1 XNA
2	Credit and cash offices	-1 XNA
3	Credit and cash offices	-1 XNA
4	Credit and cash offices	-1 XNA

CNT_PAYMENT	NAME_YIELD_GROUP	PRODUCT_COMBINATION
DAYS_FIRST_DRAWING \		
0	12.0 middle	POS mobile with interest
365243.0		
1	36.0 low_action	Cash X-Sell: low
365243.0		
2	12.0 high	Cash X-Sell: high
365243.0		
3	12.0 middle	Cash X-Sell: middle
365243.0		
4	24.0 high	Cash Street: high
NaN		

DAYS_FIRST_DUE	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE
----------------	---------------------------	---------------

DAYS_TERMINATION	\		
0	-42.0	300.0	-42.0
-37.0			
1	-134.0	916.0	365243.0
365243.0			
2	-271.0	59.0	365243.0
365243.0			
3	-482.0	-152.0	-182.0
-177.0			
4	NaN	NaN	NaN
NaN			

NFLAG_INSURED_ON_APPROVAL	
0	0.0
1	1.0
2	1.0
3	1.0
4	NaN

Removing the column values of 'XNA' and 'XAP'

```
df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XNA'].index)
df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XNA'].index)
df1=df1.drop(df1[df1['NAME_CASH_LOAN_PURPOSE']=='XAP'].index)
```

#Merge the previous application with the current application data file

```
merged_df= pd.merge(df, df1, how='inner',
on='SK_ID_CURR',suffixes='_x')
merged_df.head()
```

SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	\
0	100034	0	Revolving loans	M	N
1	100035	0	Cash loans	F	N
2	100039	0	Cash loans	M	Y
3	100046	0	Revolving loans	M	Y
4	100046	0	Revolving loans	M	Y

FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT_
AMT_ANNUIITY_ \			
0	Y	0	90000.0
9000.0			
1	Y	0	292500.0
24592.5			
2	N	1	360000.0
39069.0			
3	Y	0	180000.0
27000.0			
4	Y	0	180000.0
27000.0			

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	180000.0	Unaccompanied	Working	
1	477000.0	Unaccompanied	Commercial associate	
2	679500.0	Unaccompanied	Commercial associate	
3	540000.0	Unaccompanied	Working	
4	540000.0	Unaccompanied	Working	

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	\
0	Higher education	Single / not married	With parents	
1	Secondary / secondary special apartment	Civil marriage	House /	
2	Secondary / secondary special apartment	Married	House /	
3	Higher education apartment	Married	House /	
4	Higher education apartment	Married	House /	

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	\
0	0.030755	10341	1010	4799.0	
1	0.025164	15280	2668	5266.0	
2	0.015221	11694	2060	3557.0	
3	0.025164	16126	1761	8236.0	
4	0.025164	16126	1761	8236.0	

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START	\
0	3015	Laborers	TUESDAY	
1	3787	NaN	WEDNESDAY	
2	3557	Drivers	THURSDAY	
3	4292	Managers	TUESDAY	
4	4292	Managers	TUESDAY	

	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	16	0	0	
1	13	0	0	
2	10	0	0	
3	8	0	0	
4	8	0	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	

2	0	0
3	0	0
4	0	0

REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY \
------------------------	------------------------	---------------------------

0	0	0
0		
1	0	0
0		
2	1	1
0		
3	0	0
0		
4	0	0
0		

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE \
0	Business Entity Type 3	0.502779	0.0
1	Business Entity Type 3	0.479987	0.0
2	Self-employed	0.321745	2.0
3	Business Entity Type 3	0.738053	1.0
4	Business Entity Type 3	0.738053	1.0

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE \
0	0.0	0.0
1	0.0	0.0
2	0.0	2.0
3	0.0	1.0
4	0.0	1.0

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR \
0	0.0	NaN
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	NaN	NaN
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	NaN	NaN
1	1.0	0.0
2	0.0	1.0
3	1.0	0.0

4	1.0	0.0
---	-----	-----

AMT_REQ_CREDIT_BUREAU_YEAR	AMT_CREDIT_RANGE	AMT_INCOME_RANGE
AGE_RANGE \		
0	NaN	Low
20-30		
1	5.0	Medium
40-50		
2	1.0	High
30-40		
3	1.0	Medium
40-50		
4	1.0	Medium
40-50		

SK_ID_PREV	NAME_CONTRACT_TYPEx	AMT_ANNUITYx	AMT_APPLICATION
AMT_CREDITx \			
0	1390369	Cash loans	22430.430
109971.0			
1	1344613	Cash loans	33238.800
1260000.0			
2	1077565	Cash loans	52513.515
1487214.0			
3	1223113	Cash loans	28390.635
407911.5			
4	1529558	Cash loans	29053.215
555723.0			

AMT_DOWN_PAYMENT	AMT_GOODS_PRICEx	WEEKDAY_APPR_PROCESS_STARTx \
0	NaN	94500.0
1	NaN	1260000.0
2	NaN	1350000.0
3	NaN	337500.0
4	NaN	450000.0

HOUR_APPR_PROCESS_STARTx	FLAG_LAST_APPL_PER_CONTRACT \
0	11
1	14
2	14
3	13
4	15

NFLAG_LAST_APPL_IN_DAY	RATE_DOWN_PAYMENT	RATE_INTEREST_PRIMARY \
0	1	NaN
1	1	NaN
2	1	NaN
3	1	NaN
4	1	NaN

RATE_INTEREST_PRIVILEGED	NAME_CASH_LOAN_PURPOSE
--------------------------	------------------------

NAME_CONTRACT_STATUS	\	
0	NaN	Other
Approved		
1	NaN	Payments on other loans
Refused		
2	NaN	Buying a used car
Approved		
3	NaN	Repairs
Approved		
4	NaN	Repairs
Refused		

DAYS_DECISION	NAME_PAYMENT_TYPE	CODE_REJECT_REASON
NAME_TYPE_SUITE	\	
0	-599	Cash through the bank
NaN		XAP
1	-119	Cash through the bank
Unaccompanied		HC
2	-695	Cash through the bank
Unaccompanied		XAP
3	-539	Cash through the bank
Unaccompanied		XAP
4	-449	Cash through the bank
NaN		LIMIT

NAME_CLIENT_TYPE	NAME_GOODS_CATEGORY	NAME_PORTFOLIO	
NAME_PRODUCT_TYPE	\		
0	New	XNA	Cash
in			walk-
1	Repeater	XNA	Cash
in			walk-
2	Refreshed	XNA	Cash
in			walk-
3	New	XNA	Cash
in			walk-
4	Repeater	XNA	Cash
in			walk-

CHANNEL_TYPE	SELLERPLACE_AREA	
NAME_SELLER_INDUSTRY	\	
0	Credit and cash offices	-1
		XNA
1	Credit and cash offices	-1
		XNA
2	Channel of corporate sales	-1
		XNA
3	Credit and cash offices	-1
		XNA
4	Credit and cash offices	-1
		XNA

	CNT_PAYMENT	NAME_YIELD_GROUP	PRODUCT_COMBINATION
DAYS_FIRST_DRAWING \			
0	6.0	high	Cash Street: high
365243.0			
1	60.0	low_action	Cash Street: low
NaN			
2	42.0	low_normal	Cash Street: low
365243.0			
3	18.0	low_normal	Cash Street: low
365243.0			
4	24.0	low_normal	Cash Street: low
NaN			

	DAYS_FIRST_DUE	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE
DAYS_TERMINATION \			
0	-569.0	-419.0	-449.0
-443.0			
1	NaN	NaN	NaN
NaN			
2	-665.0	565.0	-455.0
-446.0			
3	-509.0	1.0	365243.0
365243.0			
4	NaN	NaN	NaN
NaN			

	NFLAG_INSURED_ON_APPROVAL
0	1.0
1	NaN
2	1.0
3	1.0
4	NaN

Renaming the column names after merging

```
new_df = merged_df.rename({'NAME_CONTRACT_TYPE_' :
'NAME_CONTRACT_TYPE', 'AMT_CREDIT_' : 'AMT_CREDIT', 'AMT_ANNUITY_' : 'AMT_ANNUITY',
'WEEKDAY_APPR_PROCESS_START_' :
'WEEKDAY_APPR_PROCESS_START',
'HOUR_APPR_PROCESS_START_' : 'HOUR_APPR_PROCESS_START', 'NAME_CONTRACT_TY
PEx' : 'NAME_CONTRACT_TYPE_PREV',
'AMT_CREDITx' : 'AMT_CREDIT_PREV', 'AMT_ANNUITYx' : 'AMT_ANNUITY_PREV',
'WEEKDAY_APPR_PROCESS_STARTx' : 'WEEKDAY_APPR_PROCESS_START_PREV',
```

```
'HOUR_APPR_PROCESS_STARTx': 'HOUR_APPR_PROCESS_START_PREV'}', axis=1)
new_df.head()
```

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	\
0	100034	0	Revolving loans	M	N	
1	100035	0	Cash loans	F	N	
2	100039	0	Cash loans	M	Y	
3	100046	0	Revolving loans	M	Y	
4	100046	0	Revolving loans	M	Y	

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
0	Y	0	90000.0	180000.0
1	Y	0	292500.0	665892.0
2	N	1	360000.0	733315.5
3	Y	0	180000.0	540000.0
4	Y	0	180000.0	540000.0

	AMT_GOODS_PRICE	NAME_TYPE_SUITE	NAME_INCOME_TYPE	\
0	180000.0	Unaccompanied	Working	
1	477000.0	Unaccompanied	Commercial associate	
2	679500.0	Unaccompanied	Commercial associate	
3	540000.0	Unaccompanied	Working	
4	540000.0	Unaccompanied	Working	

	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS
0	Higher education	Single / not married
1	Secondary / secondary special	Civil marriage
2	Secondary / secondary special	Married
3	Higher education	Married
4	Higher education	Married

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED
0	0.030755	10341	1010
1	0.025164	15280	2668

2	0.015221	11694	2060
3557.0			
3	0.025164	16126	1761
8236.0			
4	0.025164	16126	1761
8236.0			

	DAYS_ID_PUBLISH	OCCUPATION_TYPE	WEEKDAY_APPR_PROCESS_START	\
0	3015	Laborers	TUESDAY	
1	3787	NaN	WEDNESDAY	
2	3557	Drivers	THURSDAY	
3	4292	Managers	TUESDAY	
4	4292	Managers	TUESDAY	

	HOURL_APPR_PROCESS_START	REG_REGION_NOT_LIVE_REGION	\
0	16	0	
1	13	0	
2	10	0	
3	8	0	
4	8	0	

	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	

	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	\
0	0	0		
0				
1	0	0		
0				
2	1	1		
0				
3	0	0		
0				
4	0	0		
0				

	ORGANIZATION_TYPE	EXT_SOURCE_2	OBS_30_CNT_SOCIAL_CIRCLE	\
0	Business Entity Type 3	0.502779	0.0	
1	Business Entity Type 3	0.479987	0.0	
2	Self-employed	0.321745	2.0	
3	Business Entity Type 3	0.738053	1.0	
4	Business Entity Type 3	0.738053	1.0	

	DEF_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	\
0	0.0	0.0	

1	0.0	0.0
2	0.0	2.0
3	0.0	1.0
4	0.0	1.0

	DEF_60_CNT_SOCIAL_CIRCLE	AMT_REQ_CREDIT_BUREAU_HOUR \
0	0.0	NaN
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_DAY	AMT_REQ_CREDIT_BUREAU_WEEK \
0	NaN	NaN
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_MON	AMT_REQ_CREDIT_BUREAU_QRT \
0	NaN	NaN
1	1.0	0.0
2	0.0	1.0
3	1.0	0.0
4	1.0	0.0

	AMT_REQ_CREDIT_BUREAU_YEAR	AMT_CREDIT_RANGE	AMT_INCOME_RANGE
AGE_RANGE \			
0	NaN	Low	Low
20-30			
1	5.0	Medium	Medium
40-50			
2	1.0	High	Medium
30-40			
3	1.0	Medium	Low
40-50			
4	1.0	Medium	Low
40-50			

	SK_ID_PREV	NAME_CONTRACT_TYPE_PREV	AMT_ANNUITY_PREV
AMT_APPLICATION \			
0	1390369	Cash loans	22430.430
94500.0			
1	1344613	Cash loans	33238.800
1260000.0			
2	1077565	Cash loans	52513.515
1350000.0			
3	1223113	Cash loans	28390.635
337500.0			
4	1529558	Cash loans	29053.215

450000.0

	AMT_CREDIT_PREV	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	\
0	109971.0	NaN	94500.0	
1	1260000.0	NaN	1260000.0	
2	1487214.0	NaN	1350000.0	
3	407911.5	NaN	337500.0	
4	555723.0	NaN	450000.0	

	WEEKDAY_APPR_PROCESS_START	PREV	HOUR_APPR_PROCESS_START	PREV	\
0		FRIDAY			11
1		WEDNESDAY			14
2		MONDAY			14
3		MONDAY			13
4		MONDAY			15

	FLAG_LAST_APPL_PER_CONTRACT	NFLAG_LAST_APPL_IN_DAY
0	Y	1
NaN		
1	Y	1
NaN		
2	Y	1
NaN		
3	Y	1
NaN		
4	Y	1
NaN		

	RATE_INTEREST_PRIMARY	RATE_INTEREST_PRIVILEGED
0	NaN	NaN
Other		
1	NaN	NaN Payments on other
loans		
2	NaN	NaN Buying a
used car		
3	NaN	NaN
Repairs		
4	NaN	NaN
Repairs		

	NAME_CONTRACT_STATUS	DAYS_DECISION	NAME_PAYMENT_TYPE	\
0	Approved	-599	Cash through the bank	
1	Refused	-119	Cash through the bank	
2	Approved	-695	Cash through the bank	
3	Approved	-539	Cash through the bank	
4	Refused	-449	Cash through the bank	

CODE_REJECT_REASON NAME_TYPE_SUITE NAME_CLIENT_TYPE

NAME_GOODS_CATEGORY \

0	XAP	NaN	New
XNA			
1	HC	Unaccompanied	Repeater
XNA			
2	XAP	Unaccompanied	Refreshed
XNA			
3	XAP	Unaccompanied	New
XNA			
4	LIMIT	NaN	Repeater
XNA			

NAME_PORTFOLIO NAME_PRODUCT_TYPE CHANNEL_TYPE \

0	Cash	walk-in	Credit and cash offices
1	Cash	walk-in	Credit and cash offices
2	Cash	walk-in	Channel of corporate sales
3	Cash	walk-in	Credit and cash offices
4	Cash	walk-in	Credit and cash offices

SELLERPLACE_AREA NAME_SELLER_INDUSTRY CNT_PAYMENT NAME_YIELD_GROUP

\				
0	-1	XNA	6.0	high
1	-1	XNA	60.0	low_action
2	-1	XNA	42.0	low_normal
3	-1	XNA	18.0	low_normal
4	-1	XNA	24.0	low_normal

PRODUCT_COMBINATION DAYS_FIRST_DRAWING DAYS_FIRST_DUE \

0	Cash Street: high	365243.0	-569.0
1	Cash Street: low	NaN	NaN
2	Cash Street: low	365243.0	-665.0
3	Cash Street: low	365243.0	-509.0
4	Cash Street: low	NaN	NaN

DAYS_LAST_DUE_1ST_VERSION DAYS_LAST_DUE DAYS_TERMINATION \

0	-419.0	-449.0	-443.0
1	NaN	NaN	NaN
2	565.0	-455.0	-446.0
3	1.0	365243.0	365243.0
4	NaN	NaN	NaN

NFLAG_INSURED_ON_APPROVAL

0	1.0
1	NaN


```
2          1.0
3          1.0
4          NaN
```

Removing unwanted columns for analysis

```
new_df.drop(['SK_ID_CURR','WEEKDAY_APPR_PROCESS_START',
'HOURL_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','WEEKDAY_APPR_PROCESS_START_PREV',
'HOURL_APPR_PROCESS_START_PREV',
'FLAG_LAST_APPL_PER_CONTRACT','NFLAG_LAST_APPL_IN_DAY'],axis=1,inplace
=True)
```

```
new_df.head()
```

	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
0	0	Revolving loans	M	N	Y
1	0	Cash loans	F	N	Y
2	0	Cash loans	M	Y	N
3	0	Revolving loans	M	Y	Y
4	0	Revolving loans	M	Y	Y

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
0	0	90000.0	180000.0	9000.0
1	0	292500.0	665892.0	24592.5
2	1	360000.0	733315.5	39069.0
3	0	180000.0	540000.0	27000.0
4	0	180000.0	540000.0	27000.0

	NAME_TYPE_SUITE	NAME_INCOME_TYPE
0	Unaccompanied education	Working
1	Unaccompanied	Commercial associate Secondary / secondary

special
2 Unaccompanied Commercial associate Secondary / secondary
special
3 Unaccompanied Working Higher
education
4 Unaccompanied Working Higher
education

	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	REGION_POPULATION_RELATIVE
\			
0	Single / not married	With parents	0.030755
1	Civil marriage	House / apartment	0.025164
2	Married	House / apartment	0.015221
3	Married	House / apartment	0.025164
4	Married	House / apartment	0.025164

	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	DAYS_ID_PUBLISH	\
0	10341	1010	4799.0	3015	
1	15280	2668	5266.0	3787	
2	11694	2060	3557.0	3557	
3	16126	1761	8236.0	4292	
4	16126	1761	8236.0	4292	

	OCCUPATION_TYPE	ORGANIZATION_TYPE	EXT_SOURCE_2	\
0	Laborers	Business Entity Type 3	0.502779	
1	NaN	Business Entity Type 3	0.479987	
2	Drivers	Self-employed	0.321745	
3	Managers	Business Entity Type 3	0.738053	
4	Managers	Business Entity Type 3	0.738053	

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	\
0	0.0	0.0	
1	0.0	0.0	
2	2.0	0.0	
3	1.0	0.0	
4	1.0	0.0	

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	\
0	0.0	0.0	
1	0.0	0.0	
2	2.0	0.0	
3	1.0	0.0	
4	1.0	0.0	

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY \
0	NaN	NaN
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
0	NaN	NaN
1	0.0	1.0
2	0.0	0.0
3	0.0	1.0
4	0.0	1.0

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
AMT_CREDIT_RANGE \		
0	NaN	NaN
Low		
1	0.0	5.0
Medium		
2	1.0	1.0
High		
3	0.0	1.0
Medium		
4	0.0	1.0
Medium		

	AMT_INCOME_RANGE	AGE_RANGE	SK_ID_PREV	NAME_CONTRACT_TYPE_PREV \
0	Low	20-30	1390369	Cash loans
1	Medium	40-50	1344613	Cash loans
2	Medium	30-40	1077565	Cash loans
3	Low	40-50	1223113	Cash loans
4	Low	40-50	1529558	Cash loans

	AMT_ANNUITY_PREV	AMT_APPLICATION	AMT_CREDIT_PREV
AMT_DOWN_PAYMENT \			
0	22430.430	94500.0	109971.0
NaN			
1	33238.800	1260000.0	1260000.0
NaN			
2	52513.515	1350000.0	1487214.0
NaN			
3	28390.635	337500.0	407911.5
NaN			
4	29053.215	450000.0	555723.0
NaN			

	AMT_GOODS_PRICEx	RATE_DOWN_PAYMENT	RATE_INTEREST_PRIMARY \
0	94500.0	NaN	NaN
1	1260000.0	NaN	NaN

2	1350000.0	NaN	NaN
3	337500.0	NaN	NaN
4	450000.0	NaN	NaN

RATE_INTEREST_PRIVILEGED	NAME_CASH_LOAN_PURPOSE
NAME_CONTRACT_STATUS \	
0	NaN Other
Approved	
1	NaN Payments on other loans
Refused	
2	NaN Buying a used car
Approved	
3	NaN Repairs
Approved	
4	NaN Repairs
Refused	

DAYS_DECISION	NAME_PAYMENT_TYPE	CODE_REJECT_REASON
NAME_TYPE_SUITE \		
0	-599 Cash through the bank	XAP
NaN		
1	-119 Cash through the bank	HC
Unaccompanied		
2	-695 Cash through the bank	XAP
Unaccompanied		
3	-539 Cash through the bank	XAP
Unaccompanied		
4	-449 Cash through the bank	LIMIT
NaN		

NAME_CLIENT_TYPE	NAME_GOODS_CATEGORY	NAME_PORTFOLIO
NAME_PRODUCT_TYPE \		
0	New	XNA Cash walk-
in		
1	Repeater	XNA Cash walk-
in		
2	Refreshed	XNA Cash walk-
in		
3	New	XNA Cash walk-
in		
4	Repeater	XNA Cash walk-
in		

CHANNEL_TYPE	SELLERPLACE_AREA
NAME_SELLER_INDUSTRY \	
0	Credit and cash offices -1 XNA
1	Credit and cash offices -1 XNA
2	Channel of corporate sales -1 XNA

3	Credit and cash offices	-1	XNA
4	Credit and cash offices	-1	XNA

CNT_PAYMENT	NAME_YIELD_GROUP	PRODUCT_COMBINATION
DAYS_FIRST_DRAWING \		
0	6.0 high	Cash Street: high
365243.0		
1	60.0 low_action	Cash Street: low
NaN		
2	42.0 low_normal	Cash Street: low
365243.0		
3	18.0 low_normal	Cash Street: low
365243.0		
4	24.0 low_normal	Cash Street: low
NaN		

DAYS_FIRST_DUE	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE
DAYS_TERMINATION \		
0	-569.0	-419.0 -449.0
-443.0		
1	NaN	NaN NaN
NaN		
2	-665.0	565.0 -455.0
-446.0		
3	-509.0	1.0 365243.0
365243.0		
4	NaN	NaN NaN
NaN		

NFLAG_INSURED_ON_APPROVAL
0
1
2
3
4

new_df.head()

TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY
\				
0	0 Revolving loans	M	N	Y
1	0 Cash loans	F	N	Y
2	0 Cash loans	M	Y	N
3	0 Revolving loans	M	Y	Y

4	0	Revolving loans	M	Y	Y
---	---	-----------------	---	---	---

CNT_CHILDREN	AMT_GOODS_PRICE_ \	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
0	0	90000.0	180000.0	9000.0
1	0	292500.0	665892.0	24592.5
2	1	360000.0	733315.5	39069.0
3	0	180000.0	540000.0	27000.0
4	0	180000.0	540000.0	27000.0

NAME_TYPE_SUITE	NAME_EDUCATION_TYPE \	NAME_INCOME_TYPE
0	Unaccompanied education	Working Higher
1	Unaccompanied special	Commercial associate Secondary / secondary
2	Unaccompanied special	Commercial associate Secondary / secondary
3	Unaccompanied education	Working Higher
4	Unaccompanied education	Working Higher

NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	REGION_POPULATION_RELATIVE
0	Single / not married	With parents 0.030755
1	Civil marriage	House / apartment 0.025164
2	Married	House / apartment 0.015221
3	Married	House / apartment 0.025164
4	Married	House / apartment 0.025164

DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	DAYS_ID_PUBLISH \
0	10341	1010	4799.0 3015
1	15280	2668	5266.0 3787
2	11694	2060	3557.0 3557
3	16126	1761	8236.0 4292
4	16126	1761	8236.0 4292

	OCCUPATION_TYPE	ORGANIZATION_TYPE	EXT_SOURCE_2	\
0	Laborers	Business Entity Type 3	0.502779	
1	NaN	Business Entity Type 3	0.479987	
2	Drivers	Self-employed	0.321745	
3	Managers	Business Entity Type 3	0.738053	
4	Managers	Business Entity Type 3	0.738053	

	OBS_30_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	\
0	0.0	0.0	
1	0.0	0.0	
2	2.0	0.0	
3	1.0	0.0	
4	1.0	0.0	

	OBS_60_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	\
0	0.0	0.0	
1	0.0	0.0	
2	2.0	0.0	
3	1.0	0.0	
4	1.0	0.0	

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY	\
0	NaN	NaN	
1	0.0	0.0	
2	0.0	0.0	
3	0.0	0.0	
4	0.0	0.0	

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON	\
0	NaN	NaN	
1	0.0	1.0	
2	0.0	0.0	
3	0.0	1.0	
4	0.0	1.0	

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
0	NaN	NaN
Low		
1	0.0	5.0
Medium		
2	1.0	1.0
High		
3	0.0	1.0
Medium		
4	0.0	1.0
Medium		

	AMT_INCOME_RANGE	AGE_RANGE	SK_ID_PREV	NAME_CONTRACT	TYPE_PREV	\
0	Low	20-30	1390369		Cash loans	
1	Medium	40-50	1344613		Cash loans	
2	Medium	30-40	1077565		Cash loans	
3	Low	40-50	1223113		Cash loans	
4	Low	40-50	1529558		Cash loans	

	AMT_ANNUIITY_PREV	AMT_APPLICATION	AMT_CREDIT_PREV
AMT_DOWN_PAYMENT	\		
0	22430.430	94500.0	109971.0
NaN			
1	33238.800	1260000.0	1260000.0
NaN			
2	52513.515	1350000.0	1487214.0
NaN			
3	28390.635	337500.0	407911.5
NaN			
4	29053.215	450000.0	555723.0
NaN			

	AMT_GOODS_PRICE	RATE_DOWN_PAYMENT	RATE_INTEREST_PRIMARY	\
0	94500.0	NaN	NaN	
1	1260000.0	NaN	NaN	
2	1350000.0	NaN	NaN	
3	337500.0	NaN	NaN	
4	450000.0	NaN	NaN	

	RATE_INTEREST_PRIVILEGED	NAME_CASH_LOAN_PURPOSE
NAME_CONTRACT_STATUS	\	
0	NaN	Other
Approved		
1	NaN	Payments on other loans
Refused		
2	NaN	Buying a used car
Approved		
3	NaN	Repairs
Approved		
4	NaN	Repairs
Refused		

	DAYS_DECISION	NAME_PAYMENT_TYPE	CODE_REJECT_REASON
NAME_TYPE_SUITE	\		
0	-599	Cash through the bank	XAP
NaN			
1	-119	Cash through the bank	HC
Unaccompanied			
2	-695	Cash through the bank	XAP
Unaccompanied			
3	-539	Cash through the bank	XAP
Unaccompanied			

4	-449	Cash through the bank	LIMIT
NaN			

NAME_CLIENT_TYPE	NAME_GOODS_CATEGORY	NAME_PORTFOLIO	
NAME_PRODUCT_TYPE \			
0	New	XNA	Cash walk-
1	Repeater	XNA	Cash walk-
2	Refreshed	XNA	Cash walk-
3	New	XNA	Cash walk-
4	Repeater	XNA	Cash walk-

CHANNEL_TYPE	SELLERPLACE_AREA	
NAME_SELLER_INDUSTRY \		
0	Credit and cash offices	-1 XNA
1	Credit and cash offices	-1 XNA
2	Channel of corporate sales	-1 XNA
3	Credit and cash offices	-1 XNA
4	Credit and cash offices	-1 XNA

CNT_PAYMENT	NAME_YIELD_GROUP	PRODUCT_COMBINATION
DAYS_FIRST_DRAWING \		
0	6.0 high	Cash Street: high
1	60.0 low_action	Cash Street: low
2	42.0 low_normal	Cash Street: low
3	18.0 low_normal	Cash Street: low
4	24.0 low_normal	Cash Street: low

DAYS_FIRST_DUE	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE
DAYS_TERMINATION \		
0	-569.0	-419.0 -449.0
1	NaN	NaN NaN
2	-665.0	565.0 -455.0

-446.0			
3	-509.0	1.0	365243.0
365243.0			
4	NaN	NaN	NaN
NaN			

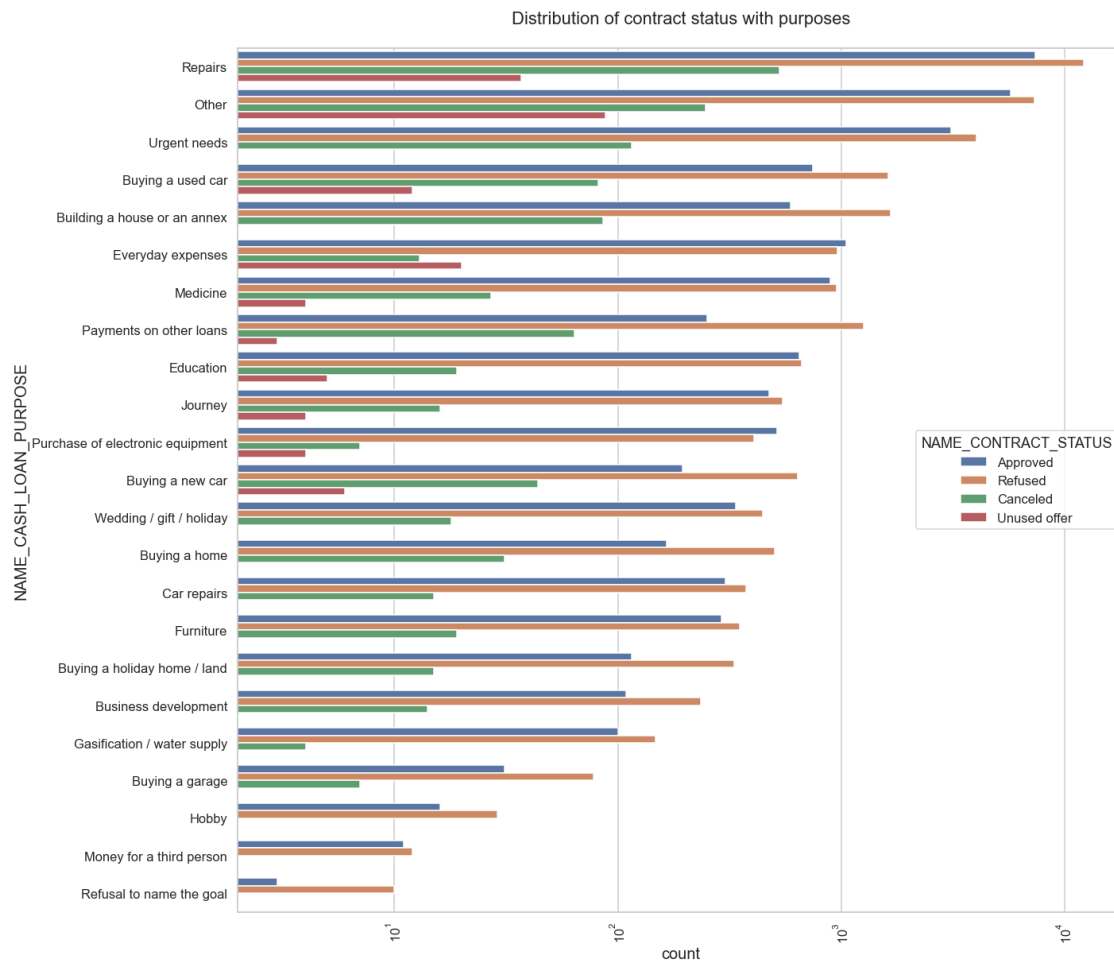
	NFLAG_INSURED_ON_APPROVAL
0	1.0
1	NaN
2	1.0
3	1.0
4	NaN

Univariate Analysis

Distribution of contract status in logarithmic scale

```
sns.set_style('whitegrid')
sns.set_context('talk')

plt.figure(figsize=(20,20))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30
plt.xticks(rotation=90)
plt.xscale('log')
plt.title('Distribution of contract status with purposes')
ax=sns.countplot(data = new_df, y='NAME_CASH_LOAN_PURPOSE',
order=new_df['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue =
'NAME_CONTRACT_STATUS',palette='deep')
```

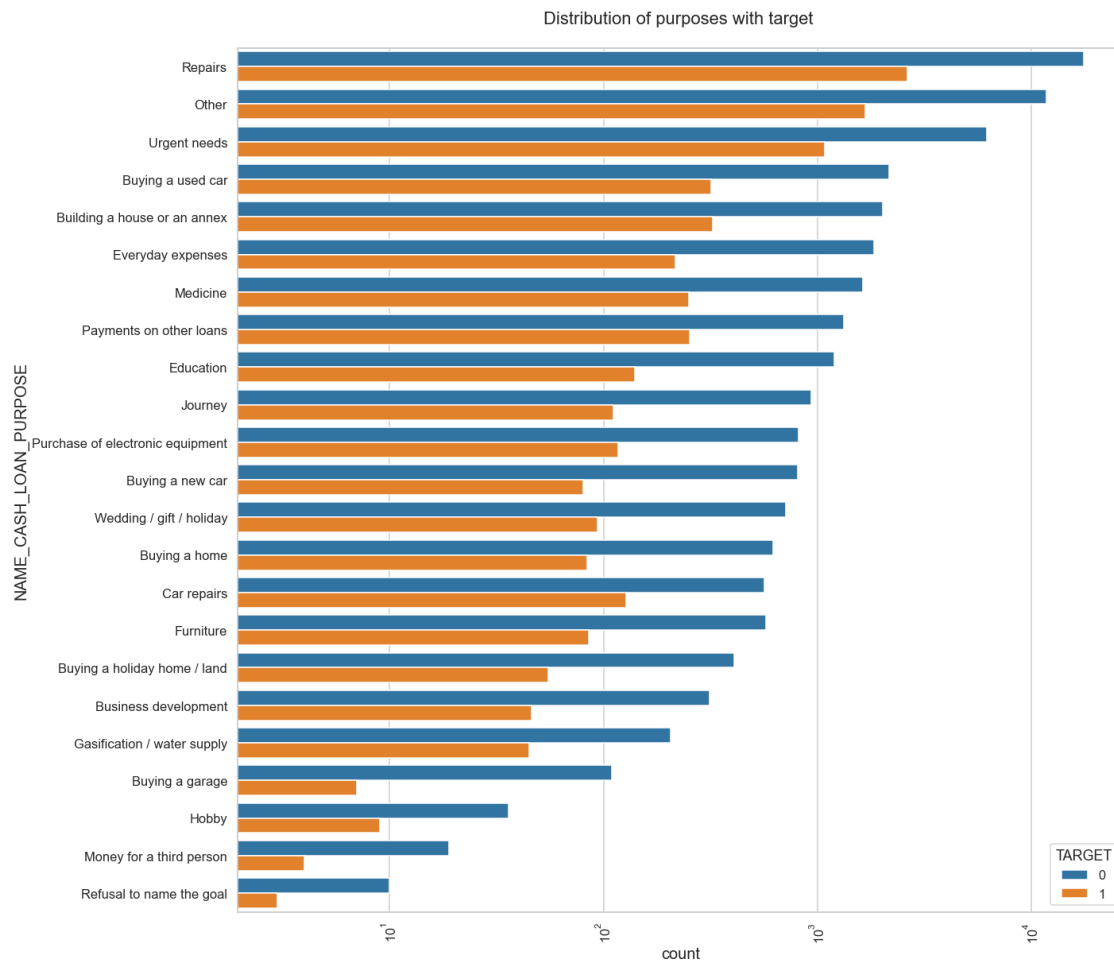


Points to be concluded from above plot: Most rejection of loans came from purpose 'Repairs'. For education purposes we have equal number of approves and rejection Paying other loans and buying a new car is having significant higher rejection than approves.

Distribution of contract status

```
sns.set_style('whitegrid')
sns.set_context('talk')

plt.figure(figsize=(20,20))
plt.rcParams["axes.labelsize"] = 20
plt.rcParams['axes.titlesize'] = 22
plt.rcParams['axes.titlepad'] = 30
plt.xticks(rotation=90)
plt.xscale('log')
plt.title('Distribution of purposes with target ')
ax = sns.countplot(data = new_df, y= 'NAME_CASH_LOAN_PURPOSE',
order=new_df['NAME_CASH_LOAN_PURPOSE'].value_counts().index,hue =
'TARGET')
```



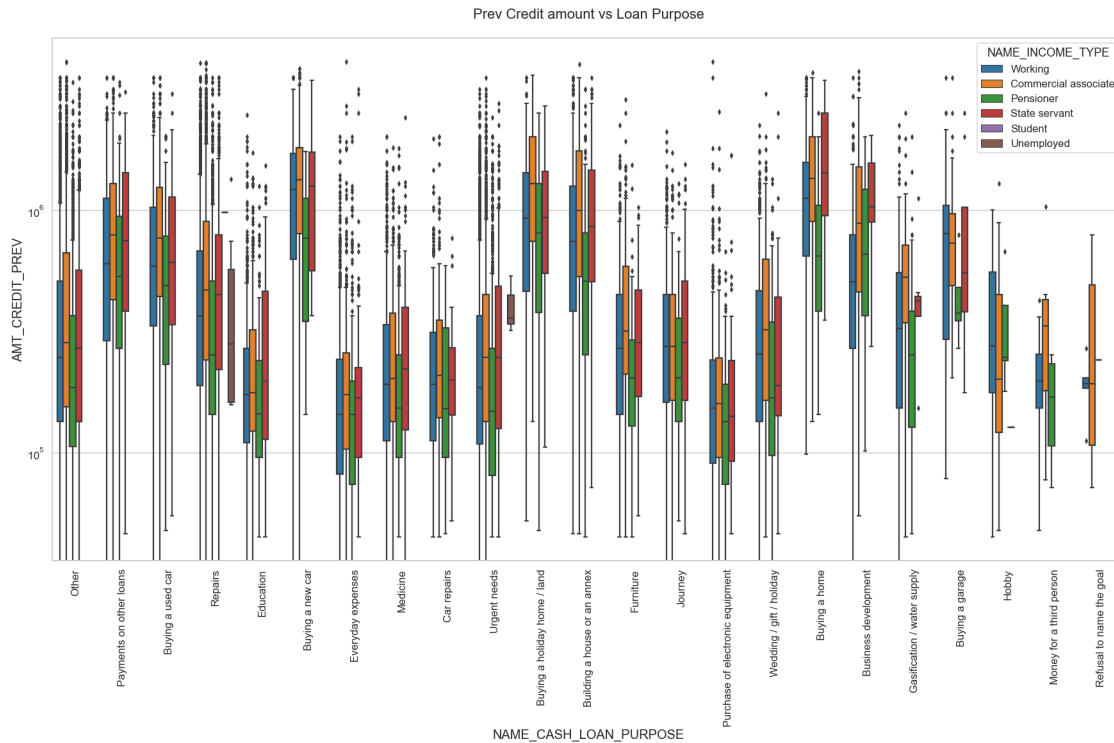
Few points we can conclude from above plot: Loan purposes with 'Repairs' are facing more difficulties in payment on time. There are few places where loan payment is significant higher than facing difficulties. They are 'Buying a garage', 'Business development', 'Buying land', 'Buying a new car' and 'Education' Hence we can focus on these purposes for which the client is having for minimal payment difficulties

Bivariate Analysis

Box plotting for Credit amount in logarithmic scale

```
plt.figure(figsize=(30,15))
plt.xticks(rotation=90)
plt.yscale('log')

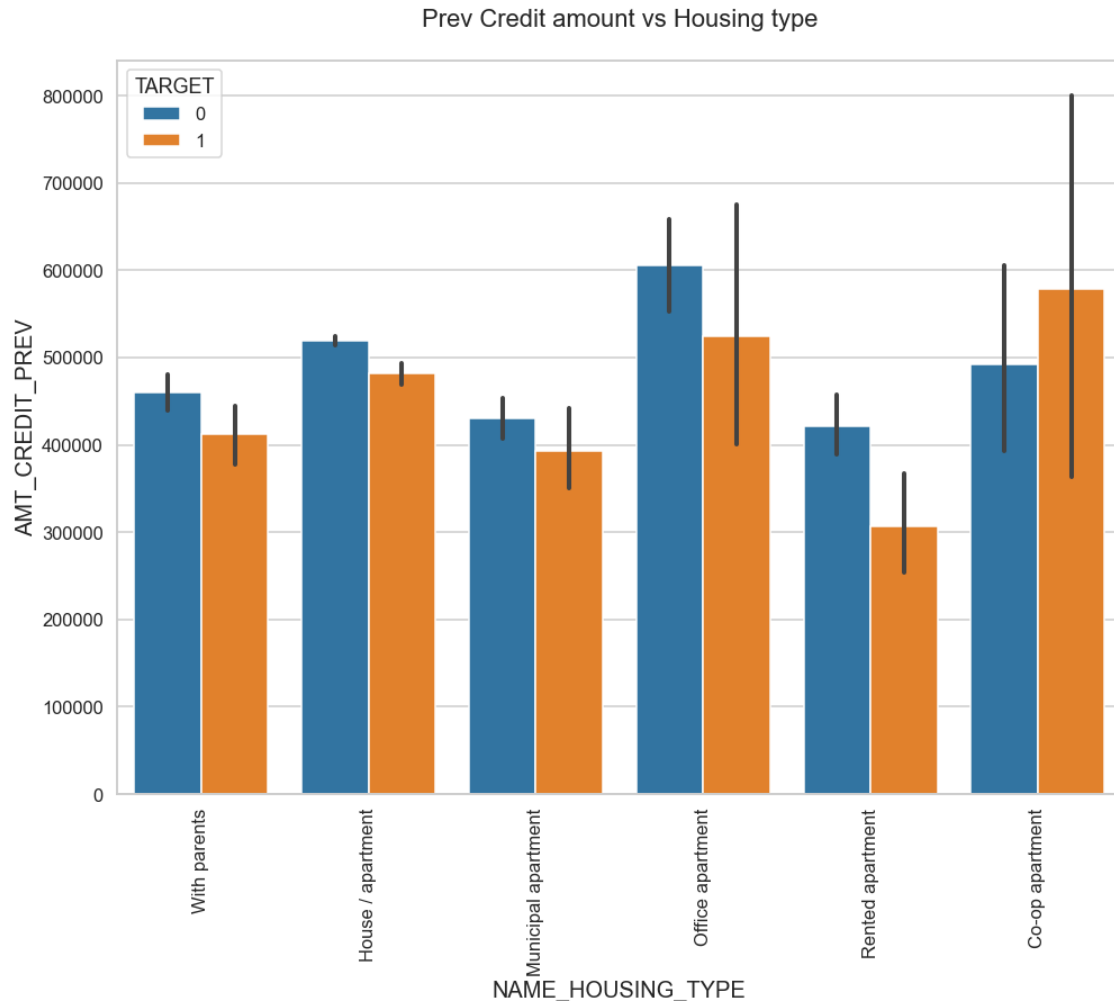
sns.boxplot(data =new_df,
x='NAME_CASH_LOAN_PURPOSE',hue='NAME_INCOME_TYPE',y='AMT_CREDIT_PREV',
orient='v')
plt.title('Prev Credit amount vs Loan Purpose')
plt.show()
```



From the above we can conclude some points- The credit amount of Loan purposes like 'Buying a home', 'Buying a land', 'Buying a new car' and 'Building a house' is higher. Income type of state servants have a significant amount of credit applied Money for third person or a Hobby is having less credits applied for.

Box plotting for Credit amount prev vs Housing type in logarithmic scale

```
plt.figure(figsize=(16,12))
plt.xticks(rotation=90)
sns.barplot(data =new_df,
y='AMT_CREDIT_PREV',hue='TARGET',x='NAME_HOUSING_TYPE',)
plt.title('Prev Credit amount vs Housing type')
plt.show()
```



Here for Housing type, office apartment is having higher credit of target 0 and co-op apartment is having higher credit of target 1. So, we can conclude that bank should avoid giving loans to the housing type of co-op apartment as they are having difficulties in payment. Bank can focus mostly on housing type with parents or House\apartment or municipal apartment for successful payments.

CONCLUSION

1. Banks should focus more on contract type 'Student', 'pensioner' and 'Businessman' with housing 'type other than 'Co-op apartment' for successful payments.
2. Banks should focus less on income type 'Working' as they are having most number of unsuccessful payments.
3. Also with loan purpose 'Repair' is having higher number of unsuccessful payments on time.
4. Get as much as clients from housing type 'With parents' as they are having least number of unsuccessful payments.