

# Importing Libraries and Dataset

```
# importing the required libraries/Modules
```

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

```
application_data = pd.read_csv("application_data.csv")
previous_application = pd.read_csv("previous_application.csv")
```

## Dataset Explore

```
application_data.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	

	...	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

[5 rows x 122 columns]

application\_data.tail()

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR
\					
49994	157871	0	Cash loans	F	N
49995	157872	0	Cash loans	M	N
49996	157873	0	Cash loans	M	N
49997	157874	0	Cash loans	F	N
49998	157875	0	Cash loans	F	N

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	\
49994	N	0	180000.0	1206000.0	
49995	N	0	126000.0	1125000.0	
49996	N	1	112500.0	900000.0	
49997	Y	0	270000.0	820638.0	
49998	Y	0	117000.0	254700.0	

	AMT_ANNUITY	...	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19
FLAG_DOCUMENT_20	\			
49994	45936.0	...	0	0

0				
49995	47794.5	...	0	0
0				
49996	26316.0	...	0	0
0				
49997	34897.5	...	0	0
0				
49998	14751.0	...	0	0
0				

FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR		
AMT_REQ_CREDIT_BUREAU_DAY \		
49994	0	0.0
0.0		
49995	0	0.0
0.0		
49996	0	0.0
0.0		
49997	0	0.0
0.0		
49998	0	0.0
0.0		

AMT_REQ_CREDIT_BUREAU_WEEK		AMT_REQ_CREDIT_BUREAU_MON \	
49994	0.0		0.0
49995	0.0		0.0
49996	0.0		0.0
49997	0.0		0.0
49998	0.0		0.0

AMT_REQ_CREDIT_BUREAU_QRT		AMT_REQ_CREDIT_BUREAU_YEAR	
49994	0.0		0.0
49995	0.0		0.0
49996	0.0		2.0
49997	2.0		4.0
49998	0.0		0.0

[5 rows x 122 columns]

application\_data.columns

```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
      'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',
      'AMT_INCOME_TOTAL',
      'AMT_CREDIT', 'AMT_ANNUITY',
      ...,
      'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
      'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
      'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
      'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
```

```
'AMT_REQ_CREDIT_BUREAU_YEAR'],  
dtype='object', length=122)
```

```
application_data.shape
```

```
(49999, 122)
```

```
application_data.describe()
```

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	\
count	49999.000000	49999.000000	49999.000000	4.999900e+04	
mean	129013.210584	0.080522	0.419848	1.707676e+05	
std	16690.512048	0.272102	0.724039	5.318191e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	
25%	114570.500000	0.000000	0.000000	1.125000e+05	
50%	129076.000000	0.000000	0.000000	1.458000e+05	
75%	143438.500000	0.000000	1.000000	2.025000e+05	
max	157875.000000	1.000000	11.000000	1.170000e+08	

	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	\
count	4.999900e+04	49998.000000	4.996100e+04	
mean	5.997006e+05	27107.377355	5.390600e+05	
std	4.024154e+05	14562.944435	3.698533e+05	
min	4.500000e+04	2052.000000	4.500000e+04	
25%	2.700000e+05	16456.500000	2.385000e+05	
50%	5.147775e+05	24939.000000	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	49999.000000	49999.000000	49999.000000	...	
mean	0.020798	-16022.042081	63219.424488	...	
std	0.013761	4361.400270	140794.605668	...	
min	0.000533	-25184.000000	-17531.000000	...	
25%	0.010006	-19644.000000	-2786.000000	...	
50%	0.018850	-15731.000000	-1221.000000	...	
75%	0.028663	-12378.500000	-292.000000	...	
max	0.072508	-7680.000000	365243.000000	...	

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	\
count	49999.000000	49999.000000	49999.000000	49999.000000	
mean	0.008500	0.000700	0.000520	0.00038	
std	0.091805	0.026449	0.022798	0.01949	
min	0.000000	0.000000	0.000000	0.00000	
25%	0.000000	0.000000	0.000000	0.00000	

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			

	AMT_REQ_CREDIT_BUREAU_HOUR	AMT_REQ_CREDIT_BUREAU_DAY \
count	43265.000000	43265.000000
mean	0.007096	0.007512
std	0.087709	0.107992
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	3.000000	6.000000

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON \
count	43265.000000	43265.000000
mean	0.032382	0.270288
std	0.194080	0.928560
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	6.000000	24.000000

	AMT_REQ_CREDIT_BUREAU_QRT	AMT_REQ_CREDIT_BUREAU_YEAR
count	43265.000000	43265.000000
mean	0.260973	1.881035
std	0.606996	1.865054
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	0.000000	3.000000
max	8.000000	25.000000

[8 rows x 106 columns]

application\_data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49999 entries, 0 to 49998
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(64), int64(42), object(16)
memory usage: 46.5+ MB
```

previous\_application.info()

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 49999 entries, 0 to 49998
```

```
Data columns (total 37 columns):
```

#	Column	Non-Null Count	Dtype
0	SK_ID_PREV	49999 non-null	int64
1	SK_ID_CURR	49999 non-null	int64
2	NAME_CONTRACT_TYPE	49999 non-null	object
3	AMT_ANNUITY	39407 non-null	float64
4	AMT_APPLICATION	49999 non-null	float64
5	AMT_CREDIT	49999 non-null	float64
6	AMT_DOWN_PAYMENT	24801 non-null	float64
7	AMT_GOODS_PRICE	39255 non-null	float64
8	WEEKDAY_APPR_PROCESS_START	49999 non-null	object
9	HOUR_APPR_PROCESS_START	49999 non-null	int64
10	FLAG_LAST_APPL_PER_CONTRACT	49999 non-null	object
11	NFLAG_LAST_APPL_IN_DAY	49999 non-null	int64
12	RATE_DOWN_PAYMENT	24801 non-null	float64
13	RATE_INTEREST_PRIMARY	165 non-null	float64
14	RATE_INTEREST_PRIVILEGED	165 non-null	float64
15	NAME_CASH_LOAN_PURPOSE	49999 non-null	object
16	NAME_CONTRACT_STATUS	49999 non-null	object
17	DAYS_DECISION	49999 non-null	int64
18	NAME_PAYMENT_TYPE	49999 non-null	object
19	CODE_REJECT_REASON	49999 non-null	object
20	NAME_TYPE_SUITE	25756 non-null	object
21	NAME_CLIENT_TYPE	49999 non-null	object
22	NAME_GOODS_CATEGORY	49999 non-null	object
23	NAME_PORTFOLIO	49999 non-null	object
24	NAME_PRODUCT_TYPE	49999 non-null	object
25	CHANNEL_TYPE	49999 non-null	object
26	SELLERPLACE_AREA	49999 non-null	int64
27	NAME_SELLER_INDUSTRY	49999 non-null	object
28	CNT_PAYMENT	39407 non-null	float64
29	NAME_YIELD_GROUP	49999 non-null	object
30	PRODUCT_COMBINATION	49991 non-null	object
31	DAYS_FIRST_DRAWING	30839 non-null	float64
32	DAYS_FIRST_DUE	30839 non-null	float64
33	DAYS_LAST_DUE_1ST_VERSION	30839 non-null	float64
34	DAYS_LAST_DUE	30839 non-null	float64
35	DAYS_TERMINATION	30839 non-null	float64
36	NFLAG_INSURED_ON_APPROVAL	30839 non-null	float64

```
dtypes: float64(15), int64(6), object(16)
```

```
memory usage: 14.1+ MB
```

```
previous_application.describe()
```

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	AMT_APPLICATION	\
count	4.999900e+04	49999.000000	39407.000000	4.999900e+04	
mean	1.922254e+06	278983.187604	15482.596847	1.688925e+05	

std	5.351980e+05	102780.124434	14530.971854	2.822035e+05
min	1.000001e+06	100007.000000	0.000000	0.000000e+00
25%	1.457920e+06	189919.500000	6122.835000	2.204550e+04
50%	1.920889e+06	279264.000000	10879.920000	7.155000e+04
75%	2.388632e+06	368527.500000	19669.140000	1.800000e+05
max	2.845367e+06	456254.000000	234478.395000	3.826372e+06

	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	\
count	4.999900e+04	2.480100e+04	3.925500e+04	
mean	1.885429e+05	6.557571e+03	2.151414e+05	
std	3.084736e+05	1.744458e+04	3.024993e+05	
min	0.000000e+00	0.000000e+00	0.000000e+00	
25%	2.605500e+04	0.000000e+00	4.941000e+04	
50%	7.890750e+04	1.566000e+03	1.040175e+05	
75%	1.981058e+05	7.875000e+03	2.250000e+05	
max	4.104351e+06	1.035000e+06	3.826372e+06	

	HOUR_APPR_PROCESS_START	NFLAG_LAST_APPL_IN_DAY
RATE_DOWN_PAYMENT	\	
count	49999.000000	49999.000000
24801.000000		
mean	12.478330	0.996500
0.079083		
std	3.333012	0.059058
0.107658		
min	0.000000	0.000000
0.000000		
25%	10.000000	1.000000
0.000000		
50%	12.000000	1.000000
0.049732		
75%	15.000000	1.000000
0.108909		
max	23.000000	1.000000
0.944776		

	...	RATE_INTEREST_PRIVILEGED	DAYS_DECISION	SELLERPLACE_AREA
\				
count	...	165.000000	49999.000000	4.999900e+04
mean	...	0.787674	-900.112622	4.016558e+02
std	...	0.091985	786.531303	1.793772e+04
min	...	0.424419	-2922.000000	-1.000000e+00
25%	...	0.715645	-1335.000000	-1.000000e+00
50%	...	0.835095	-599.000000	1.000000e+01

75%	...	0.852537	-292.000000	1.000000e+02
max	...	0.867336	-2.000000	4.000000e+06

	CNT_PAYMENT	DAYS_FIRST_DRAWING	DAYS_FIRST_DUE \
count	39407.000000	30839.000000	30839.000000
mean	15.555891	344485.142806	14217.240150
std	13.985174	84683.650627	73348.984383
min	0.000000	-2910.000000	-2891.000000
25%	6.000000	365243.000000	-1642.000000
50%	12.000000	365243.000000	-822.000000
75%	18.000000	365243.000000	-404.000000
max	60.000000	365243.000000	365243.000000

	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE	DAYS_TERMINATION \
count	30839.000000	30839.000000	30839.000000
mean	31528.148611	76724.982101	81666.162586
std	103691.881189	149757.893751	153101.159809
min	-2800.000000	-2850.000000	-2844.000000
25%	-1270.000000	-1337.000000	-1293.000000
50%	-366.000000	-536.000000	-500.000000
75%	113.000000	-71.000000	-45.000000
max	365243.000000	365243.000000	365243.000000

	NFLAG_INSURED_ON_APPROVAL
count	30839.000000
mean	0.322352
std	0.467384
min	0.000000
25%	0.000000
50%	0.000000
75%	1.000000
max	1.000000

[8 rows x 21 columns]

previous\_application.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	NAME_SELLER_INDUSTRY	CNT_PAYMENT	\
0		15	...	Connectivity	12.0
1		11	...	XNA	36.0
2		11	...	XNA	12.0
3		7	...	XNA	12.0
4		9	...	XNA	24.0

	NAME_YIELD_GROUP	PRODUCT_COMBINATION	DAYS_FIRST_DRAWING	\
0	middle	POS mobile with interest	365243.0	
1	low_action	Cash X-Sell: low	365243.0	
2	high	Cash X-Sell: high	365243.0	
3	middle	Cash X-Sell: middle	365243.0	
4	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

[5 rows x 37 columns]

```
previous_application.tail()
```

	SK_ID_PREV	SK_ID_CURR	NAME_CONTRACT_TYPE	AMT_ANNUITY	\
49994	1171956	339569	Cash loans	NaN	
49995	1904808	363980	Cash loans	NaN	
49996	2331005	231295	Cash loans	22176.405	
49997	1960897	346691	Cash loans	NaN	
49998	1979352	363244	Cash loans	24909.390	

	AMT_APPLICATION	AMT_CREDIT	AMT_DOWN_PAYMENT	AMT_GOODS_PRICE	\
49994	0.0	0.0	NaN	NaN	
49995	0.0	0.0	NaN	NaN	
49996	180000.0	216418.5	NaN	180000.0	
49997	0.0	0.0	NaN	NaN	
49998	360000.0	409896.0	NaN	360000.0	

	WEEKDAY_APPR_PROCESS_START	HOUR_APPR_PROCESS_START	...	\
49994	THURSDAY	11	...	
49995	FRIDAY	10	...	
49996	TUESDAY	12	...	
49997	WEDNESDAY	16	...	
49998	FRIDAY	18	...	

	NAME_SELLER_INDUSTRY	CNT_PAYMENT	NAME_YIELD_GROUP	\
49994	XNA	NaN	XNA	
49995	XNA	NaN	XNA	
49996	XNA	12.0	middle	
49997	XNA	NaN	XNA	
49998	XNA	36.0	high	

	PRODUCT_COMBINATION	DAYS_FIRST_DRAWING	DAYS_FIRST_DUE	\
49994	Cash	NaN	NaN	
49995	Cash	NaN	NaN	
49996	Cash X-Sell: middle	365243.0	-670.0	
49997	Cash	NaN	NaN	
49998	Cash X-Sell: high	NaN	NaN	

	DAYS_LAST_DUE_1ST_VERSION	DAYS_LAST_DUE	DAYS_TERMINATION	\
49994	NaN	NaN	NaN	
49995	NaN	NaN	NaN	
49996	-340.0	-340.0	-338.0	
49997	NaN	NaN	NaN	
49998	NaN	NaN	NaN	

NFLAG\_INSURED\_ON\_APPROVAL

```
49994      NaN
49995      NaN
49996      1.0
49997      NaN
49998      NaN
```

```
[5 rows x 37 columns]
```

```
previous_application.shape
```

```
(49999, 37)
```

## A. Identify Missing Data and Deal with it Appropriately

# Top Correlations for Different Scenarios

```
a = application_data.isnull().sum()
a
```

```
SK_ID_CURR      0
TARGET          0
NAME_CONTRACT_TYPE  0
CODE_GENDER     0
FLAG_OWN_CAR    0
```

```
...
AMT_REQ_CREDIT_BUREAU_DAY    6734
AMT_REQ_CREDIT_BUREAU_WEEK  6734
AMT_REQ_CREDIT_BUREAU_MON   6734
AMT_REQ_CREDIT_BUREAU_QRT   6734
AMT_REQ_CREDIT_BUREAU_YEAR  6734
Length: 122, dtype: int64
```

Creating bar chart to visualize the proportion of missing values for each variable.

```
# Calculate the proportion of missing values for columns having  
missing values more than 0
```

```

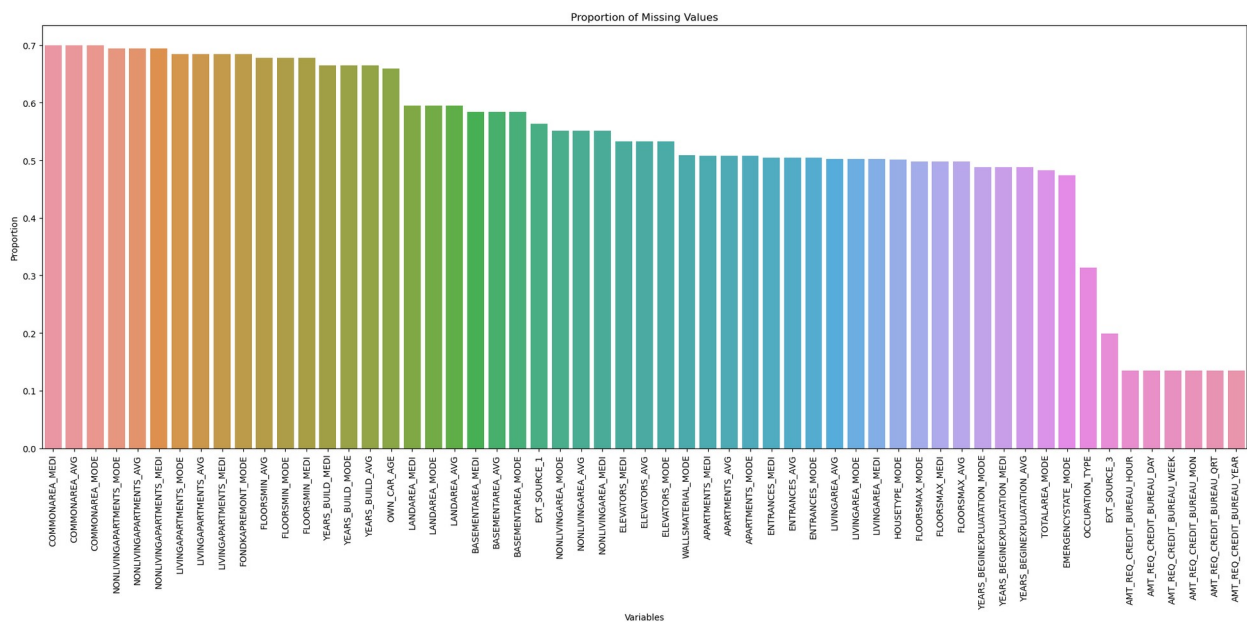
mean_val = application_data.isnull().mean()

# Sorting the mean_val for better visualization
mean_val_sorted = mean_val.sort_values(ascending=False)

missing_var_mean = mean_val_sorted[mean_val_sorted>0.1]

# Create a bar chart using seaborn
plt.figure(figsize=(20, 10))
sns.barplot(x=missing_var_mean.index, y=missing_var_mean.values)
plt.title('Proportion of Missing Values')
plt.xlabel('Variables')
plt.ylabel('Proportion')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()

```



```

a = a[a>(len(application_data)*0.5)]
print(a)
len(a)

```

OWN_CAR_AGE	32950
EXT_SOURCE_1	28172
APARTMENTS_AVG	25385
BASEMENTAREA_AVG	29199
YEARS_BUILD_AVG	33239
COMMONAREA_AVG	34960
ELEVATORS_AVG	26651
ENTRANCES_AVG	25195
FLOORSMIN_AVG	33894

LANDAREA_AVG	29721
LIVINGAPARTMENTS_AVG	34226
LIVINGAREA_AVG	25137
NONLIVINGAPARTMENTS_AVG	34714
NONLIVINGAREA_AVG	27572
APARTMENTS_MODE	25385
BASEMENTAREA_MODE	29199
YEARS_BUILD_MODE	33239
COMMONAREA_MODE	34960
ELEVATORS_MODE	26651
ENTRANCES_MODE	25195
FLOORSMIN_MODE	33894
LANDAREA_MODE	29721
LIVINGAPARTMENTS_MODE	34226
LIVINGAREA_MODE	25137
NONLIVINGAPARTMENTS_MODE	34714
NONLIVINGAREA_MODE	27572
APARTMENTS_MEDI	25385
BASEMENTAREA_MEDI	29199
YEARS_BUILD_MEDI	33239
COMMONAREA_MEDI	34960
ELEVATORS_MEDI	26651
ENTRANCES_MEDI	25195
FLOORSMIN_MEDI	33894
LANDAREA_MEDI	29721
LIVINGAPARTMENTS_MEDI	34226
LIVINGAREA_MEDI	25137
NONLIVINGAPARTMENTS_MEDI	34714
NONLIVINGAREA_MEDI	27572
FONDKAPREMONT_MODE	34191
HOUSETYPE_MODE	25075
WALLSMATERIAL_MODE	25459

dtype: int64

41

*# Here we need OWN\_CAR\_AGE and EXT\_SOURCE\_1 columns thus removing that entries from the series a*

```
a.pop("OWN_CAR_AGE")
a.pop("EXT_SOURCE_1")
```

28172

This columns have more than 50% missing values

Description of this columns :- Normalized information about building where the client lives, What is average (\_AVG suffix), modus (\_MODE suffix), median (\_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

We don't need this information for our analysis thus removing those columns

```
# drop those columns from the application_data
```

```
application_data = application_data.drop(columns=a.index)
```

```
# Shape of the dataset after dropping those columns
```

```
application_data.shape
```

```
(49999, 83)
```

```
application_data.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	

	...	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

```

```
[5 rows x 83 columns]
```

*# Let's see now which columns have null values so that we can work on them*

```

a = application_data.isnull().sum()
a = a[a>0]
print(a)
len(a)

```

```

AMT_ANNUITY 1
AMT_GOODS_PRICE 38
NAME_TYPE_SUITE 192
OWN_CAR_AGE 32950
OCCUPATION_TYPE 15654
CNT_FAM_MEMBERS 1
EXT_SOURCE_1 28172
EXT_SOURCE_2 126
EXT_SOURCE_3 9944
YEARS_BEGINEXPLUATATION_AVG 24394
FLOORSMAX_AVG 24875
YEARS_BEGINEXPLUATATION_MODE 24394
FLOORSMAX_MODE 24875
YEARS_BEGINEXPLUATATION_MEDI 24394
FLOORSMAX_MEDI 24875
TOTALAREA_MODE 24148

```

EMERGENCYSTATE_MODE	23698
OBS_30_CNT_SOCIAL_CIRCLE	168
DEF_30_CNT_SOCIAL_CIRCLE	168
OBS_60_CNT_SOCIAL_CIRCLE	168
DEF_60_CNT_SOCIAL_CIRCLE	168
DAYS_LAST_PHONE_CHANGE	1
AMT_REQ_CREDIT_BUREAU_HOUR	6734
AMT_REQ_CREDIT_BUREAU_DAY	6734
AMT_REQ_CREDIT_BUREAU_WEEK	6734
AMT_REQ_CREDIT_BUREAU_MON	6734
AMT_REQ_CREDIT_BUREAU_QRT	6734
AMT_REQ_CREDIT_BUREAU_YEAR	6734

dtype: int64

28

## Observation

1) AMT\_REQ\_CREDIT\_BUREAU\_HOUR/DAY/WEEK/MON/QRT/YEAR has the Number of enquiries to Credit Bureau about the client before application thus null values in this columns mean that there are 0 enquires thus filling null values in this columns with 0.

2) NAME\_TYPE\_SUITE has null values where it is not provided by applicant but if it is not provided then it should be "Unaccompanied".

3) OCCUPATION\_TYPE has null values where it is not provided by applicant let's replace it with "Unknown".

4) CNT\_FAM\_MEMBERS has 1 null value also its family\_details are unknown so it is safe to replace its value to 0

*# Filling those null values with the observed value*

```
keys = ['AMT_REQ_CREDIT_BUREAU_HOUR', "AMT_REQ_CREDIT_BUREAU_DAY",
"AMT_REQ_CREDIT_BUREAU_WEEK", "AMT_REQ_CREDIT_BUREAU_MON",
"AMT_REQ_CREDIT_BUREAU_QRT", "AMT_REQ_CREDIT_BUREAU_YEAR",
"NAME_TYPE_SUITE", "OCCUPATION_TYPE", "CNT_FAM_MEMBERS"]
values = [0,0,0,0,0,0,"Unaccompanied", "Unknown", 0]
```

```
filldict = dict(zip(keys, values))
```

```
application_data.fillna(value=filldict, inplace=True)
```

*# Removing the Normalized information about building where the client lives as there are lots of null values and we aren't gonna use them*

```
application_data =
application_data.drop(columns=["YEARS_BEGINEXPLUATATION_AVG",
```



```
"FLOORSMAX_AVG", "YEARS_BEGINEXPLUATATION_MODE", "FLOORSMAX_MODE",
"YEARS_BEGINEXPLUATATION_MEDI", "FLOORSMAX_MEDI", "TOTALAREA_MODE", "EMER
GENCYSTATE_MODE"])
```

## Handling Duplicate values

```
# Finding duplicated values
```

```
application_data.duplicated().sum()
```

```
0
```

## Changing the columns having neagive values.

```
# This values might be entered negative accendently .
# We can easily see that age can't have negative value.
```

```
application_data[['DAYS_BIRTH' , 'DAYS_EMPLOYED' , 'DAYS_REGISTRATION' ,
'DAYS_ID_PUBLISH']]
```

	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	DAYS_ID_PUBLISH
0	-9461	-637	-3648	-2120
1	-16765	-1188	-1186	-291
2	-19046	-225	-4260	-2531
3	-19005	-3039	-9833	-2437
4	-19932	-3038	-4311	-3458
...	...	...	...	...
49994	-10667	-285	-2521	-3333
49995	-20211	-4651	-11281	-3722
49996	-10280	-1158	-8620	-2604
49997	-23485	-2181	-2662	-4200
49998	-19251	365243	-12934	-2783

```
[49999 rows x 4 columns]
```

```
# Using absolute fucntion to convert negative values to positive
```

```
application_data[['DAYS_BIRTH' , 'DAYS_EMPLOYED' , 'DAYS_REGISTRATION' ,
'DAYS_ID_PUBLISH']] =
application_data[['DAYS_BIRTH' , 'DAYS_EMPLOYED' , 'DAYS_REGISTRATION' ,
'DAYS_ID_PUBLISH']].abs()
```

```
application_data[['DAYS_BIRTH' , 'DAYS_EMPLOYED' , 'DAYS_REGISTRATION' ,
'DAYS_ID_PUBLISH']]
```

	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_REGISTRATION	DAYS_ID_PUBLISH
0	9461	637	3648	2120
1	16765	1188	1186	291
2	19046	225	4260	2531
3	19005	3039	9833	2437
4	19932	3038	4311	3458

...	...	...	...	...
49994	10667	285	2521	3333
49995	20211	4651	11281	3722
49996	10280	1158	8620	2604
49997	23485	2181	2662	4200
49998	19251	365243	12934	2783

[49999 rows x 4 columns]

So we Identified Missing values and Handled them.

## B. Identify Outliers in the Dataset

# Top Correlations for Different Scenarios

```
# Select numerical columns for analysis of Outliers
numerical_columns =
application_data.select_dtypes(include=[np.number]).columns

sns.set_theme(style="whitegrid")

# Created an empty dictionary to store outliers as values and
variable name as keys
dictoutlier = {}

for i in numerical_columns:

    # Created an empty list to store outliers
    outliers = []

    # to Calculate IQR of data i
    q1 = np.percentile(application_data[i], 25)
    q3 = np.percentile(application_data[i], 75)
    iqr = q3 - q1

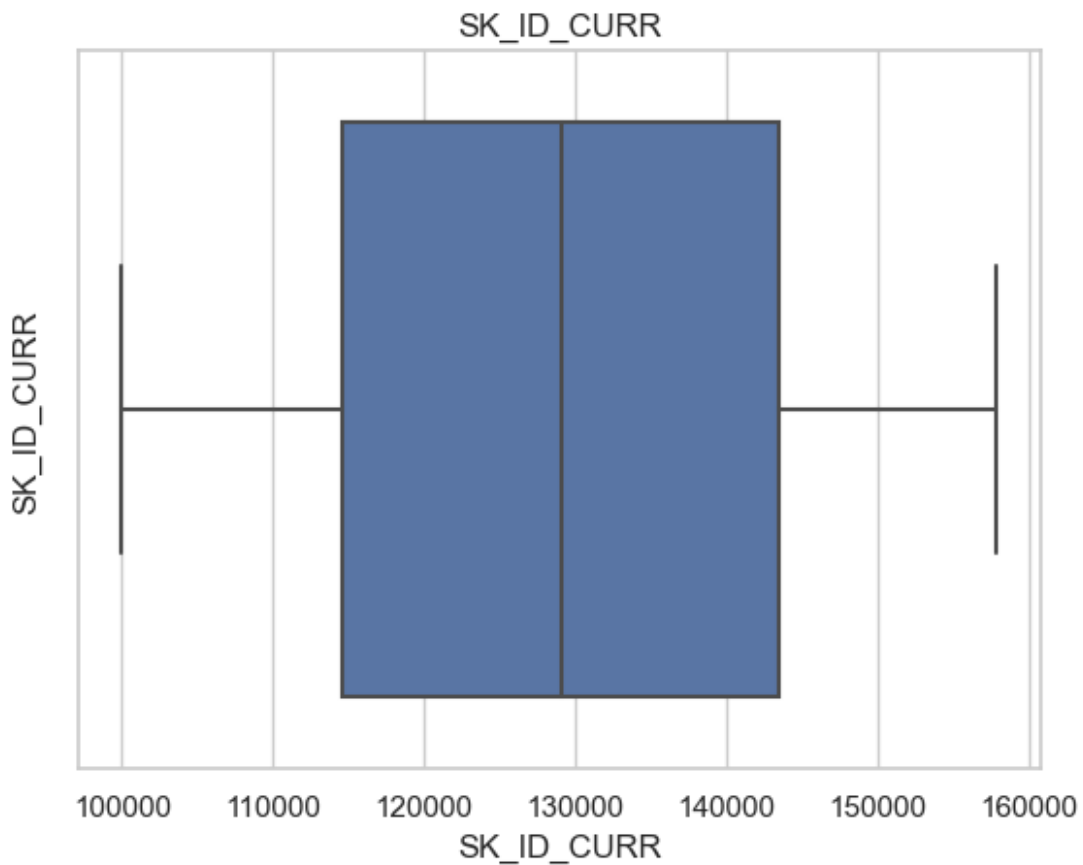
    # Define lower and upper bounds for outliers
    lower_bound = q1 - 1.5 * iqr
    upper_bound = q3 + 1.5 * iqr
```

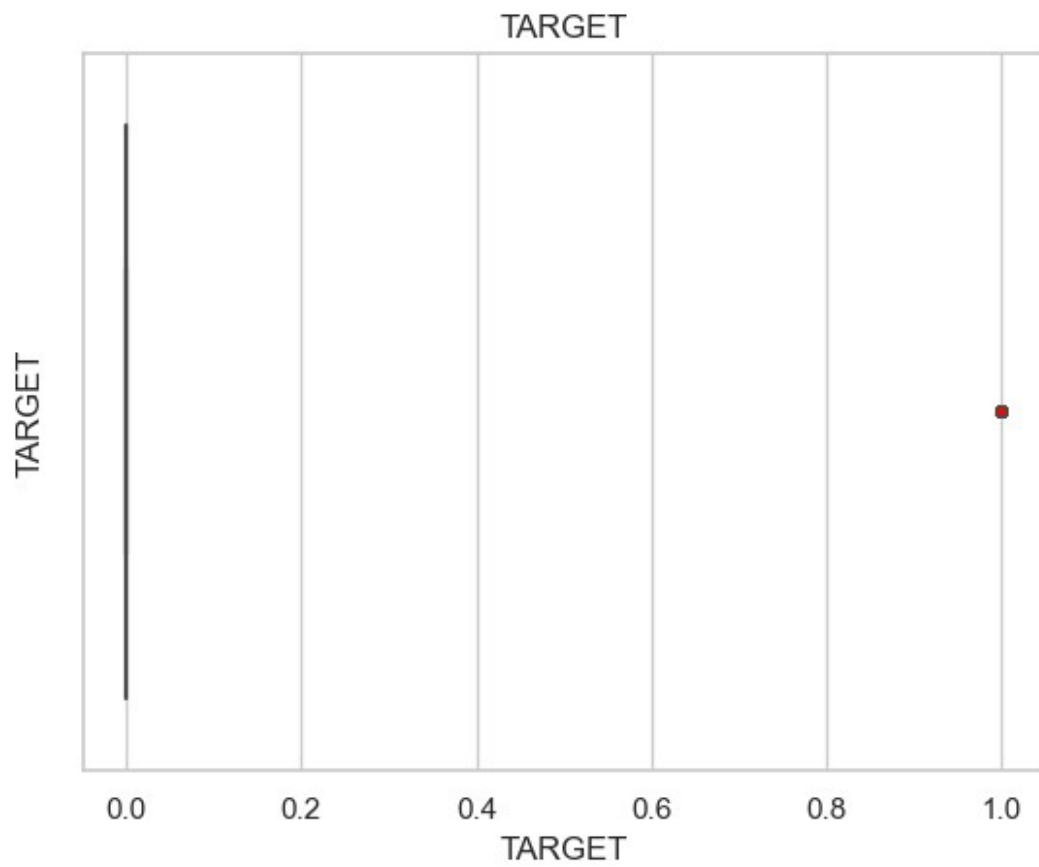
```

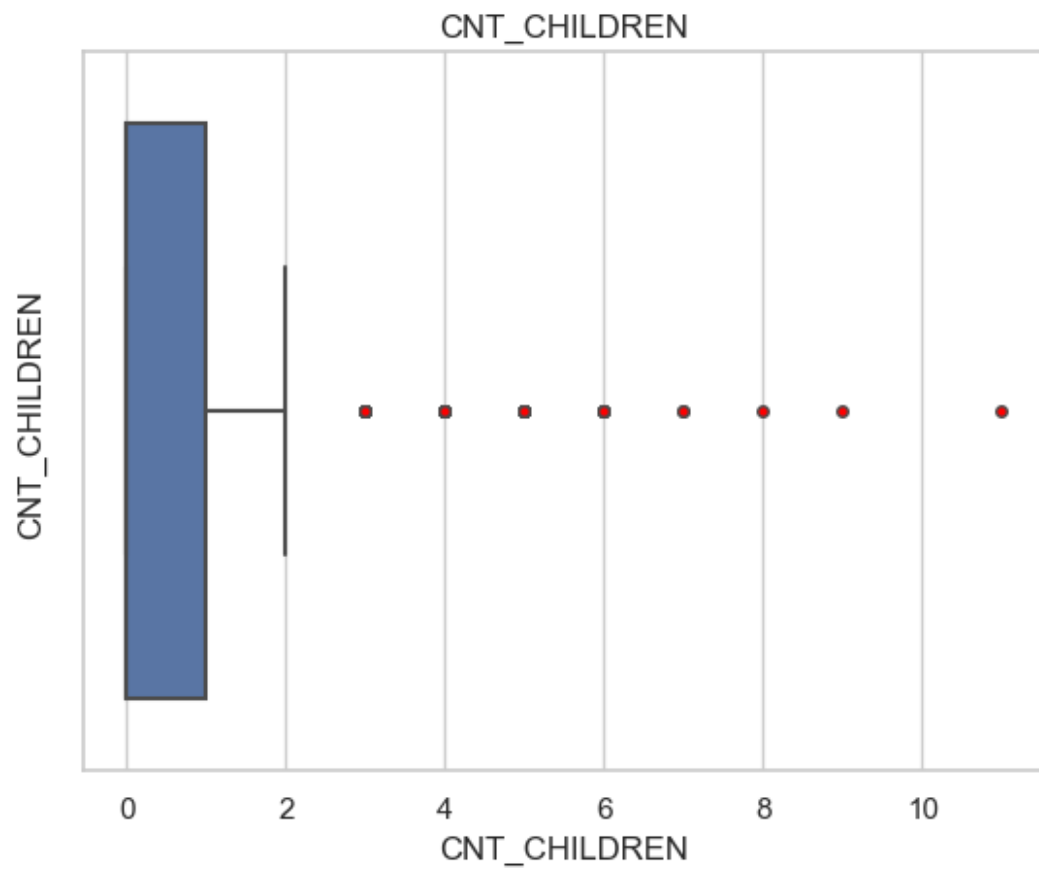
    # find and store outliers in the variable i
    outliers = [x for x in application_data[i] if x < lower_bound or x
> upper_bound]
    dictoutlier[i] = outliers

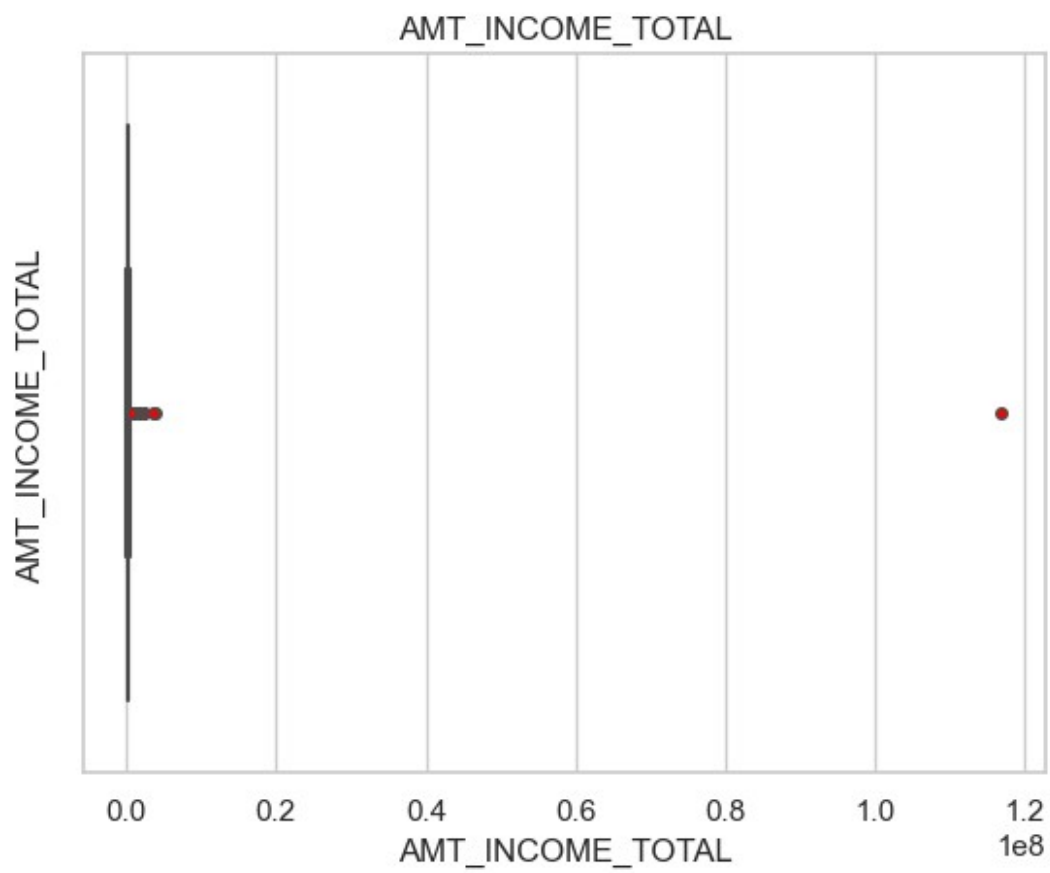
    # Plot the box plot with variable name as title and outliers
    marked marked with red color dots
    sns.boxplot(x = application_data[i], flierprops=dict(marker='o',
markerfacecolor='red', markersize=4))
    plt.title(i)
    plt.ylabel(i)
    plt.show()

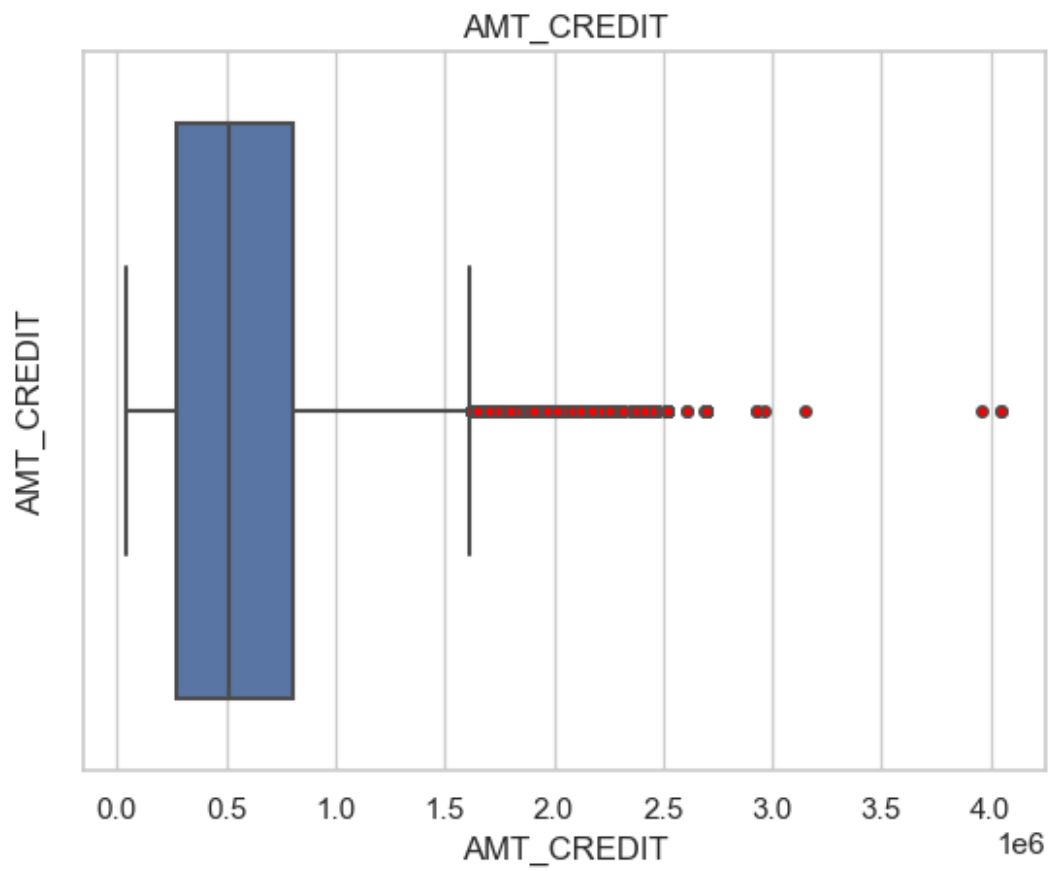
```

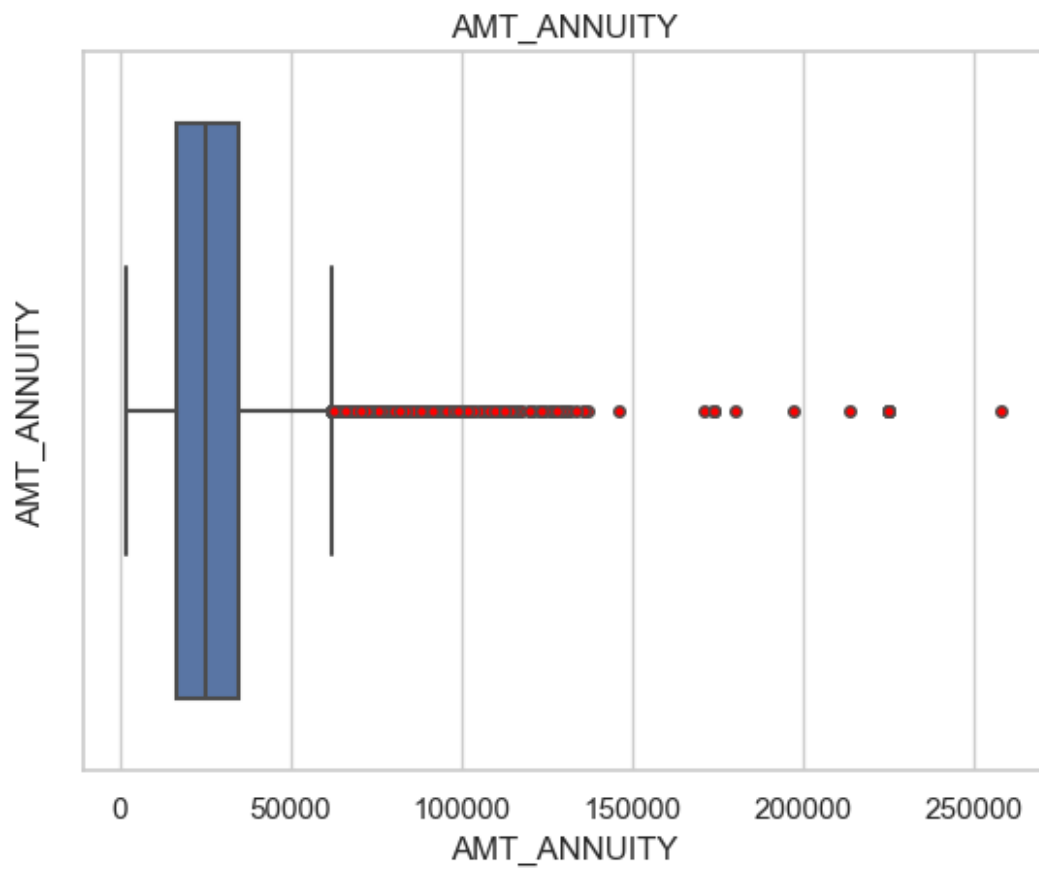




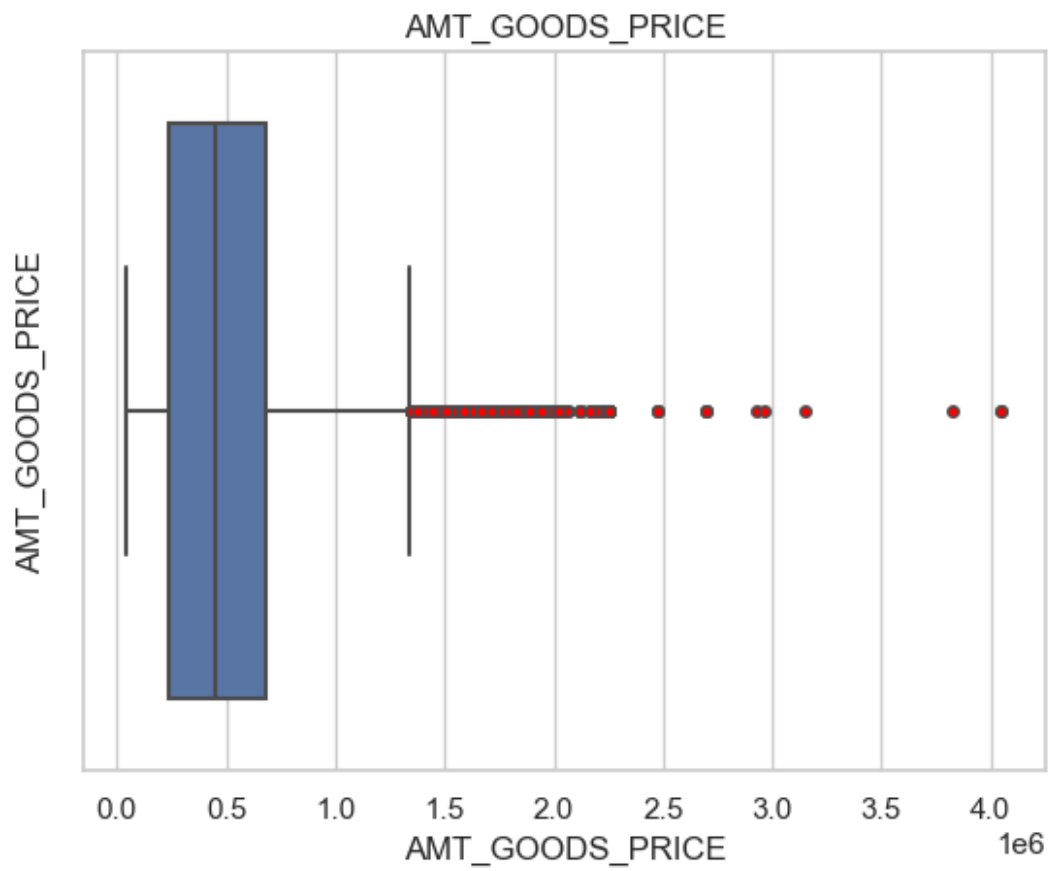


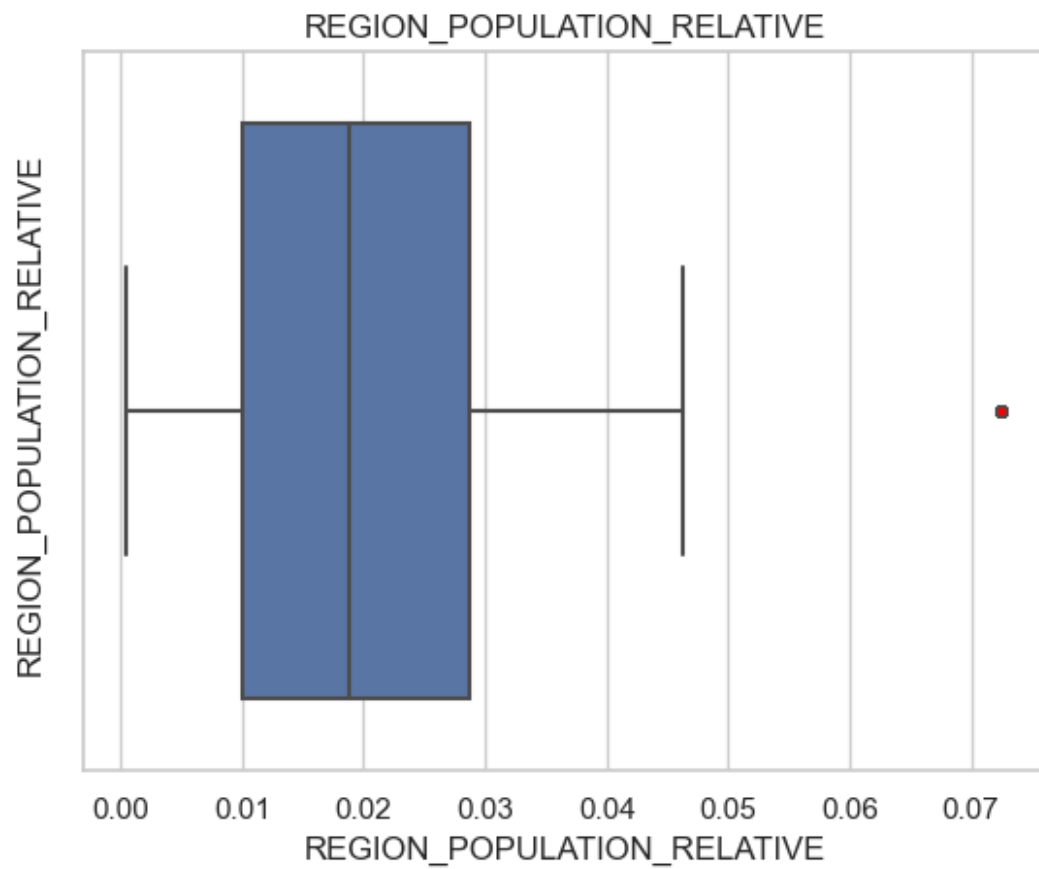


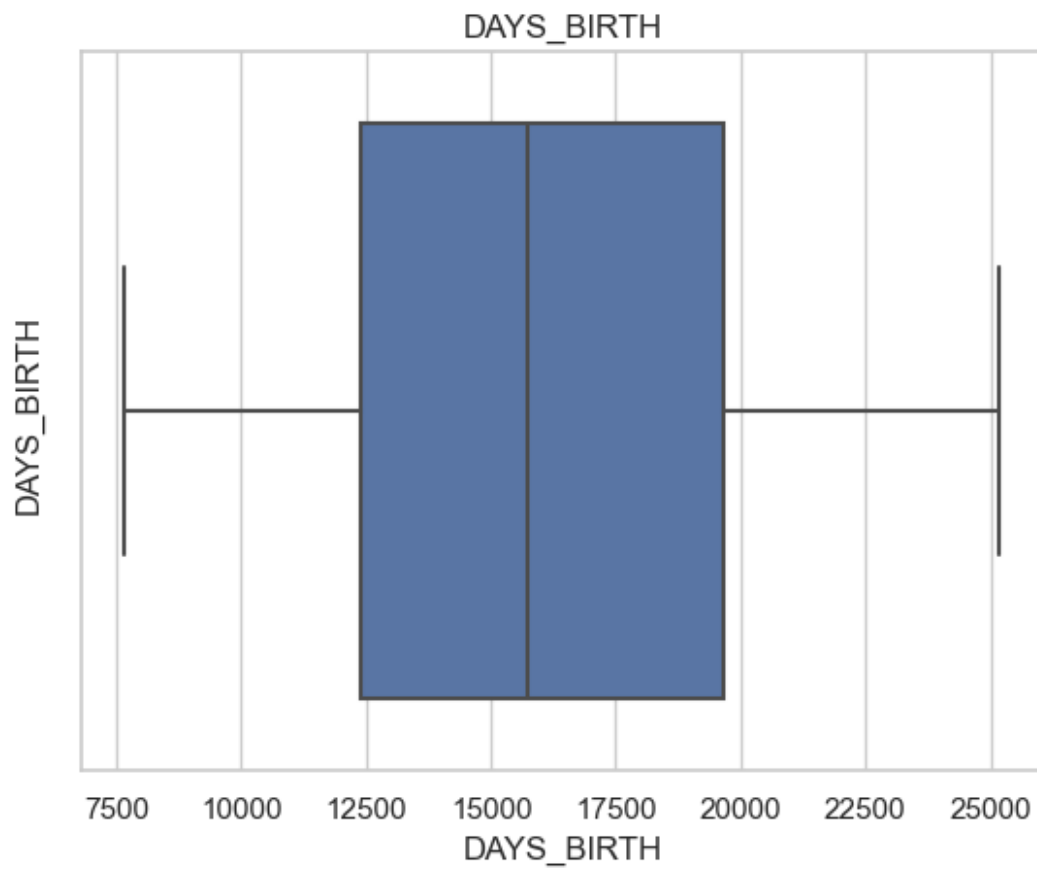


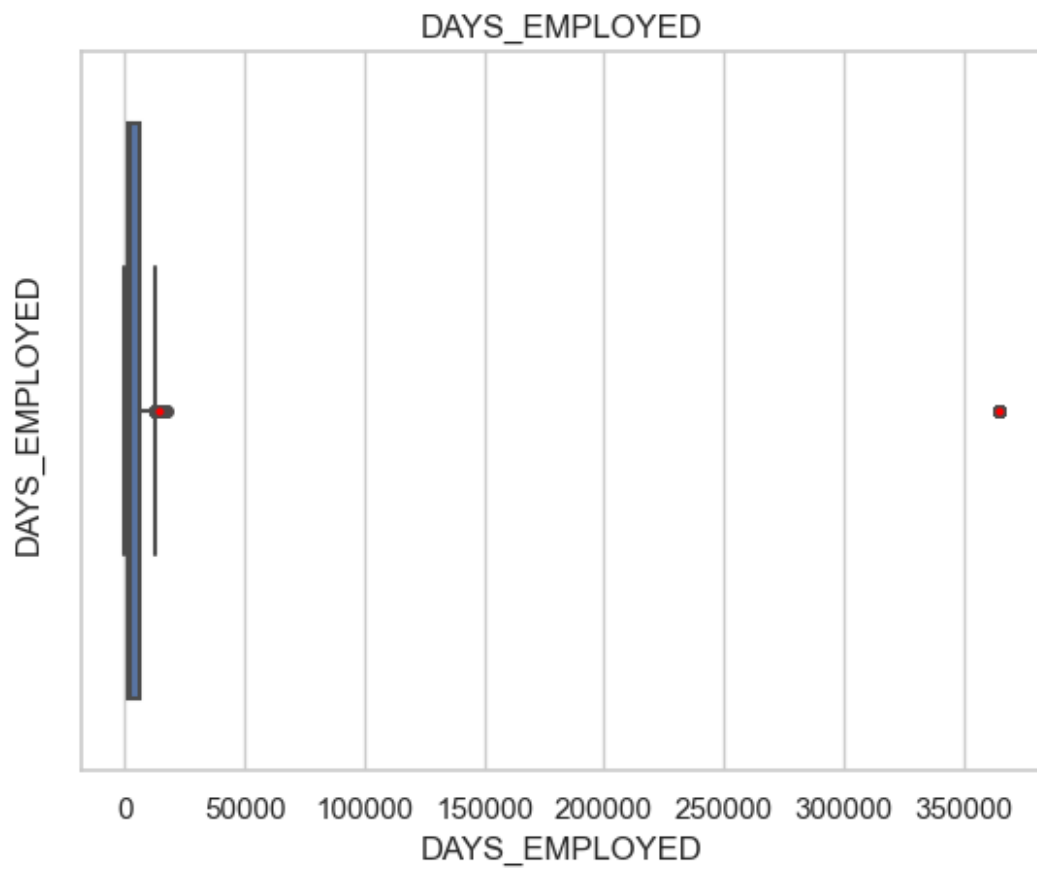


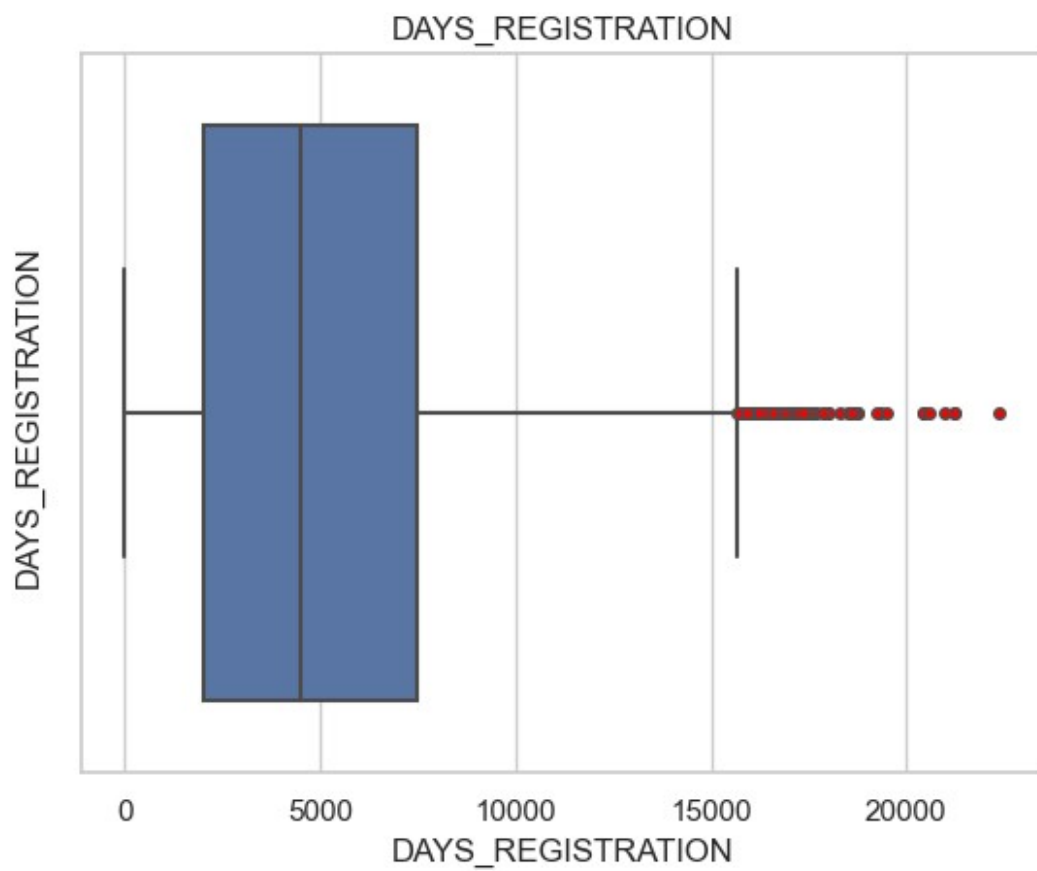


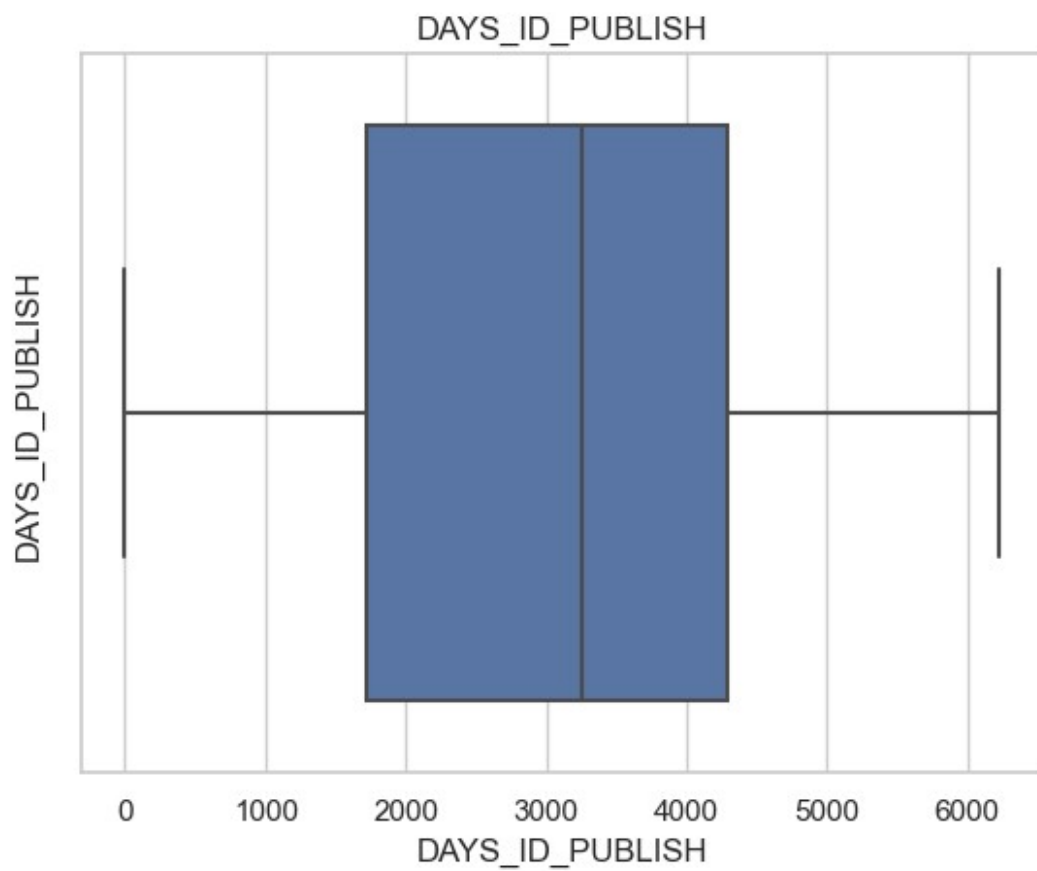


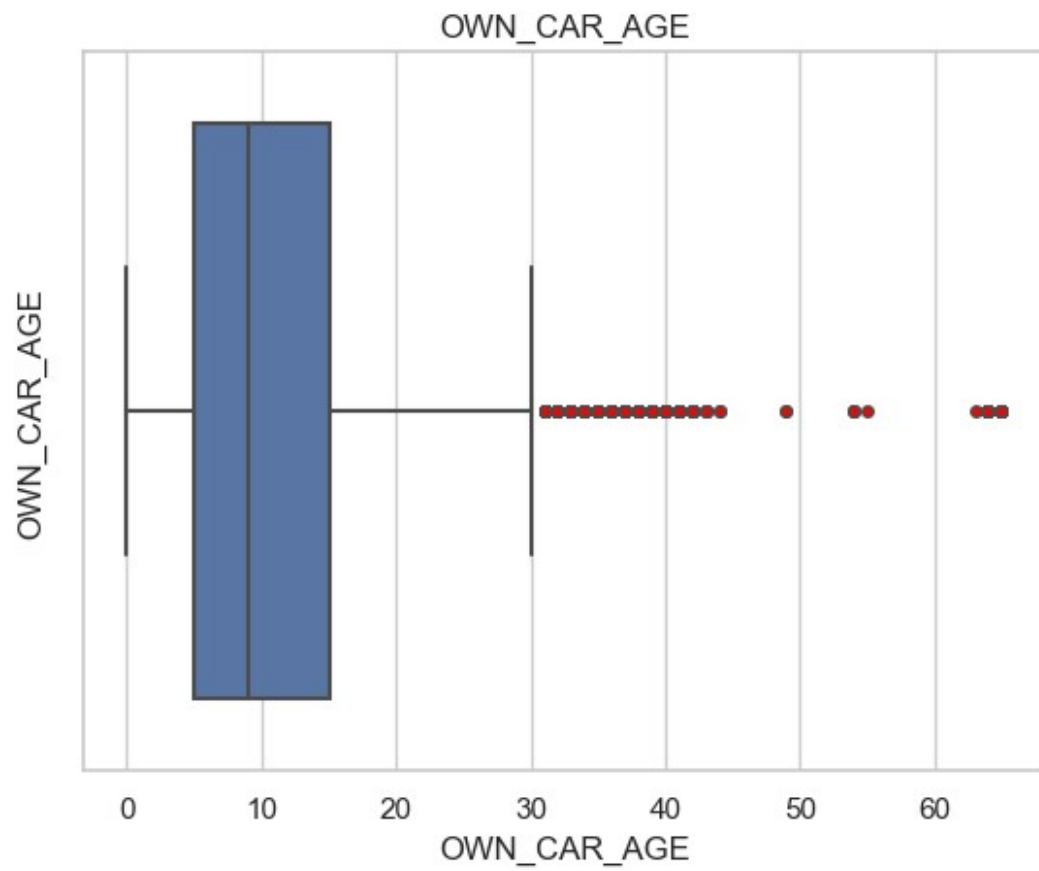


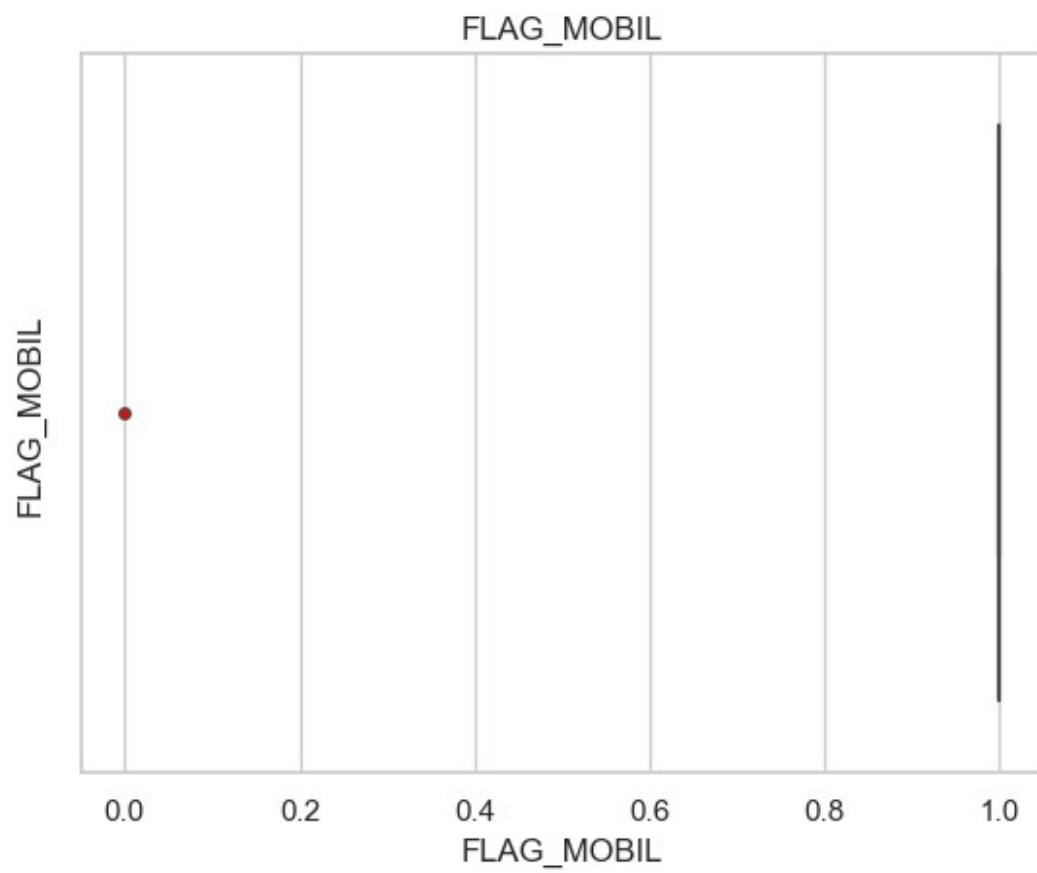




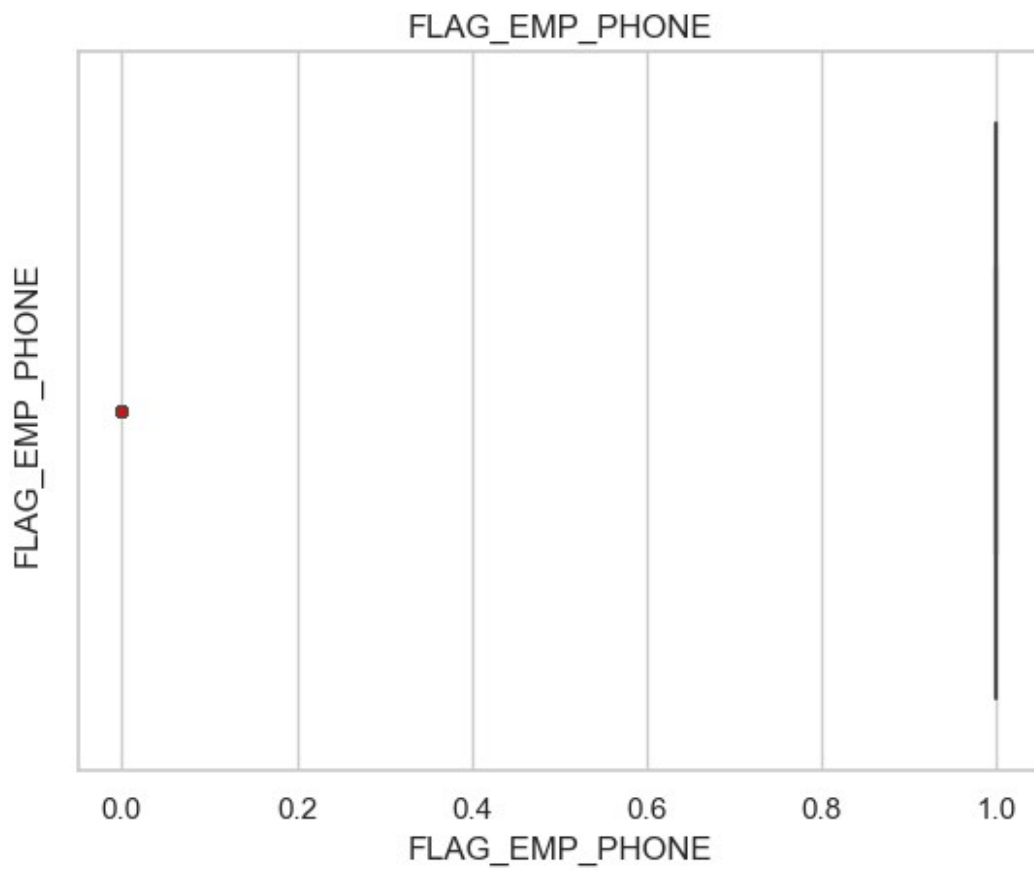


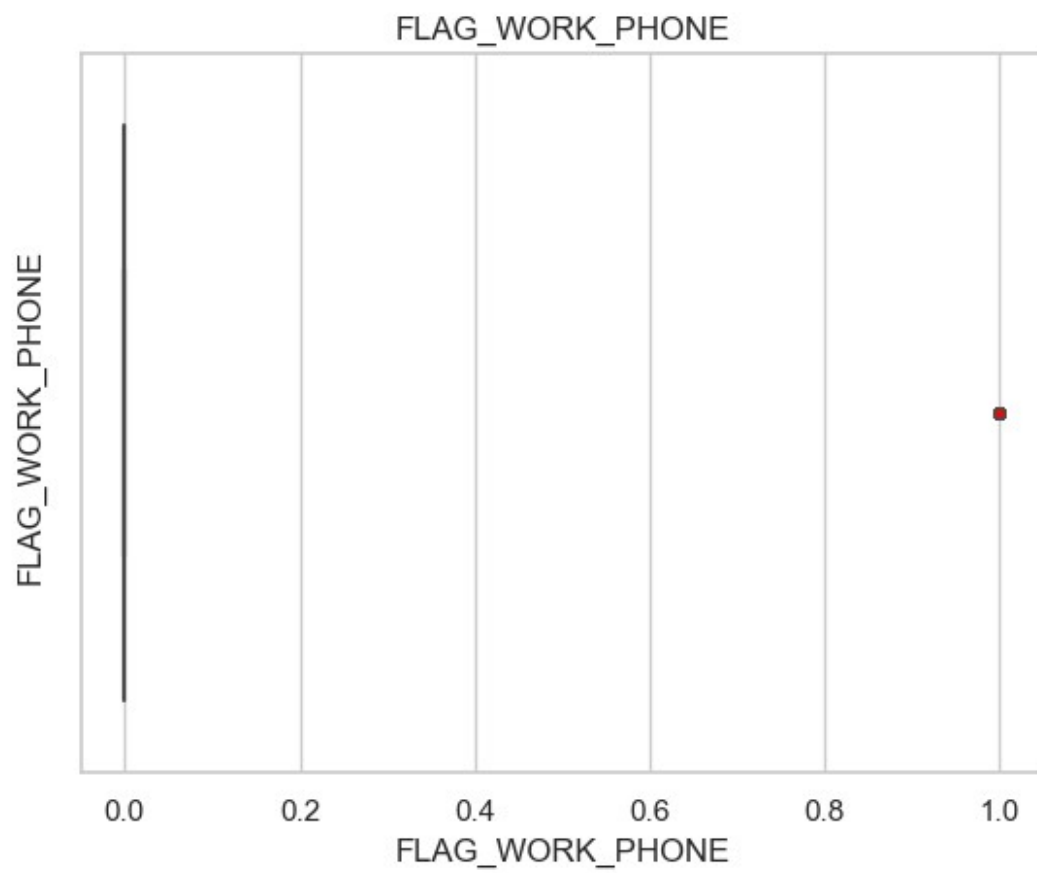


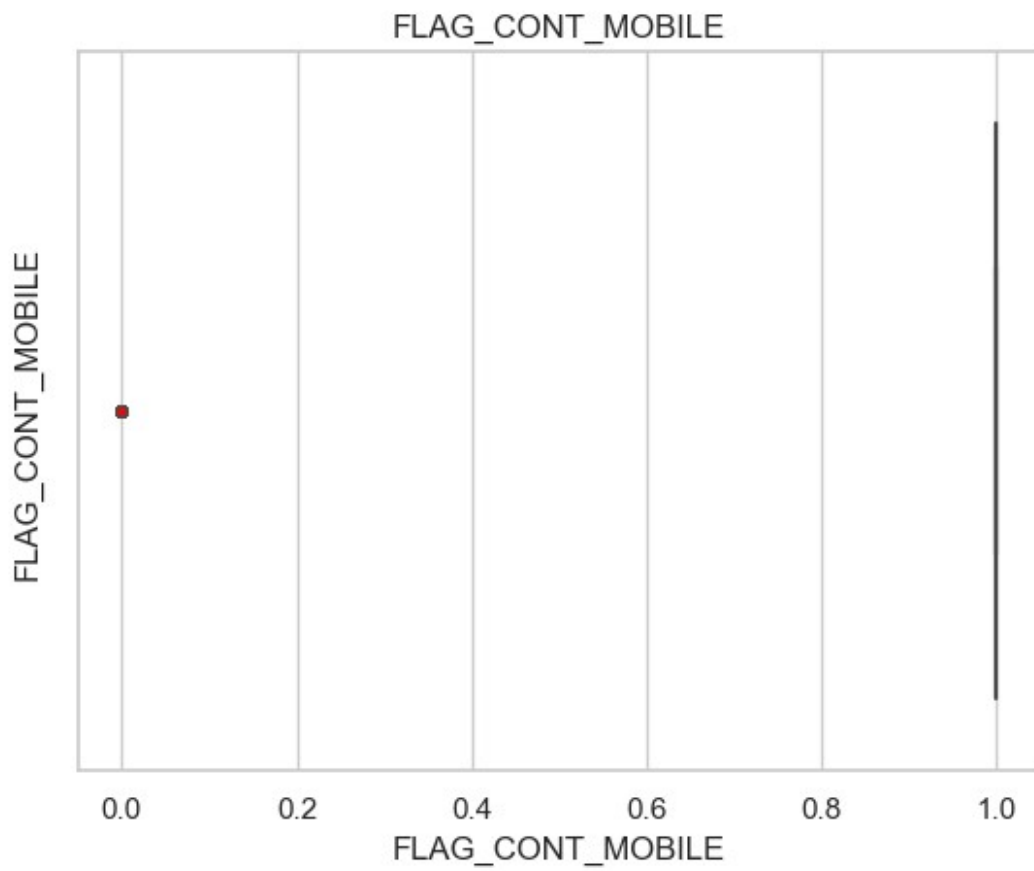


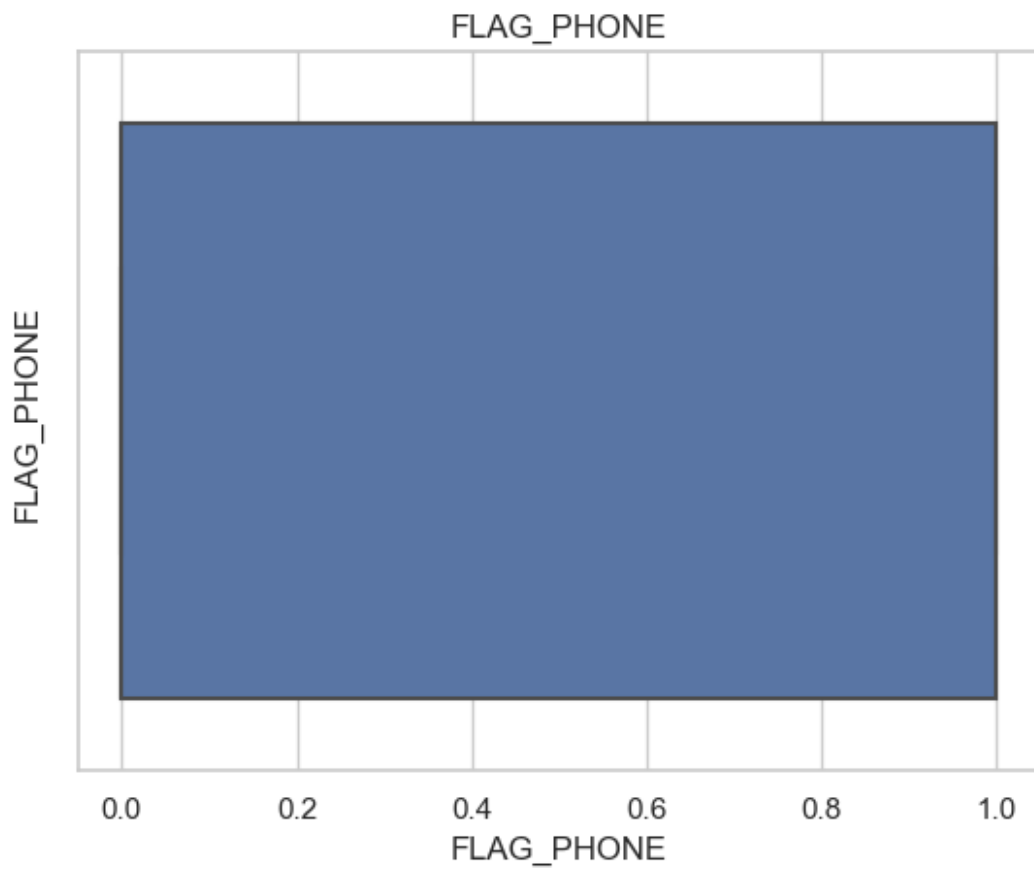


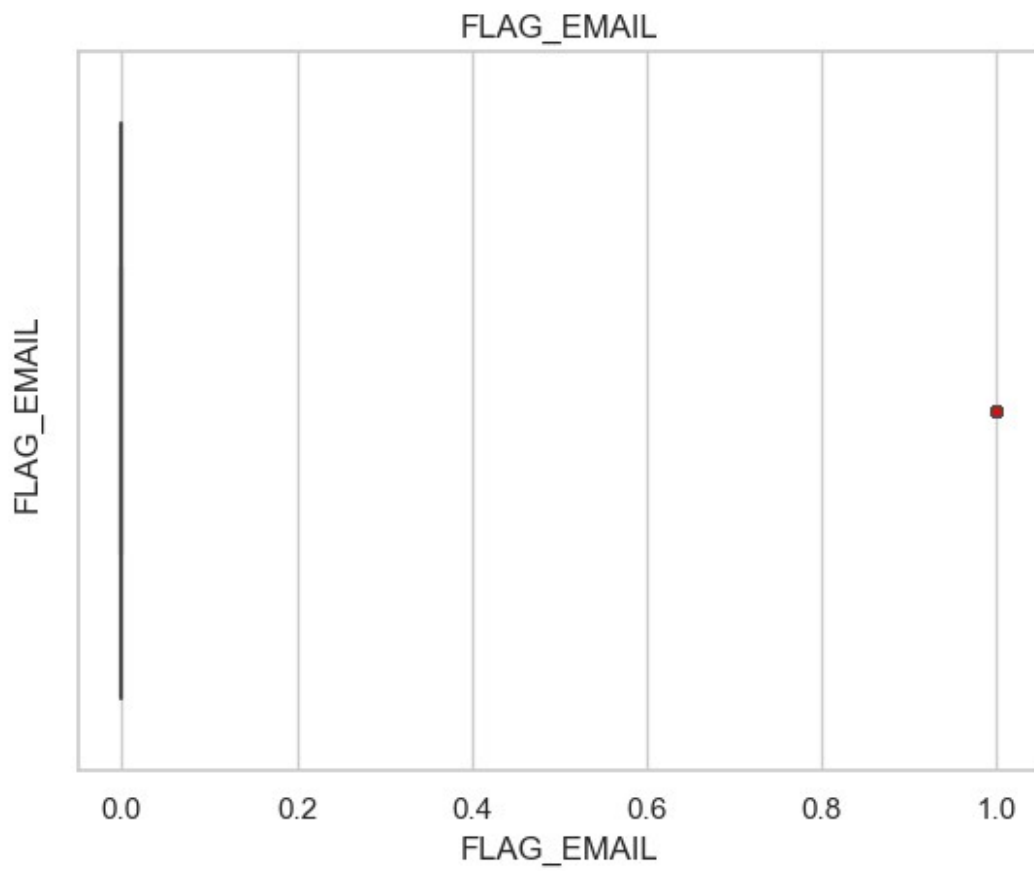


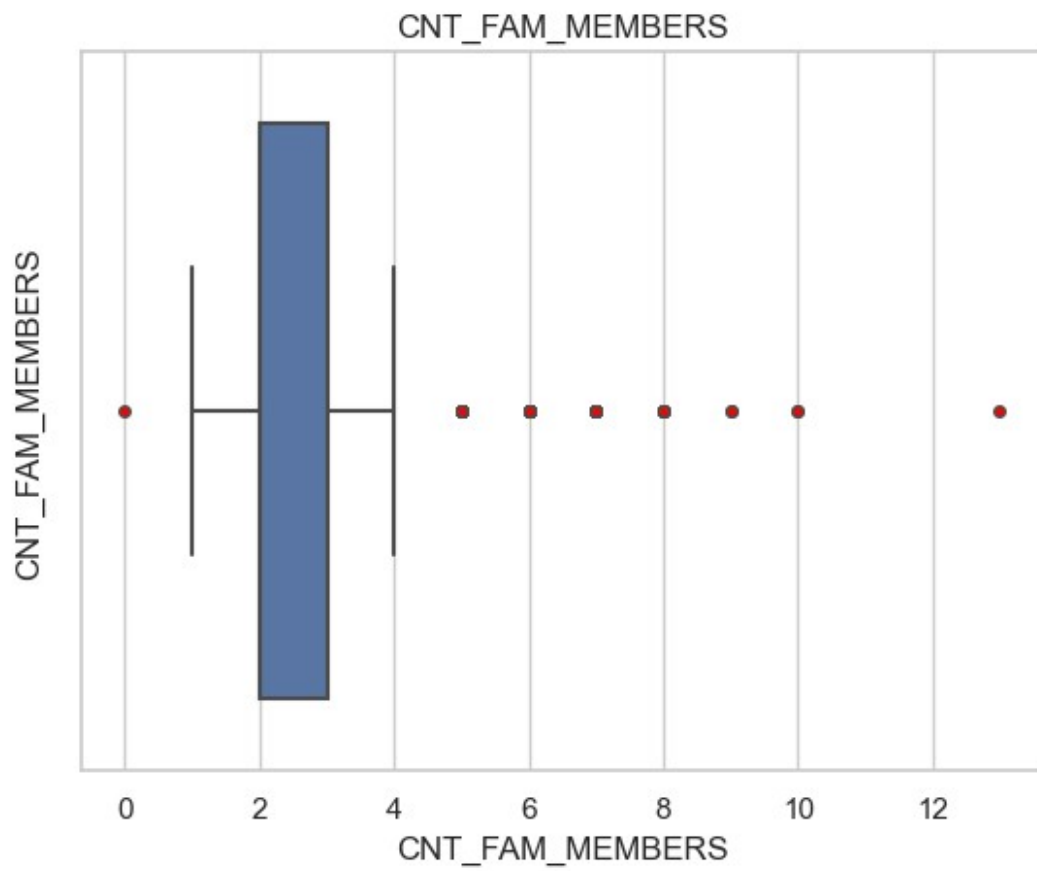


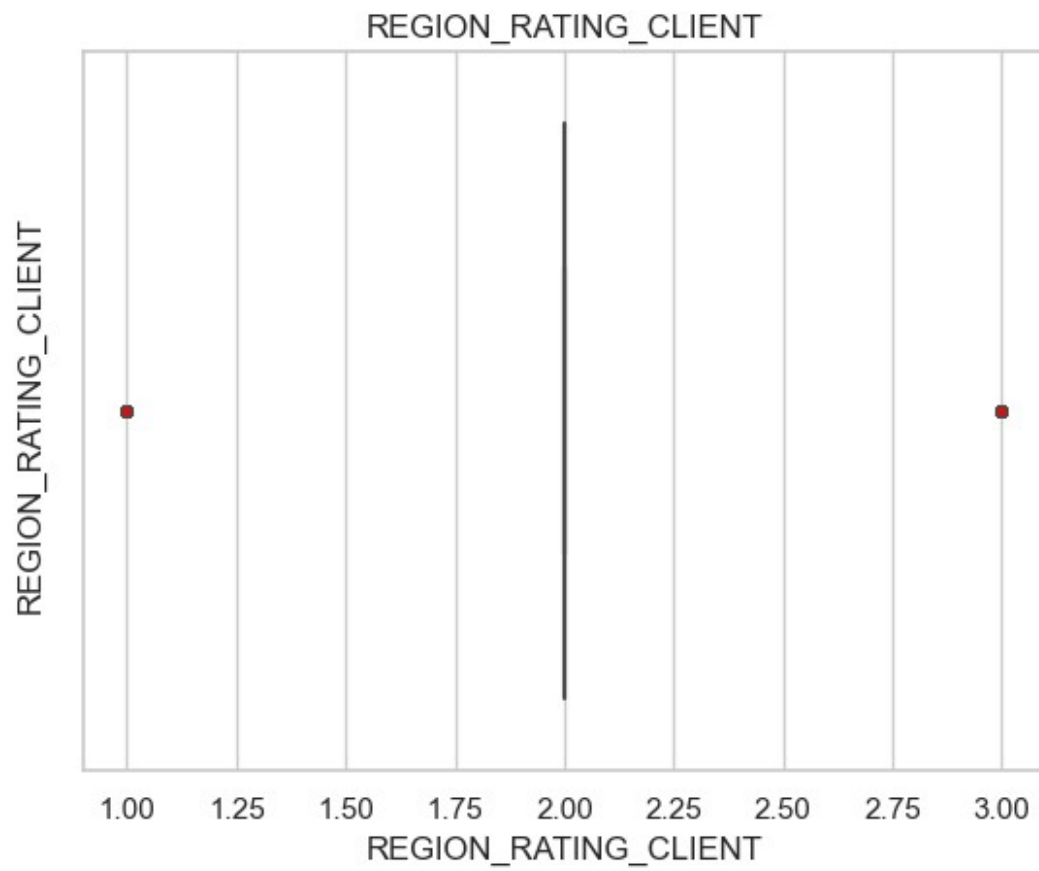


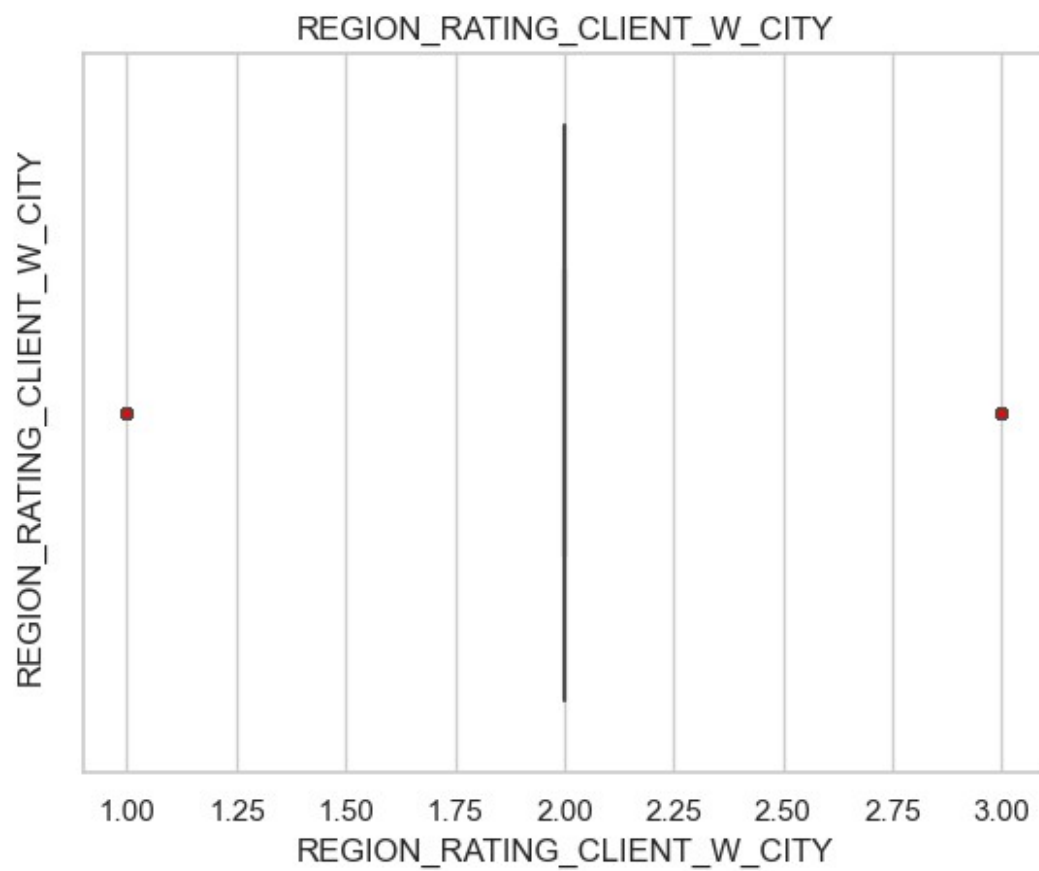




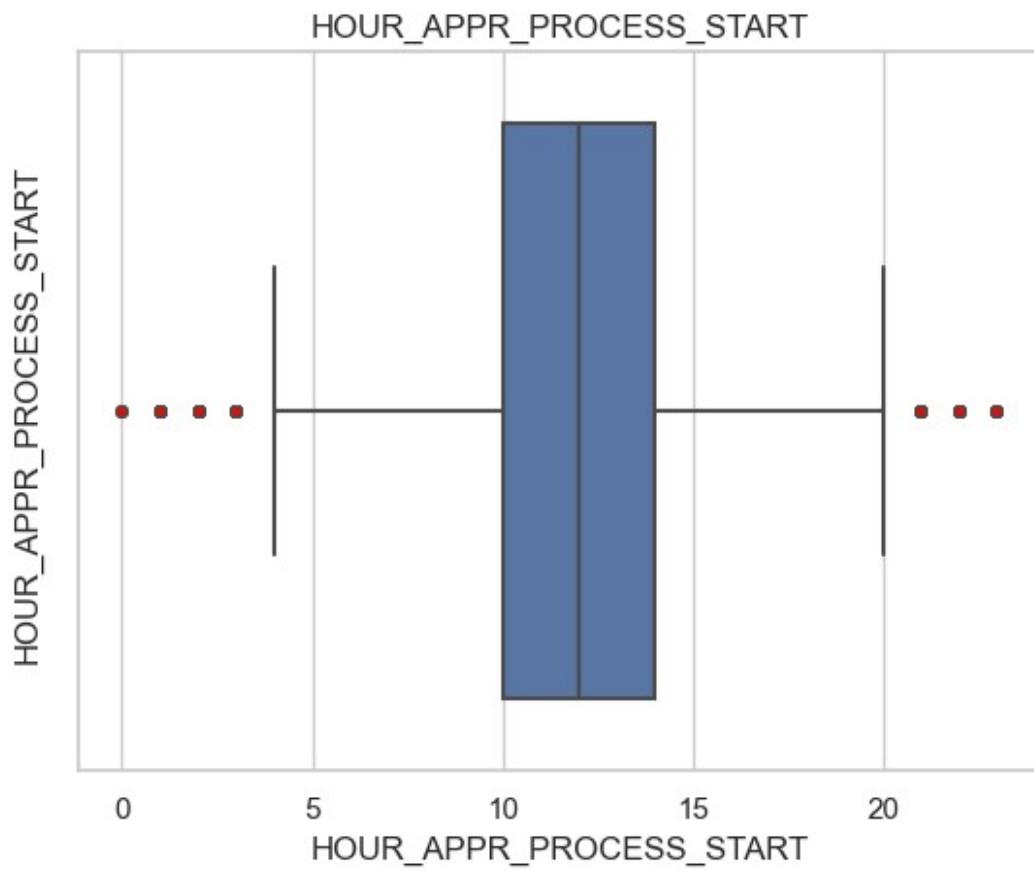


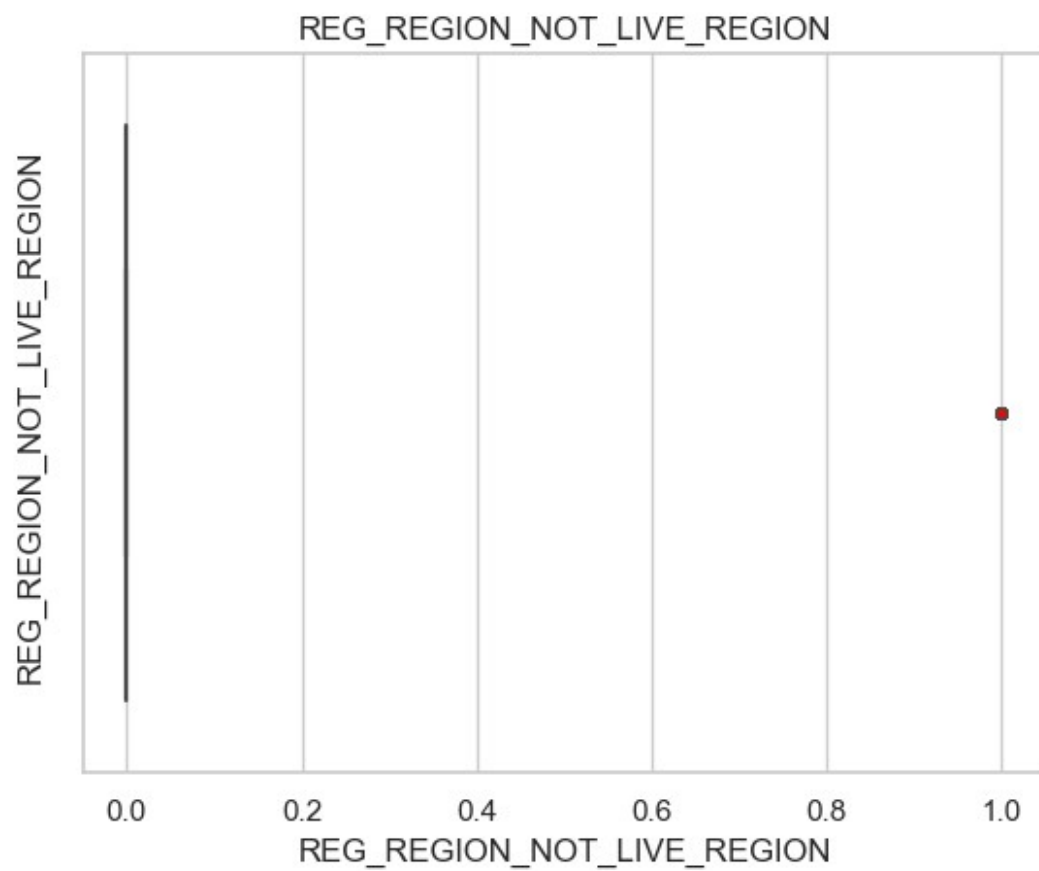


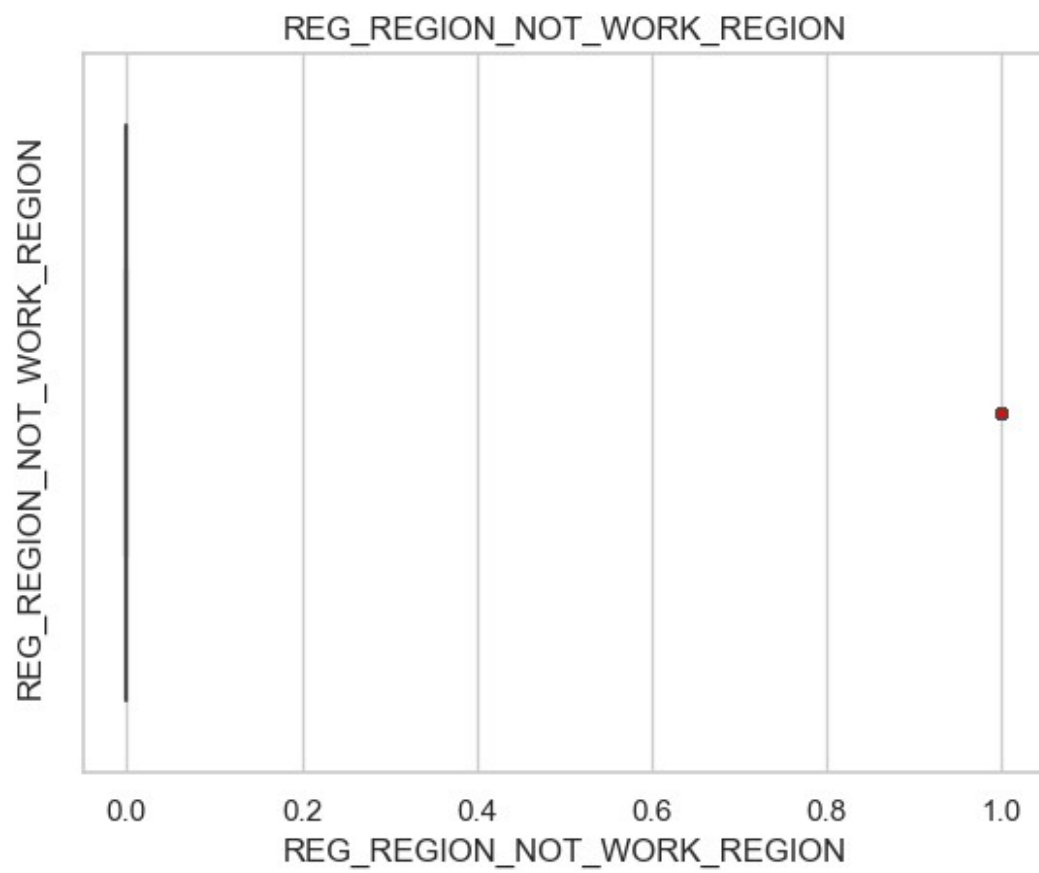


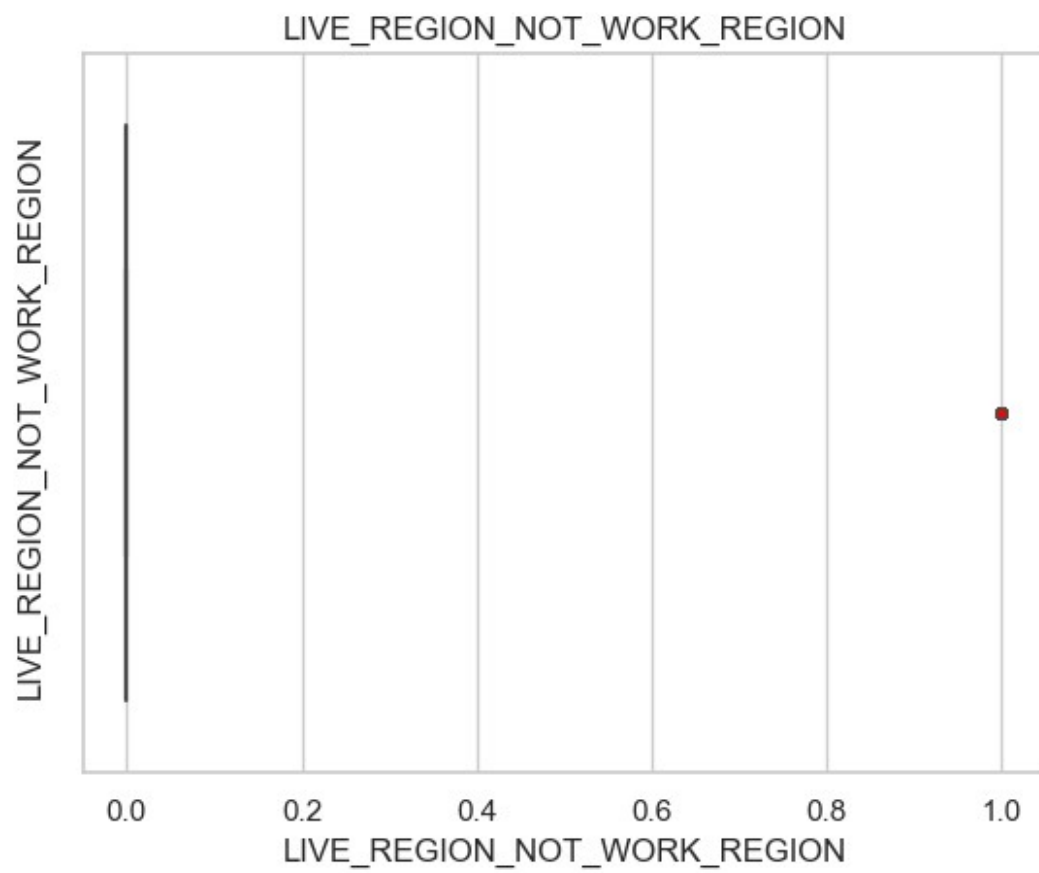


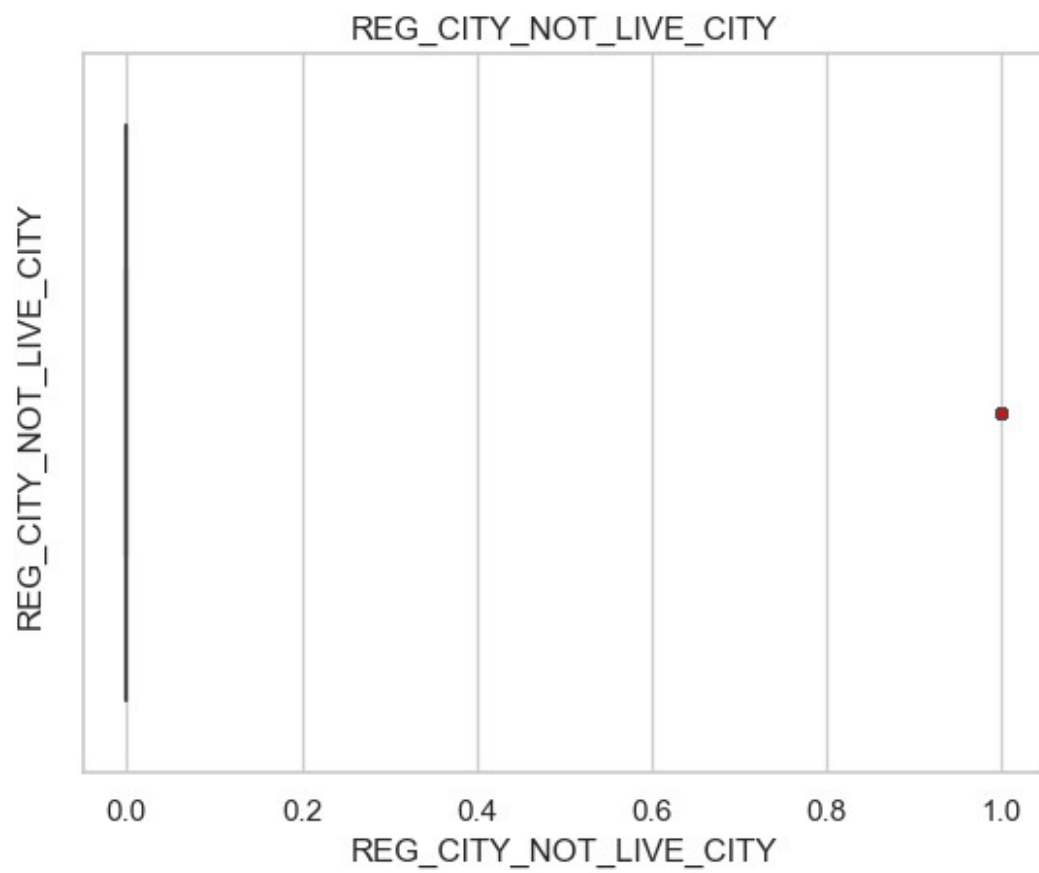


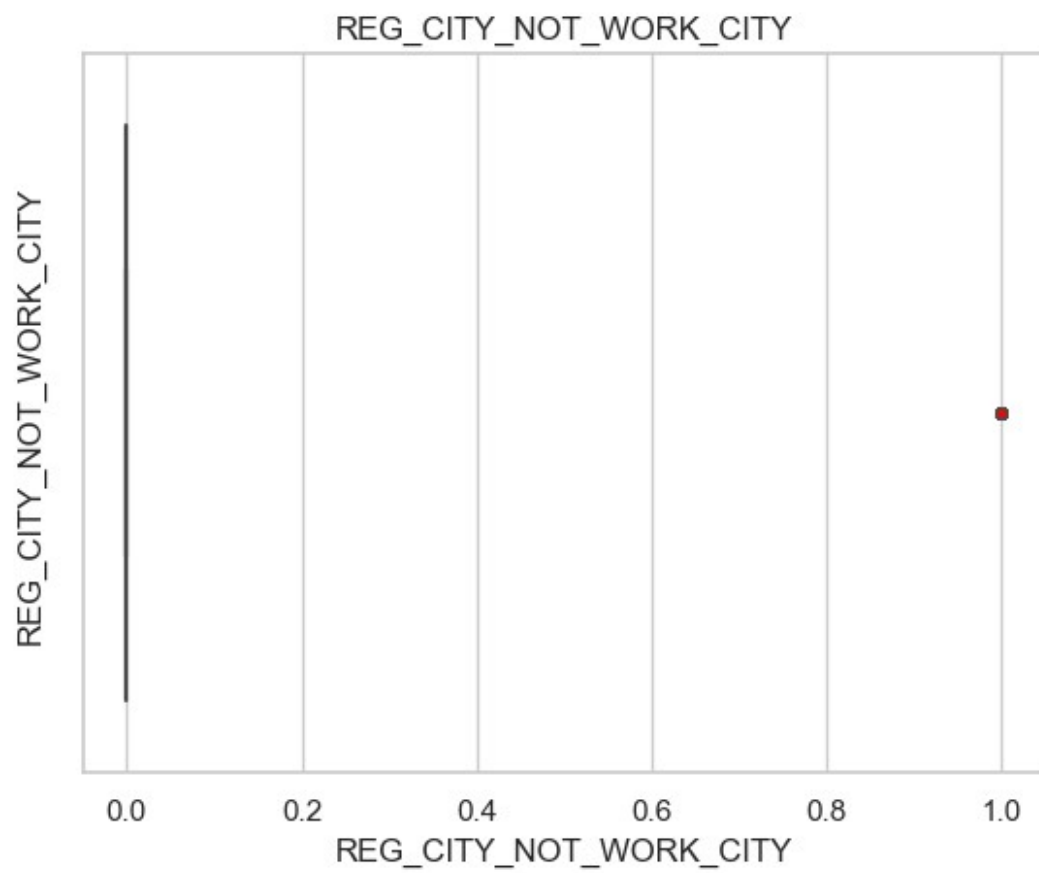


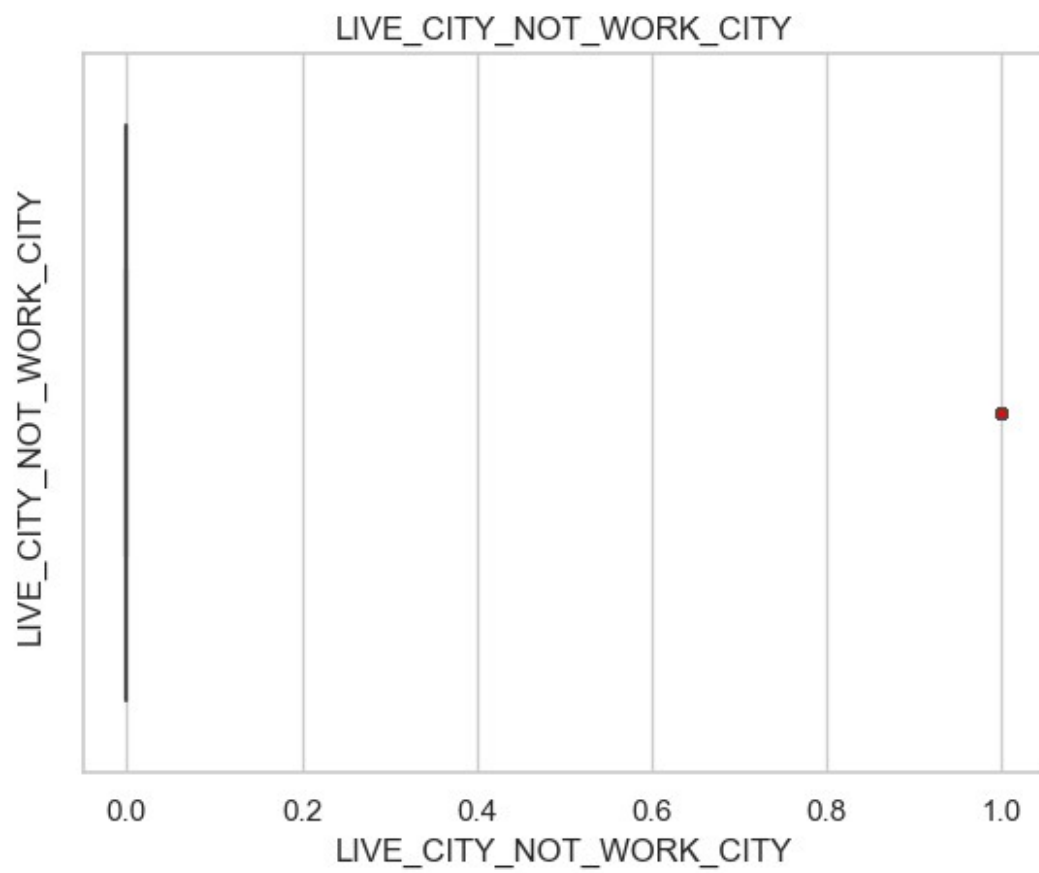


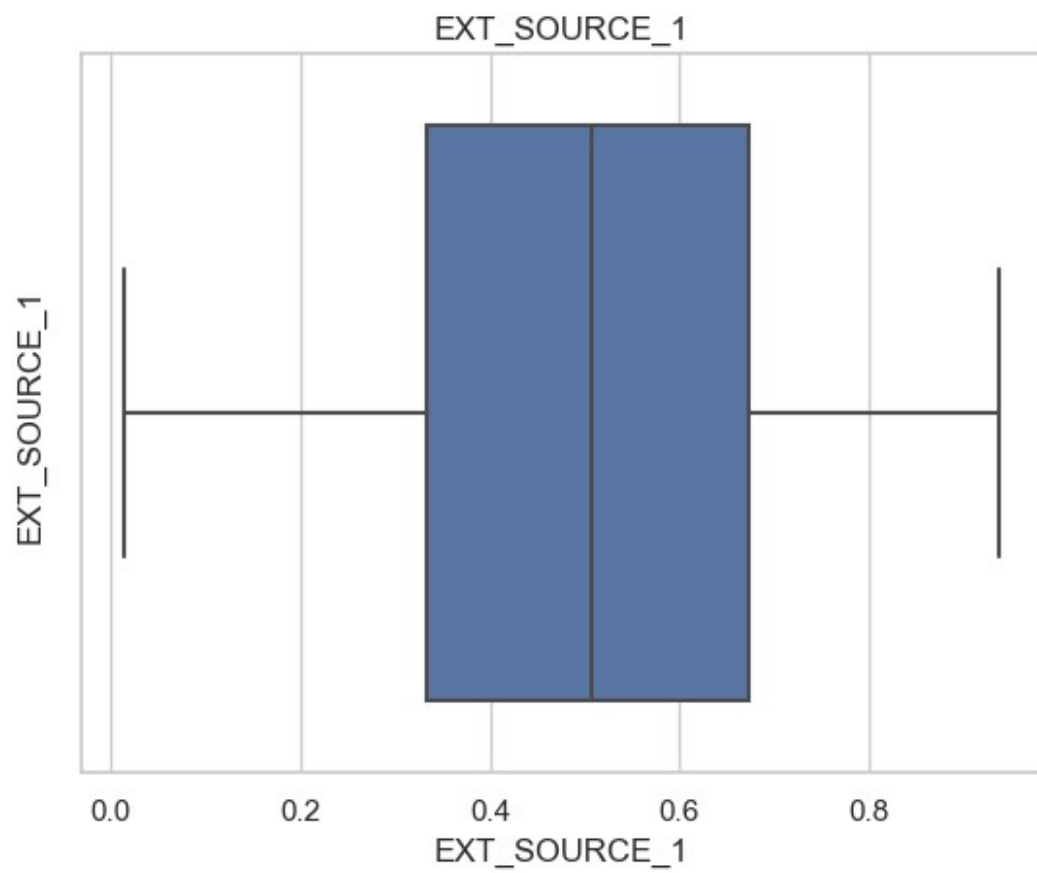




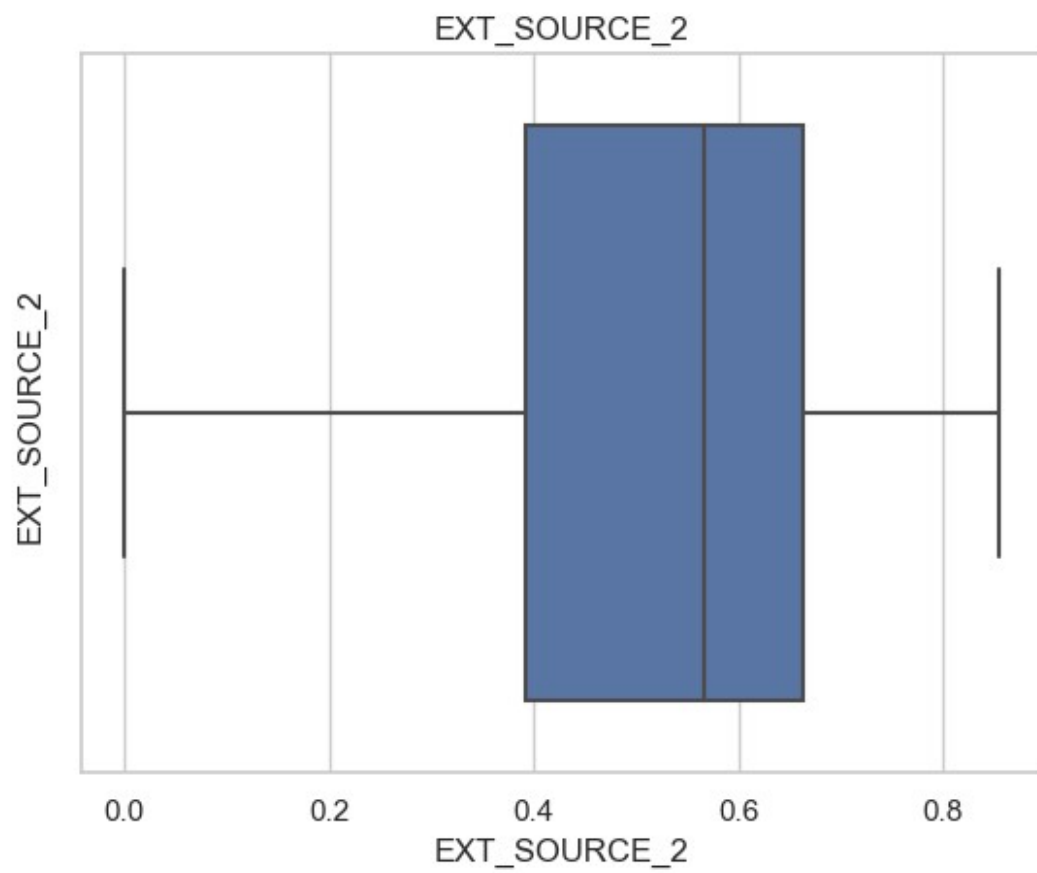


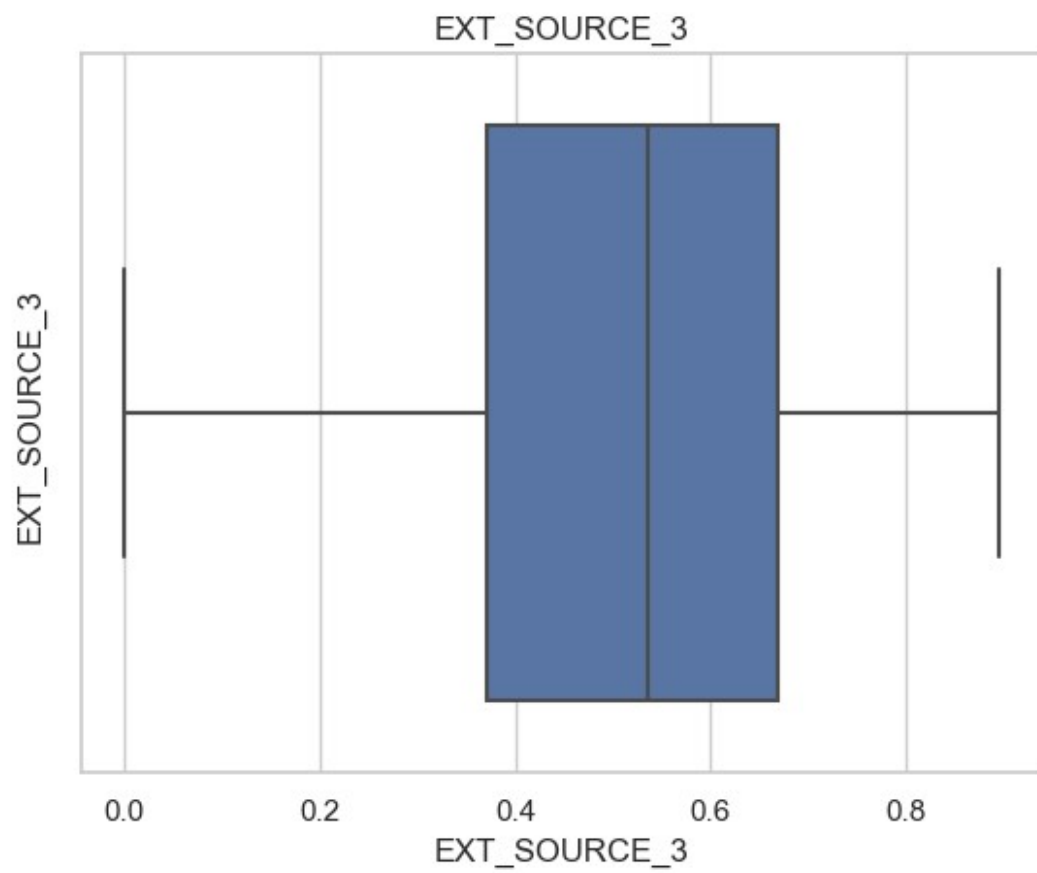


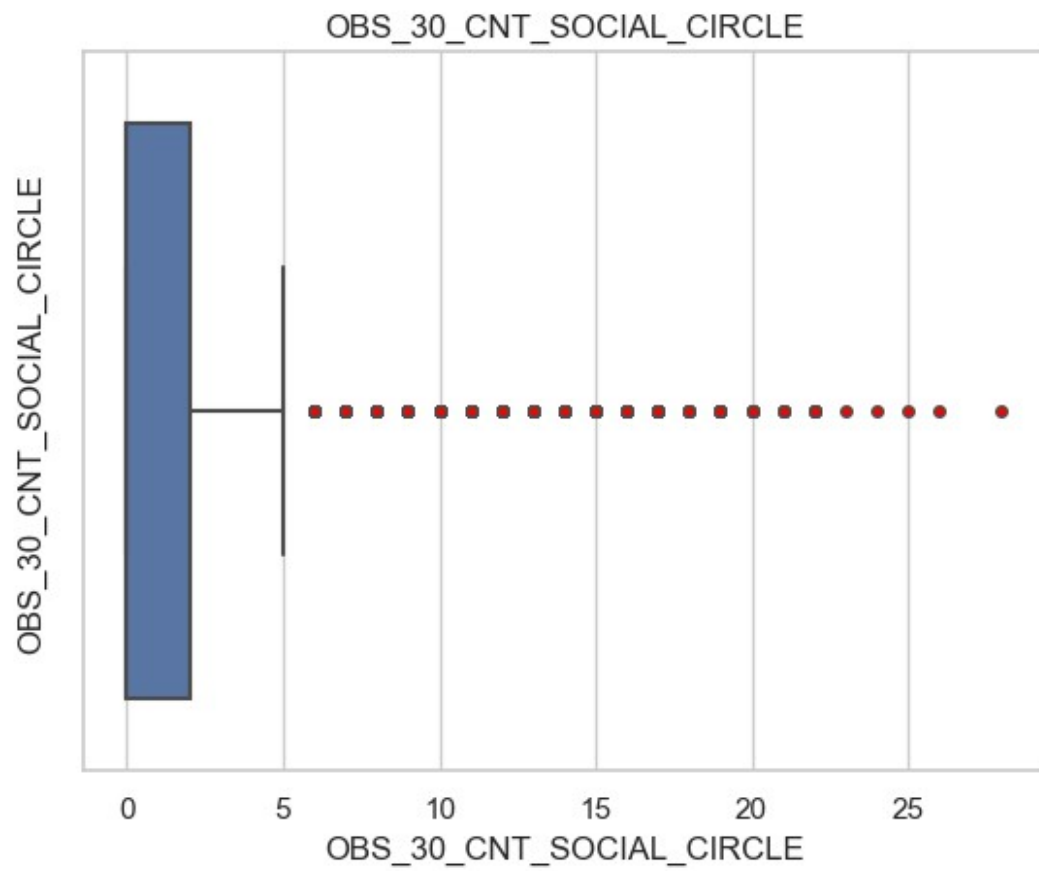


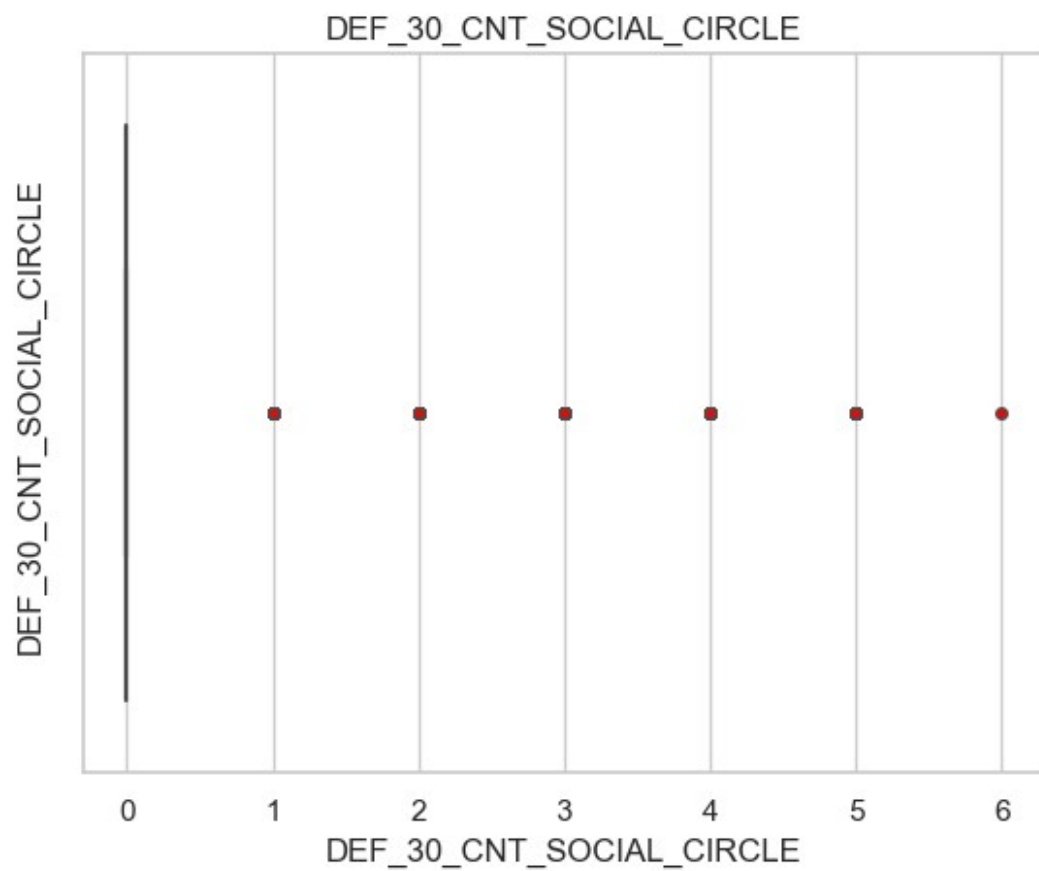


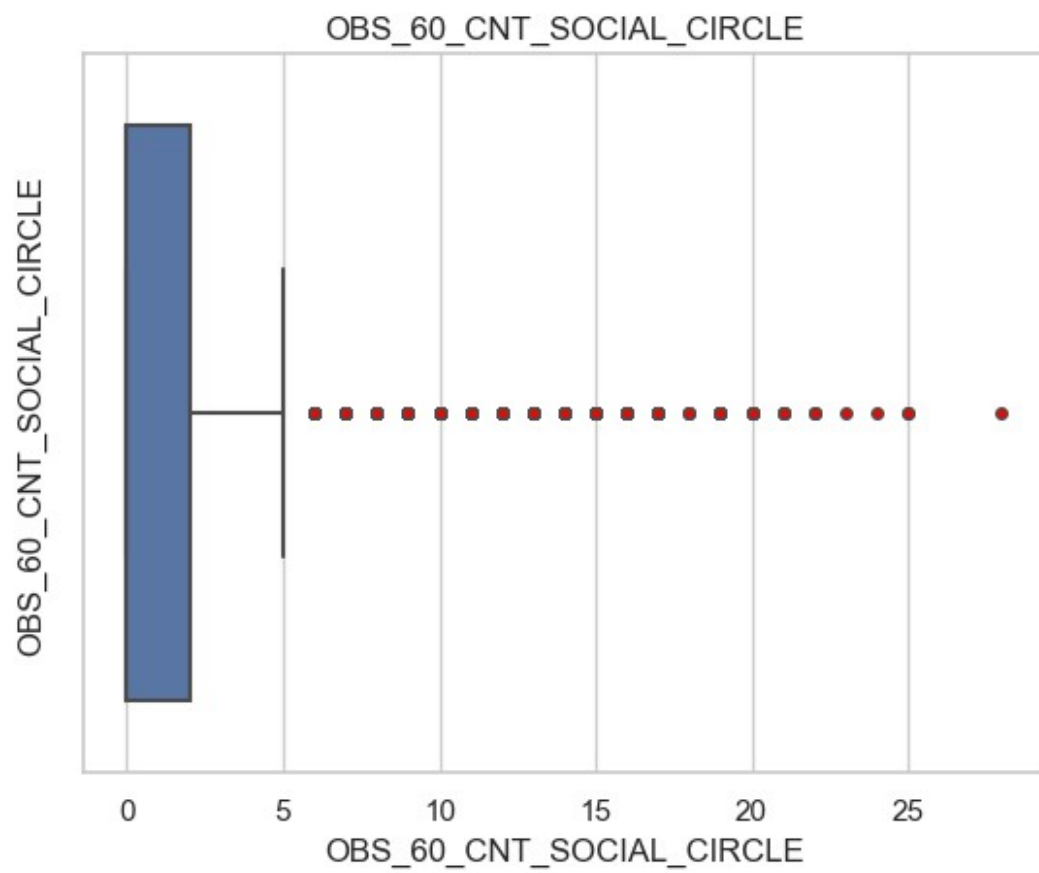


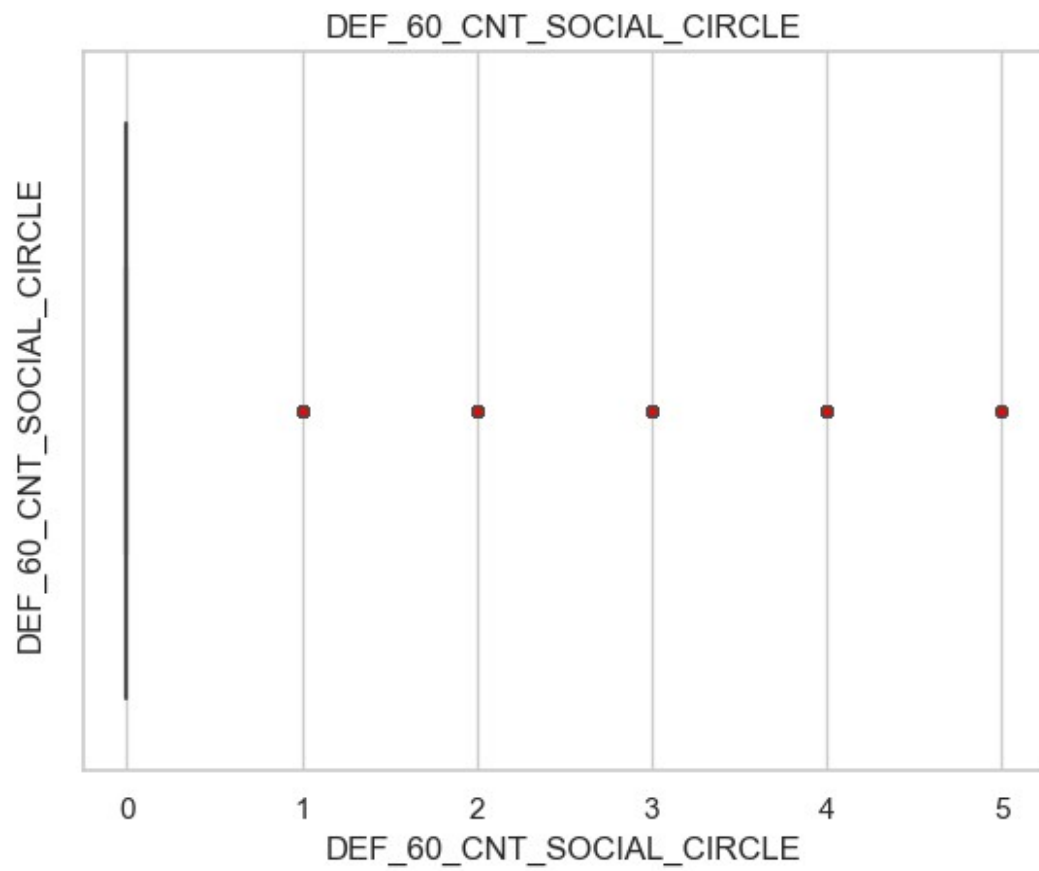


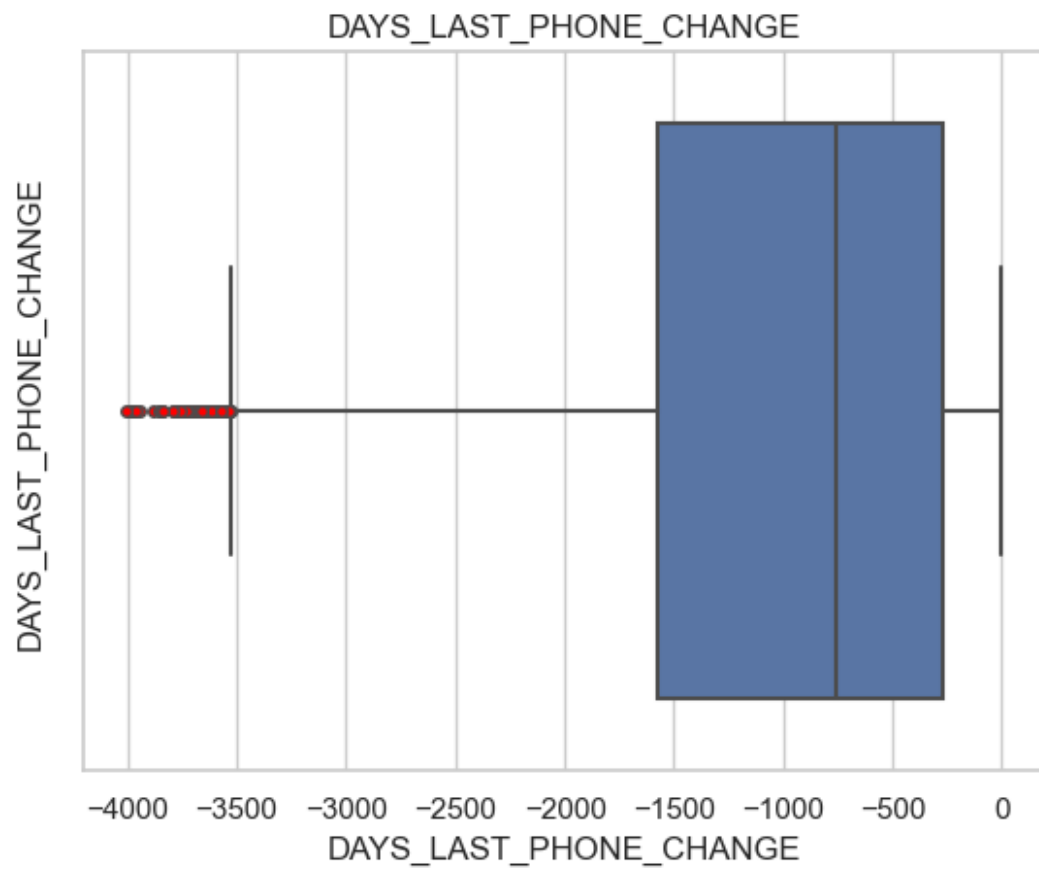


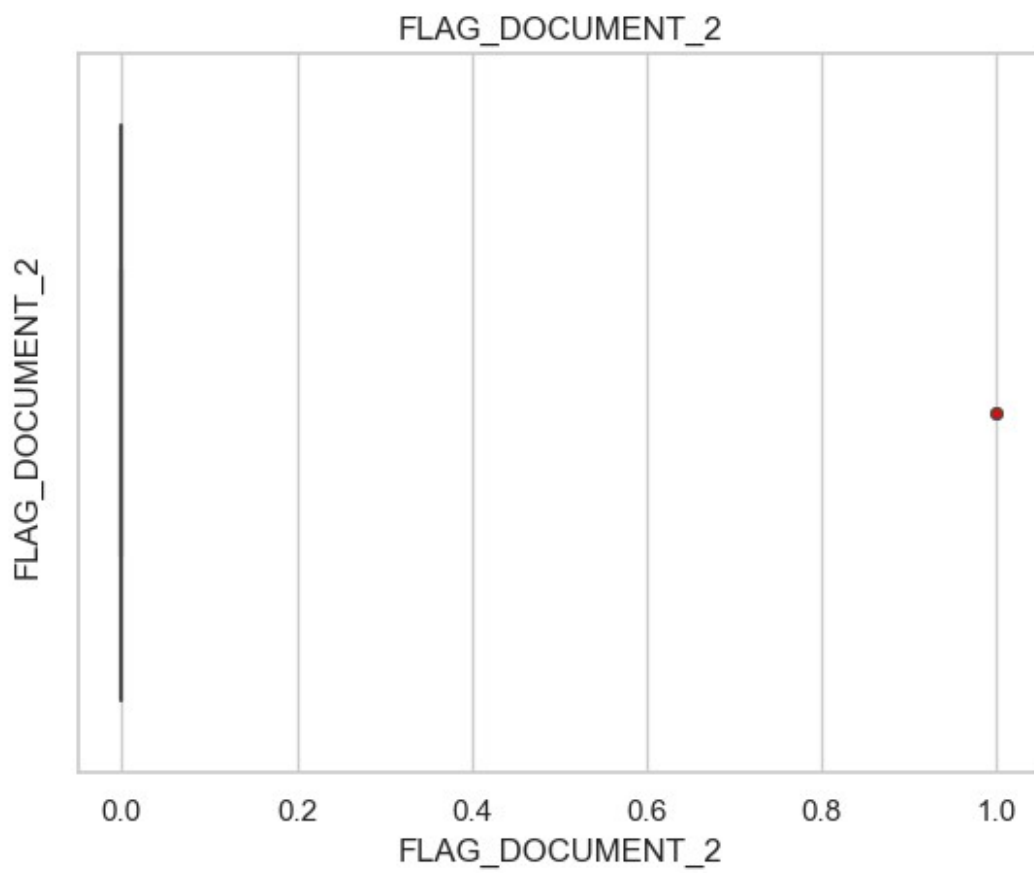




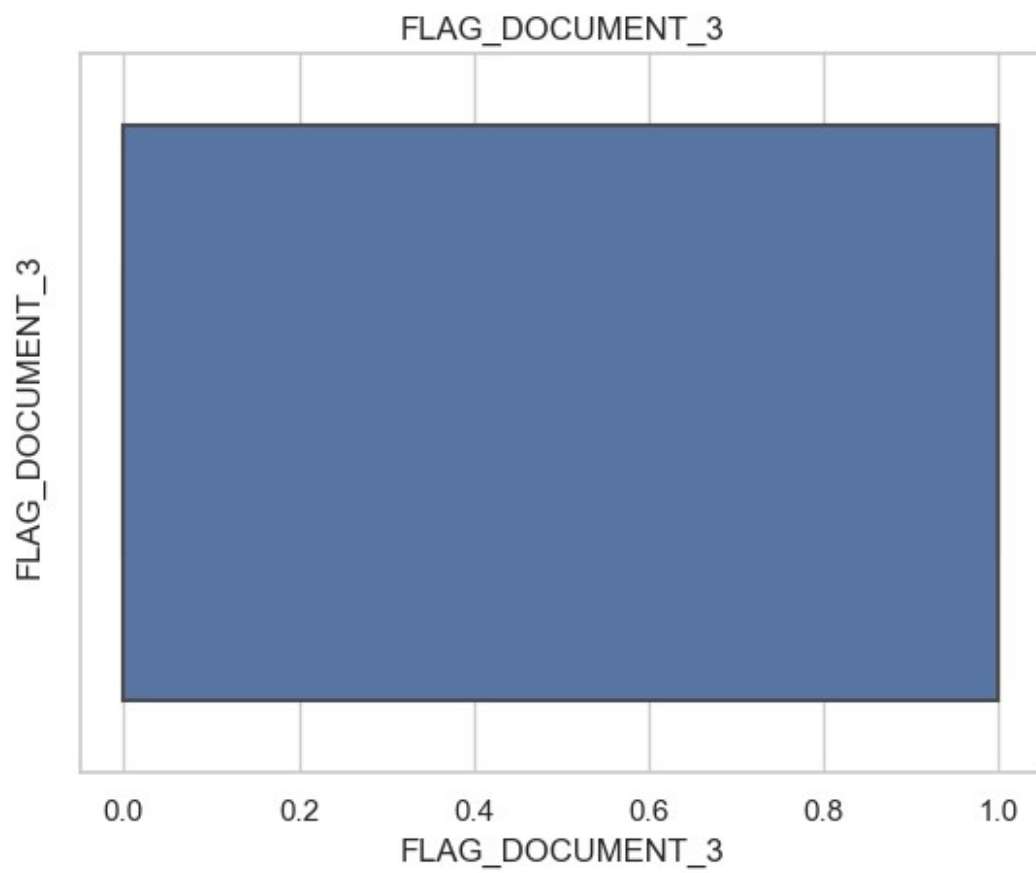


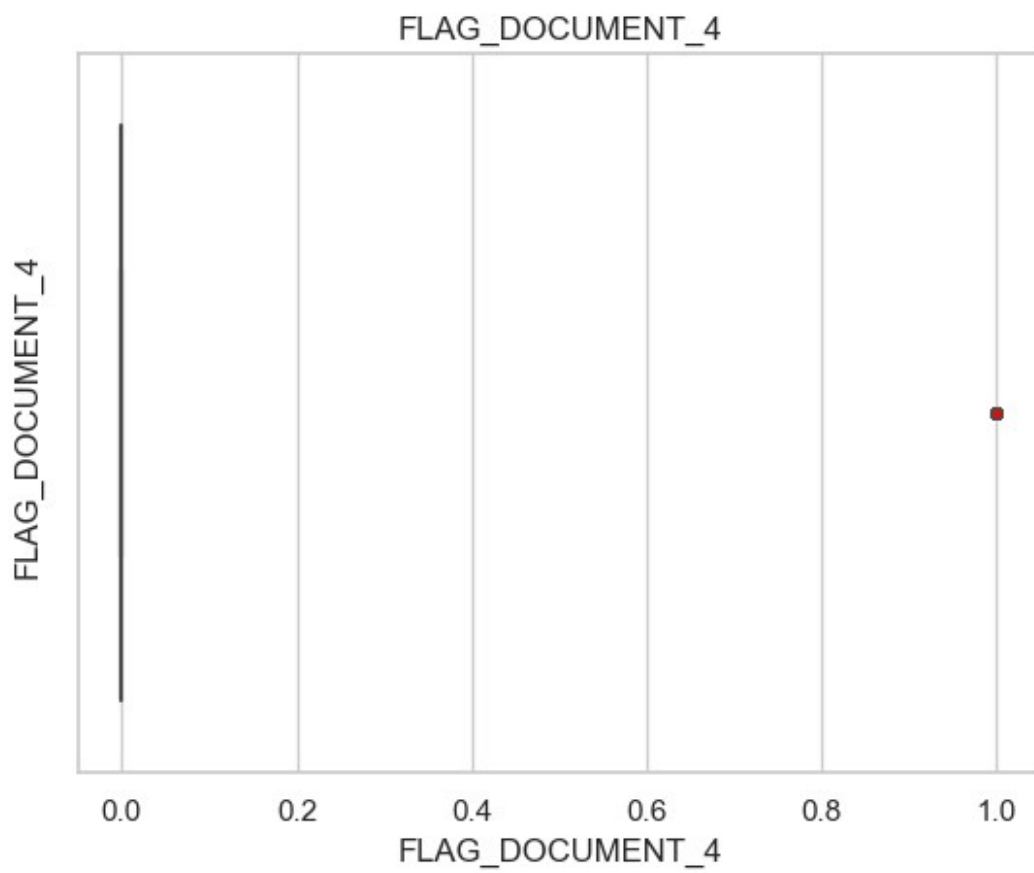


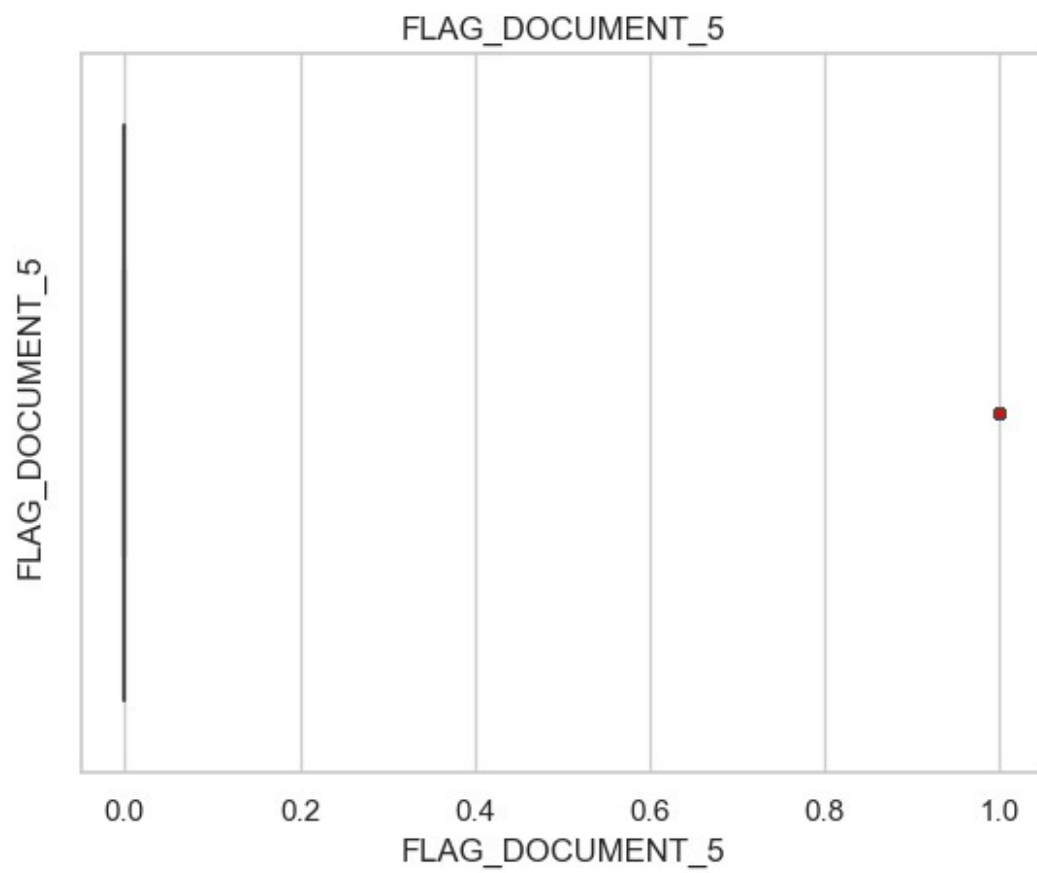


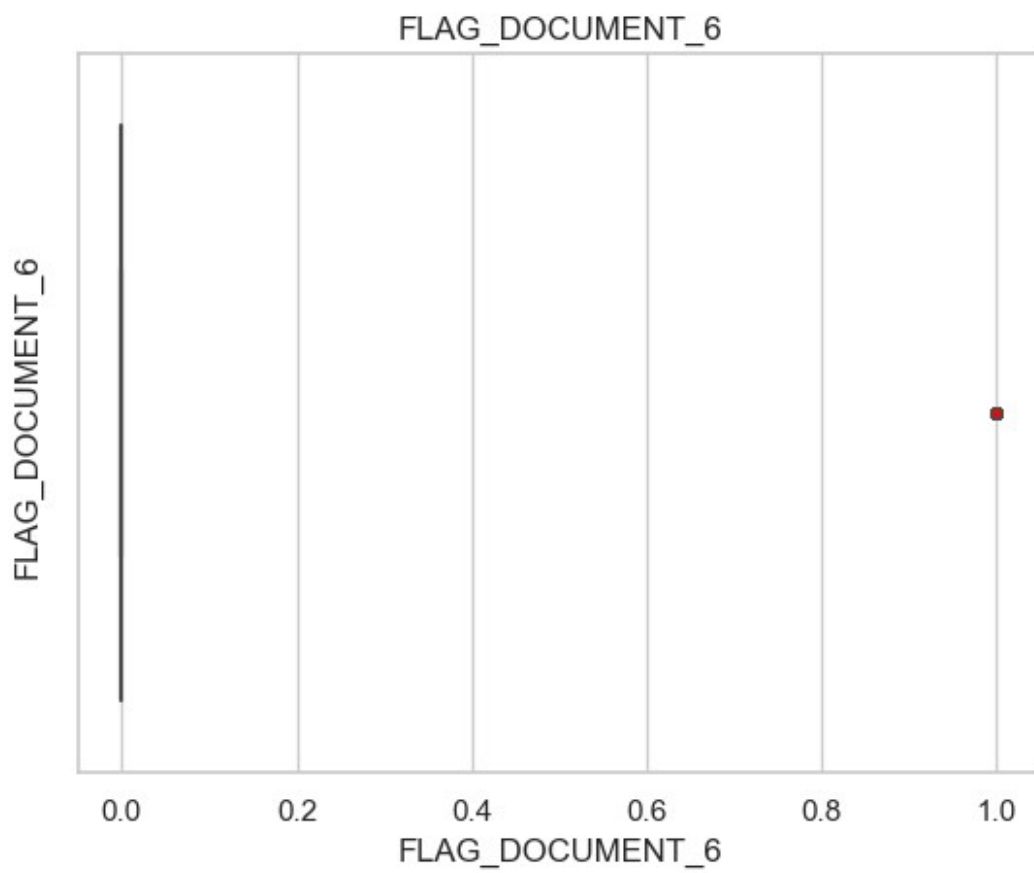


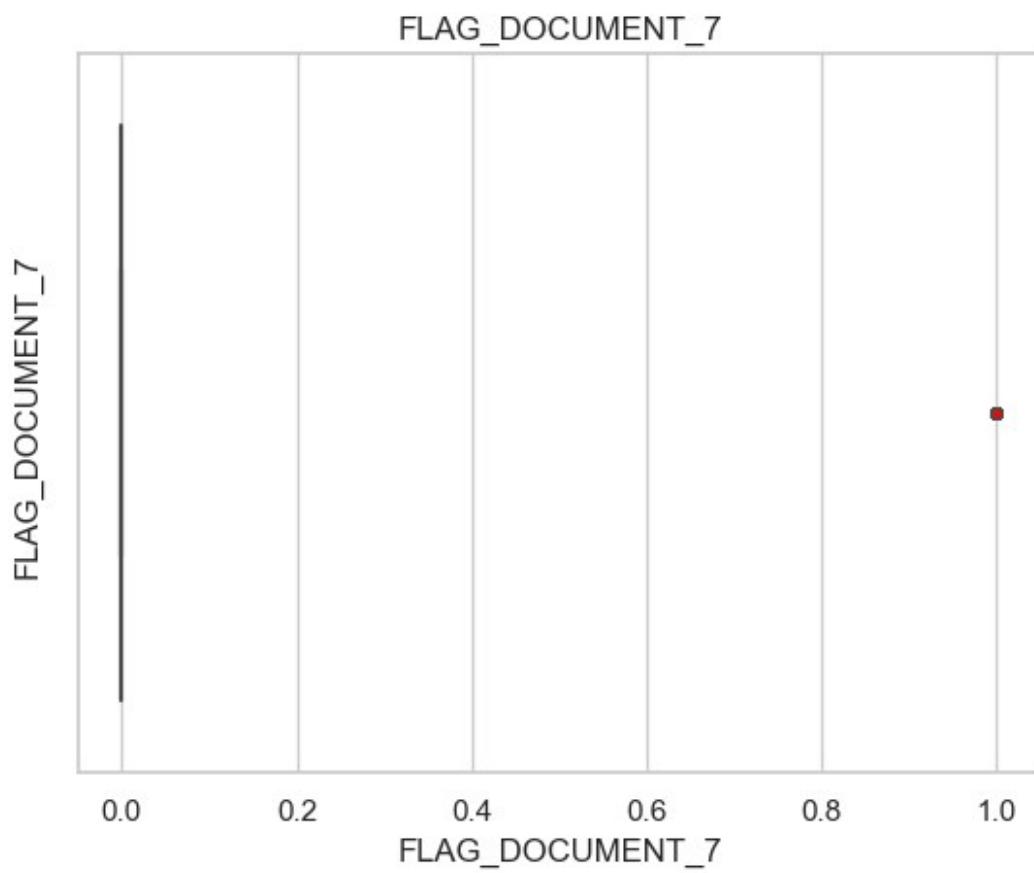


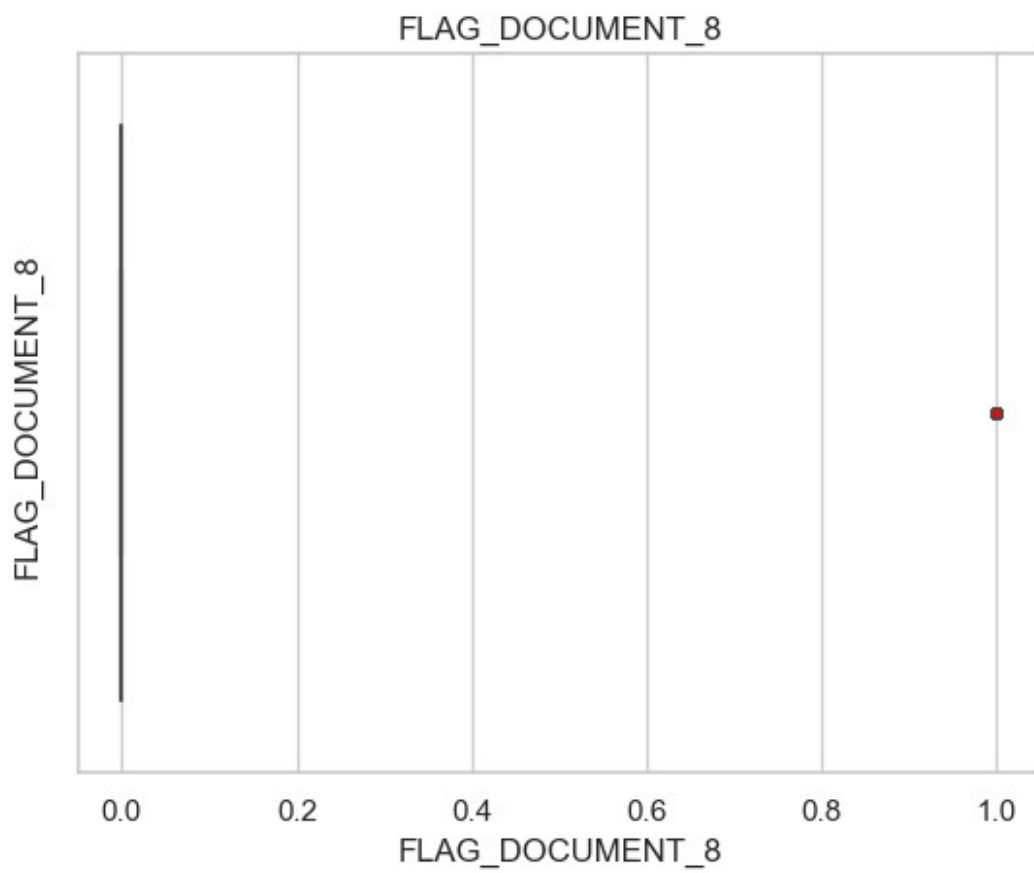


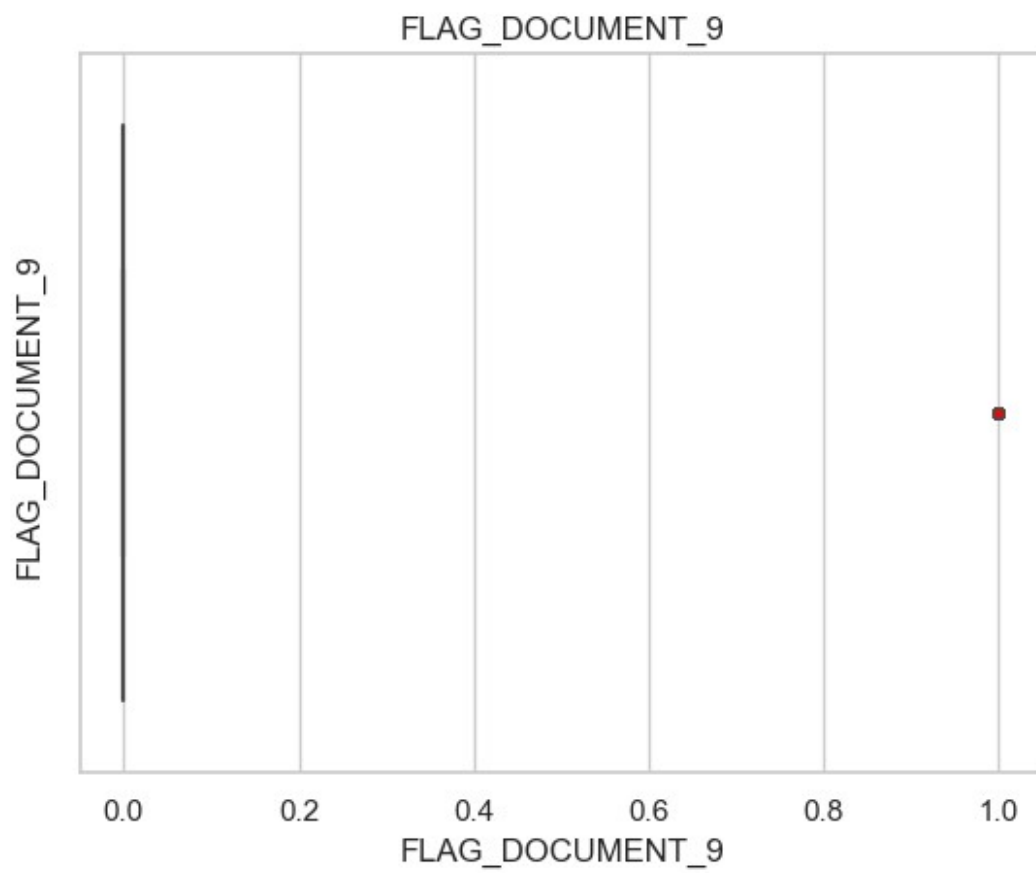


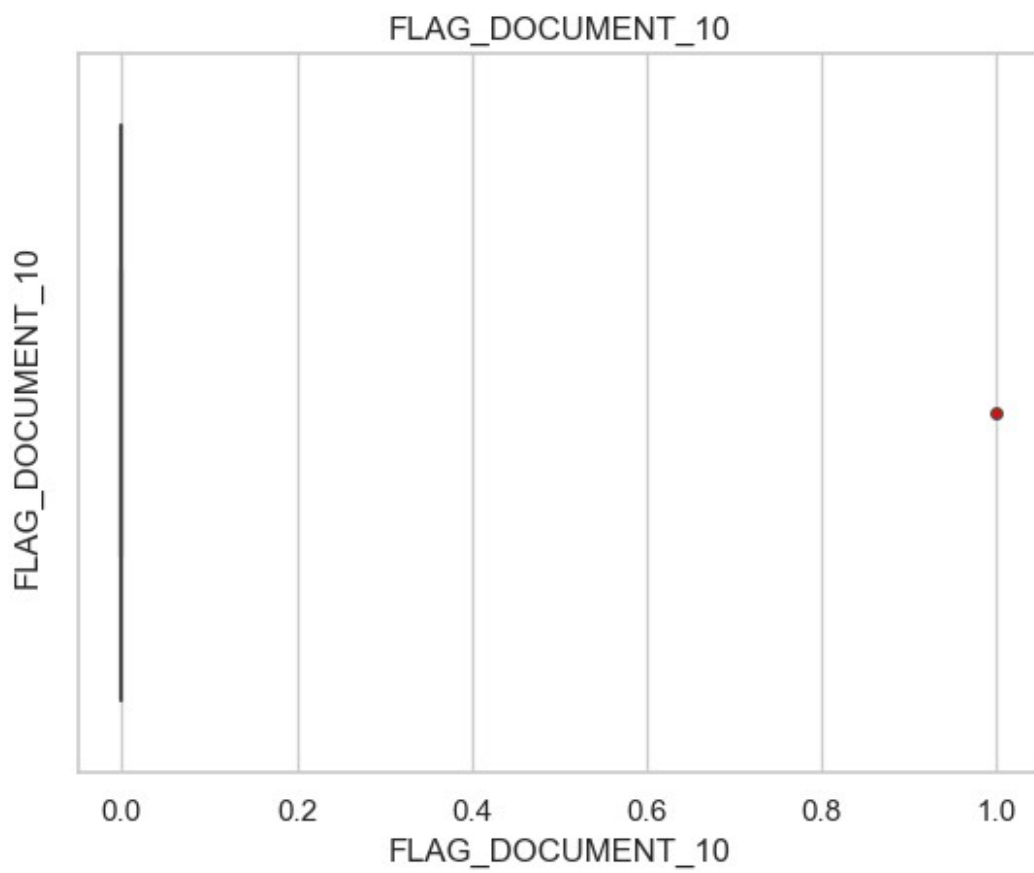




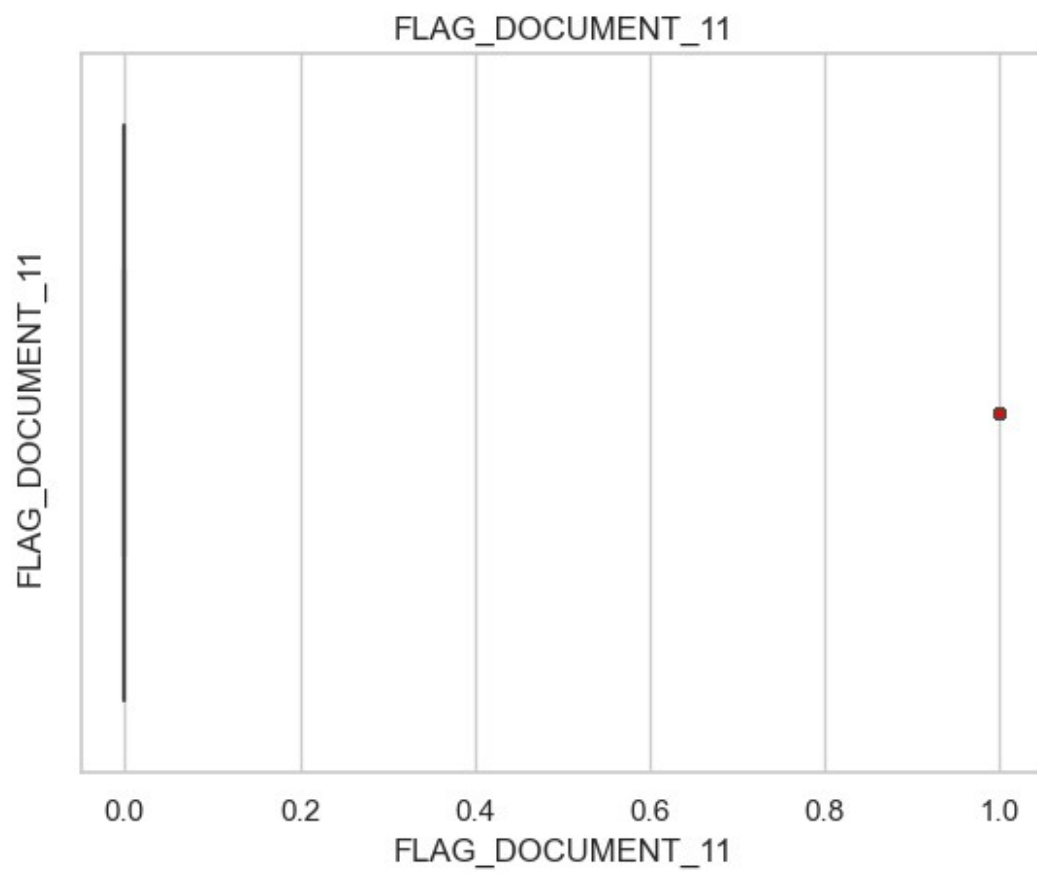


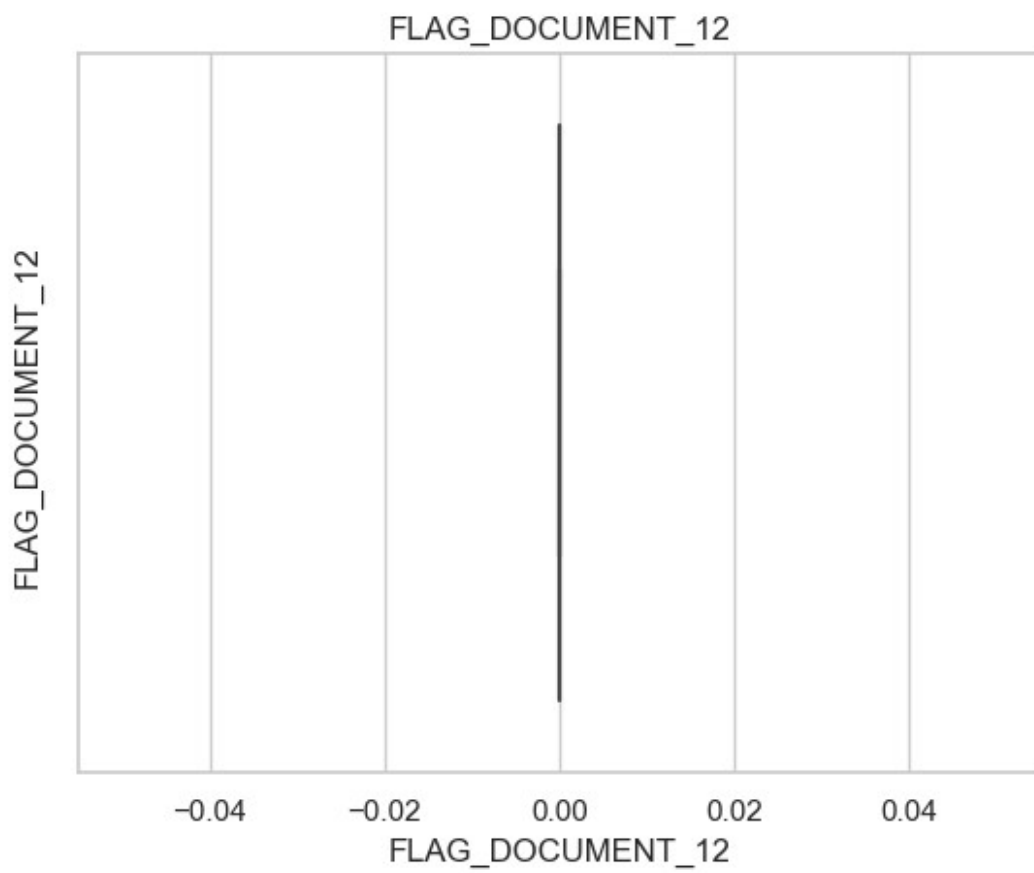


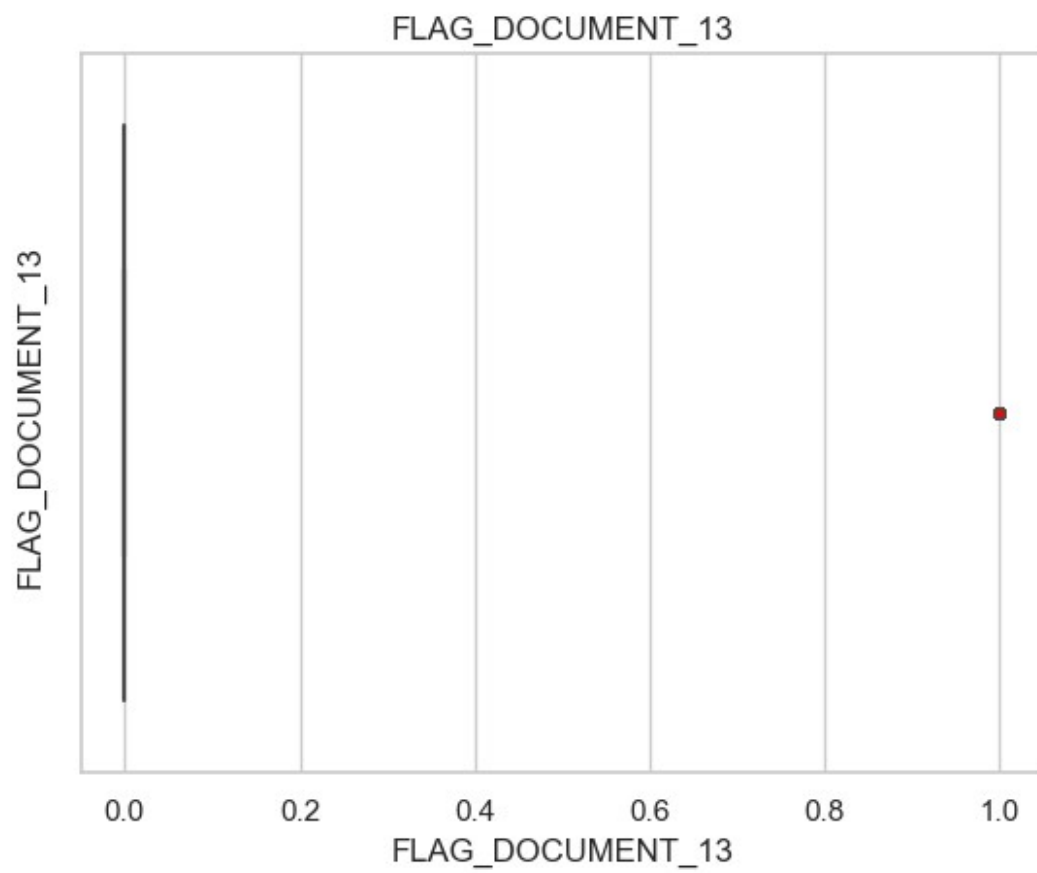


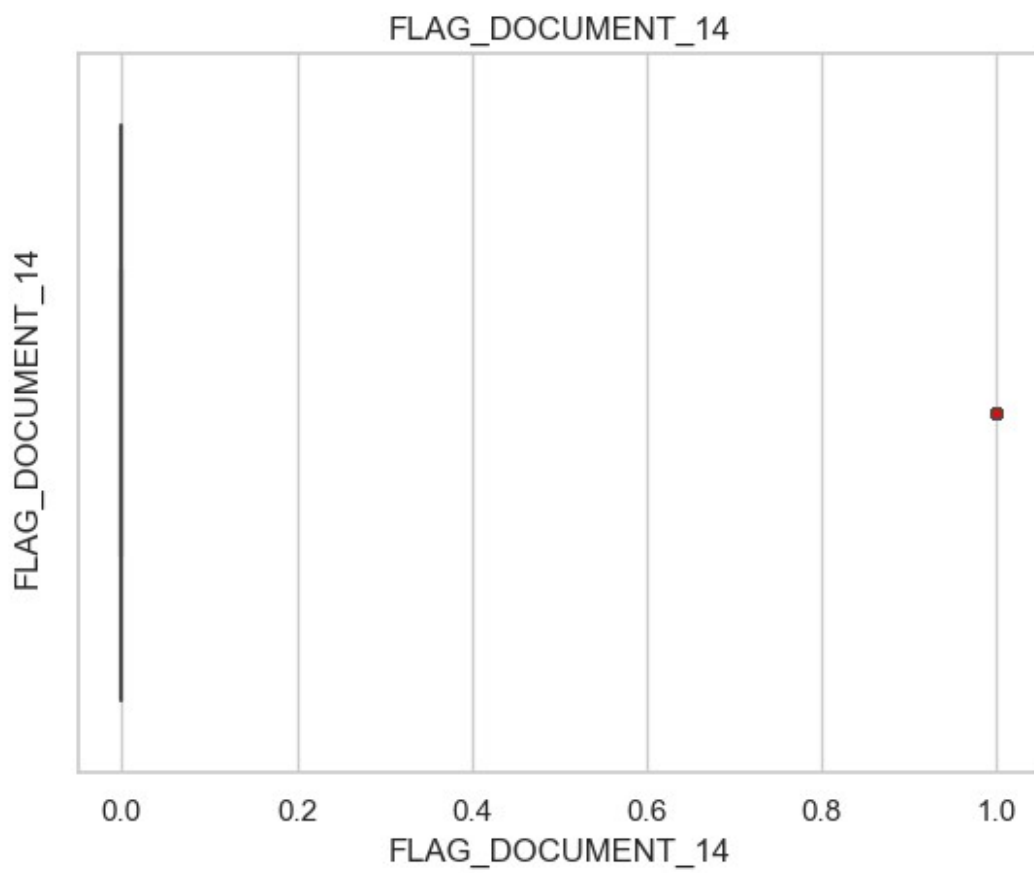


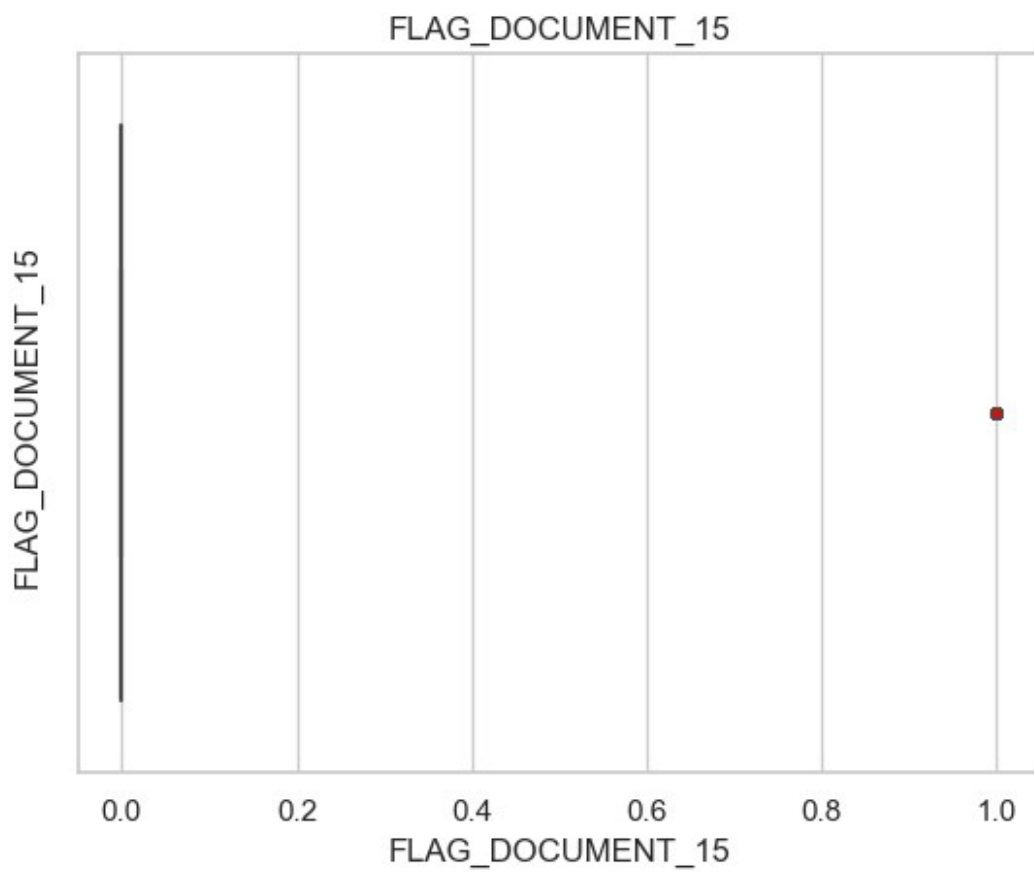


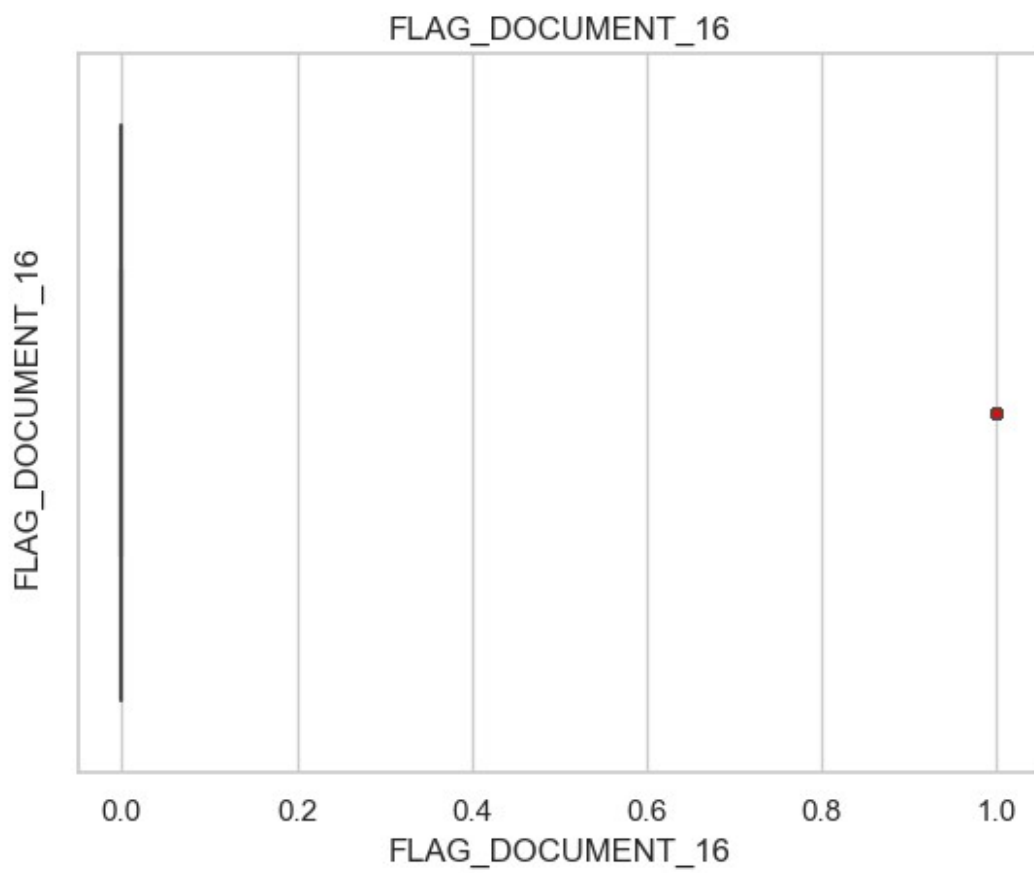


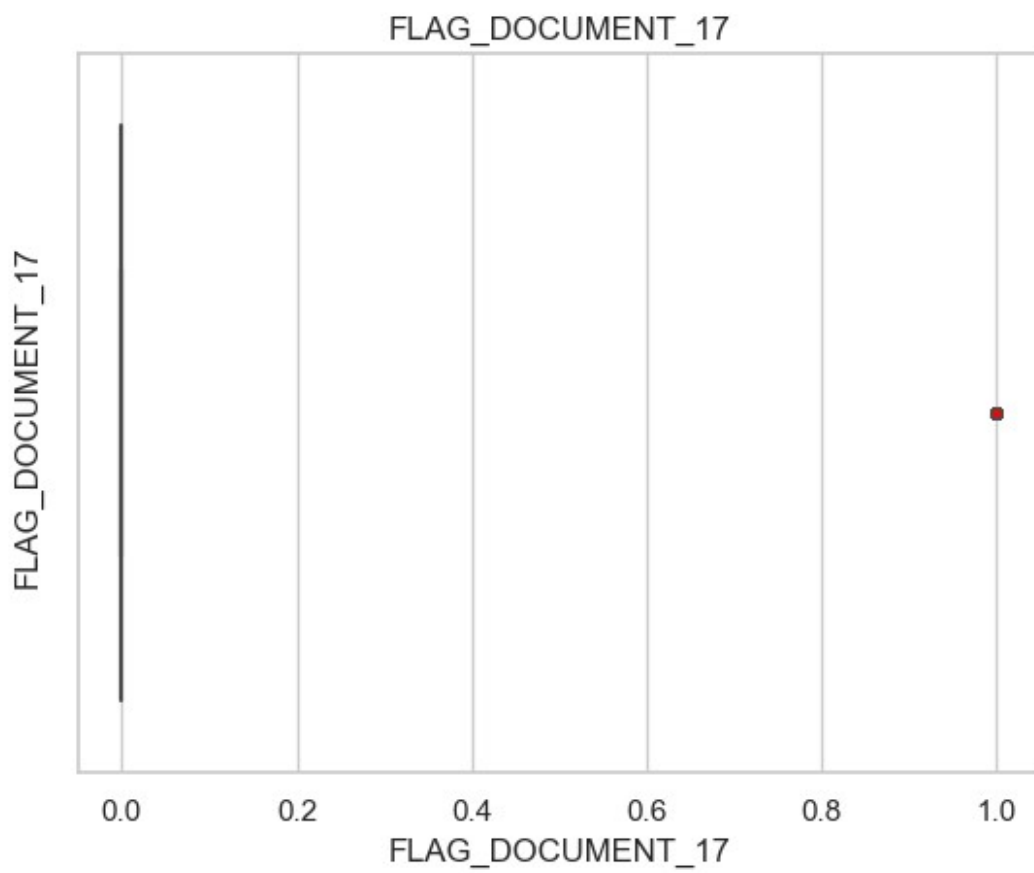


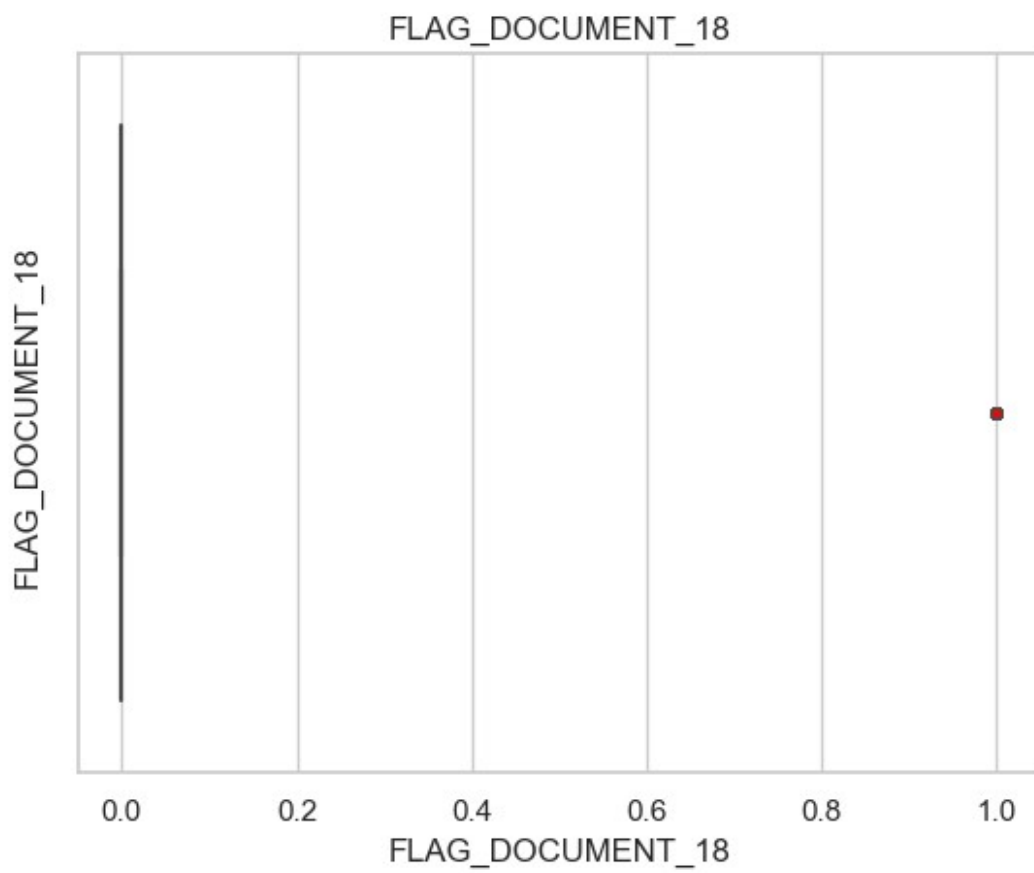




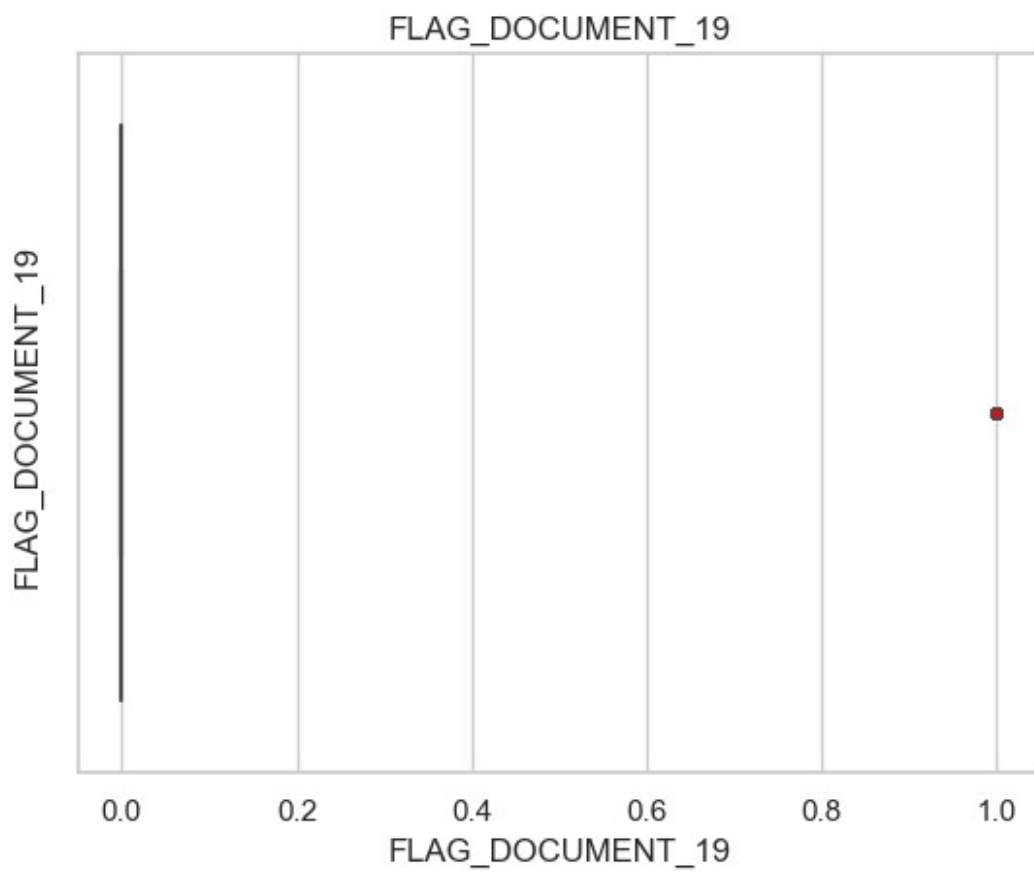


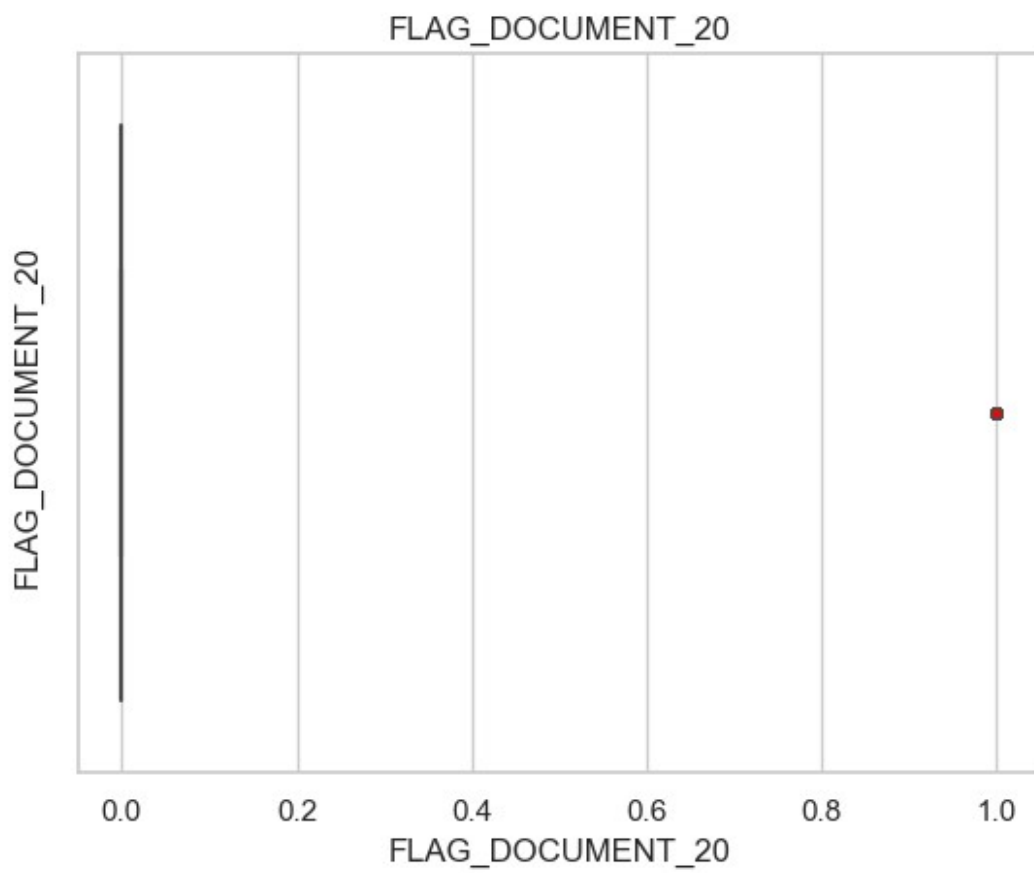


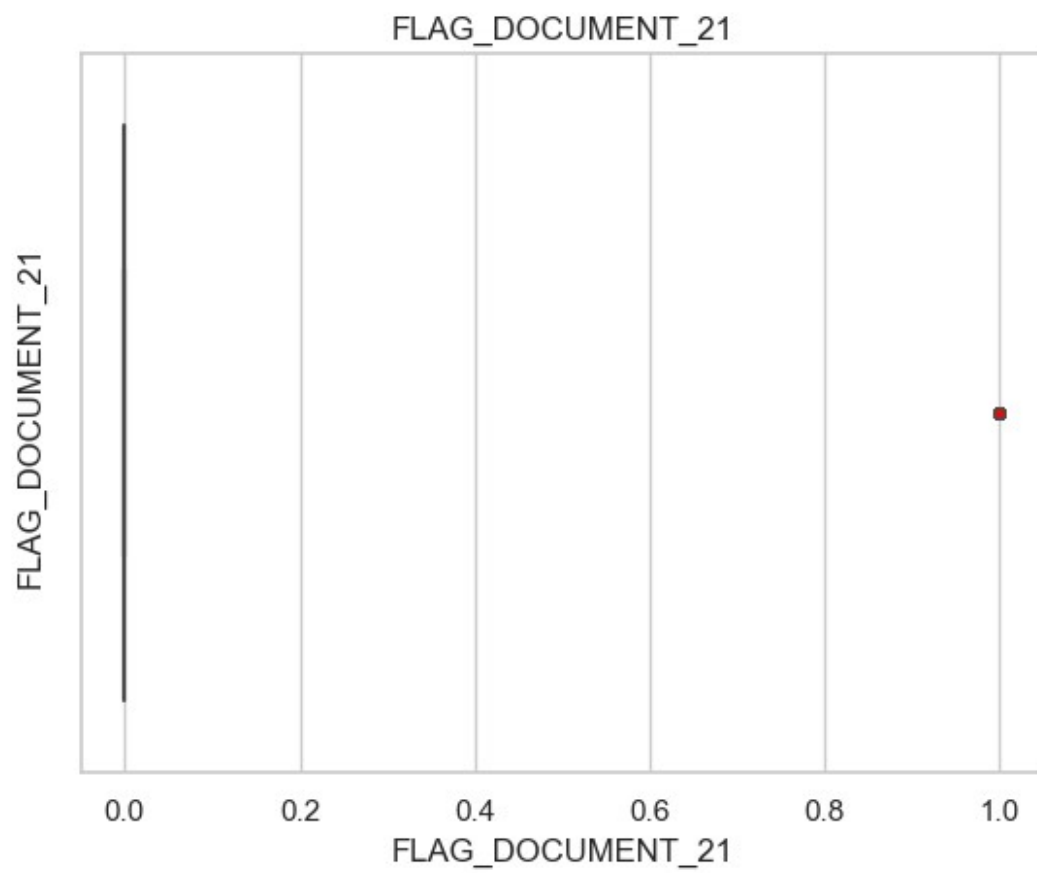


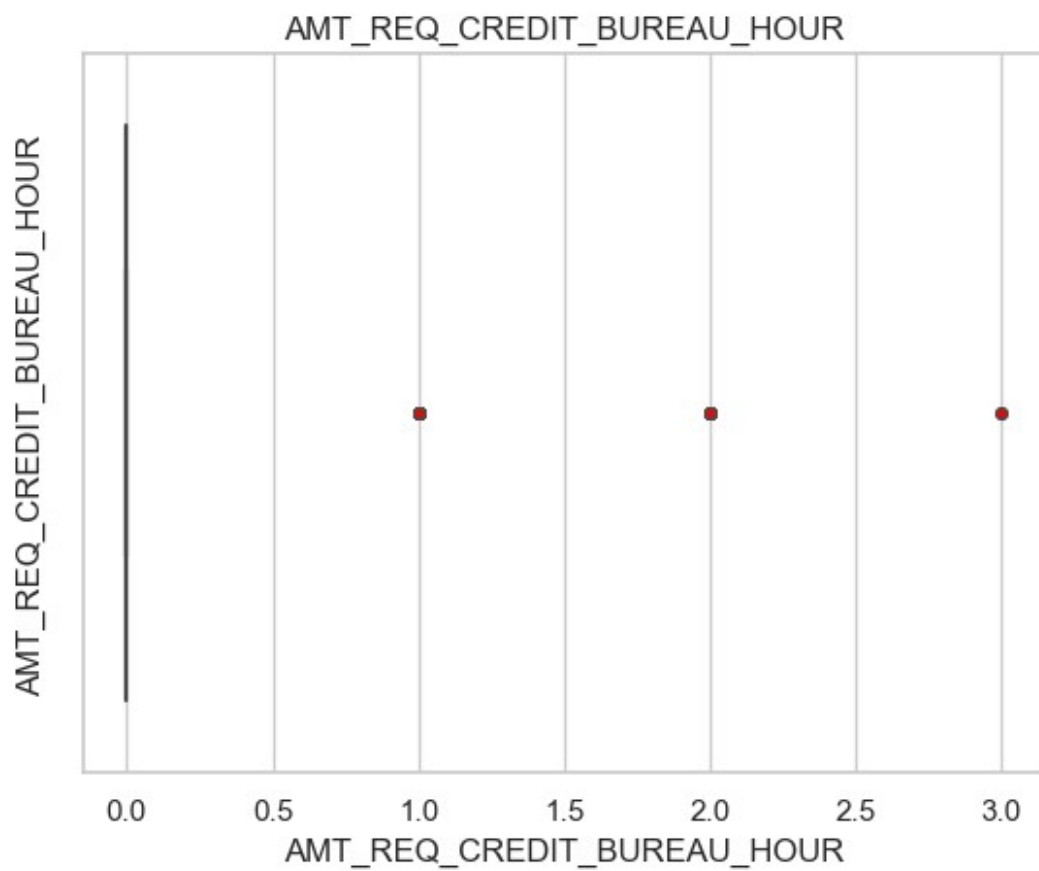


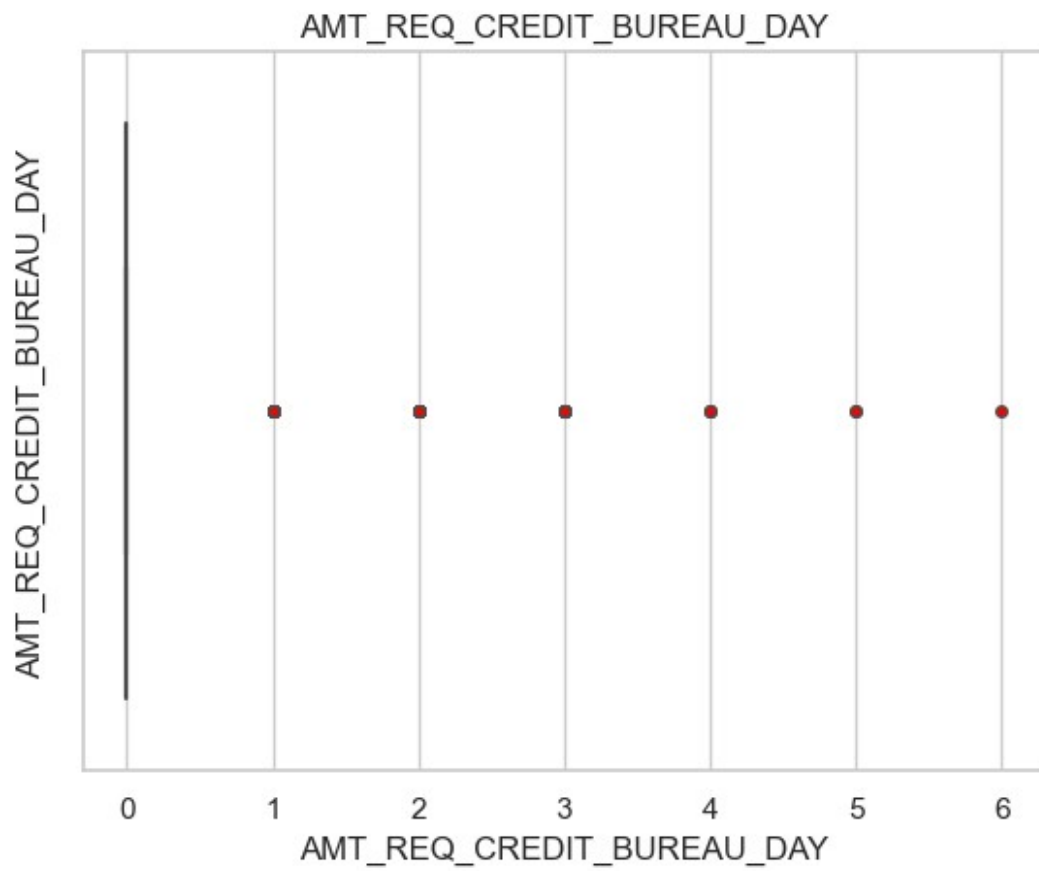


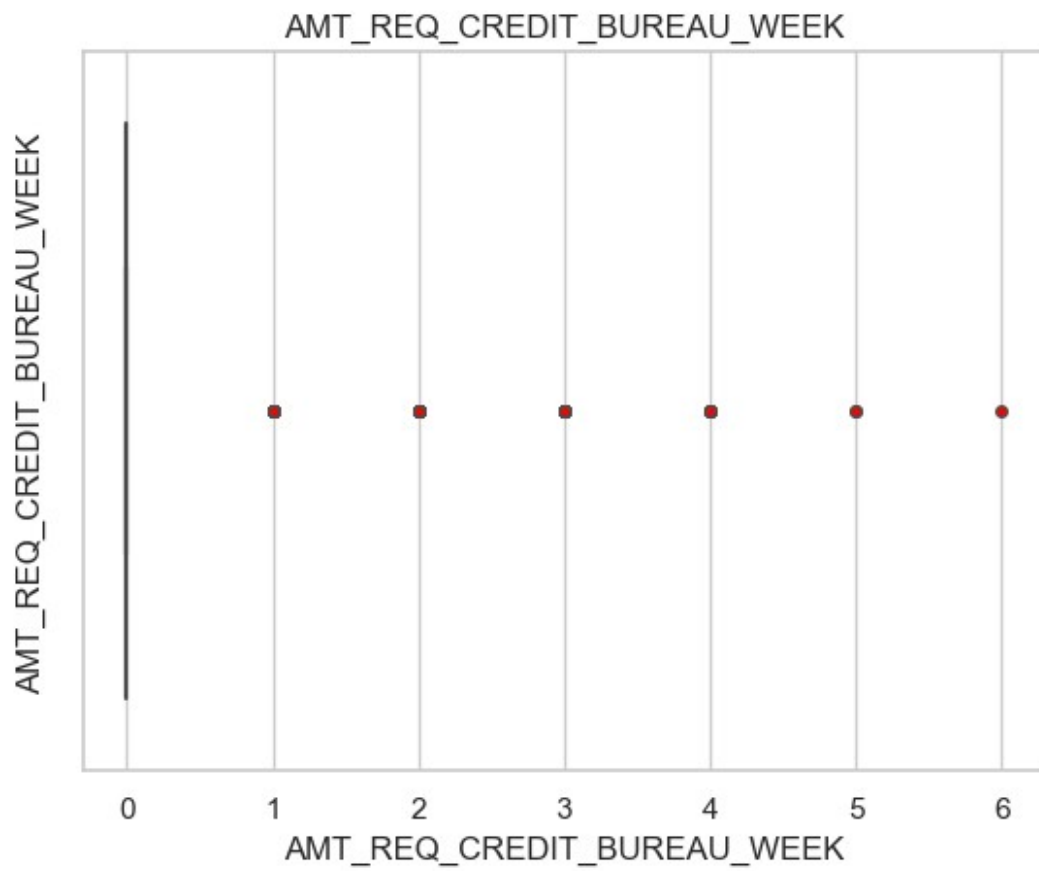


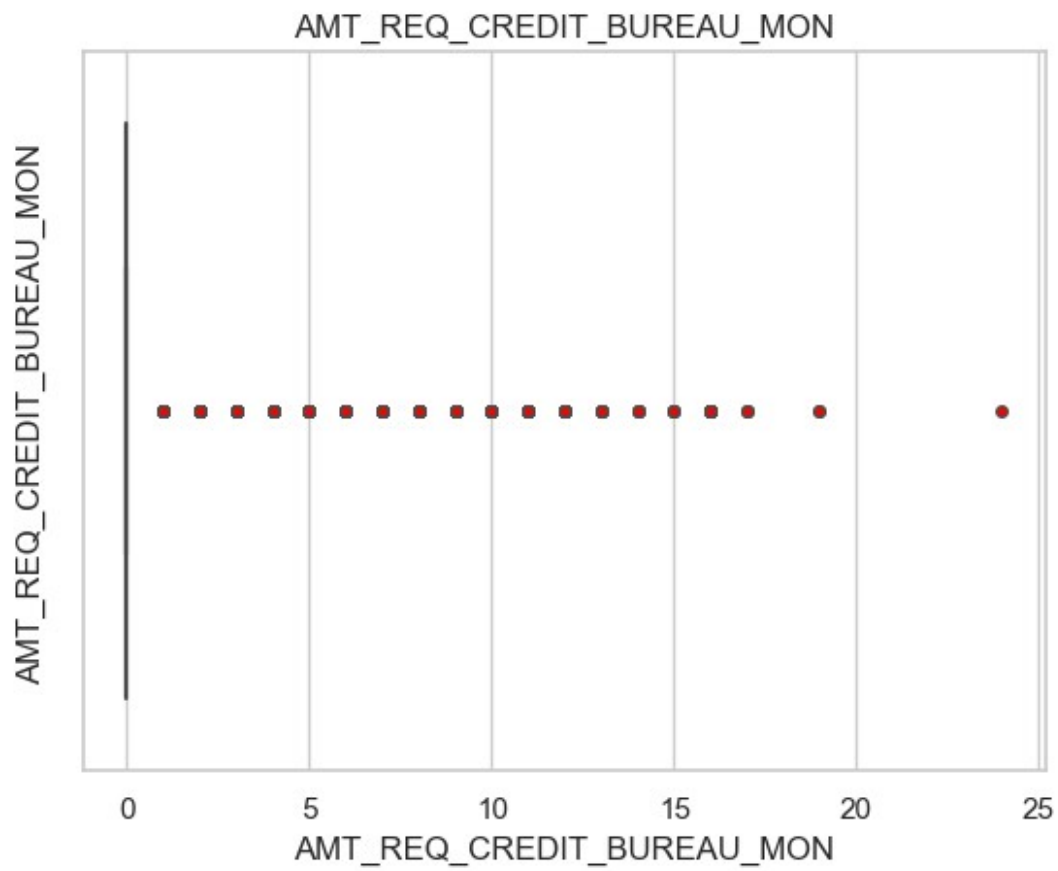


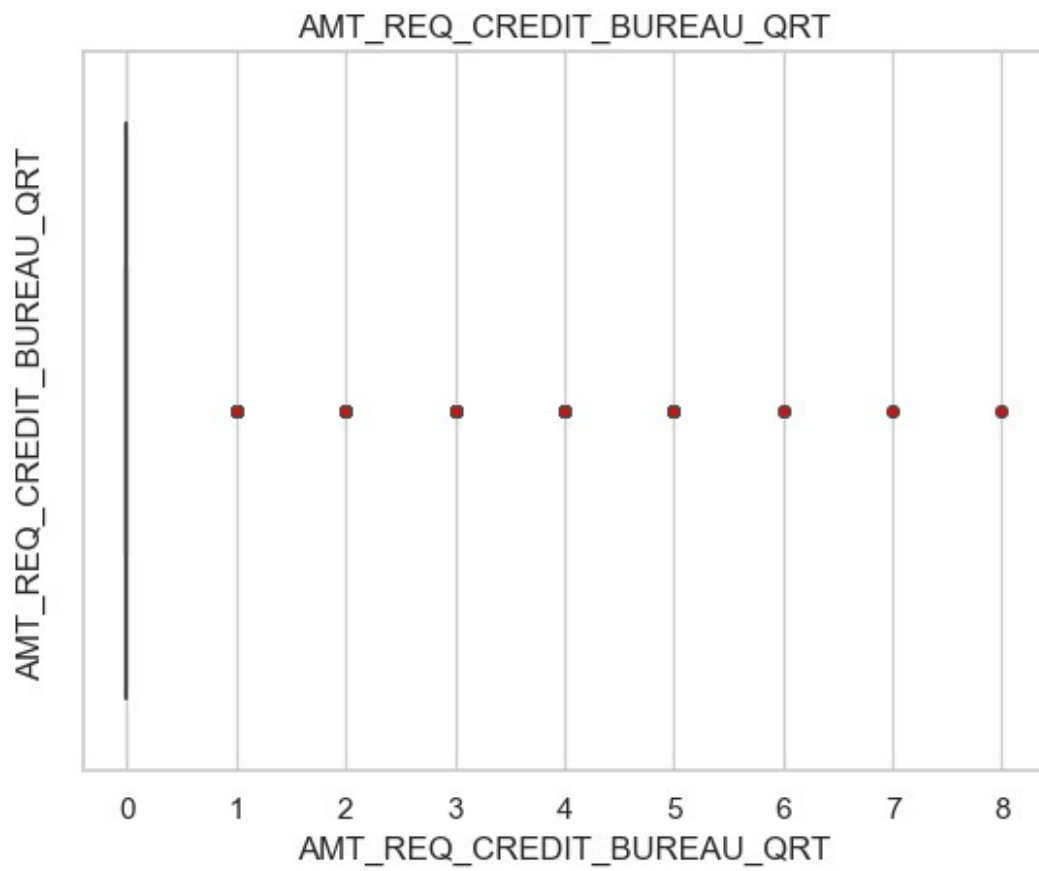




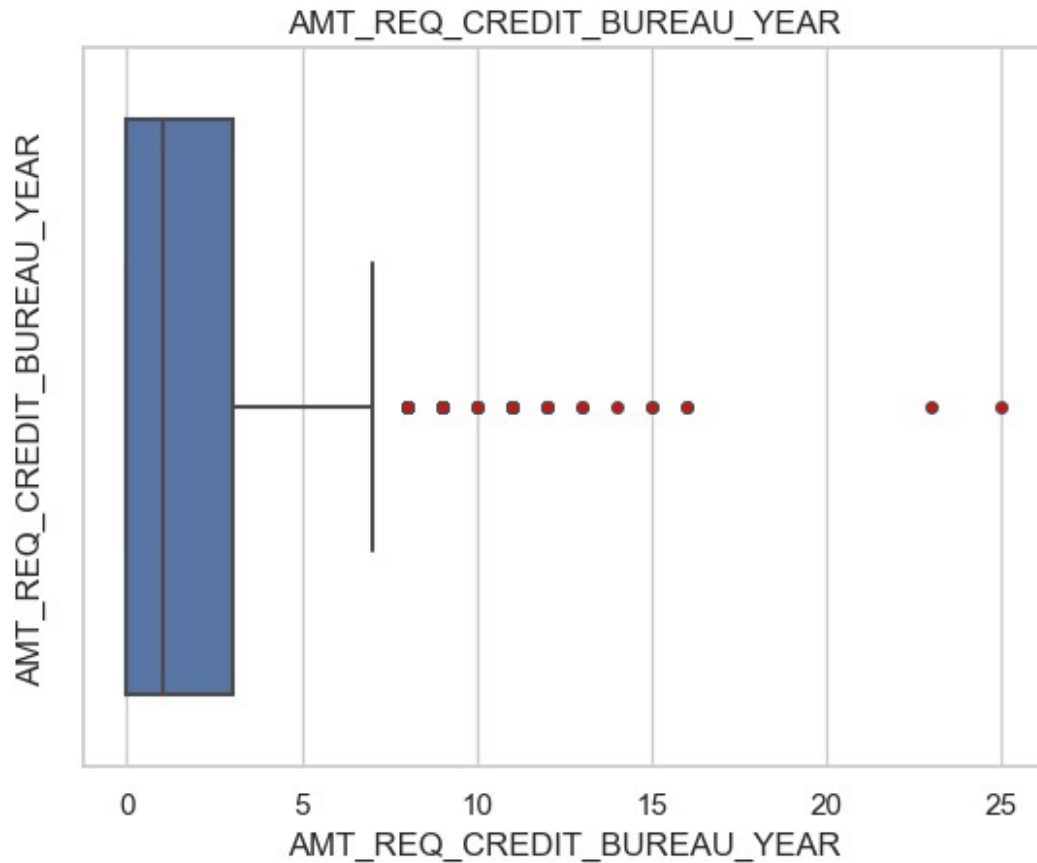












```
# let's see how many outliers each variable have
```

```
for key, value in dictoutlier.items():
    if len(value) > 0:
        print(f"Length of {key}: {len(value)}")
```

```
Length of TARGET: 4026
Length of CNT_CHILDREN: 723
Length of AMT_INCOME_TOTAL: 2295
Length of AMT_CREDIT: 1063
Length of REGION_POPULATION_RELATIVE: 1329
Length of DAYS_EMPLOYED: 9082
Length of DAYS_REGISTRATION: 96
Length of FLAG_MOBIL: 1
Length of FLAG_EMP_PHONE: 8926
Length of FLAG_WORK_PHONE: 9963
Length of FLAG_CONT_MOBILE: 101
Length of FLAG_EMAIL: 2783
Length of CNT_FAM_MEMBERS: 684
Length of REGION_RATING_CLIENT: 13035
Length of REGION_RATING_CLIENT_W_CITY: 12658
Length of HOUR_APPR_PROCESS_START: 353
Length of REG_REGION_NOT_LIVE_REGION: 750
```

```
Length of REG_REGION_NOT_WORK_REGION: 2496
Length of LIVE_REGION_NOT_WORK_REGION: 1982
Length of REG_CITY_NOT_LIVE_CITY: 3998
Length of REG_CITY_NOT_WORK_CITY: 11608
Length of LIVE_CITY_NOT_WORK_CITY: 8985
Length of FLAG_DOCUMENT_2: 2
Length of FLAG_DOCUMENT_4: 9
Length of FLAG_DOCUMENT_5: 785
Length of FLAG_DOCUMENT_6: 4335
Length of FLAG_DOCUMENT_7: 11
Length of FLAG_DOCUMENT_8: 4038
Length of FLAG_DOCUMENT_9: 184
Length of FLAG_DOCUMENT_10: 1
Length of FLAG_DOCUMENT_11: 213
Length of FLAG_DOCUMENT_13: 161
Length of FLAG_DOCUMENT_14: 158
Length of FLAG_DOCUMENT_15: 41
Length of FLAG_DOCUMENT_16: 501
Length of FLAG_DOCUMENT_17: 15
Length of FLAG_DOCUMENT_18: 425
Length of FLAG_DOCUMENT_19: 35
Length of FLAG_DOCUMENT_20: 26
Length of FLAG_DOCUMENT_21: 19
Length of AMT_REQ_CREDIT_BUREAU_HOUR: 295
Length of AMT_REQ_CREDIT_BUREAU_DAY: 272
Length of AMT_REQ_CREDIT_BUREAU_WEEK: 1314
Length of AMT_REQ_CREDIT_BUREAU_MON: 7140
Length of AMT_REQ_CREDIT_BUREAU_QRT: 8134
Length of AMT_REQ_CREDIT_BUREAU_YEAR: 552
```

*# let's see how many unique outliers each variable have*

```
for key, value in dictoutlier.items():
    if len(value) > 0:
        print(f"Length of {key}: {len(set(value))}")
```

```
Length of TARGET: 1
Length of CNT_CHILDREN: 8
Length of AMT_INCOME_TOTAL: 120
Length of AMT_CREDIT: 262
Length of REGION_POPULATION_RELATIVE: 1
Length of DAYS_EMPLOYED: 151
Length of DAYS_REGISTRATION: 96
Length of FLAG_MOBIL: 1
Length of FLAG_EMP_PHONE: 1
Length of FLAG_WORK_PHONE: 1
Length of FLAG_CONT_MOBILE: 1
Length of FLAG_EMAIL: 1
Length of CNT_FAM_MEMBERS: 8
Length of REGION_RATING_CLIENT: 2
```

```
Length of REGION_RATING_CLIENT_W_CITY: 2
Length of HOUR_APPR_PROCESS_START: 7
Length of REG_REGION_NOT_LIVE_REGION: 1
Length of REG_REGION_NOT_WORK_REGION: 1
Length of LIVE_REGION_NOT_WORK_REGION: 1
Length of REG_CITY_NOT_LIVE_CITY: 1
Length of REG_CITY_NOT_WORK_CITY: 1
Length of LIVE_CITY_NOT_WORK_CITY: 1
Length of FLAG_DOCUMENT_2: 1
Length of FLAG_DOCUMENT_4: 1
Length of FLAG_DOCUMENT_5: 1
Length of FLAG_DOCUMENT_6: 1
Length of FLAG_DOCUMENT_7: 1
Length of FLAG_DOCUMENT_8: 1
Length of FLAG_DOCUMENT_9: 1
Length of FLAG_DOCUMENT_10: 1
Length of FLAG_DOCUMENT_11: 1
Length of FLAG_DOCUMENT_13: 1
Length of FLAG_DOCUMENT_14: 1
Length of FLAG_DOCUMENT_15: 1
Length of FLAG_DOCUMENT_16: 1
Length of FLAG_DOCUMENT_17: 1
Length of FLAG_DOCUMENT_18: 1
Length of FLAG_DOCUMENT_19: 1
Length of FLAG_DOCUMENT_20: 1
Length of FLAG_DOCUMENT_21: 1
Length of AMT_REQ_CREDIT_BUREAU_HOUR: 3
Length of AMT_REQ_CREDIT_BUREAU_DAY: 6
Length of AMT_REQ_CREDIT_BUREAU_WEEK: 6
Length of AMT_REQ_CREDIT_BUREAU_MON: 19
Length of AMT_REQ_CREDIT_BUREAU_QRT: 8
Length of AMT_REQ_CREDIT_BUREAU_YEAR: 11
```

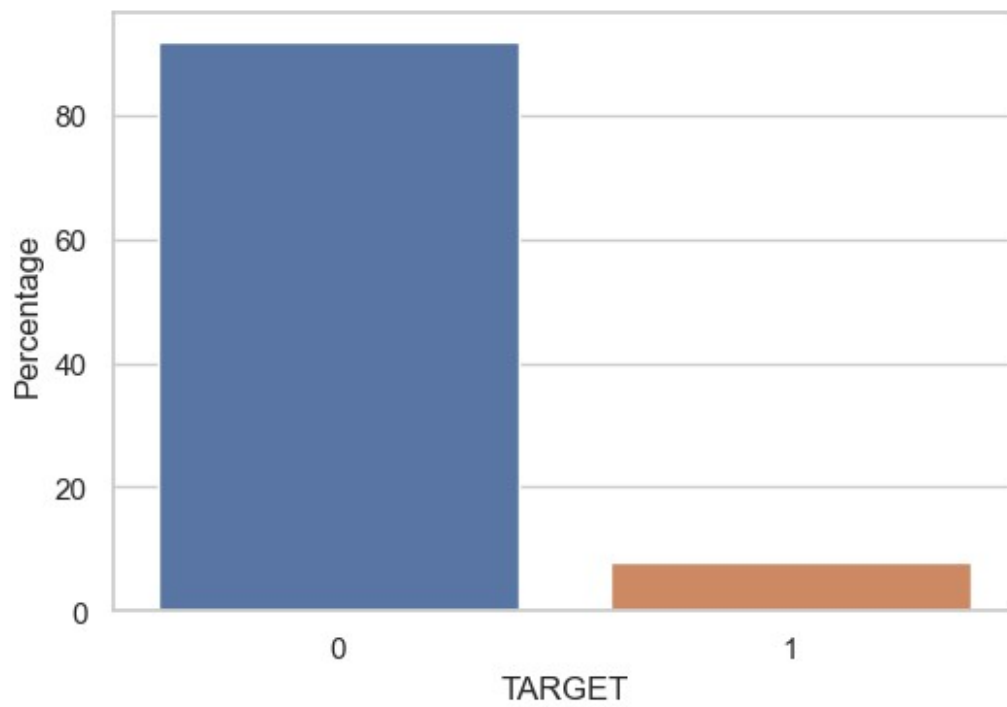
So here, outliers for each variable is found and stored in a dictionary named dictoutliers. We can use this result in our futhur study.

## C. Analyze Data Imbalance:

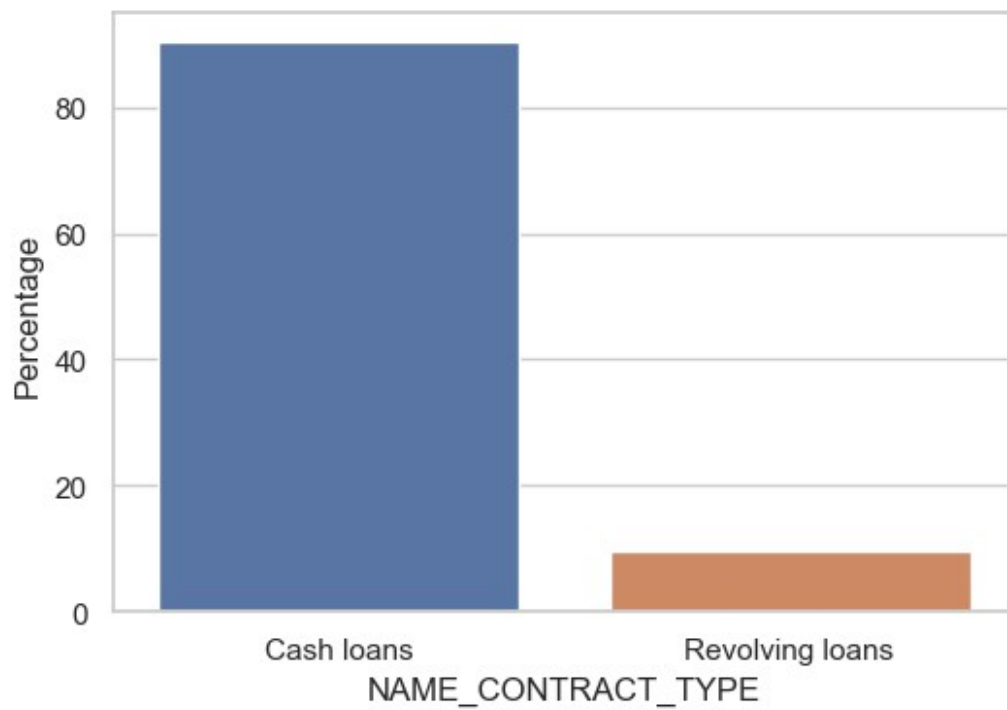
# Top Correlations for Different Scenarios

```
class_frequencies =  
application_data["NAME_CONTRACT_TYPE"].value_counts()  
  
print(class_frequencies)  
type(class_frequencies)  
class_frequencies  
  
Cash loans      45276  
Revolving loans  4723  
Name: NAME_CONTRACT_TYPE, dtype: int64  
  
Cash loans      45276  
Revolving loans  4723  
Name: NAME_CONTRACT_TYPE, dtype: int64  
  
for i in application_data.columns:  
    # Calculate the class frequencies  
    class_frequencies = application_data[i].value_counts()  
  
    # Create a bar chart to visualize Data imbalance.  
    # Using if condition to give only those we are categorical  
    variables.  
  
    if len(class_frequencies)<=3:  
        # printing the percentage of each value_count in list  
        percentage =  
np.around((class_frequencies.values)/len(application_data[i])*100)  
        print(percentage)  
  
        # Create a bar chart to visualize Data imbalance.  
        plt.figure(figsize=(6, 4))  
        sns.barplot(x = class_frequencies.index, y =  
(class_frequencies.values)/len(application_data[i])*100)  
        plt.xlabel(i)  
        plt.ylabel("Percentage")  
        plt.show()
```

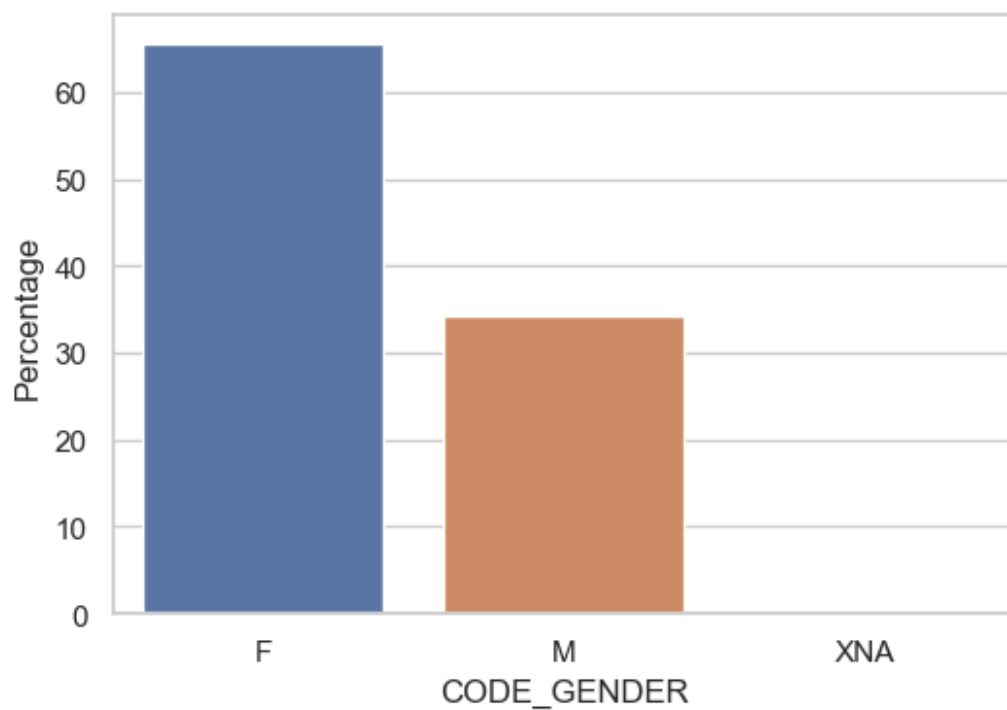
[92. 8.]



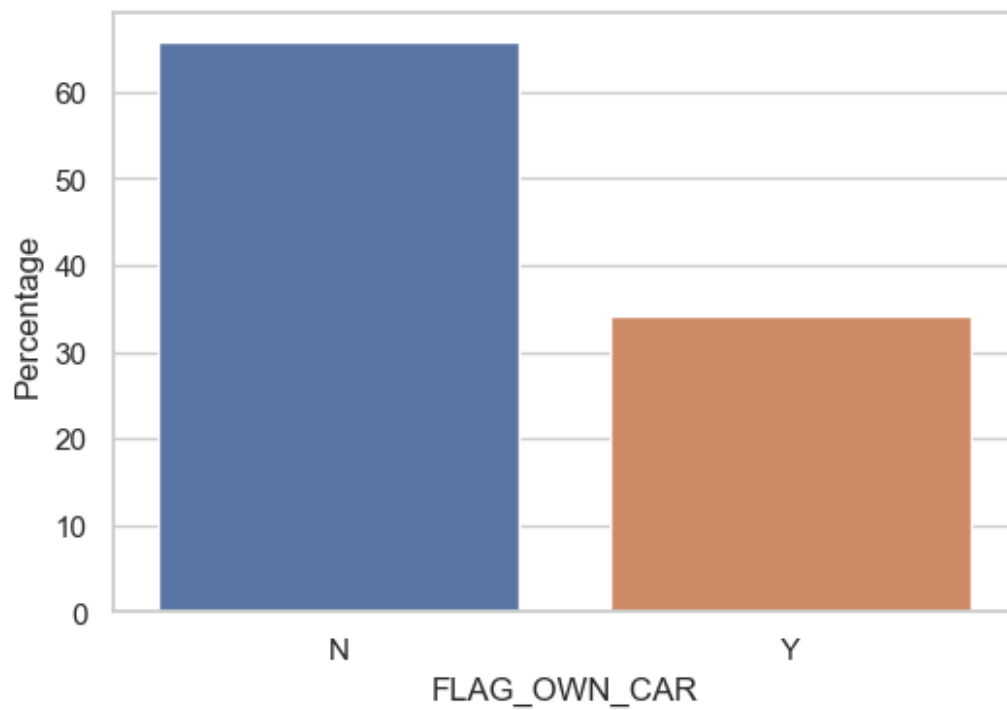
[91. 9.]



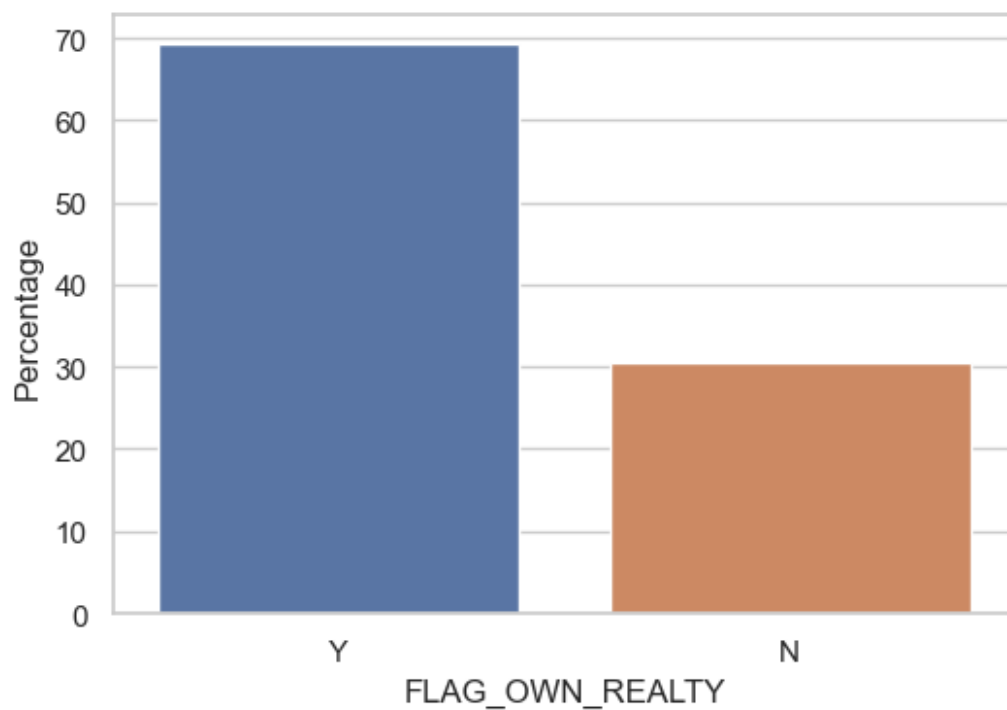
[66. 34. 0.]



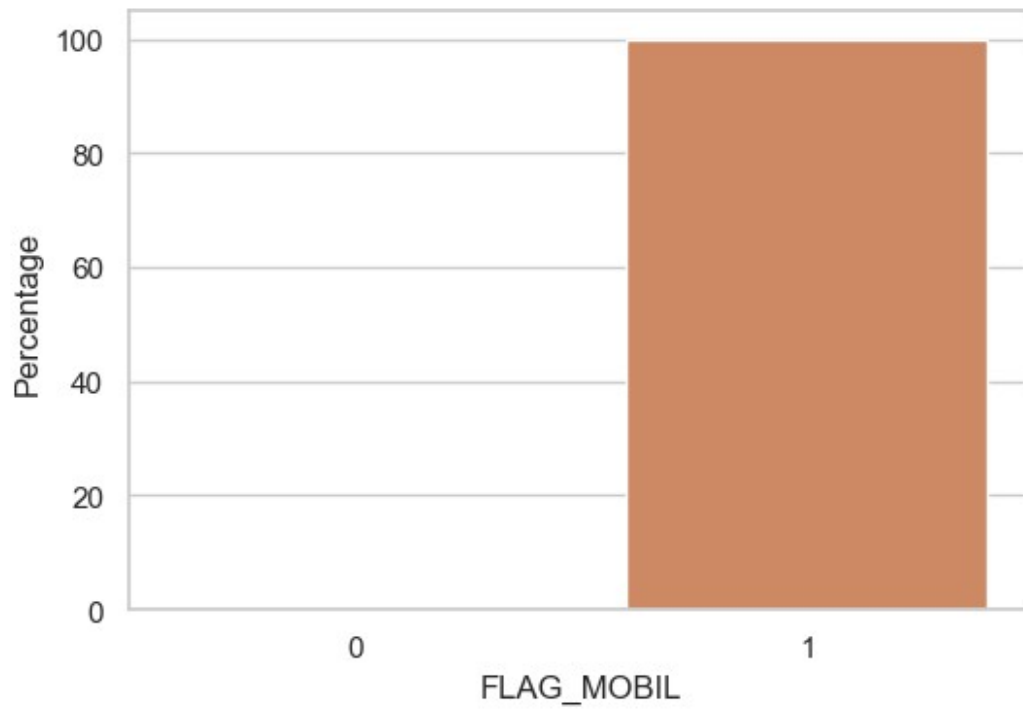
[66. 34.]



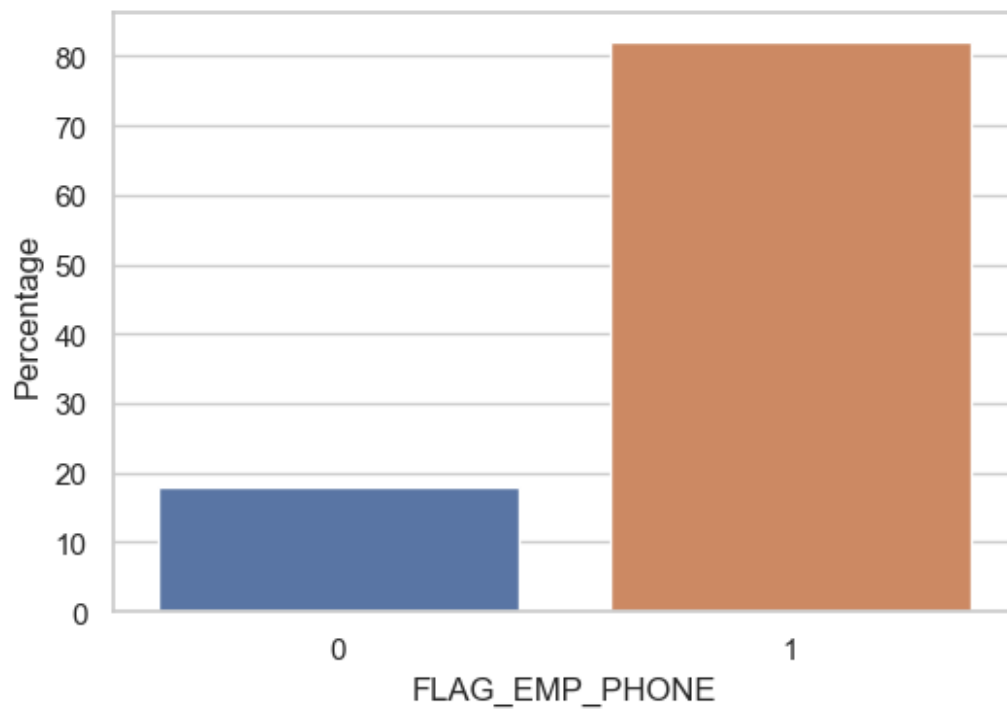
[69. 31.]



[100. 0.]

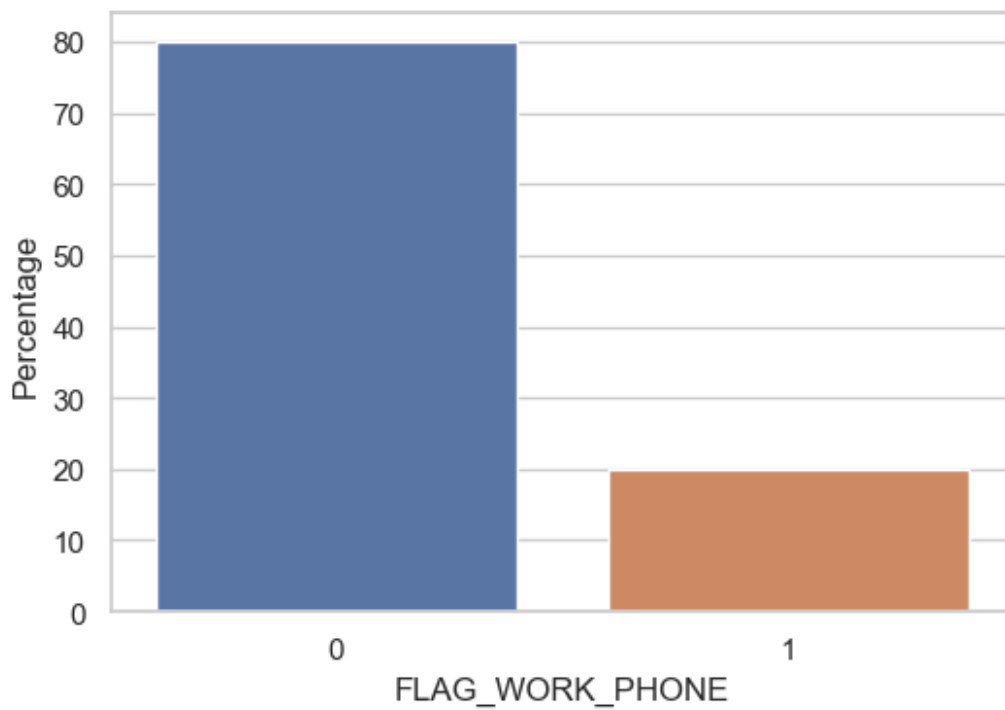


[82. 18.]

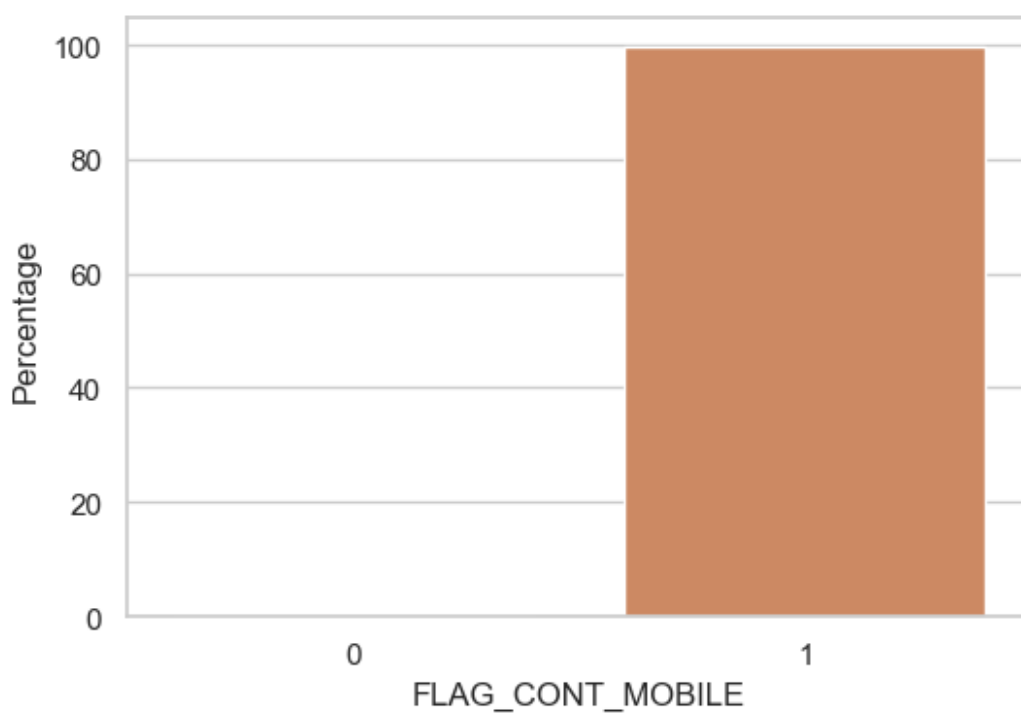


[80. 20.]

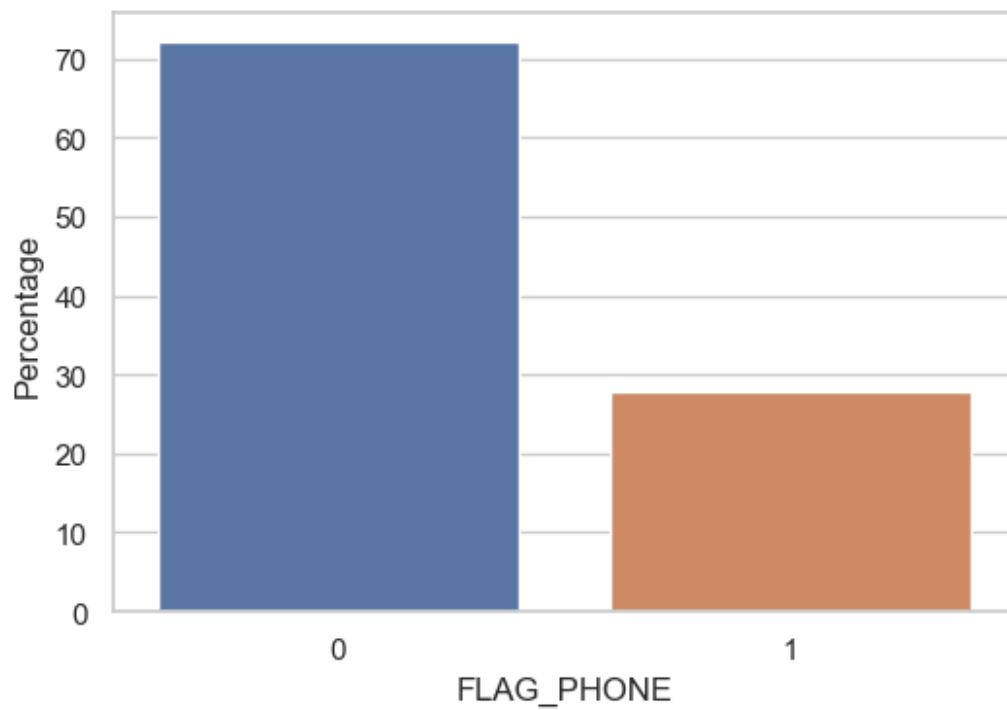




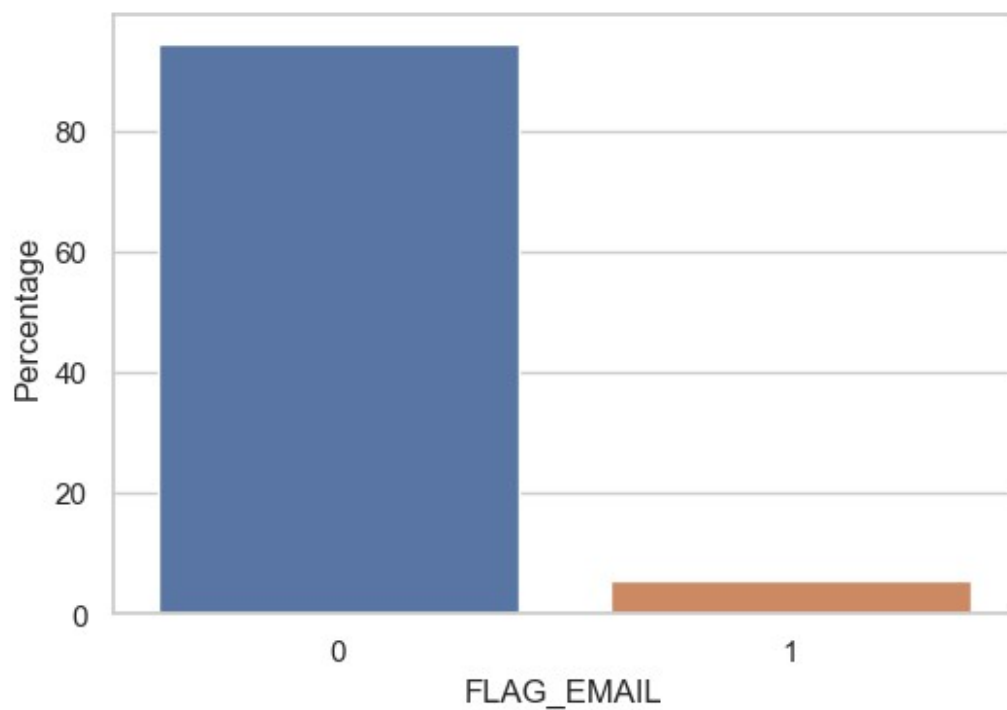
[100. 0.]



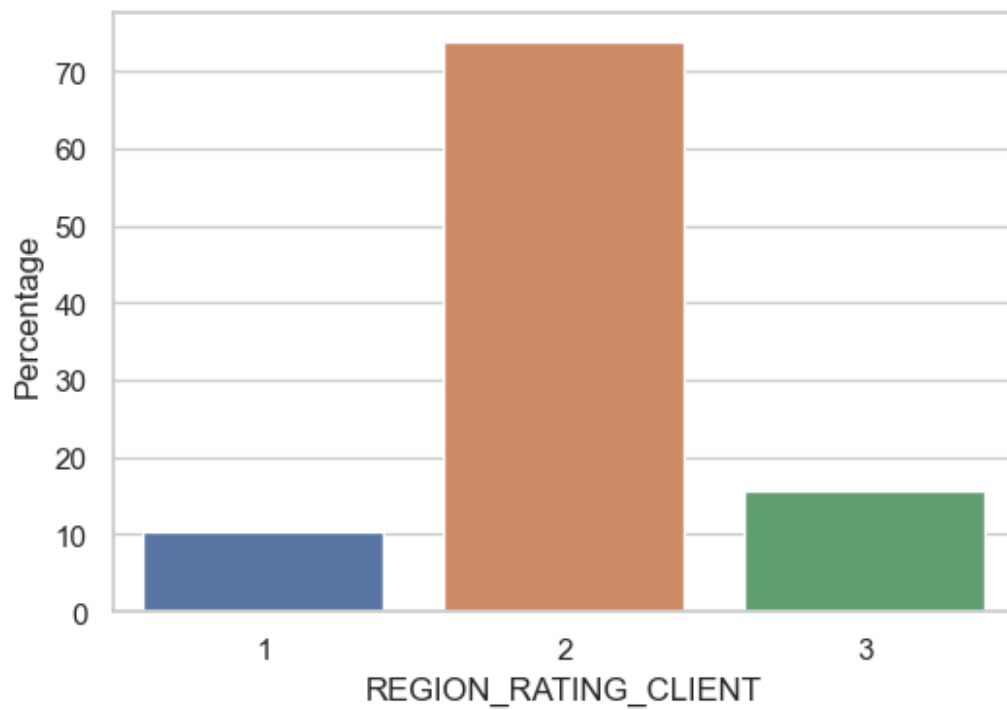
[72. 28.]



[94. 6.]



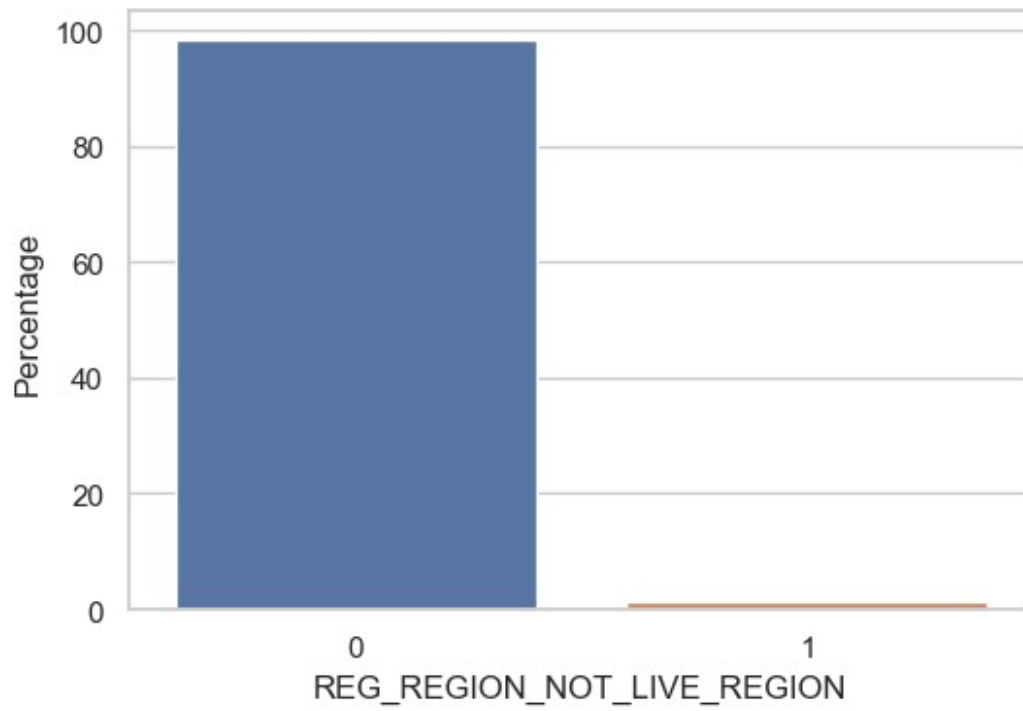
[74. 16. 10.]



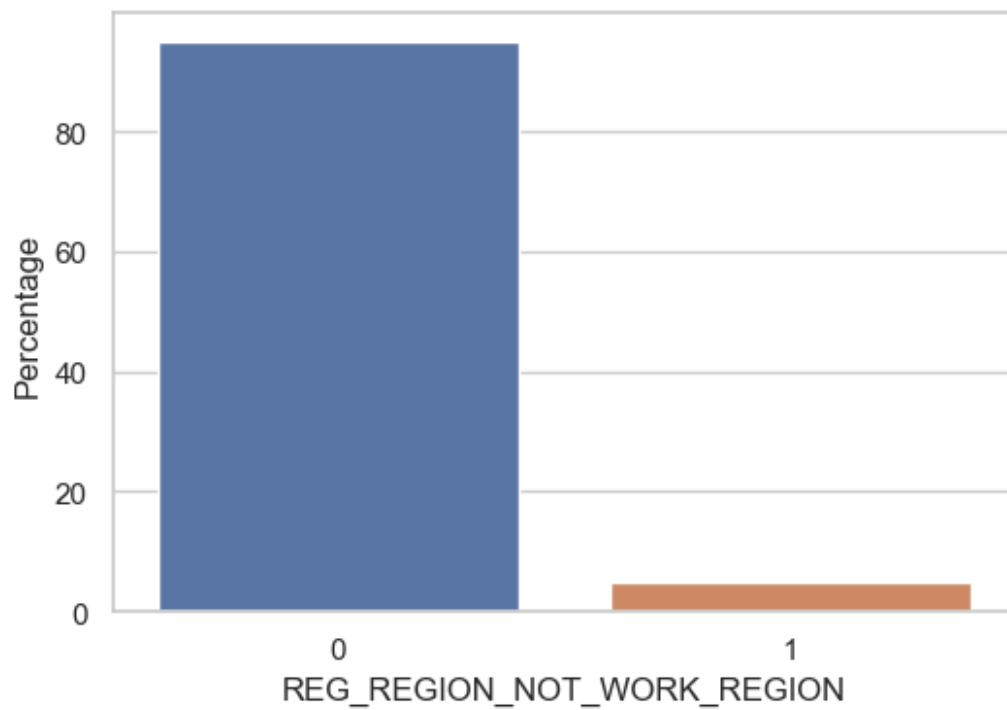
[75. 14. 11.]



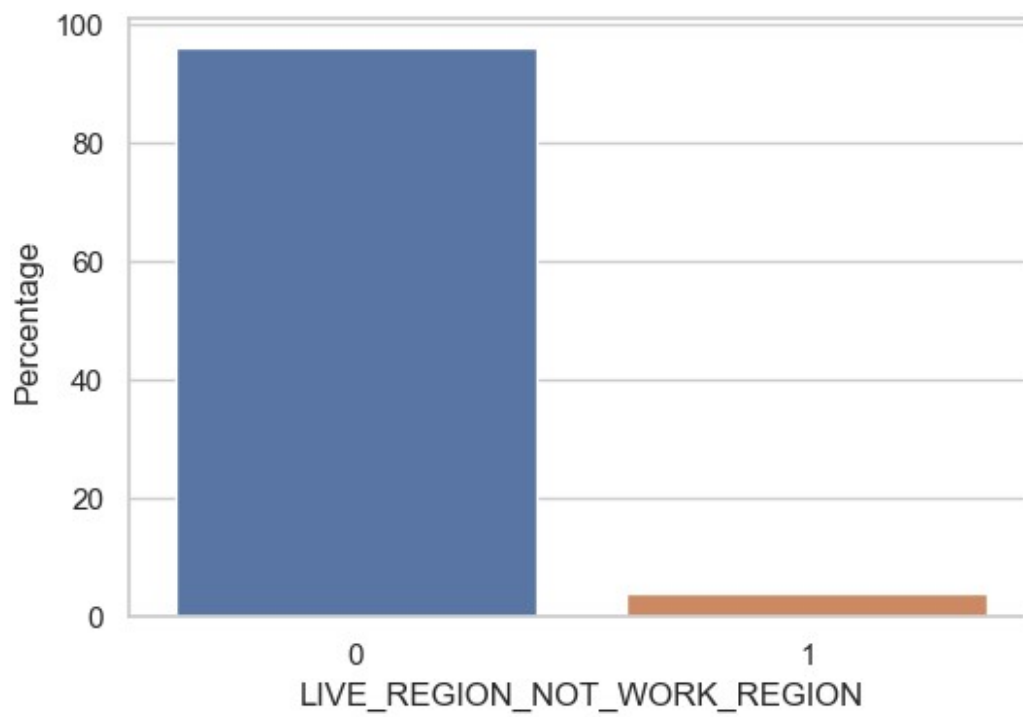
[98. 2.]



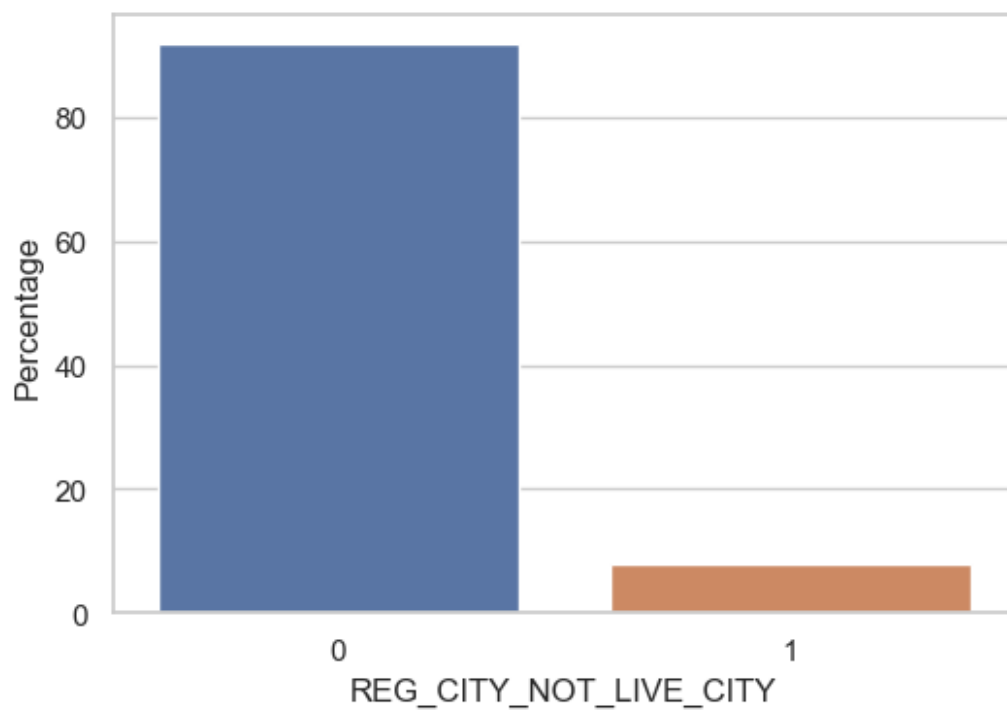
[95. 5.]



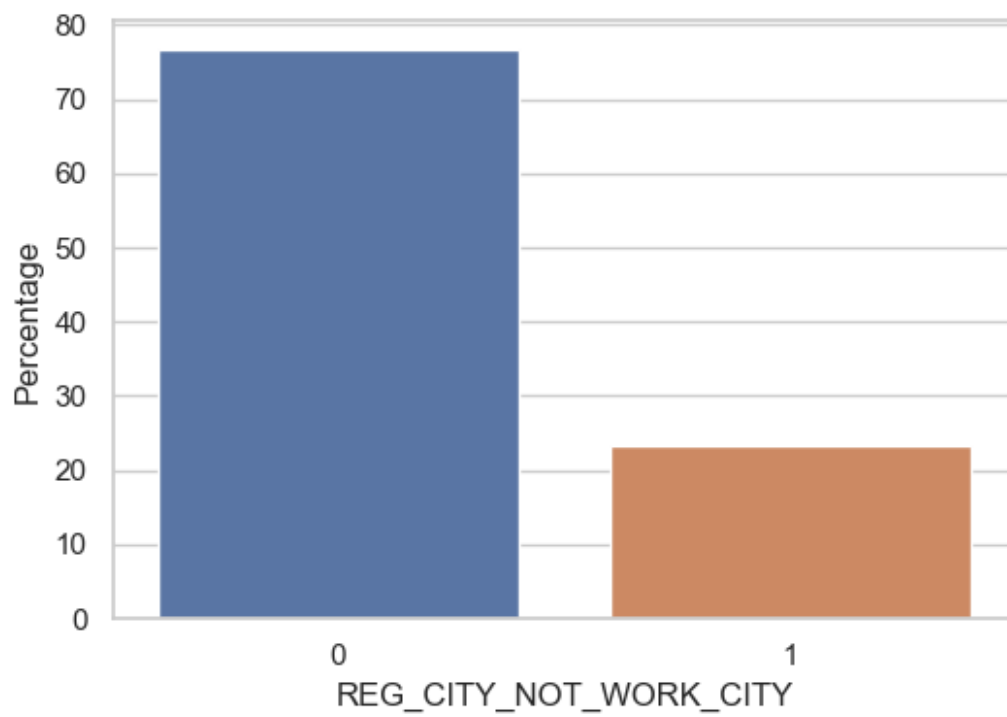
[96. 4.]



[92. 8.]



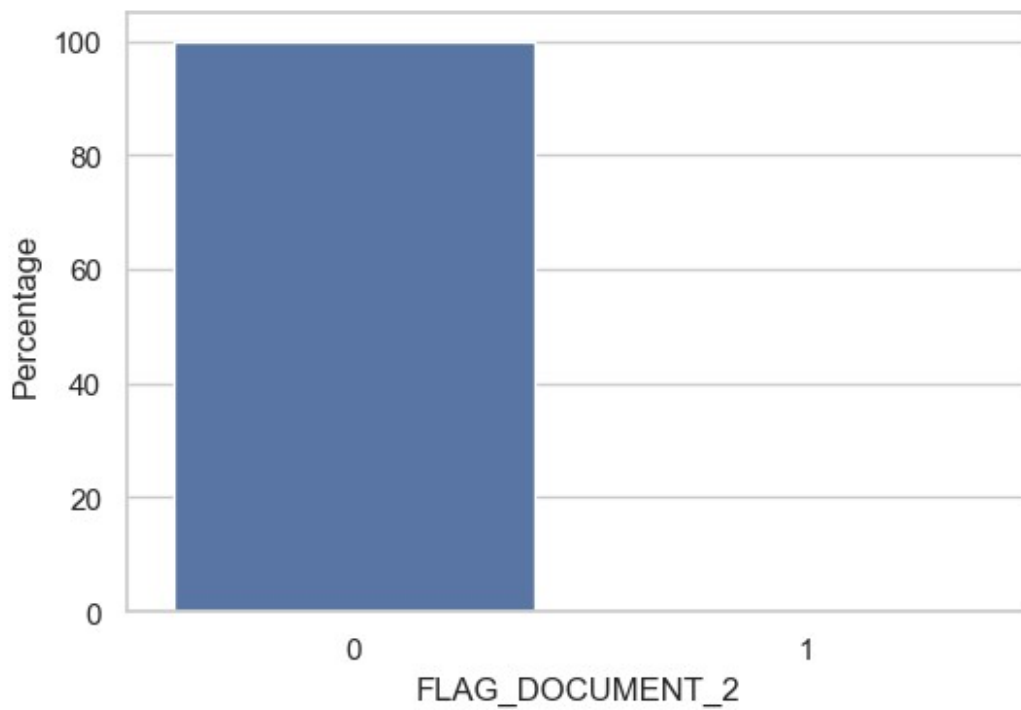
[77. 23.]



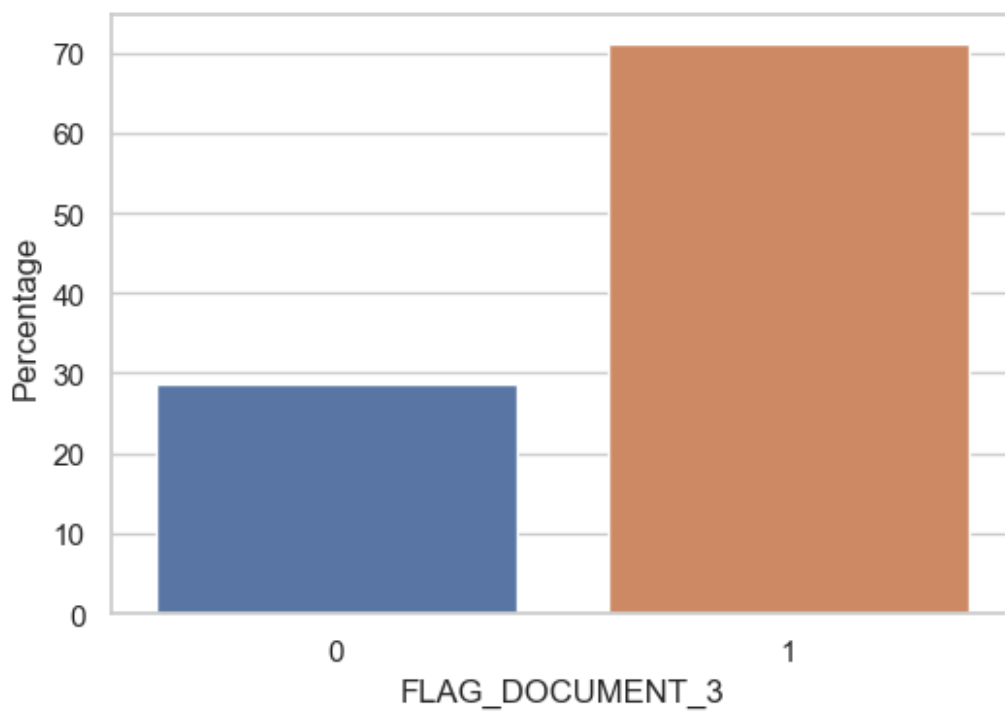
[82. 18.]



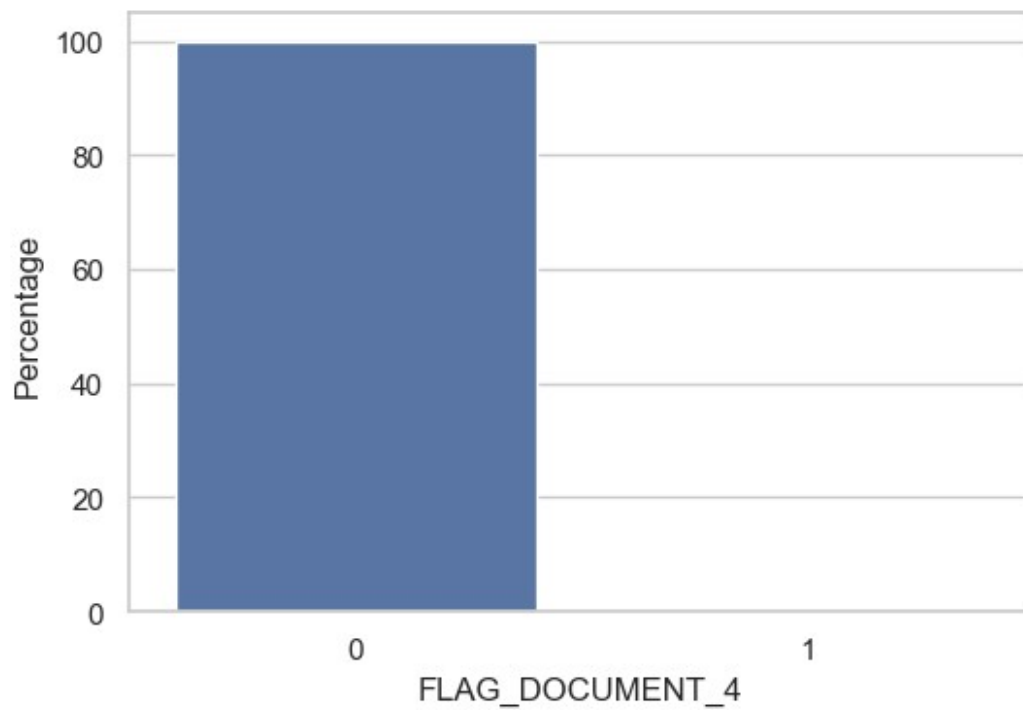
[100. 0.]



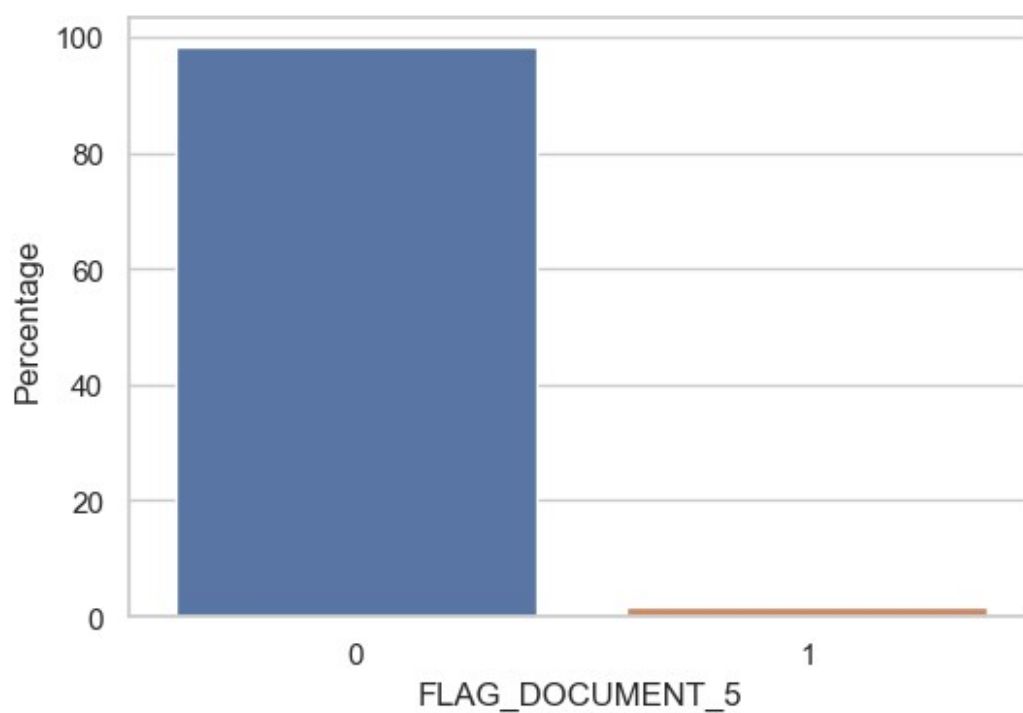
[71. 29.]



[100. 0.]

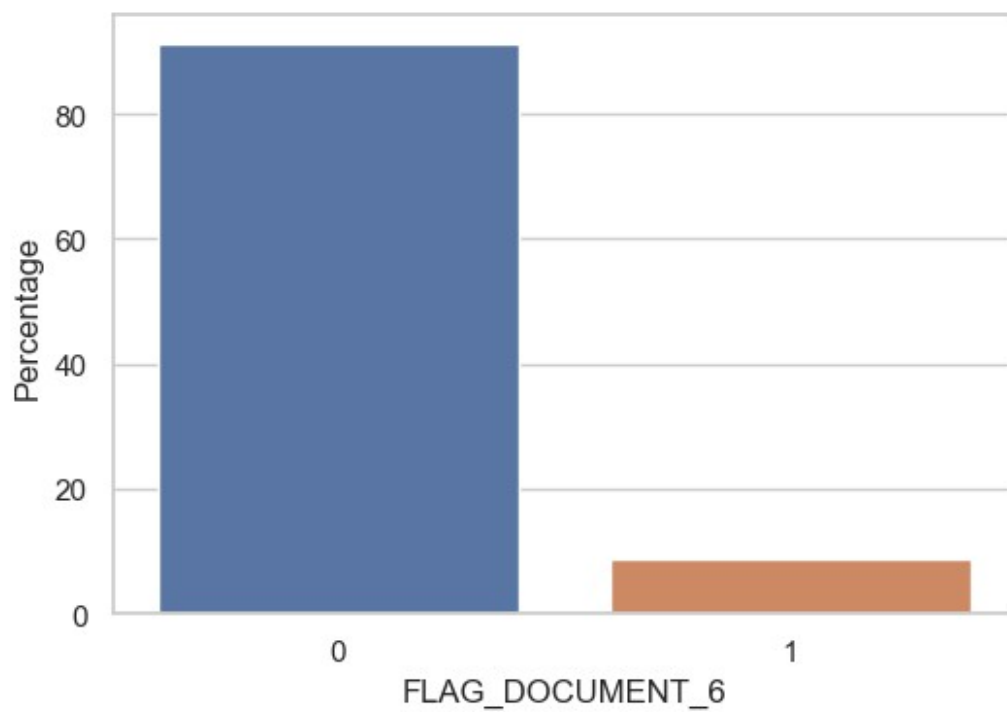


[98. 2.]

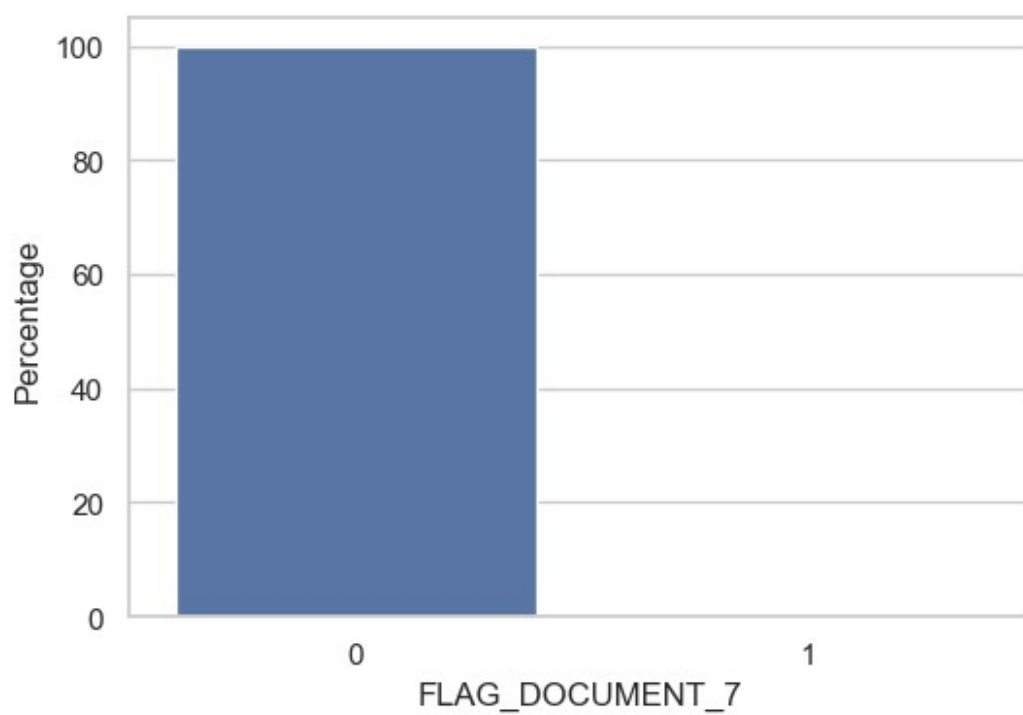


[91. 9.]

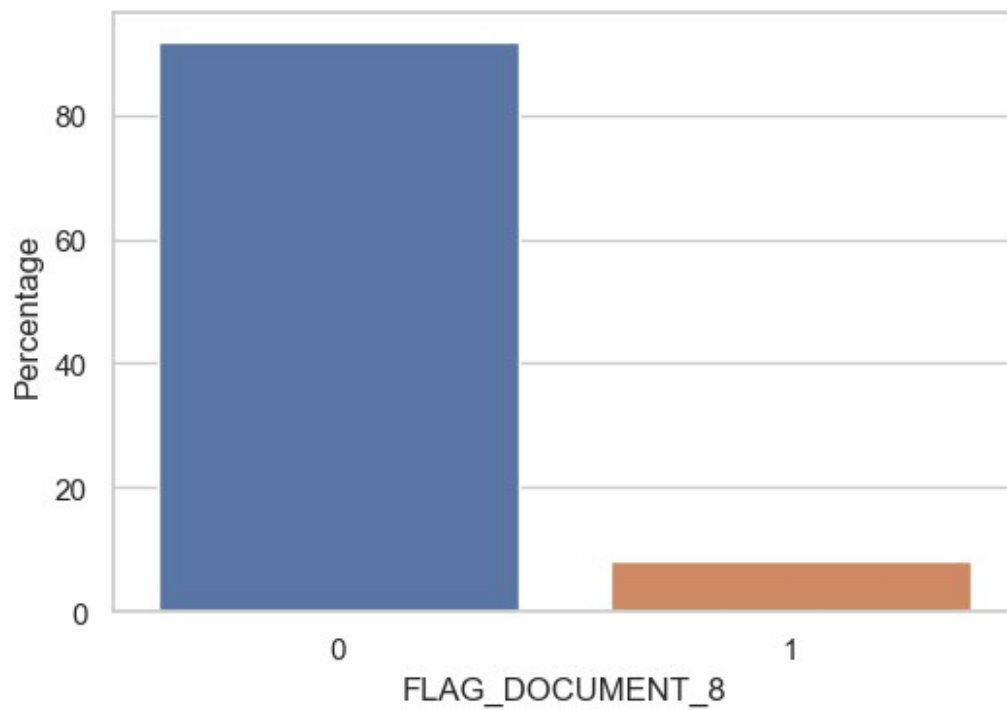




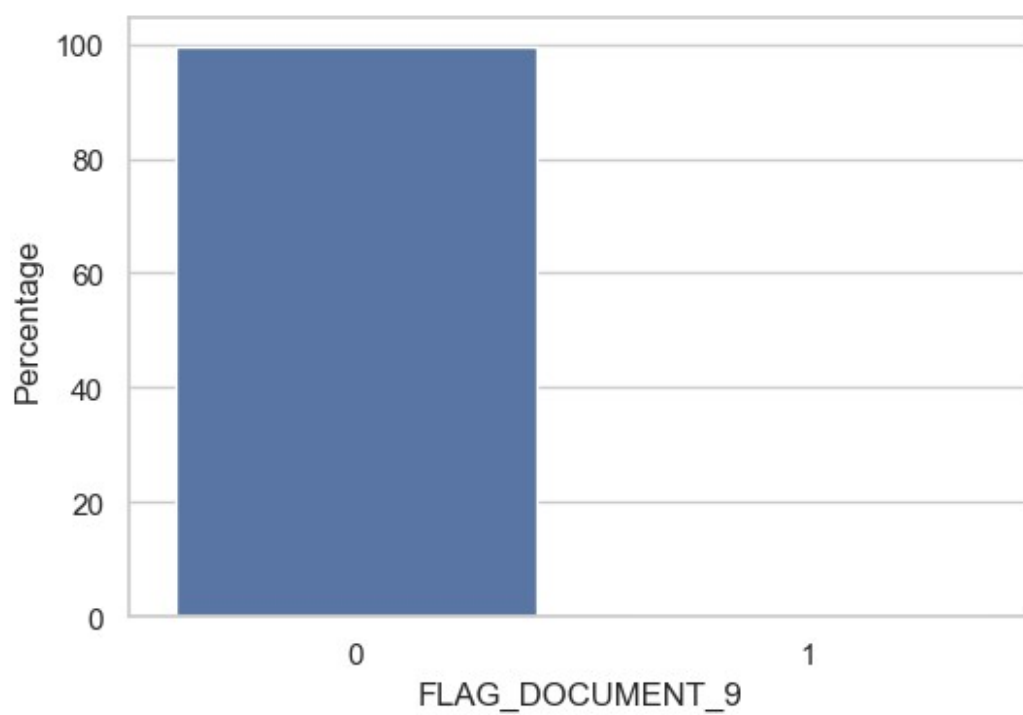
[100. 0.]



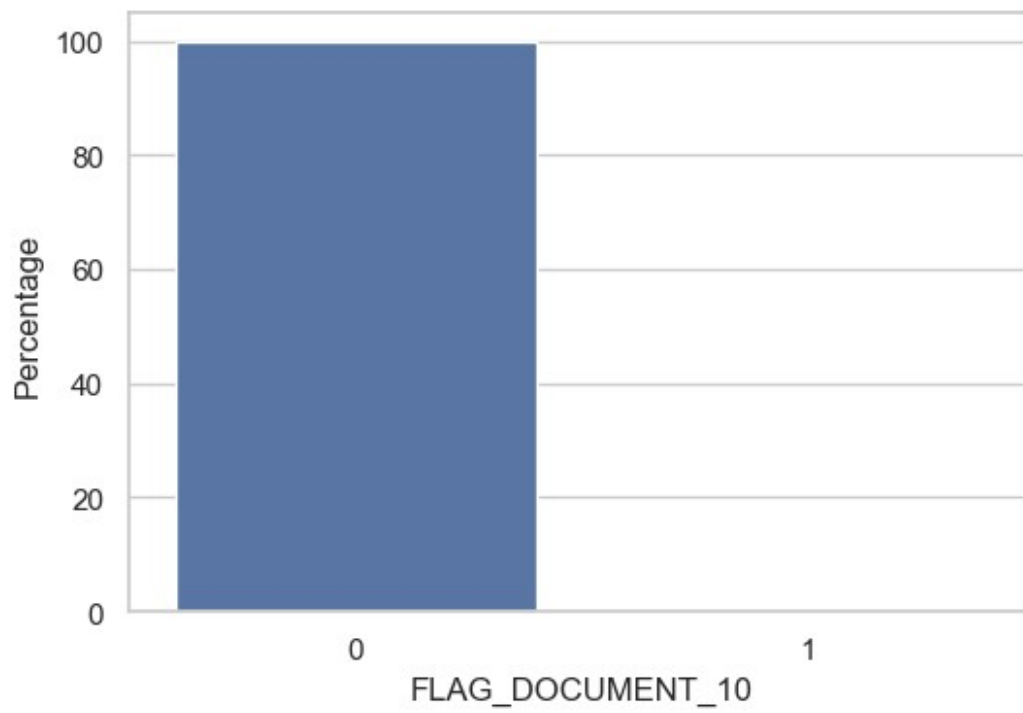
[92. 8.]



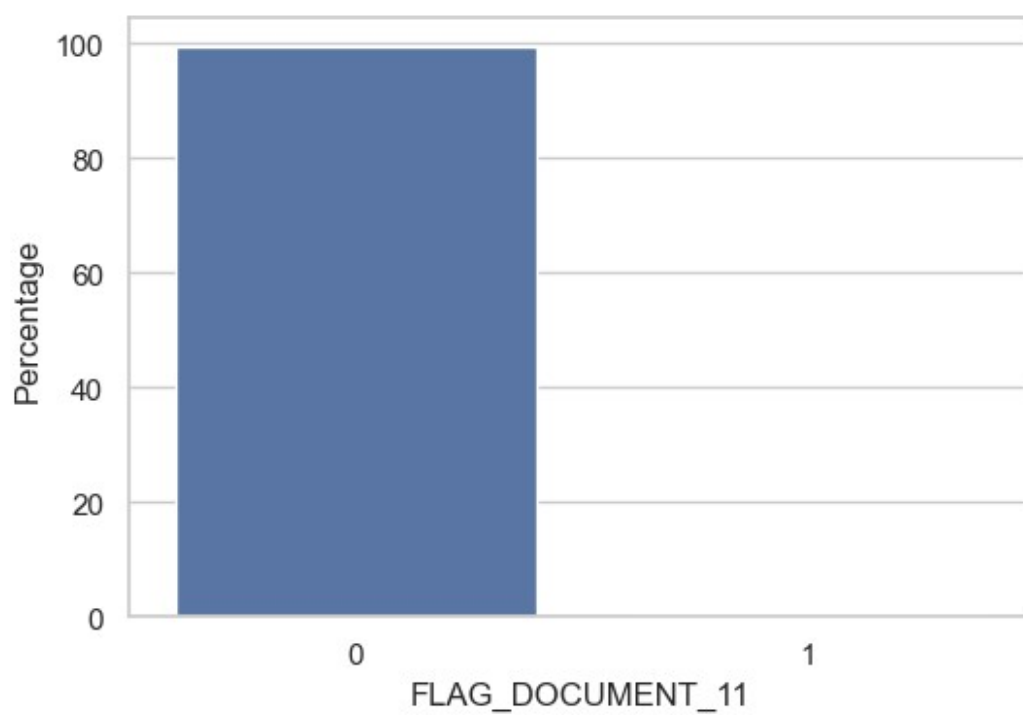
```
[100.  0.]
```



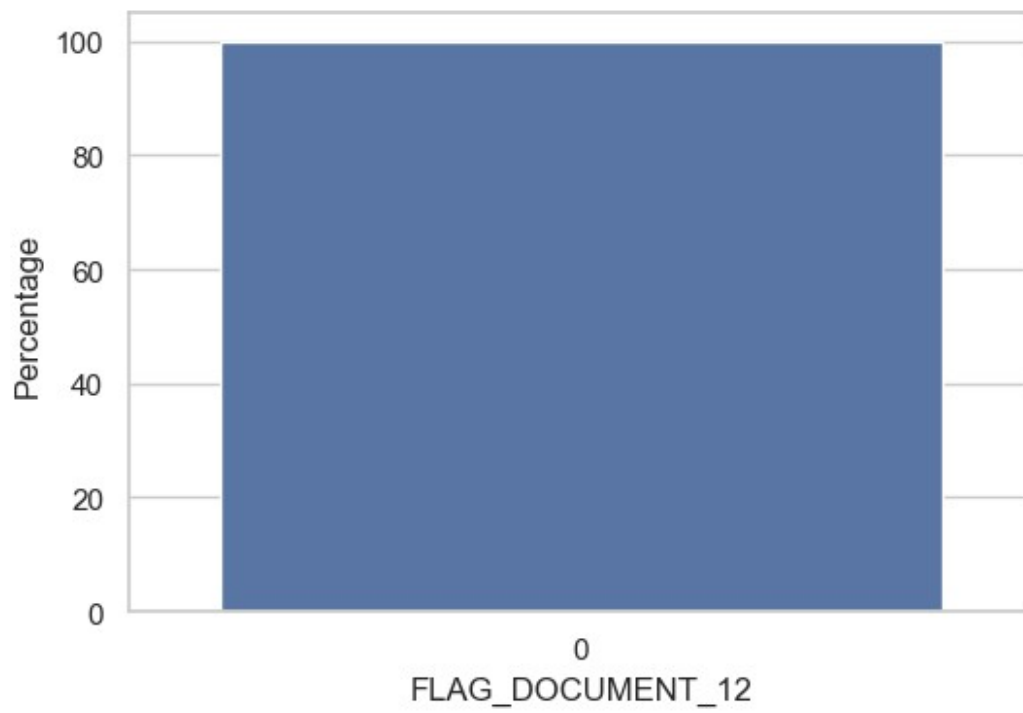
```
[100.  0.]
```



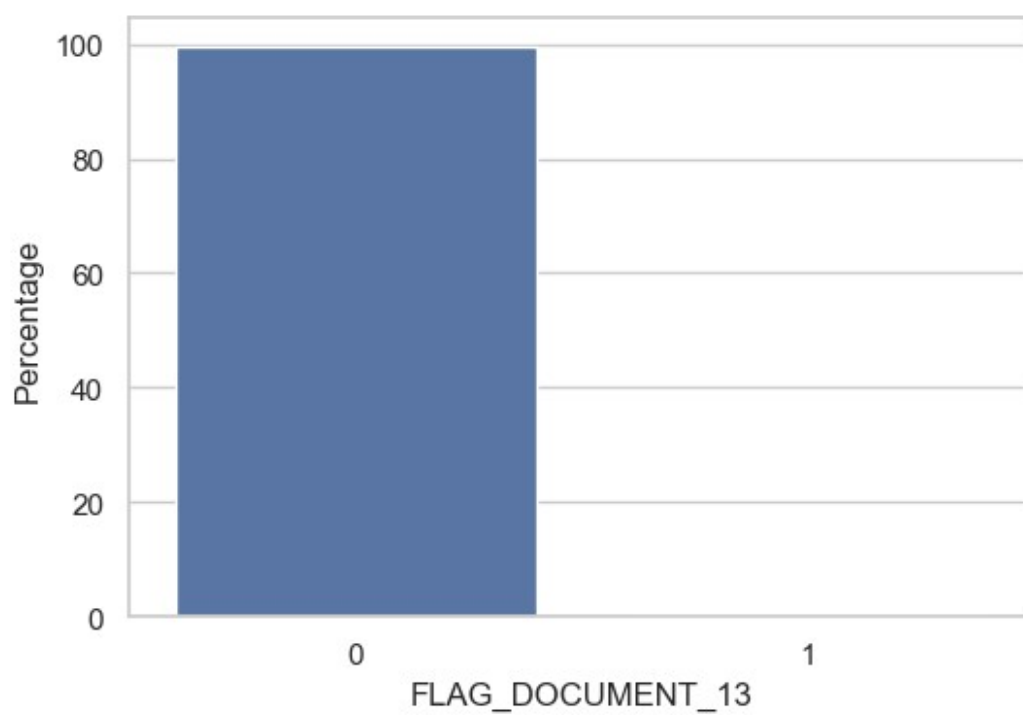
```
[100.  0.]
```



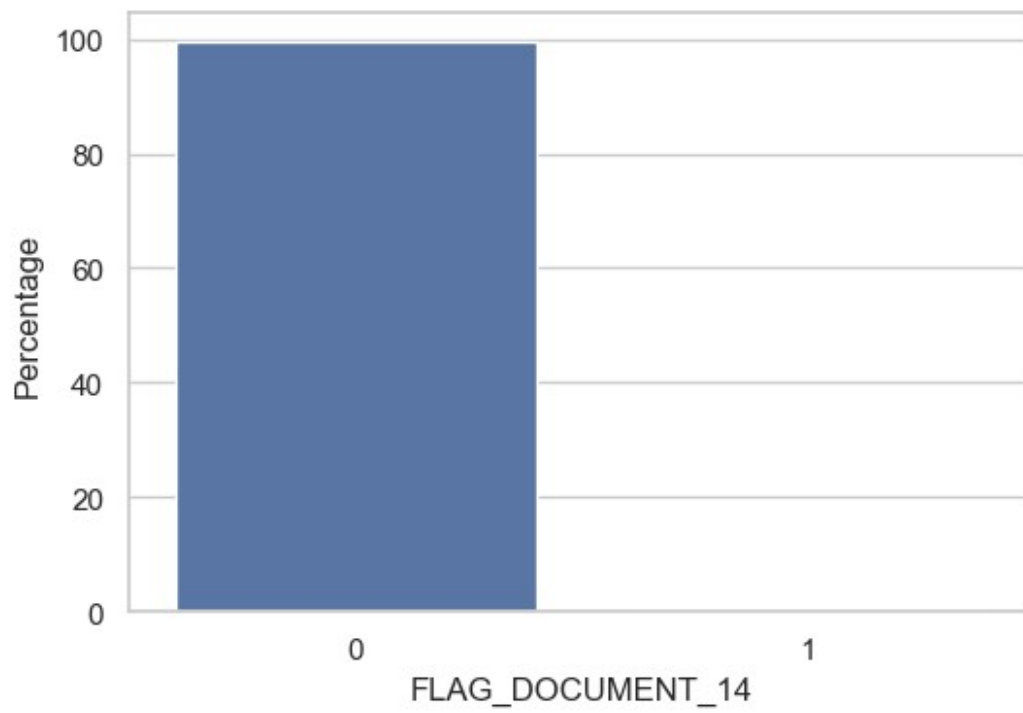
```
[100.]
```



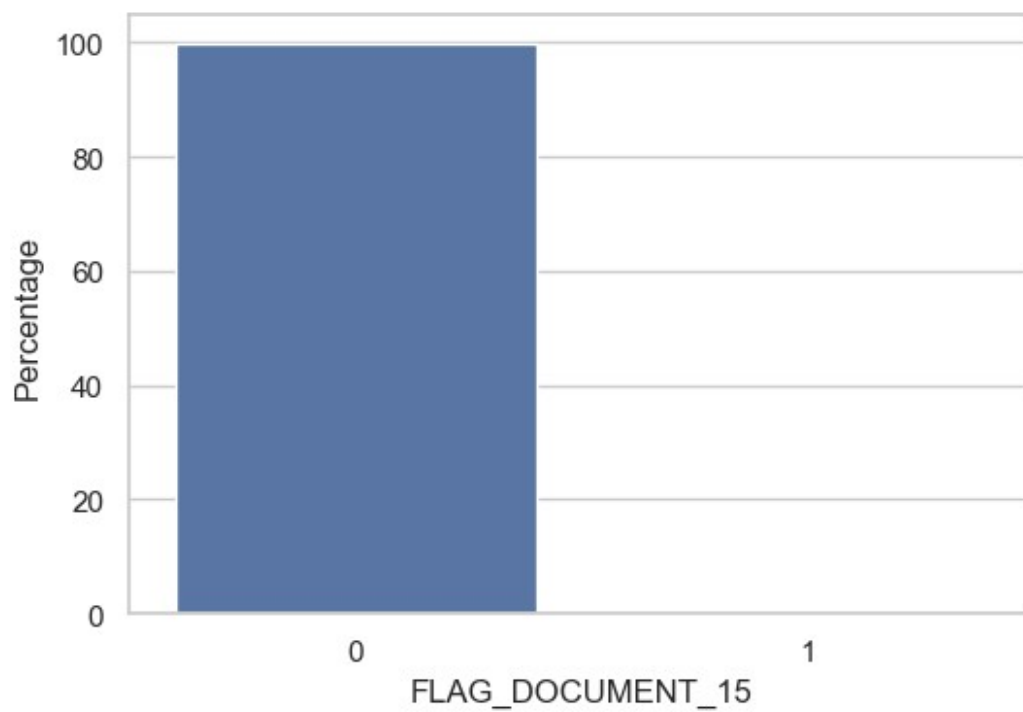
```
[100.  0.]
```



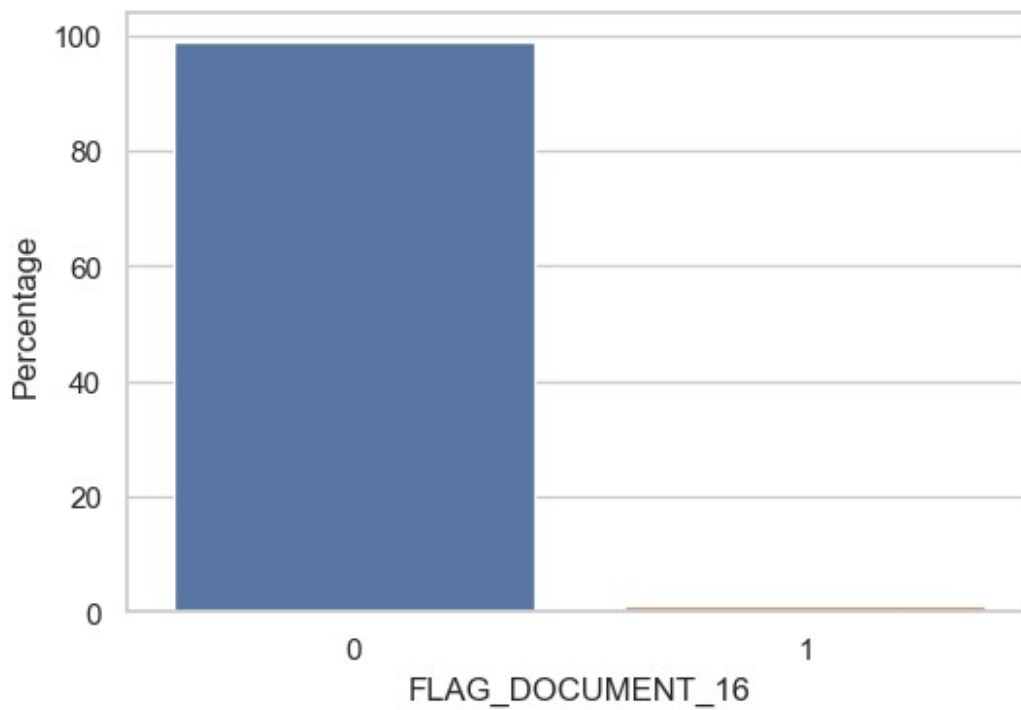
```
[100.  0.]
```



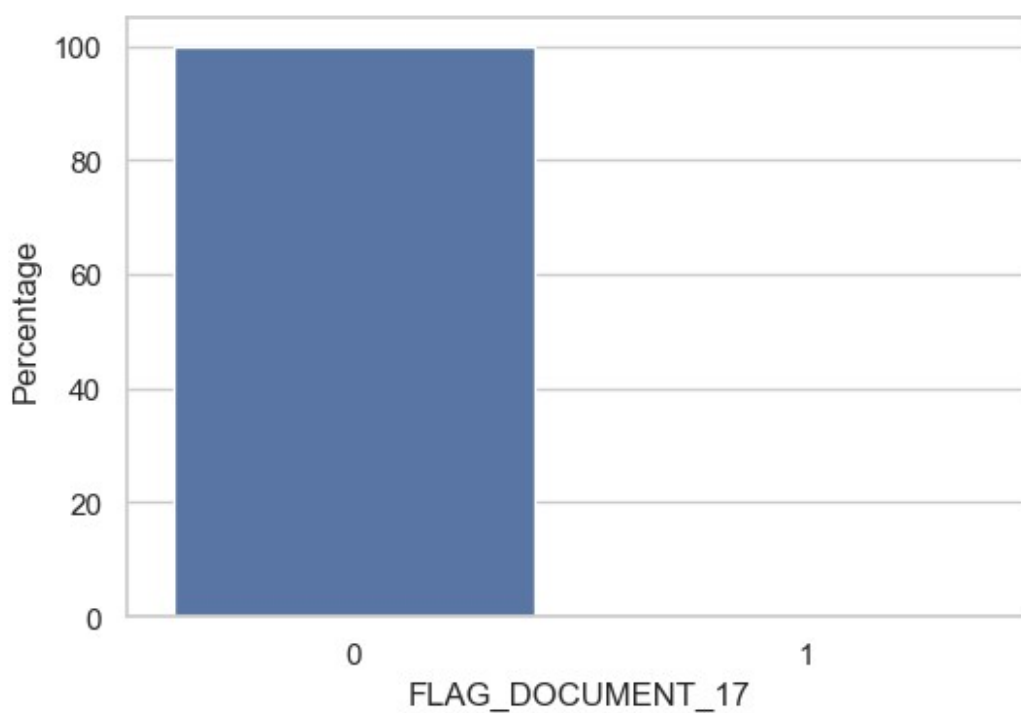
[100. 0.]



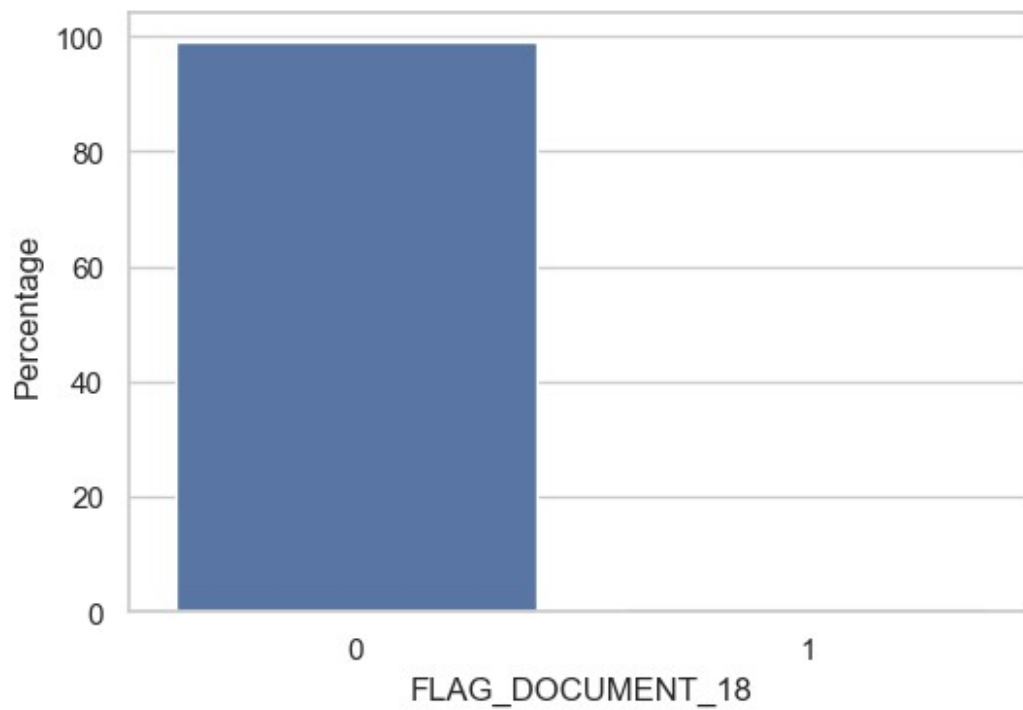
[99. 1.]



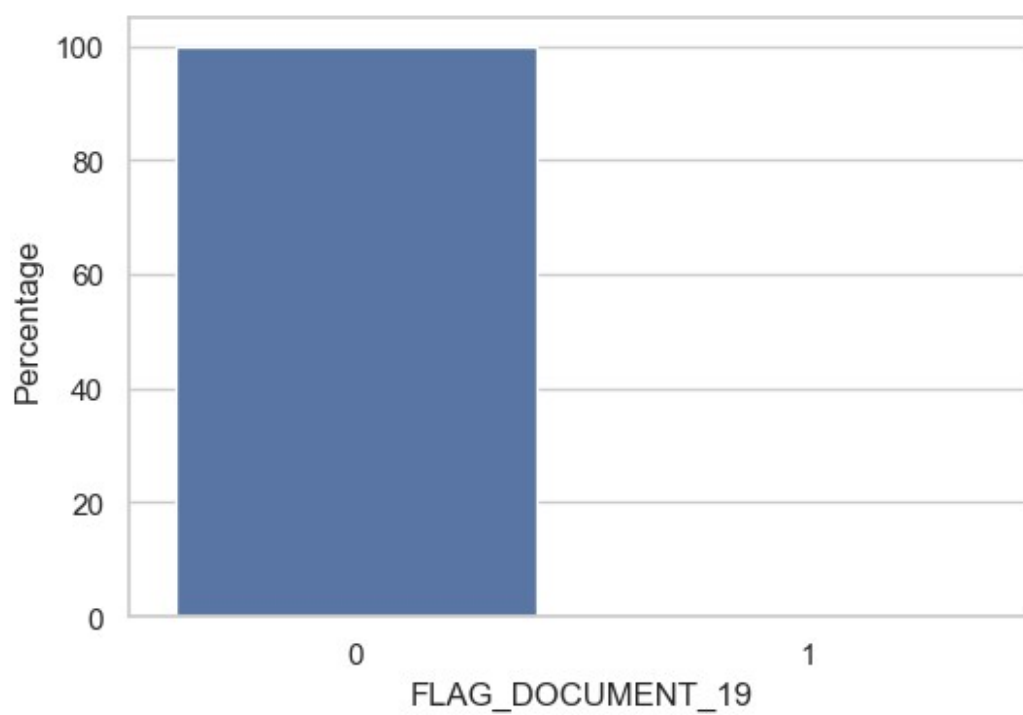
[100. 0.]



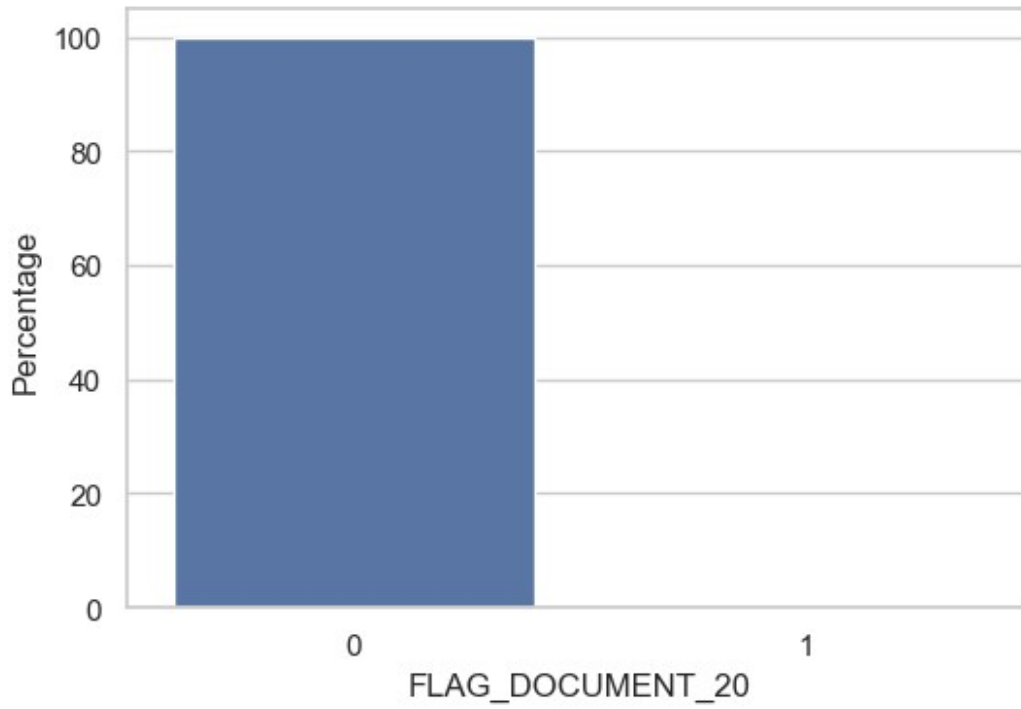
[99. 1.]



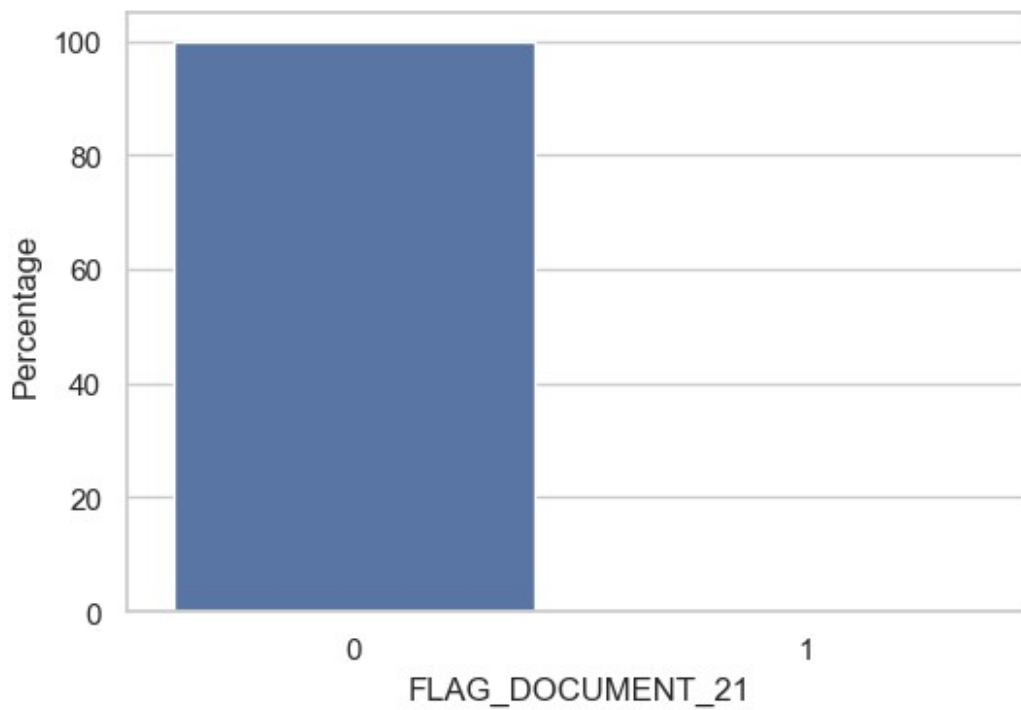
```
[100.  0.]
```



```
[100.  0.]
```



```
[100.  0.]
```



```
for i in application_data.columns:  
    # Calculate the class frequencies  
    class_frequencies = application_data[i].value_counts()
```



```

# Create a bar chart to visualize Data imbalance.
# Using if condition to give only those we are categorical
variables.

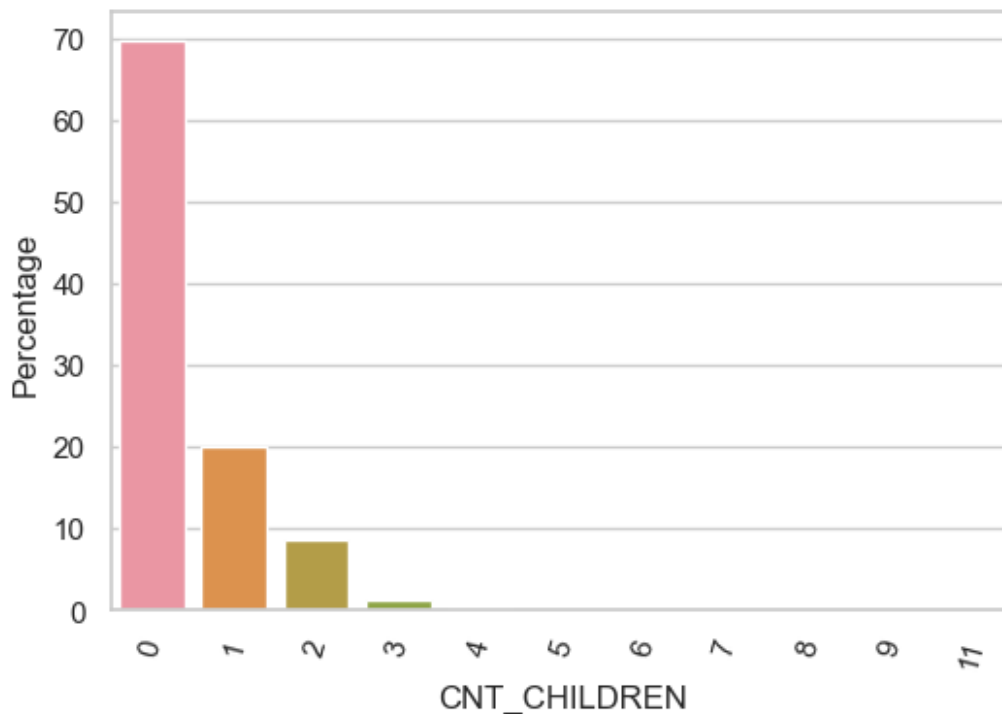
if len(class_frequencies)<=15 and len(class_frequencies)>3:

    # printing the percentage of each value_count in list
    percentage =
np.around((class_frequencies.values)/len(application_data[i])*100)
    print(percentage)

    # Create a bar chart to visualize Data imbalance.
    plt.figure(figsize=(6, 4))
    sns.barplot(x = class_frequencies.index, y =
(class_frequencies.values)/len(application_data[i])*100)
    plt.xlabel(i)
    plt.ylabel("Percentage")
    plt.xticks(rotation=75)
    plt.show()

[70. 20.  9.  1.  0.  0.  0.  0.  0.  0.  0.]

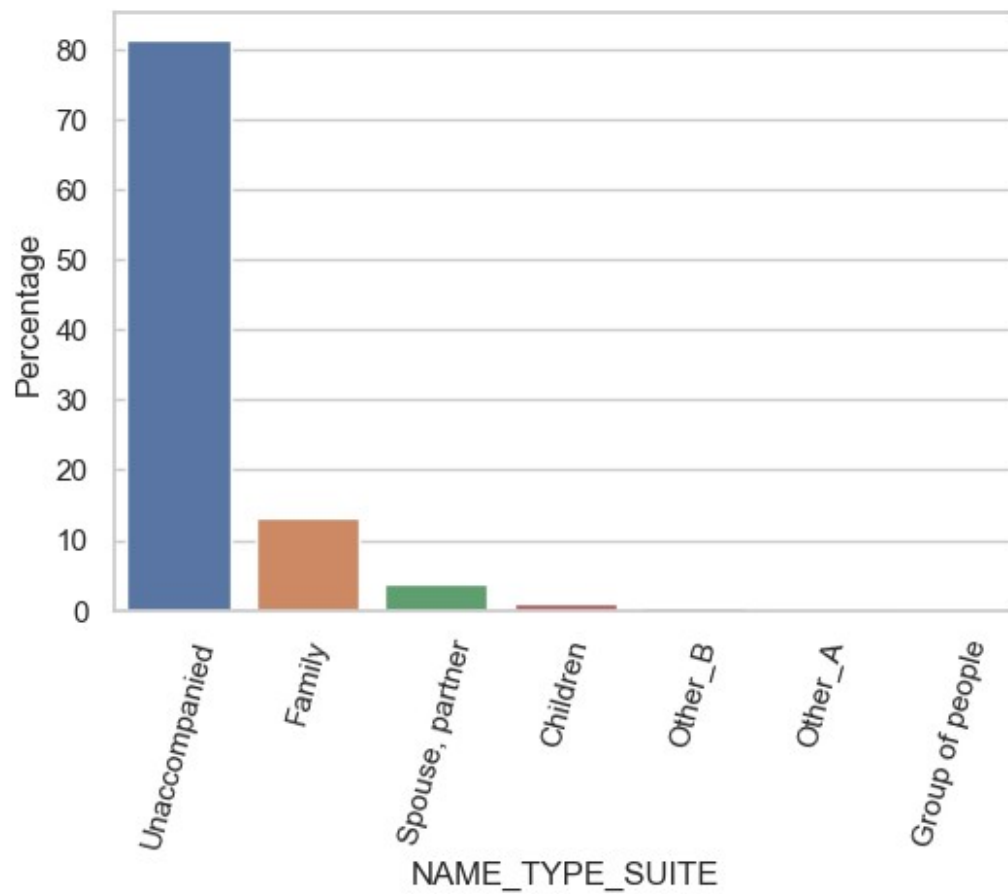
```



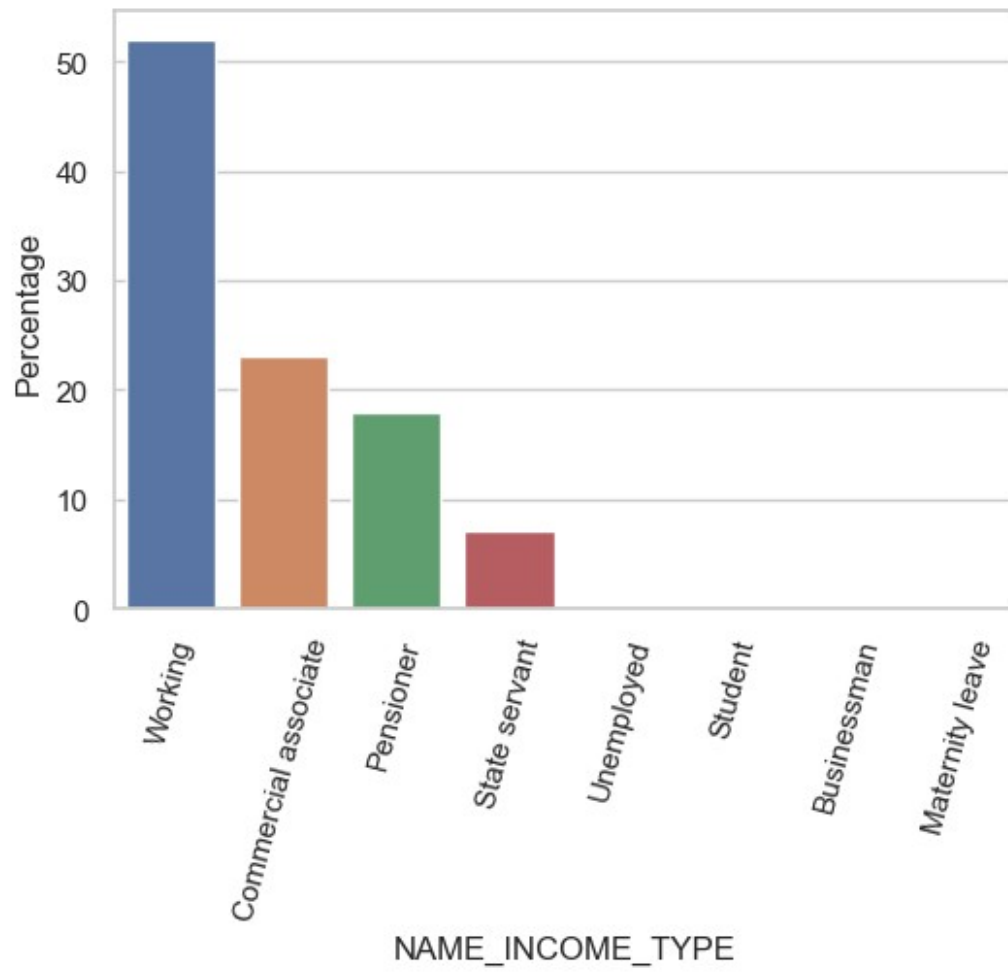
```

[81. 13.  4.  1.  1.  0.  0.]

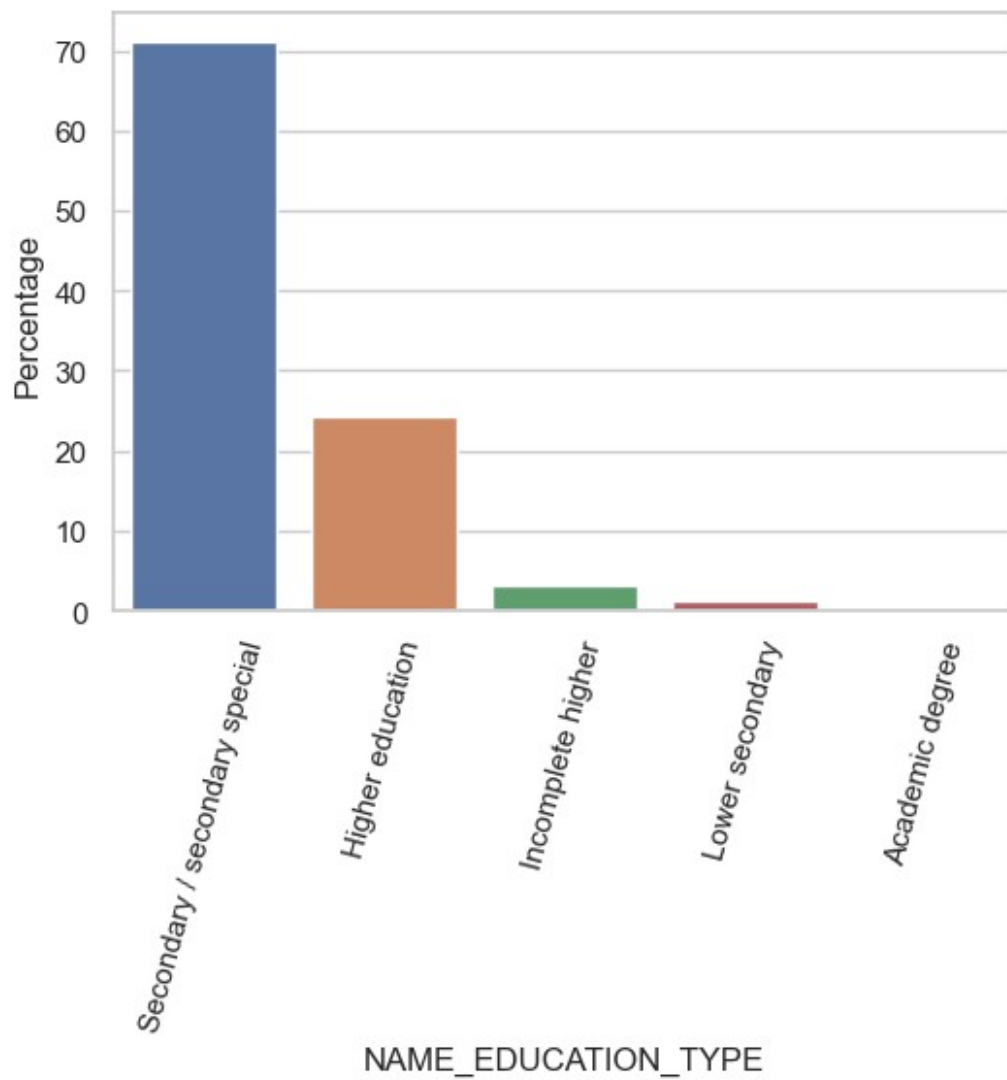
```



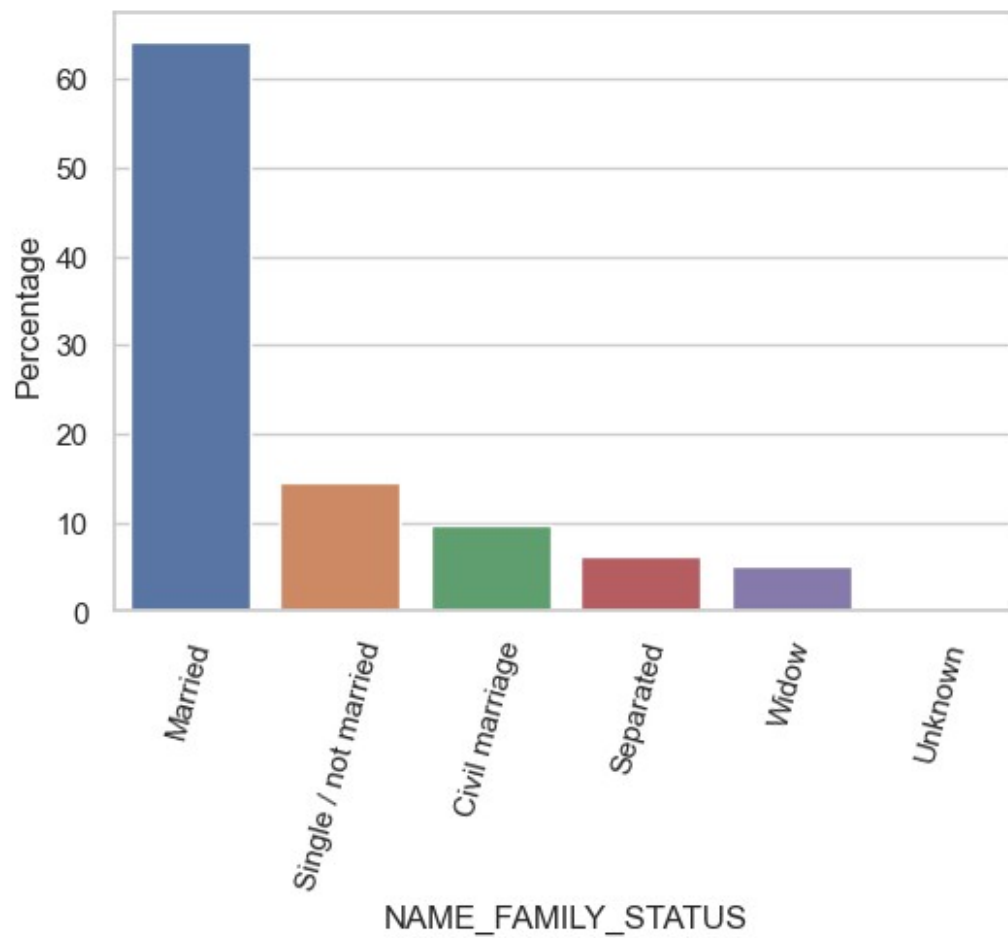
[52. 23. 18. 7. 0. 0. 0. 0.]



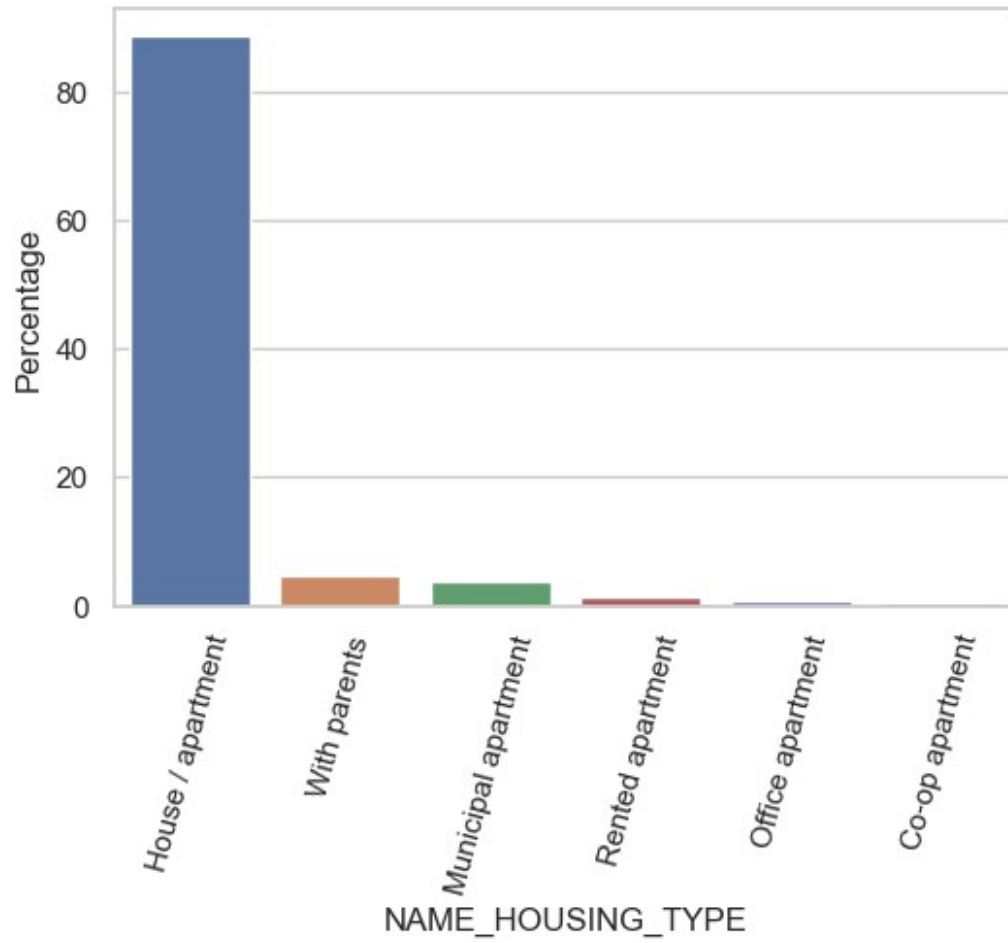
[71. 24. 3. 1. 0.]



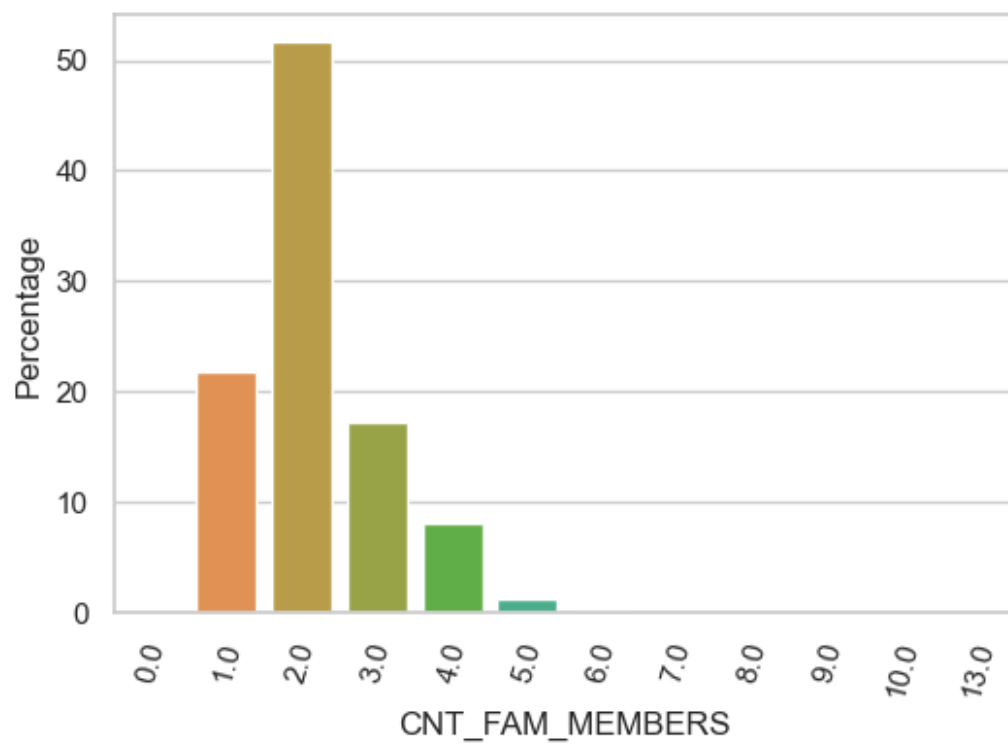
[64. 15. 10. 6. 5. 0.]



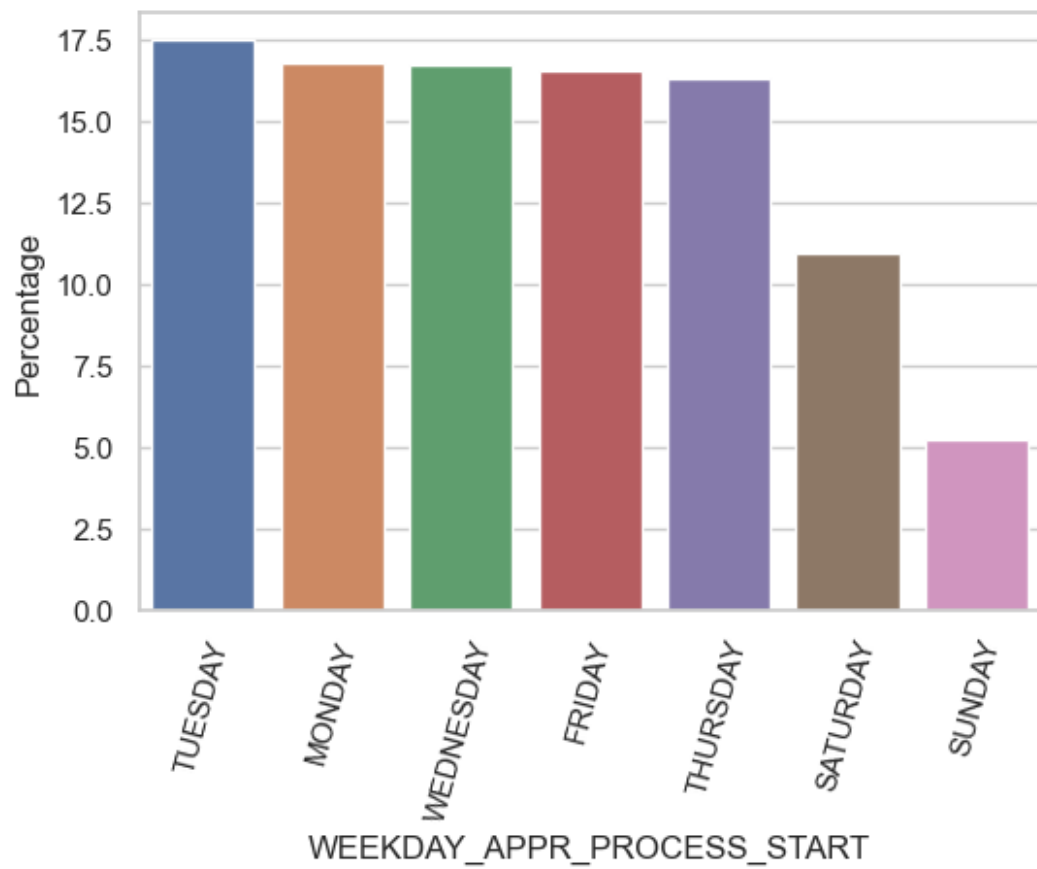
```
[89.  5.  4.  2.  1.  0.]
```



```
[52. 22. 17.  8.  1.  0.  0.  0.  0.  0.  0.  0.]
```

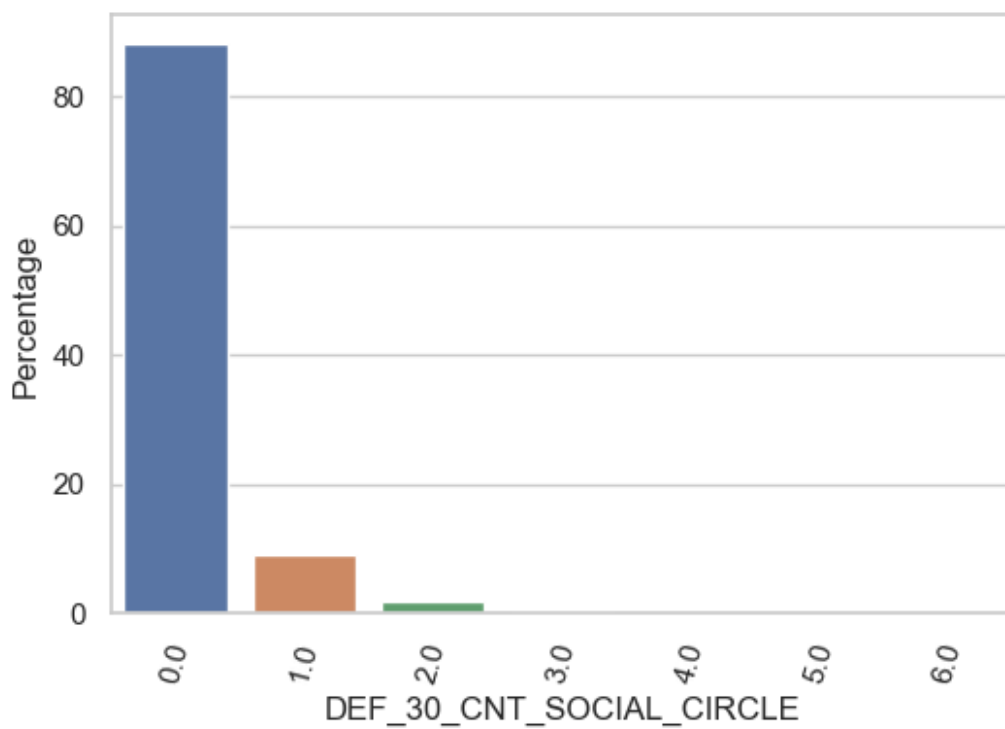


```
[17. 17. 17. 17. 16. 11.  5.]
```

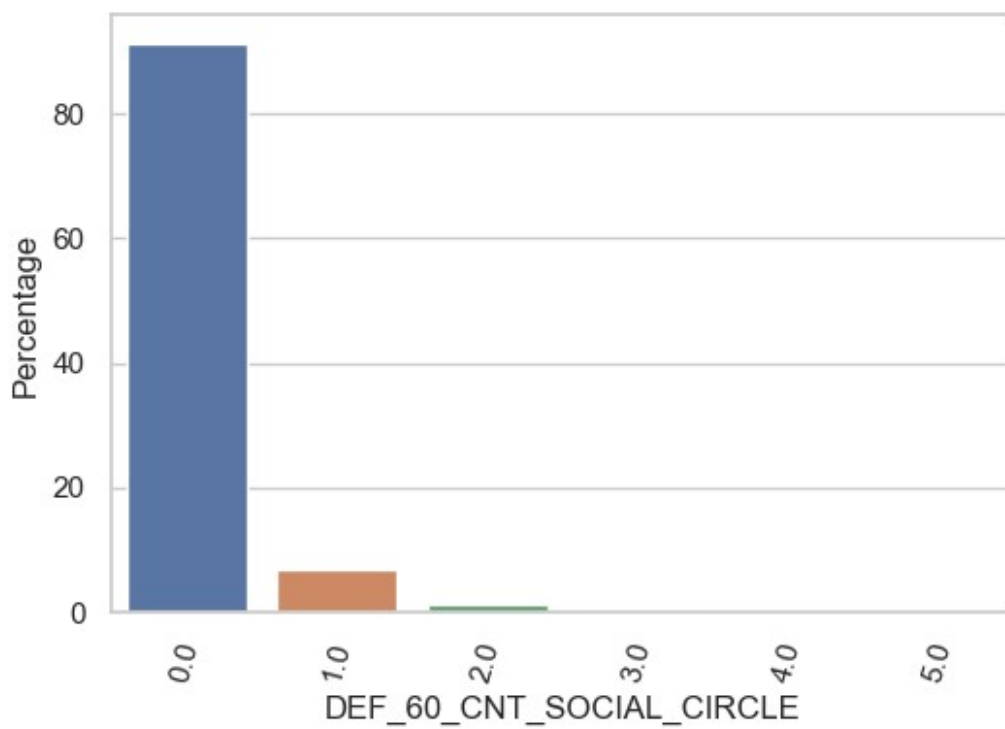


[88. 9. 2. 0. 0. 0. 0.]

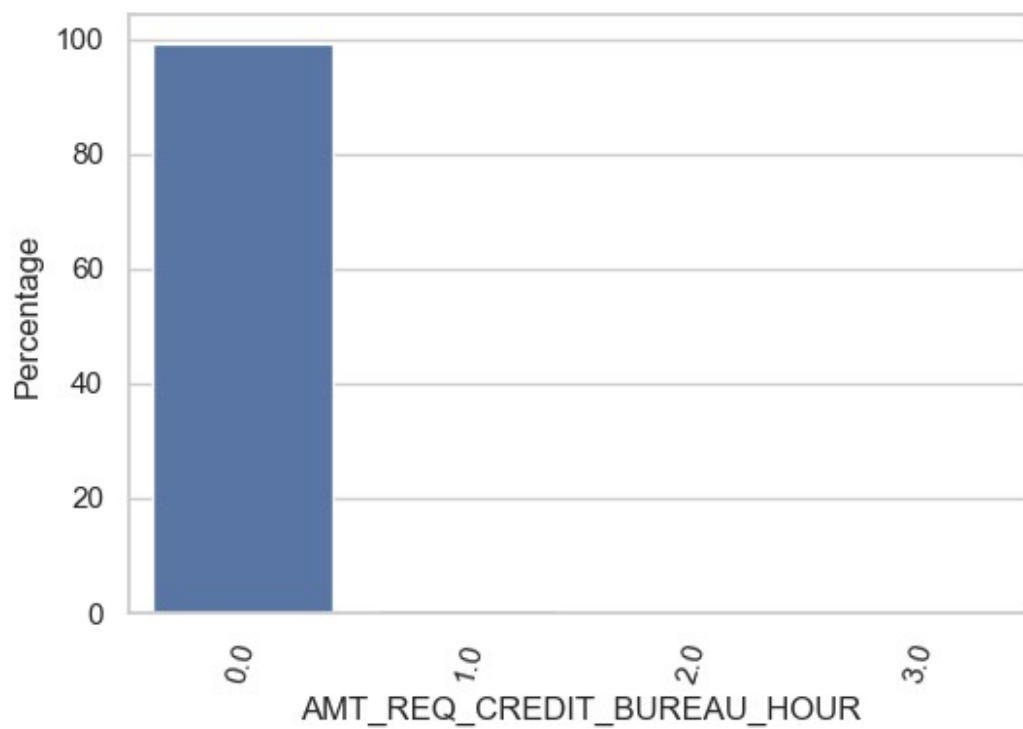




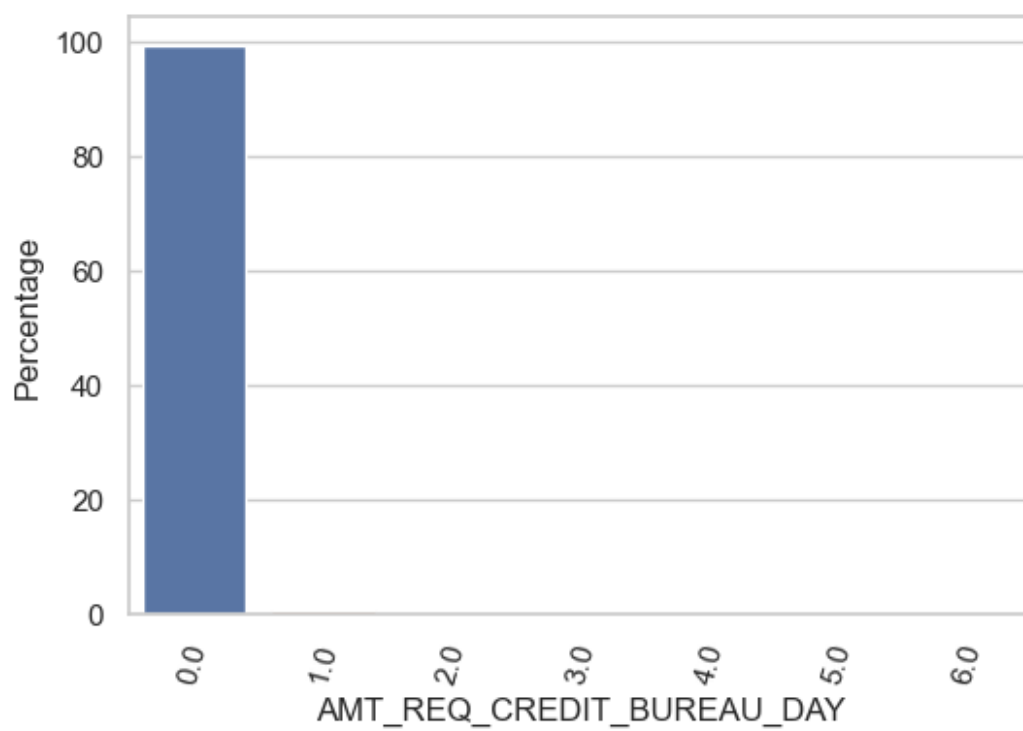
```
[91.  7.  1.  0.  0.  0.]
```



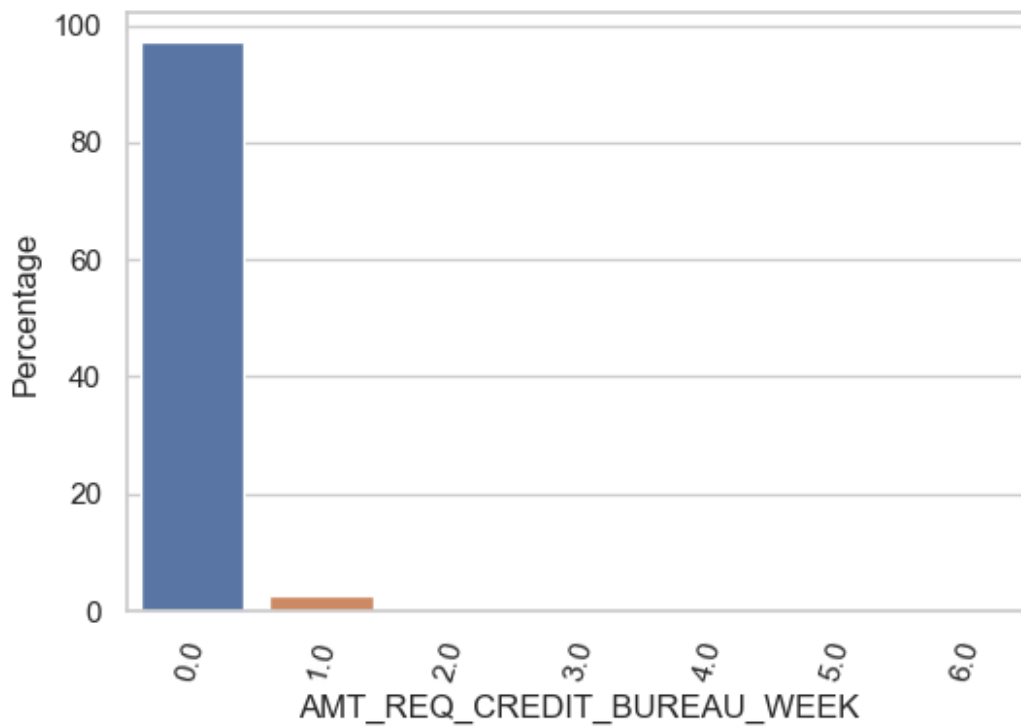
```
[99.  1.  0.  0.]
```



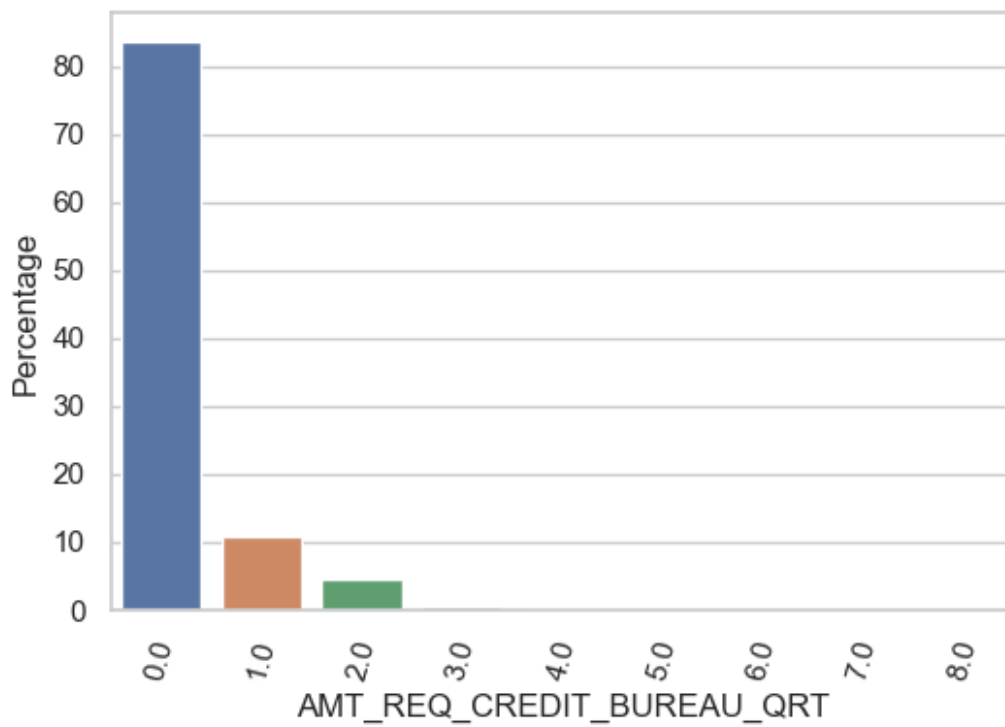
[99. 0. 0. 0. 0. 0. 0.]



[97. 3. 0. 0. 0. 0. 0.]



```
[84. 11.  5.  1.  0.  0.  0.  0.  0.]
```



## Inference/Observation from the analysis of Data Imbalance

```
# target variable shows us that 92% percent people have the value 1  
i.e. client with payment difficulties  
# NAME_CONTRACT_TYPE has the 91% of loans of Cash Loans type.  
# CODE_GENDER data imbalance shows us that there are 66% female  
applicatns and 34% male applicants  
# FLAG_OWN_CAR data imbalance shows us that 66% applicants don't own  
car.  
# FLAG_OWN_REALTY data imbalance shows us that 69% applicants own  
house.  
# CNT_CHILDREN data imbalance shows us that 70% applicants don't have  
childrens.  
# NAME_TYPE_SUITE data imbalance shows us that 81% of the applicants  
are unaccompanied  
# NAME_INCOME_TYPE data imbalance shows us that 52% applicants are  
working.  
# NAME_FAMILY_STATUS data imbalance shows us that 64% applicants are  
married.  
# NAME_HOUSINGIN_TYPE data imbalance shows us that 52% applicants are  
live in House/Apartment.  
# CNT_FAM_MEMBERS data imbalance shows us that 52% applicants have 2  
family members  
# and 22%, 17% applicants have 1 & 3 family members respectively
```

## D. Perform Univariate, Segmented Univariate, and Bivariate Analysis

# Top Correlations for Different Scenarios

```
application_data.columns
```

```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',  
      'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',  
      'AMT_INCOME_TOTAL',  
      'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',  
      'NAME_TYPE_SUITE',  
      'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',  
      'NAME_FAMILY_STATUS',  
      'NAME_HOUSING_TYPE', 'REGION_POPULATION_RELATIVE',  
      'DAYS_BIRTH',  
      'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH',  
      'OWN_CAR_AGE',  
      'FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE',  
      'FLAG_CONT_MOBILE',  
      'FLAG_PHONE', 'FLAG_EMAIL', 'OCCUPATION_TYPE',  
      'CNT_FAM_MEMBERS',  
      'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY',  
      'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',  
      'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',  
      'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',  
      'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',  
      'ORGANIZATION_TYPE', 'EXT_SOURCE_1', 'EXT_SOURCE_2',  
      'EXT_SOURCE_3',  
      'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE',  
      'OBS_60_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',  
      'DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3',  
      'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6',  
      'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9',  
      'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12',  
      'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15',  
      'FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18',  
      'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21',  
      'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
```

```
'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
dtype='object')
```

## Univariate Analysis

Univariate analysis focuses on examining the distribution and summary statistics of individual variables.

```
# Calculated Summary Stats for all numeric variables using the
describe function.
```

```
summary_stats = application_data.describe()
```

```
# createing the seperate table using the summary_stats for each
variable
```

```
from tabulate import tabulate
```

```
# create separate tables for each variable
```

```
for col in summary_stats.columns:
    col_table = summary_stats[[col]].transpose()
```

```
# Converted the table to a string using tabulate
```

```
table_str = tabulate(col_table, tablefmt='grid')
```

```
print(f"Summary Statistics for {col}:\n{table_str}\n")
```

```
plt.show()
```

```
Summary Statistics for SK_ID_CURR:
```

```
+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+
| SK_ID_CURR | 49999 | 129013 | 16690.5 | 100002 | 114570 | 129076 |
143438 | 157875 |
+-----+-----+-----+-----+-----+-----+-----+
+-----+-----+
```

```
Summary Statistics for TARGET:
```

```
+-----+-----+-----+-----+-----+-----+-----+-----+
| TARGET | 49999 | 0.0805216 | 0.272102 | 0 | 0 | 0 | 0 | 1 |
+-----+-----+-----+-----+-----+-----+-----+-----+
```

```
Summary Statistics for CNT_CHILDREN:
```

```
+-----+-----+-----+-----+-----+-----+-----+-----+
| CNT_CHILDREN | 49999 | 0.419848 | 0.724039 | 0 | 0 | 0 | 1 | 11 |
+-----+-----+-----+-----+-----+-----+-----+-----+
```

```
Summary Statistics for AMT_INCOME_TOTAL:
```

```
+-----+-----+-----+-----+-----+-----+
+-----+-----+
| AMT_INCOME_TOTAL | 49999 | 170768 | 531819 | 25650 | 112500 | 145800
```

| 202500 | 1.17e+08 |

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+-----+

#### Summary Statistics for AMT\_CREDIT:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+  
| AMT\_CREDIT | 49999 | 599701 | 402415 | 45000 | 270000 | 514778 |  
808650 | 4.05e+06 |  
+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

#### Summary Statistics for AMT\_ANNUITY:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+  
| AMT\_ANNUITY | 49998 | 27107.4 | 14562.9 | 2052 | 16456.5 | 24939 |  
34596 | 258026 |  
+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

#### Summary Statistics for AMT\_GOODS\_PRICE:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+  
| AMT\_GOODS\_PRICE | 49961 | 539060 | 369853 | 45000 | 238500 | 450000 |  
679500 | 4.05e+06 |  
+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

#### Summary Statistics for REGION\_POPULATION\_RELATIVE:

+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+-----+-----+-----+  
| REGION\_POPULATION\_RELATIVE | 49999 | 0.0207983 | 0.0137606 |  
0.000533 | 0.010006 | 0.01885 | 0.028663 | 0.072508 |  
+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+-----+-----+-----+

#### Summary Statistics for DAYS\_BIRTH:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+  
| DAYS\_BIRTH | 49999 | 16022 | 4361.4 | 7680 | 12378.5 | 15731 | 19644 |  
25184 |  
+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

#### Summary Statistics for DAYS\_EMPLOYED:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+  
| DAYS\_EMPLOYED | 49999 | 67160.3 | 138958 | 0 | 933 | 2216 | 5718 |  
365243 |  
+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

+-----+

Summary Statistics for DAYS\_REGISTRATION:

```
+-----+-----+-----+-----+-----+-----+
+-----+-----+
| DAYS_REGISTRATION | 49999 | 4977.28 | 3525.55 | 0 | 1998 | 4490 |
7463.5 | 22392 |
+-----+-----+-----+-----+-----+-----+
+-----+-----+
```

Summary Statistics for DAYS\_ID\_PUBLISH:

```
+-----+-----+-----+-----+-----+-----+
+-----+
| DAYS_ID_PUBLISH | 49999 | 2996.8 | 1509.24 | 0 | 1722 | 3261 | 4297
| 6232 |
+-----+-----+-----+-----+-----+-----+
+-----+
```

Summary Statistics for OWN\_CAR\_AGE:

```
+-----+-----+-----+-----+-----+-----+
| OWN_CAR_AGE | 17049 | 12.0257 | 11.8875 | 0 | 5 | 9 | 15 | 65 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_MOBIL:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_MOBIL | 49999 | 0.99998 | 0.00447218 | 0 | 1 | 1 | 1 | 1 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_EMP\_PHONE:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_EMP_PHONE | 49999 | 0.821476 | 0.382957 | 0 | 1 | 1 | 1 | 1 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_WORK\_PHONE:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_WORK_PHONE | 49999 | 0.199264 | 0.399451 | 0 | 0 | 0 | 0 | 1 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_CONT\_MOBILE:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_CONT_MOBILE | 49999 | 0.99798 | 0.0448999 | 0 | 1 | 1 | 1 | 1 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_PHONE:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_PHONE | 49999 | 0.277726 | 0.447882 | 0 | 0 | 0 | 1 | 1 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_EMAIL:

```
+-----+-----+-----+-----+-----+-----+
```





```
+---+---+---+
| LIVE_REGION_NOT_WORK_REGION | 49999 | 0.0396408 | 0.195116 | 0 | 0 |
0 | 0 | 1 |
```

Summary Statistics for REG\_CITY\_NOT\_LIVE\_CITY:

```
+---+---+
| REG_CITY_NOT_LIVE_CITY | 49999 | 0.0799616 | 0.271236 | 0 | 0 | 0 |
0 | 1 |
```

Summary Statistics for REG\_CITY\_NOT\_WORK\_CITY:

```
+---+---+
| REG_CITY_NOT_WORK_CITY | 49999 | 0.232165 | 0.422218 | 0 | 0 | 0 | 0
| 1 |
```

Summary Statistics for LIVE\_CITY\_NOT\_WORK\_CITY:

```
+---+---+
| LIVE_CITY_NOT_WORK_CITY | 49999 | 0.179704 | 0.383944 | 0 | 0 | 0 |
0 | 1 |
```

Summary Statistics for EXT\_SOURCE\_1:

```
+---+---+
| EXT_SOURCE_1 | 21827 | 0.502257 | 0.211017 | 0.0145681 | 0.333476 |
0.506884 | 0.673923 | 0.93825 |
```

Summary Statistics for EXT\_SOURCE\_2:

```
+---+---+
| EXT_SOURCE_2 | 49873 | 0.513824 | 0.191165 | 8.17e-08 | 0.391722 |
0.565585 | 0.663402 | 0.855 |
```

Summary Statistics for EXT\_SOURCE\_3:

```
+---+---+
| EXT_SOURCE_3 | 40055 | 0.511881 | 0.1947 | 0.000527265 | 0.37065 |
```

0.535276 | 0.669057 | 0.89601 |

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+-----+-----+-----+-----+

Summary Statistics for OBS\_30\_CNT\_SOCIAL\_CIRCLE:

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

| OBS\_30\_CNT\_SOCIAL\_CIRCLE | 49831 | 1.42078 | 2.30209 | 0 | 0 | 0 | 2  
| 28 |

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

Summary Statistics for DEF\_30\_CNT\_SOCIAL\_CIRCLE:

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

| DEF\_30\_CNT\_SOCIAL\_CIRCLE | 49831 | 0.141819 | 0.44054 | 0 | 0 | 0 |  
0 | 6 |

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

Summary Statistics for OBS\_60\_CNT\_SOCIAL\_CIRCLE:

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

| OBS\_60\_CNT\_SOCIAL\_CIRCLE | 49831 | 1.40366 | 2.28178 | 0 | 0 | 0 | 2  
| 28 |

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

Summary Statistics for DEF\_60\_CNT\_SOCIAL\_CIRCLE:

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

| DEF\_60\_CNT\_SOCIAL\_CIRCLE | 49831 | 0.0983324 | 0.357264 | 0 | 0 | 0  
| 0 | 5 |

+-----+-----+-----+-----+-----+-----+-----+  
+---+---+

Summary Statistics for DAYS\_LAST\_PHONE\_CHANGE:

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

| DAYS\_LAST\_PHONE\_CHANGE | 49998 | -964.296 | 829.486 | -4002 | -1573  
| -755 | -270 | 0 |

+-----+-----+-----+-----+-----+-----+-----+  
+-----+-----+-----+

Summary Statistics for FLAG\_DOCUMENT\_2:

+-----+-----+-----+-----+-----+-----+-----+  
+---+

| FLAG\_DOCUMENT\_2 | 49999 | 4.00008e-05 | 0.00632456 | 0 | 0 | 0 | 0 |  
1 |

+-----+-----+-----+-----+-----+-----+-----+

### Summary Statistics for FLAG\_DOCUMENT\_3:

### Summary Statistics for FLAG\_DOCUMENT\_4:

### Summary Statistics for FLAG\_DOCUMENT\_5:

### Summary Statistics for FLAG\_DOCUMENT\_6:

### Summary Statistics for FLAG\_DOCUMENT\_7:

### Summary Statistics for FLAG\_DOCUMENT\_8:

### Summary Statistics for FLAG DOCUMENT 9:

## Summary Statistics for FLAG DOCUMENT 10:

+-----+-----+-----+-----+
+---+
FLAG DOCUMENT 10   49999   2.00004e-05   0.00447218   0   0   0   0

```
| 1 |
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_11:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_11 | 49999 | 0.00426009 | 0.0651308 | 0 | 0 | 0 | 0 |
1 |
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_12:

```
+-----+-----+-----+-----+-----+-----+
| FLAG_DOCUMENT_12 | 49999 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
+-----+-----+-----+-----+-----+-----+
```

Summary Statistics for FLAG\_DOCUMENT\_13:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_13 | 49999 | 0.00322006 | 0.0566547 | 0 | 0 | 0 | 0 |
1 |
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_14:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_14 | 49999 | 0.00316006 | 0.0561261 | 0 | 0 | 0 | 0 |
1 |
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_15:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_15 | 49999 | 0.000820016 | 0.0286245 | 0 | 0 | 0 | 0 |
1 |
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_16:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_16 | 49999 | 0.0100202 | 0.0995992 | 0 | 0 | 0 | 0 | 1
|
+-----+-----+-----+-----+-----+-----+
+---+
```

Summary Statistics for FLAG\_DOCUMENT\_17:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_17 | 49999 | 0.000300006 | 0.0173183 | 0 | 0 | 0 | 0 |
1 |
```

Summary Statistics for FLAG\_DOCUMENT\_18:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_18 | 49999 | 0.00850017 | 0.0918046 | 0 | 0 | 0 | 0 |
1 |
```

Summary Statistics for FLAG\_DOCUMENT\_19:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_19 | 49999 | 0.000700014 | 0.0264488 | 0 | 0 | 0 | 0 |
1 |
```

Summary Statistics for FLAG\_DOCUMENT\_20:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_20 | 49999 | 0.00052001 | 0.022798 | 0 | 0 | 0 | 0 |
1 |
```

Summary Statistics for FLAG\_DOCUMENT\_21:

```
+-----+-----+-----+-----+-----+-----+
+---+
| FLAG_DOCUMENT_21 | 49999 | 0.000380008 | 0.0194903 | 0 | 0 | 0 | 0 |
1 |
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_HOUR:

```
+-----+-----+-----+-----+-----+-----+
+---+---+---+
| AMT_REQ_CREDIT_BUREAU_HOUR | 49999 | 0.00614012 | 0.0816245 | 0 | 0
| 0 | 0 | 3 |
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_DAY:

```
+-----+-----+-----+-----+-----+-----+
+---+---+---+
```

```
| AMT_REQ_CREDIT_BUREAU_DAY | 49999 | 0.00650013 | 0.10049 | 0 | 0 | 0 |
| 0 | 6 |
+-----+-----+-----+-----+-----+
+---+---+---+
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_WEEK:

```
+-----+-----+-----+-----+-----+
+---+---+---+
| AMT_REQ_CREDIT_BUREAU_WEEK | 49999 | 0.0280206 | 0.180876 | 0 | 0 |
0 | 0 | 6 |
+-----+-----+-----+-----+-----+
+---+---+---+
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_MON:

```
+-----+-----+-----+-----+-----+
+---+---+---+
| AMT_REQ_CREDIT_BUREAU_MON | 49999 | 0.233885 | 0.868682 | 0 | 0 | 0 |
| 0 | 24 |
+-----+-----+-----+-----+-----+
+---+---+---+
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_QRT:

```
+-----+-----+-----+-----+-----+
+---+---+---+
| AMT_REQ_CREDIT_BUREAU_QRT | 49999 | 0.225825 | 0.571627 | 0 | 0 | 0 |
| 0 | 8 |
+-----+-----+-----+-----+-----+
+---+---+---+
```

Summary Statistics for AMT\_REQ\_CREDIT\_BUREAU\_YEAR:

```
+-----+-----+-----+-----+-----+
+---+---+---+
| AMT_REQ_CREDIT_BUREAU_YEAR | 49999 | 1.62769 | 1.84995 | 0 | 0 | 1 |
3 | 25 |
+-----+-----+-----+-----+-----+
+---+---+---+
```

## Segmented Univariate Analysis:

```
for i in application_data.columns:
    # Calculate the class frequencies
    class_frequencies = application_data[i].value_counts()

    # Create a pie chart to performt Univariate Analysis.
    # Using if condition to give only those we are categorical
    variables.
```

```

if len(class_frequencies)<=10:

    print(class_frequencies)
    # printing the percentage of each value_count in list
    percentage =
np.around((class_frequencies.values)/len(application_data[i])*100)
    print(percentage)

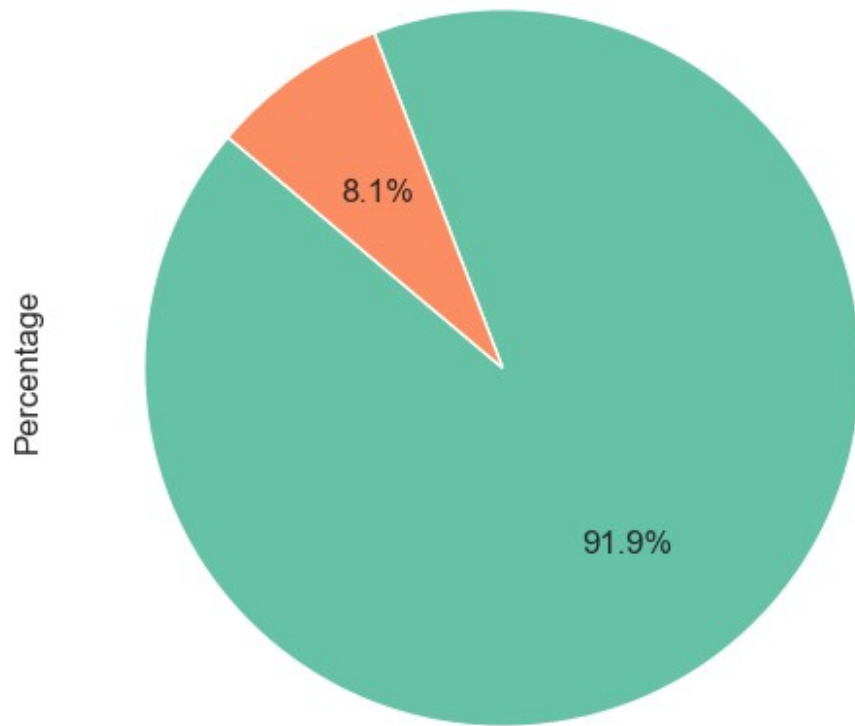
    # Create a bar chart to visualize Data imbalance.
    plt.figure(figsize=(6, 6))
    #sns.pie(x = class_frequencies.index, y =
(class_frequencies.values)/len(application_data[i])*100)
    sns.set_palette("Set2") # You can choose a different color
palette

plt.pie((class_frequencies.values)/len(application_data[i])*100,
autopct='%1.1f%%', startangle=140)
    plt.xlabel(i)
    plt.ylabel("Percentage")
    plt.show()

0      45973
1       4026
Name: TARGET, dtype: int64
[92.  8.]

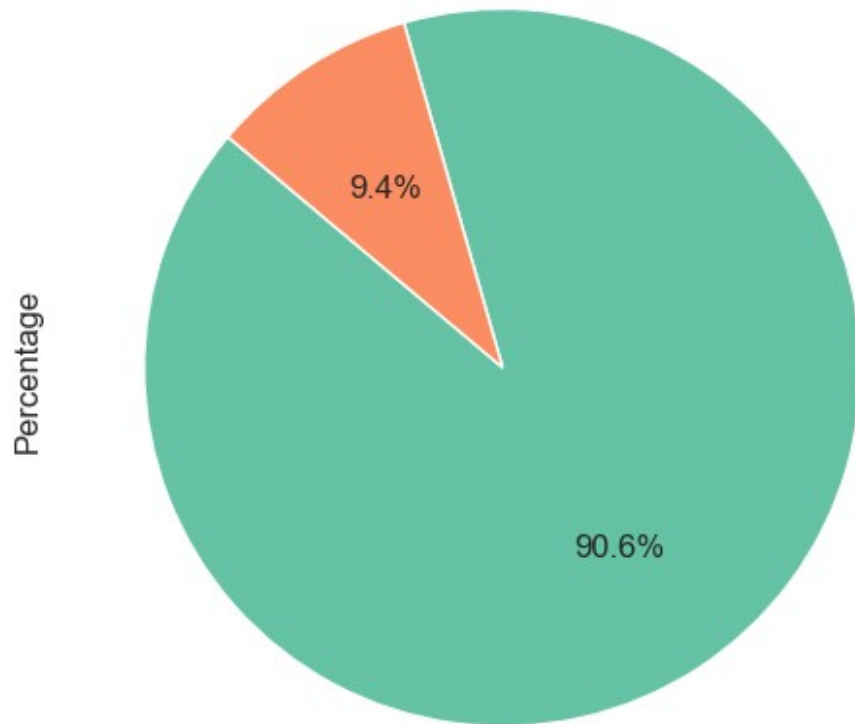
```





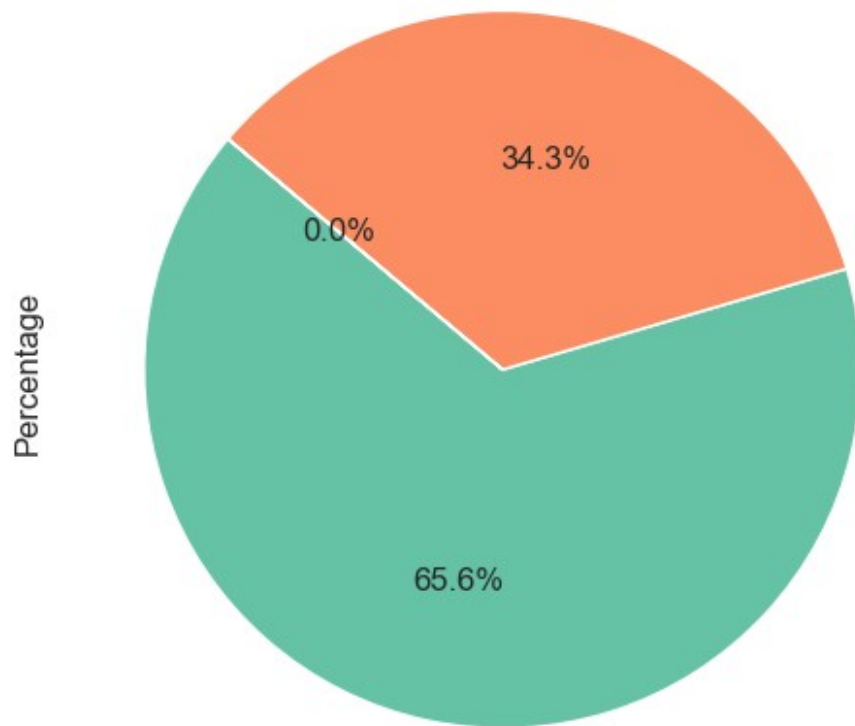
TARGET

```
Cash loans      45276
Revolving loans   4723
Name: NAME_CONTRACT_TYPE, dtype: int64
[91.  9.]
```



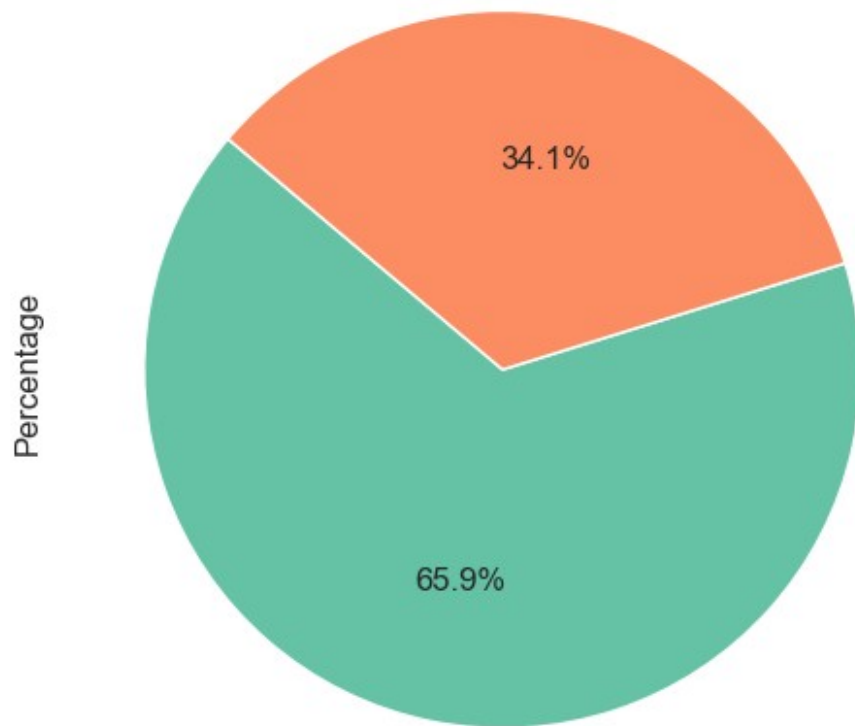
NAME\_CONTRACT\_TYPE

```
F      32823
M      17174
XNA         2
Name: CODE_GENDER, dtype: int64
[66. 34.  0.]
```



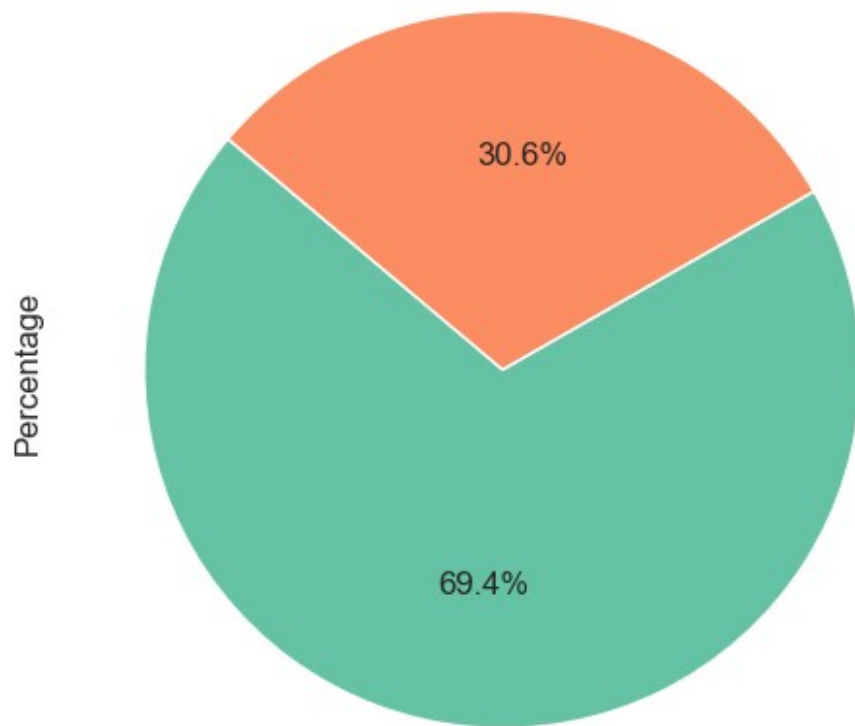
CODE\_GENDER

```
N    32949
Y    17050
Name: FLAG_OWN_CAR, dtype: int64
[66. 34.]
```



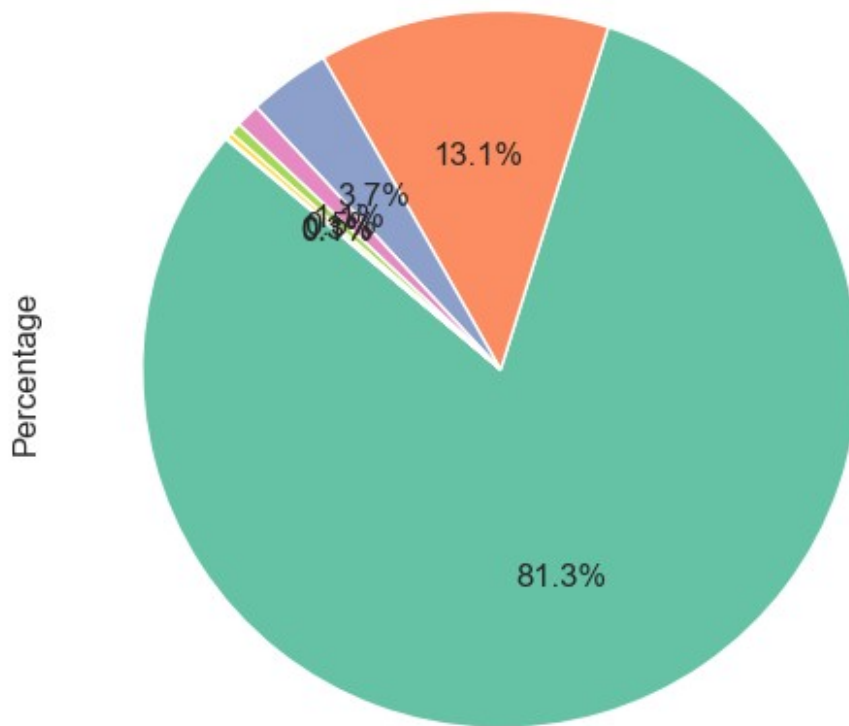
FLAG\_OWN\_CAR

```
Y      34691
N      15308
Name: FLAG_OWN_REALTY, dtype: int64
[69. 31.]
```



FLAG\_OWN\_REALTY

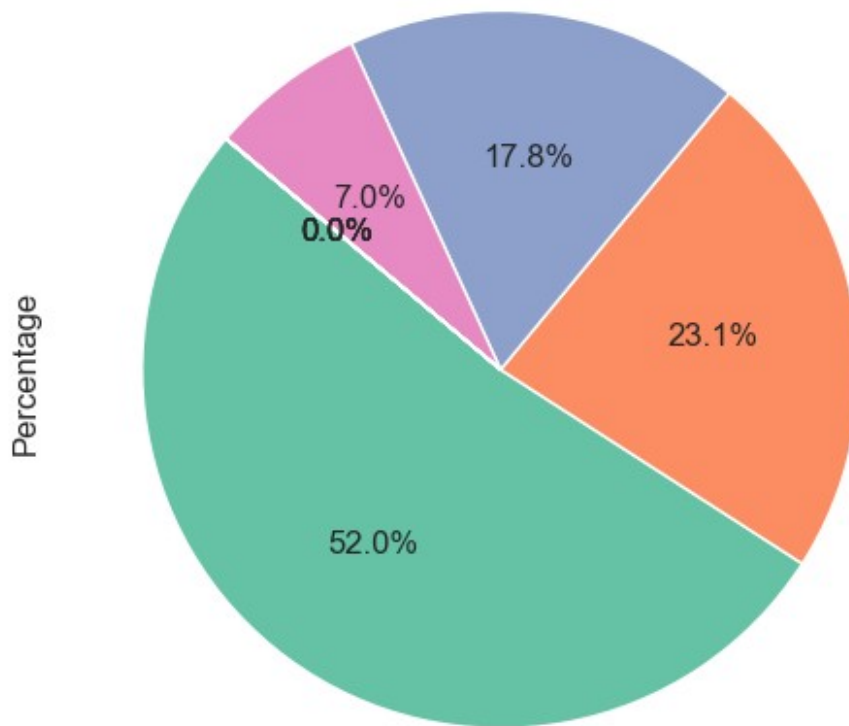
```
Unaccompanied      40627
Family              6549
Spouse, partner     1849
Children            542
Other_B             259
Other_A             137
Group of people      36
Name: NAME_TYPE_SUITE, dtype: int64
[81. 13.  4.  1.  1.  0.  0.]
```



NAME\_TYPE\_SUITE

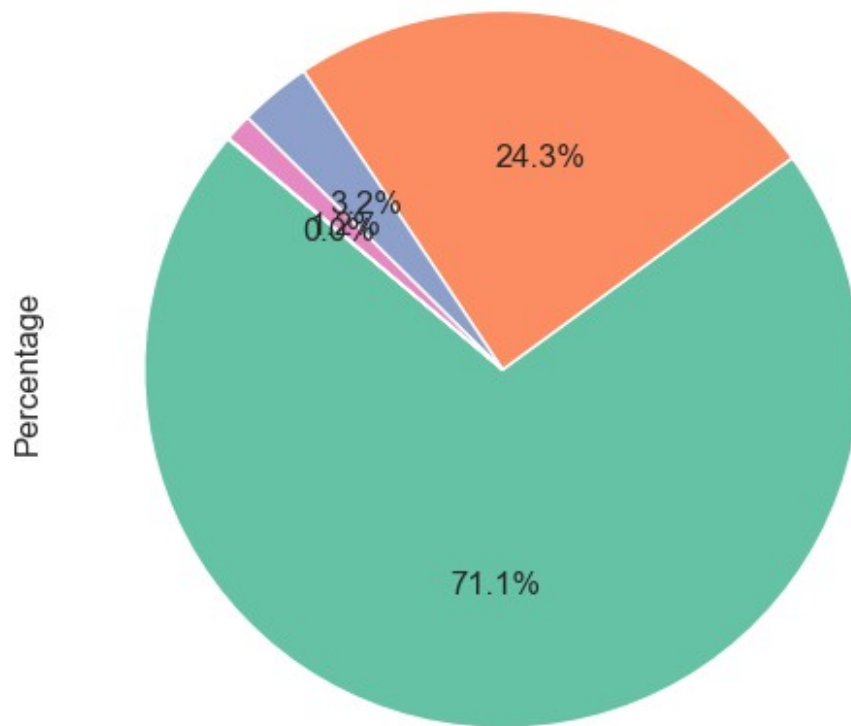
Working	26010
Commercial associate	11543
Pensioner	8920
State servant	3512
Unemployed	6
Student	5
Businessman	2
Maternity leave	1

Name: NAME\_INCOME\_TYPE, dtype: int64  
[52. 23. 18. 7. 0. 0. 0. 0.]



NAME\_INCOME\_TYPE

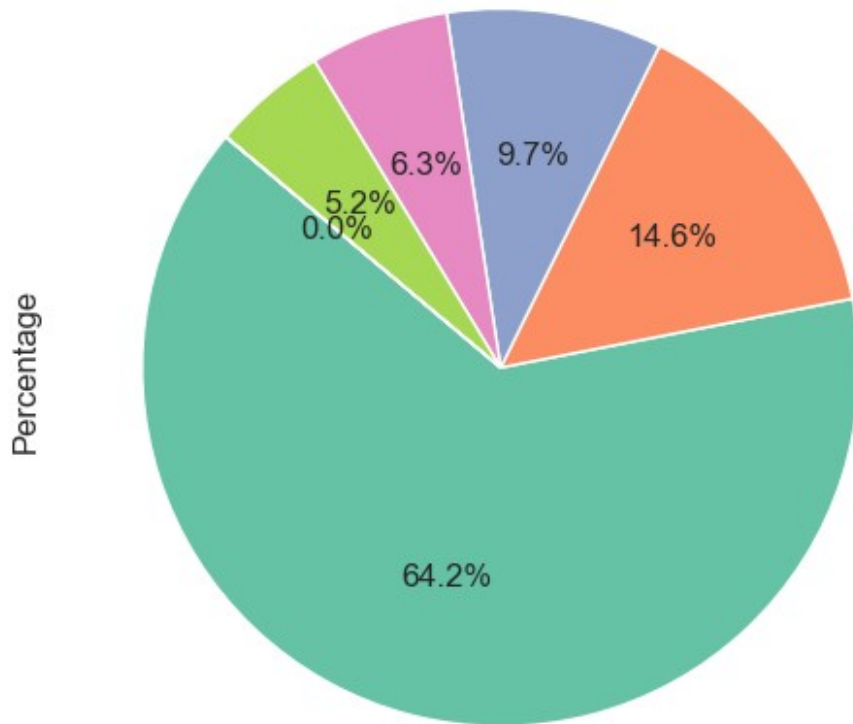
```
Secondary / secondary special    35572
Higher education                 12167
Incomplete higher                1620
Lower secondary                 620
Academic degree                 20
Name: NAME_EDUCATION_TYPE, dtype: int64
[71. 24.  3.  1.  0.]
```



NAME\_EDUCATION\_TYPE

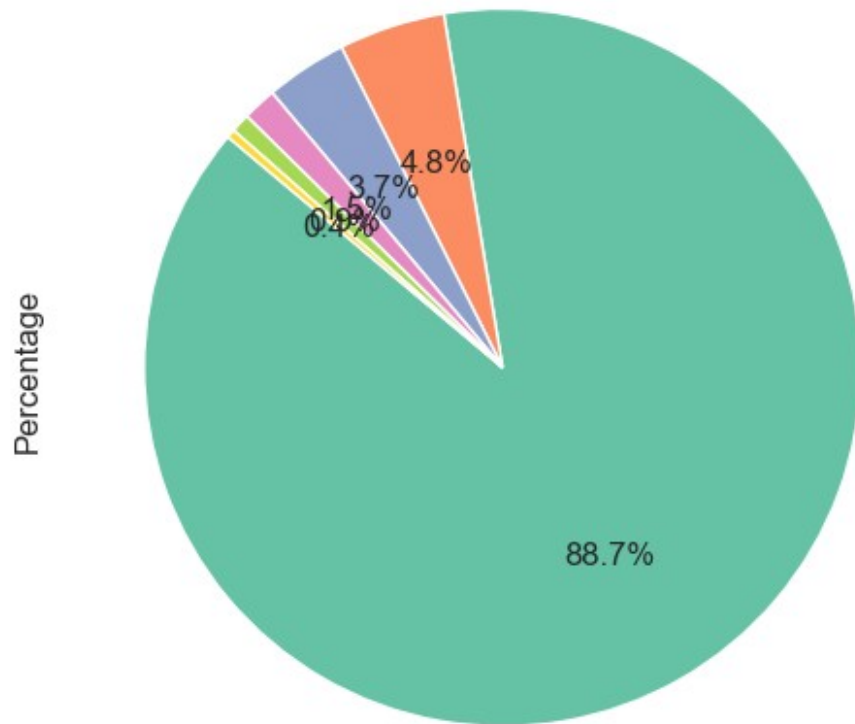
```
Married          32094
Single / not married  7306
Civil marriage    4859
Separated         3142
Widow            2597
Unknown           1
Name: NAME_FAMILY_STATUS, dtype: int64
[64. 15. 10.  6.  5.  0.]
```





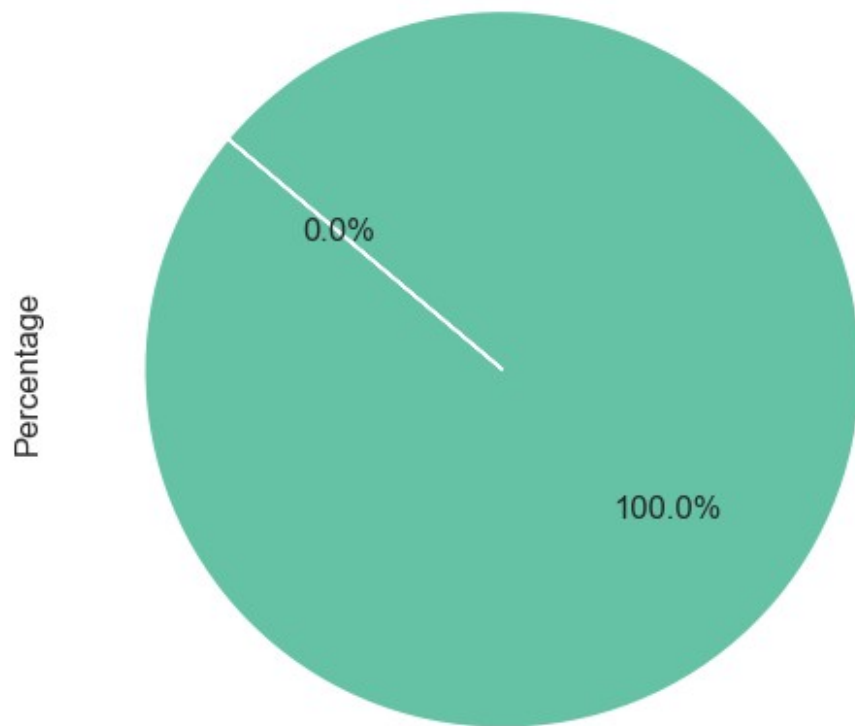
NAME\_FAMILY\_STATUS

```
House / apartment      44368
With parents           2399
Municipal apartment    1845
Rented apartment       769
Office apartment       427
Co-op apartment        191
Name: NAME_HOUSING_TYPE, dtype: int64
[89.  5.  4.  2.  1.  0.]
```



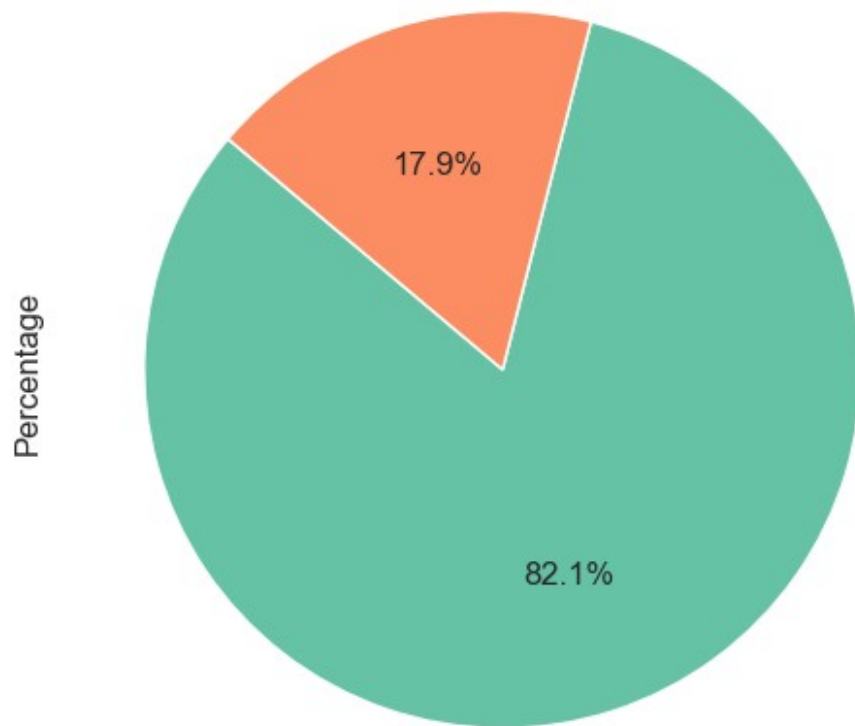
NAME\_HOUSING\_TYPE

```
1    49998
0         1
Name: FLAG_MOBIL, dtype: int64
[100.    0.]
```



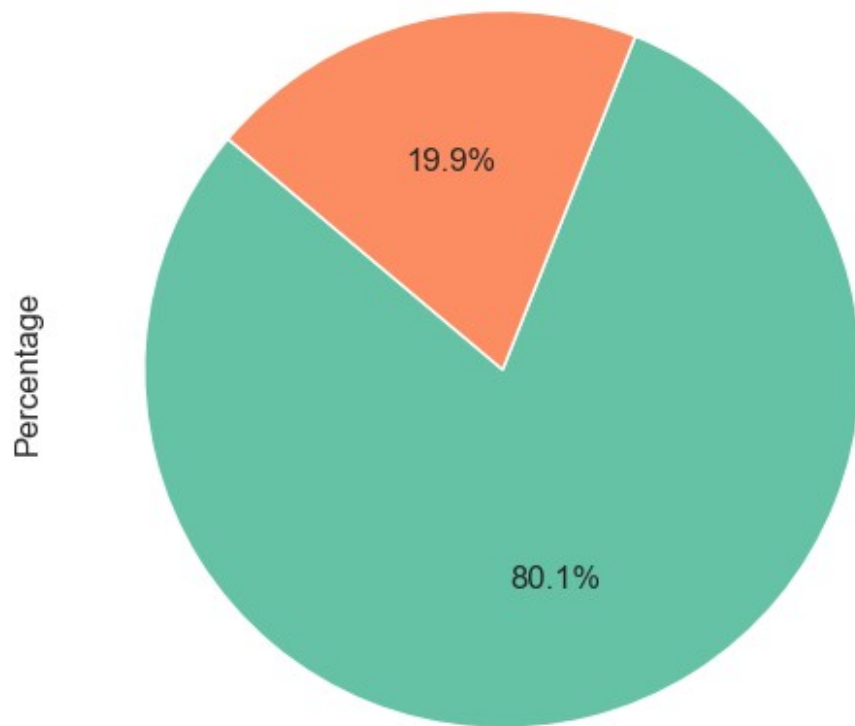
FLAG\_MOBIL

```
1    41073
0     8926
Name: FLAG_EMP_PHONE, dtype: int64
[82. 18.]
```



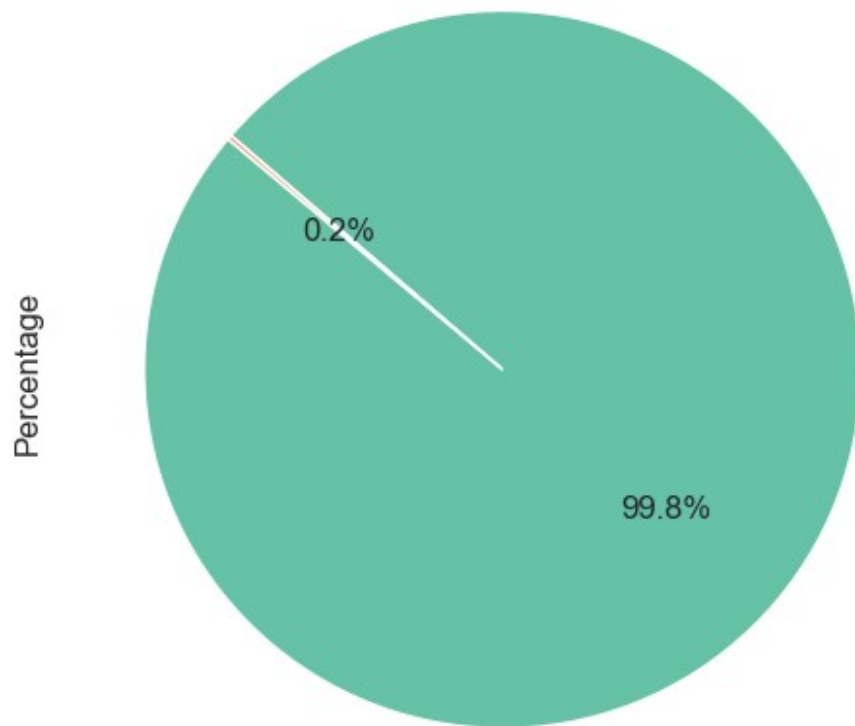
FLAG\_EMP\_PHONE

```
0    40036
1     9963
Name: FLAG_WORK_PHONE, dtype: int64
[80. 20.]
```



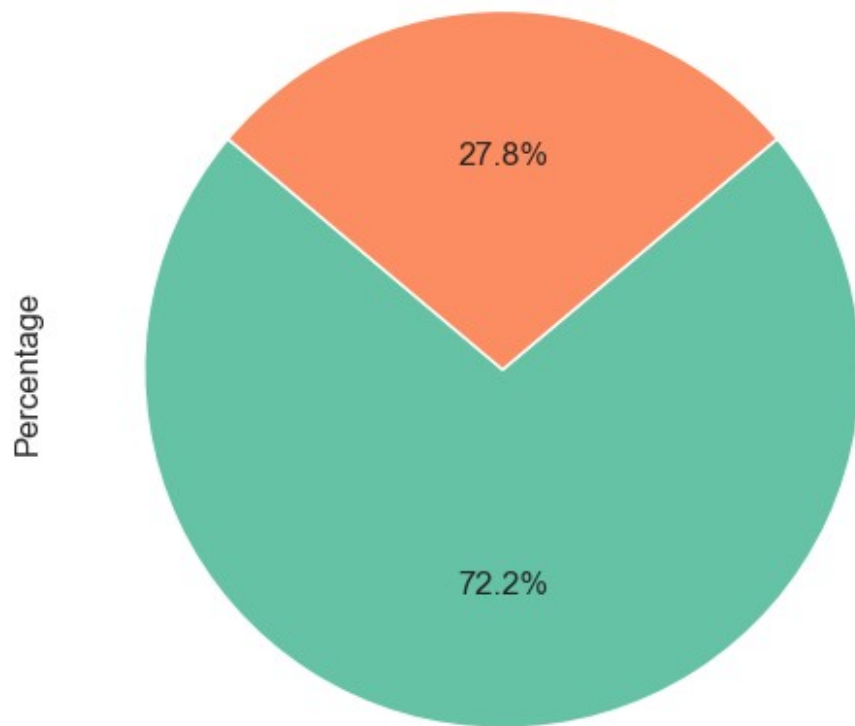
FLAG\_WORK\_PHONE

```
1    49898
0      101
Name: FLAG_CONT_MOBILE, dtype: int64
[100.    0.]
```



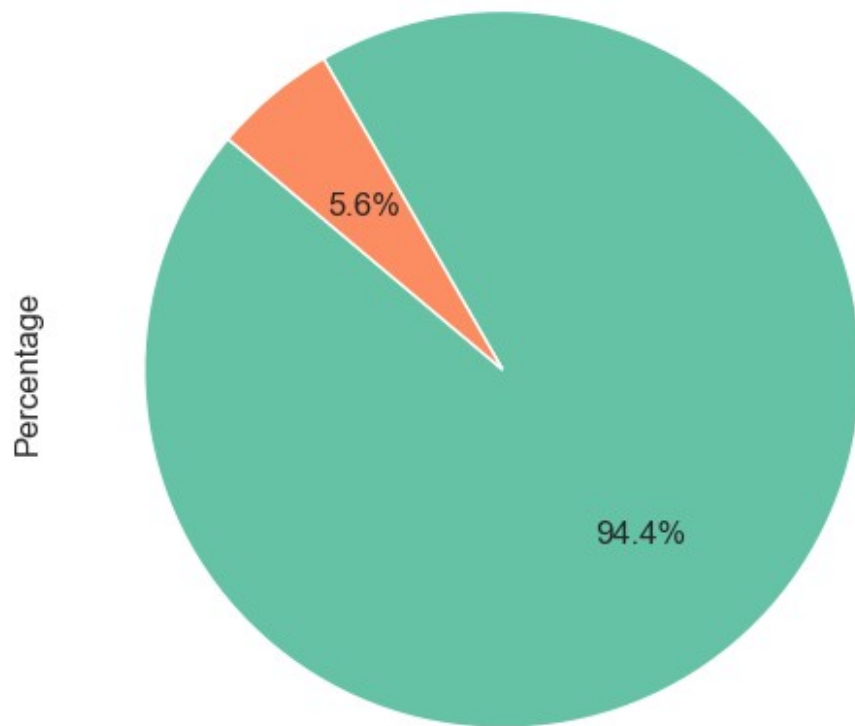
FLAG\_CONT\_MOBILE

```
0    36113
1     13886
Name: FLAG_PHONE, dtype: int64
[72. 28.]
```



FLAG\_PHONE

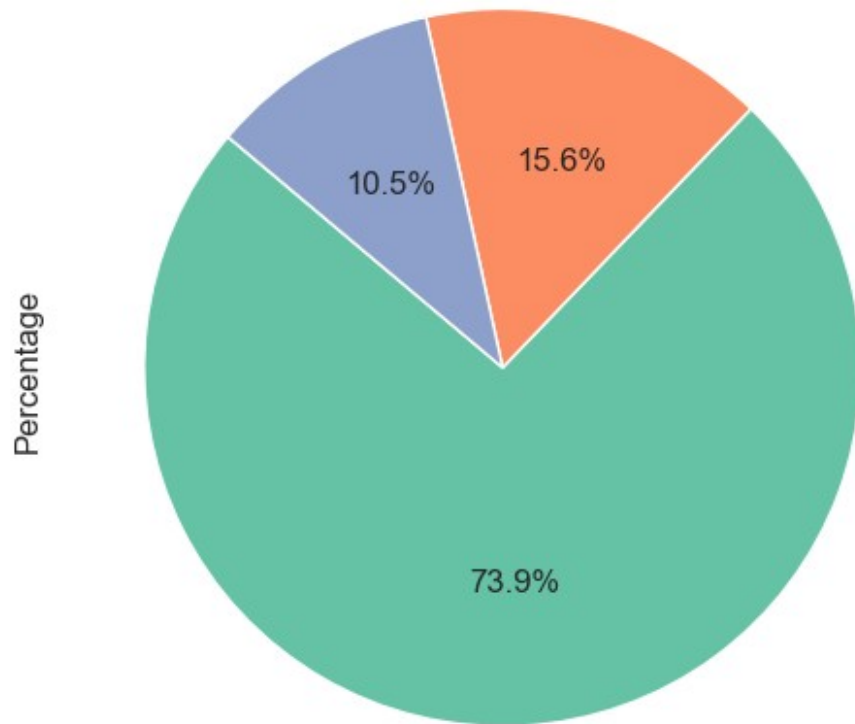
```
0    47216
1     2783
Name: FLAG_EMAIL, dtype: int64
[94.  6.]
```



FLAG\_EMAIL

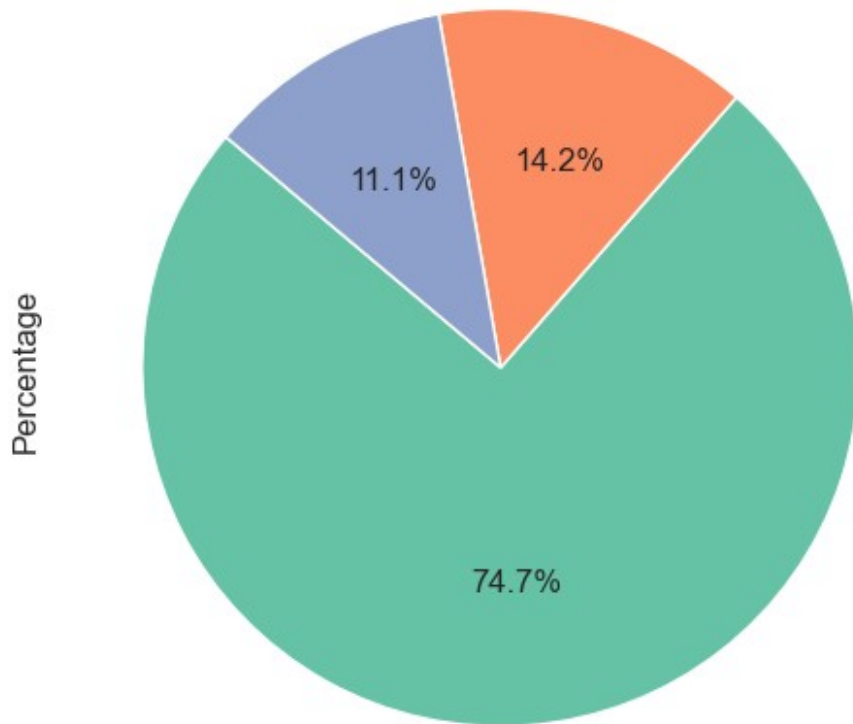
```
2    36964
3     7809
1     5226
Name: REGION_RATING_CLIENT, dtype: int64
[74. 16. 10.]
```





REGION\_RATING\_CLIENT

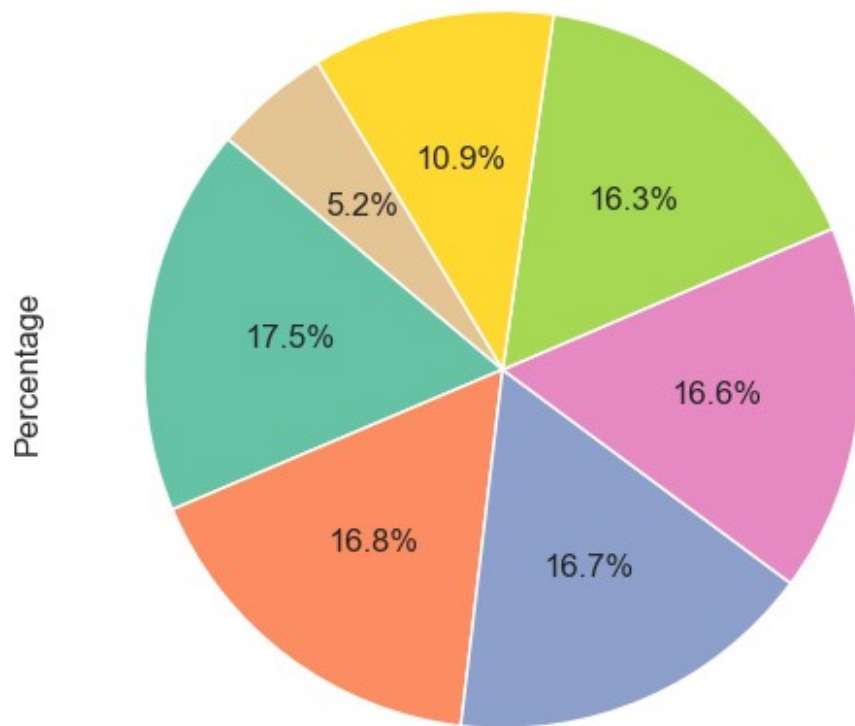
```
2    37341
3     7097
1     5561
Name: REGION_RATING_CLIENT_W_CITY, dtype: int64
[75. 14. 11.]
```



REGION\_RATING\_CLIENT\_W\_CITY

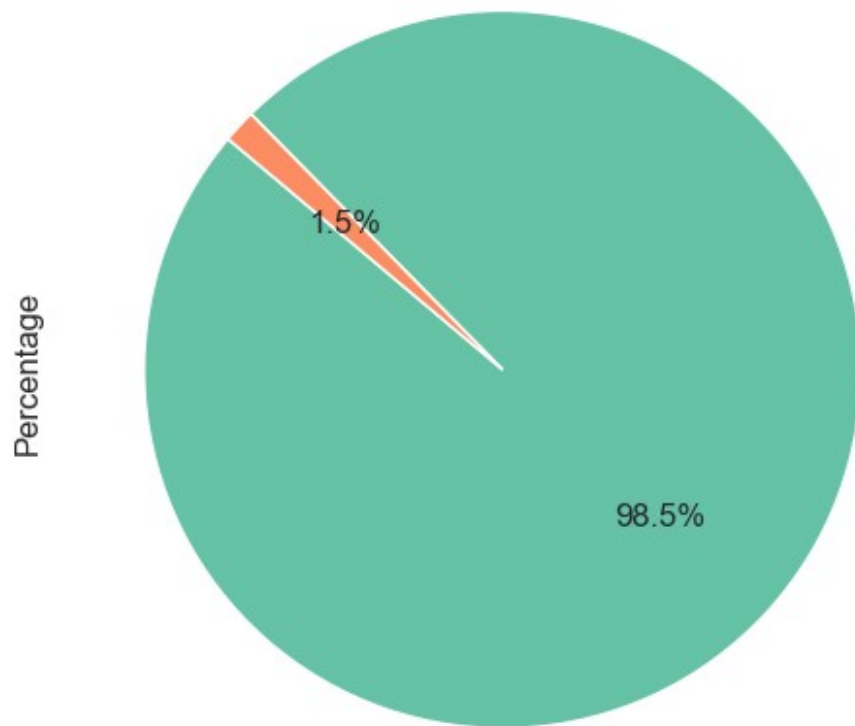
TUESDAY	8741
MONDAY	8385
WEDNESDAY	8355
FRIDAY	8286
THURSDAY	8149
SATURDAY	5467
SUNDAY	2616

Name: WEEKDAY\_APPR\_PROCESS\_START, dtype: int64  
[17. 17. 17. 17. 16. 11. 5.]



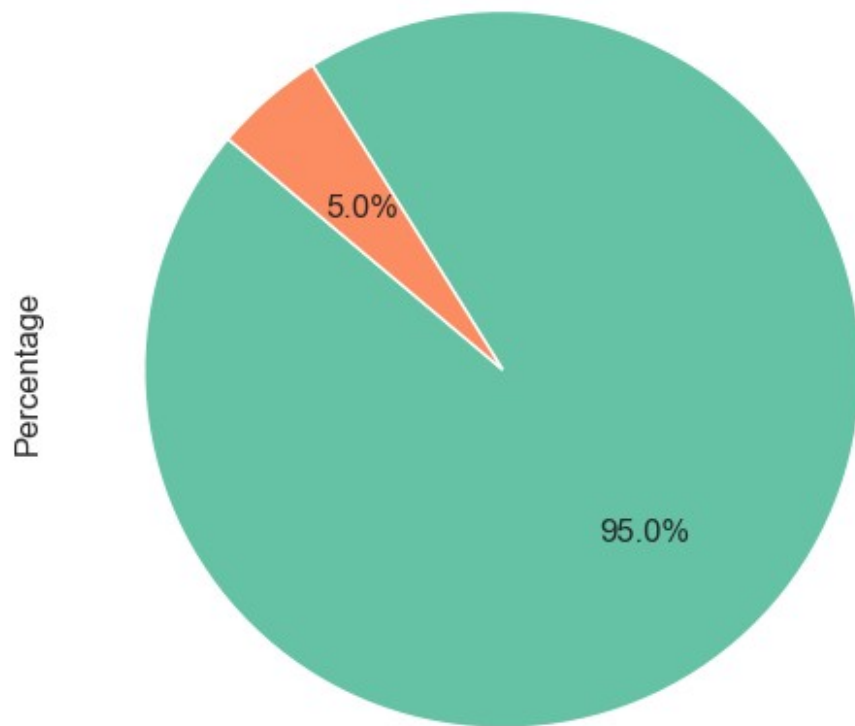
WEEKDAY\_APPR\_PROCESS\_START

```
0    49249
1      750
Name: REG_REGION_NOT_LIVE_REGION, dtype: int64
[98.  2.]
```



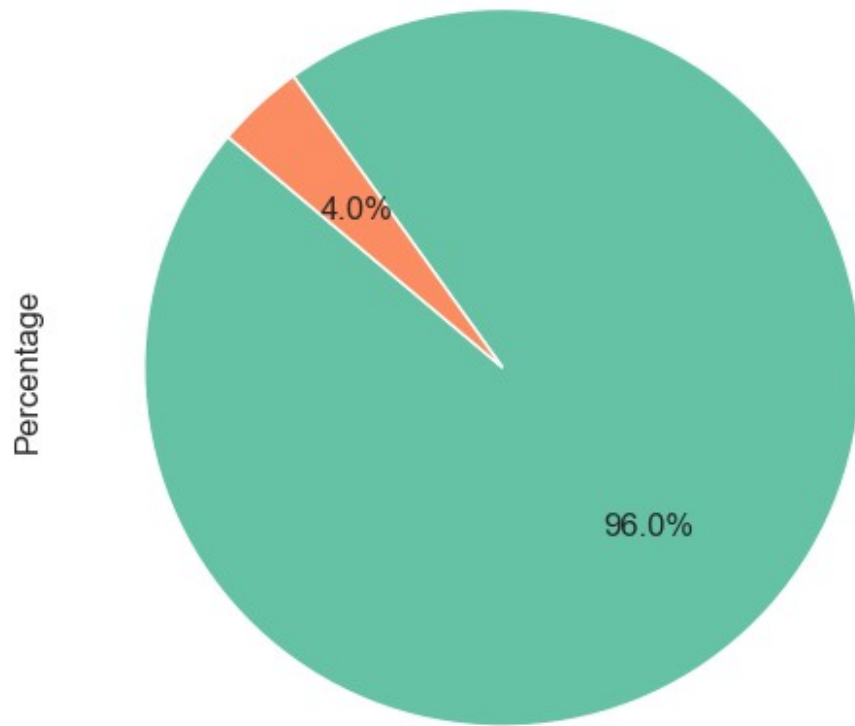
REG\_REGION\_NOT\_LIVE\_REGION

```
0    47503
1     2496
Name: REG_REGION_NOT_WORK_REGION, dtype: int64
[95.  5.]
```



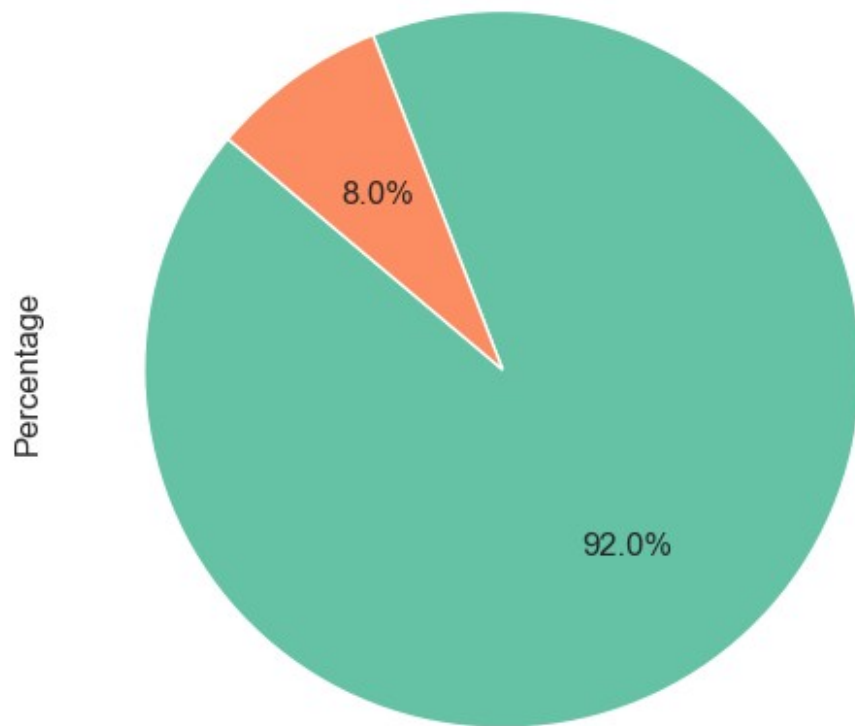
REG\_REGION\_NOT\_WORK\_REGION

```
0    48017
1     1982
Name: LIVE_REGION_NOT_WORK_REGION, dtype: int64
[96.  4.]
```



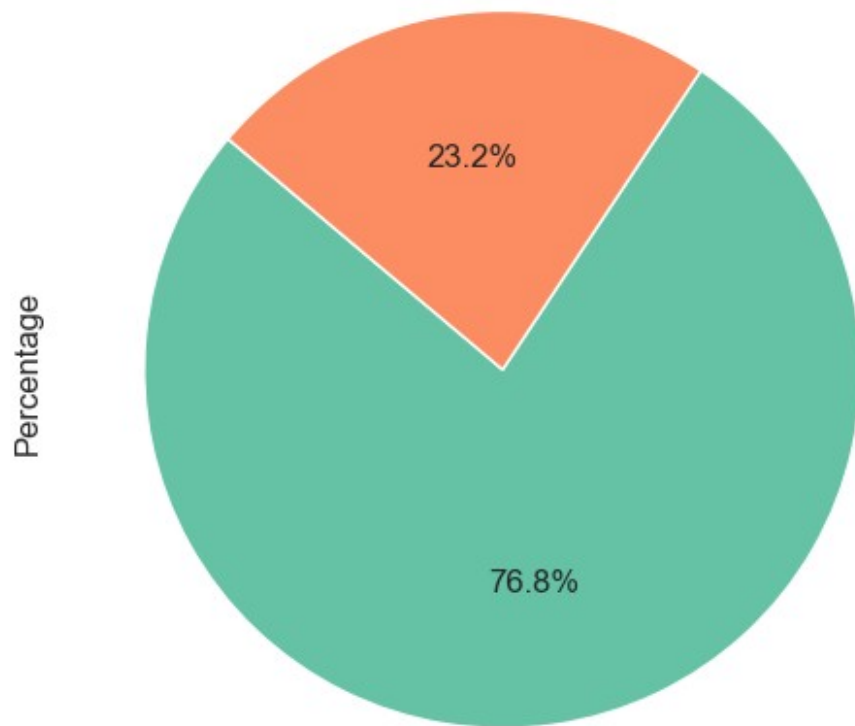
LIVE\_REGION\_NOT\_WORK\_REGION

```
0    46001
1     3998
Name: REG_CITY_NOT_LIVE_CITY, dtype: int64
[92.  8.]
```



REG\_CITY\_NOT\_LIVE\_CITY

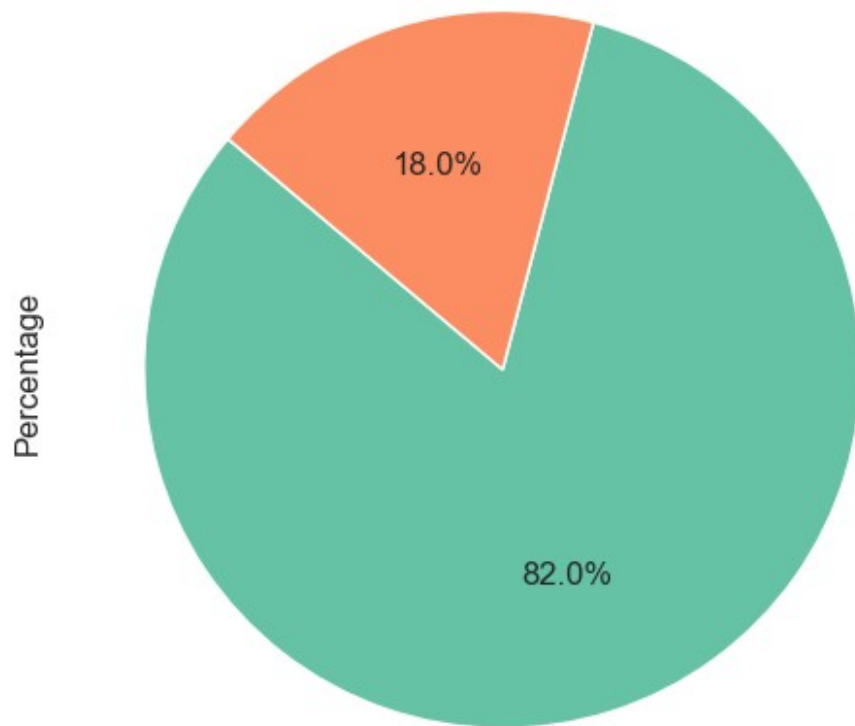
```
0    38391
1     11608
Name: REG_CITY_NOT_WORK_CITY, dtype: int64
[77. 23.]
```



REG\_CITY\_NOT\_WORK\_CITY

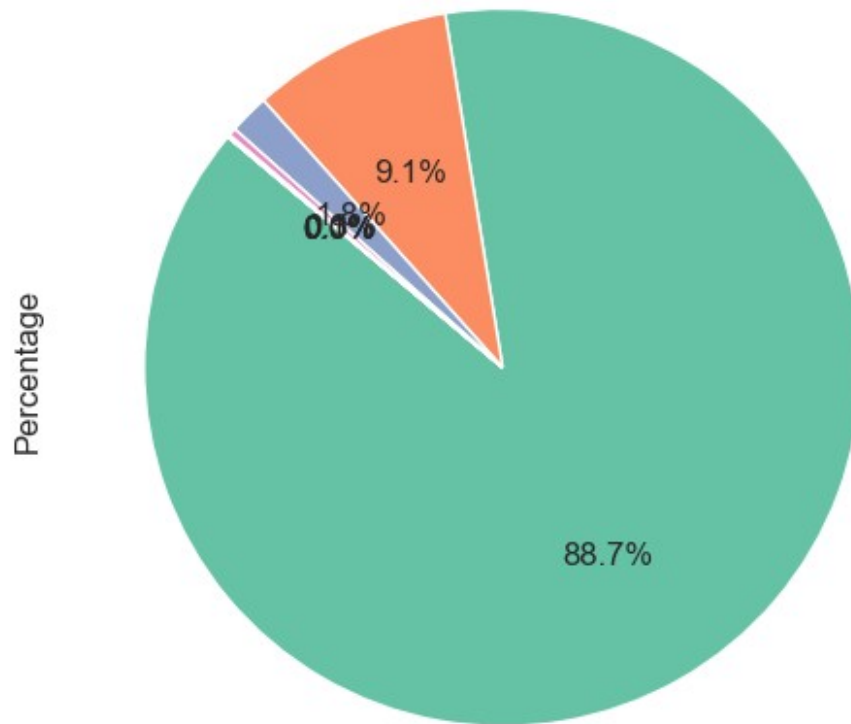
```
0    41014
1     8985
Name: LIVE_CITY_NOT_WORK_CITY, dtype: int64
[82. 18.]
```





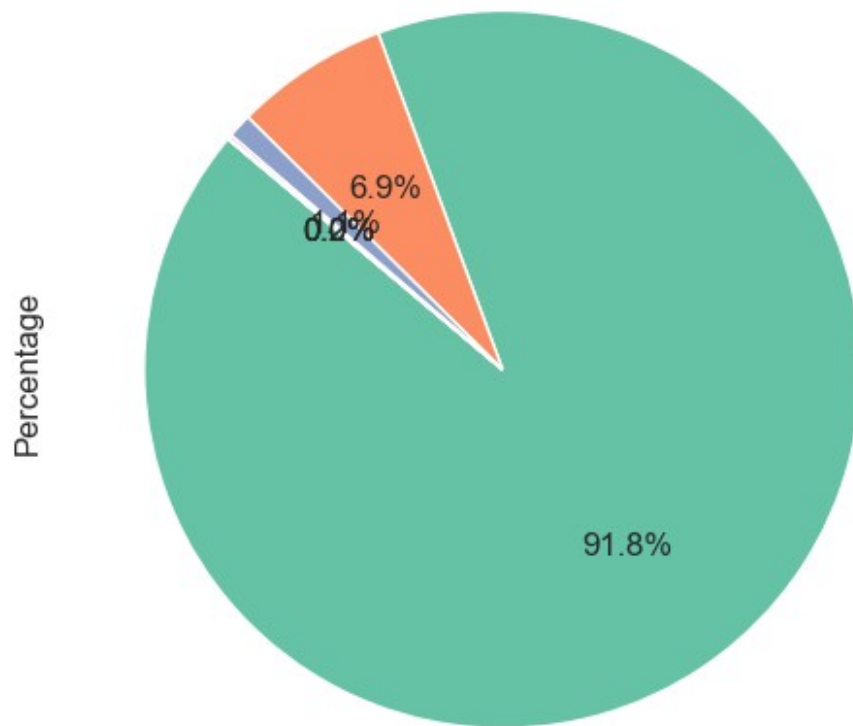
LIVE\_CITY\_NOT\_WORK\_CITY

```
0.0    44189
1.0     4514
2.0       899
3.0       173
4.0        45
5.0        10
6.0         1
Name: DEF_30_CNT_SOCIAL_CIRCLE, dtype: int64
[88.  9.  2.  0.  0.  0.  0.]
```



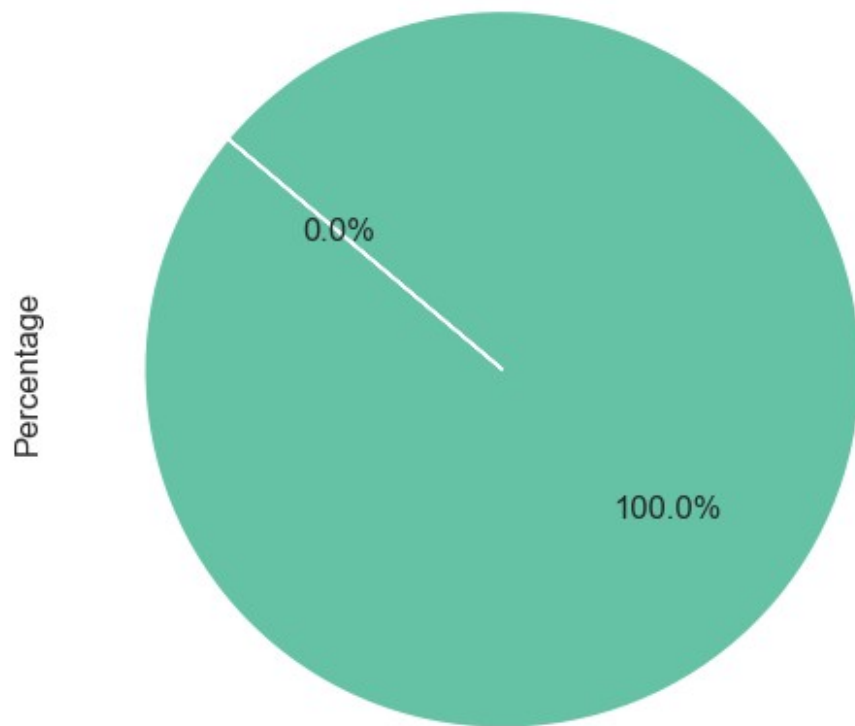
DEF\_30\_CNT\_SOCIAL\_CIRCLE

```
0.0    45723
1.0    3457
2.0     543
3.0      80
4.0      23
5.0       5
Name: DEF_60_CNT_SOCIAL_CIRCLE, dtype: int64
[91.  7.  1.  0.  0.  0.]
```



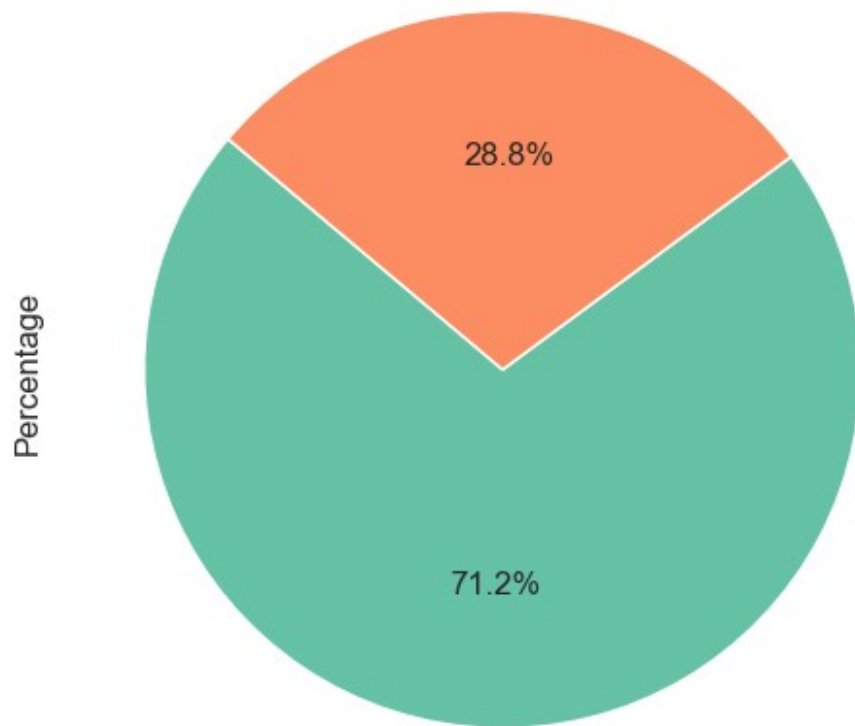
DEF\_60\_CNT\_SOCIAL\_CIRCLE

```
0    49997
1         2
Name: FLAG_DOCUMENT_2, dtype: int64
[100.    0.]
```



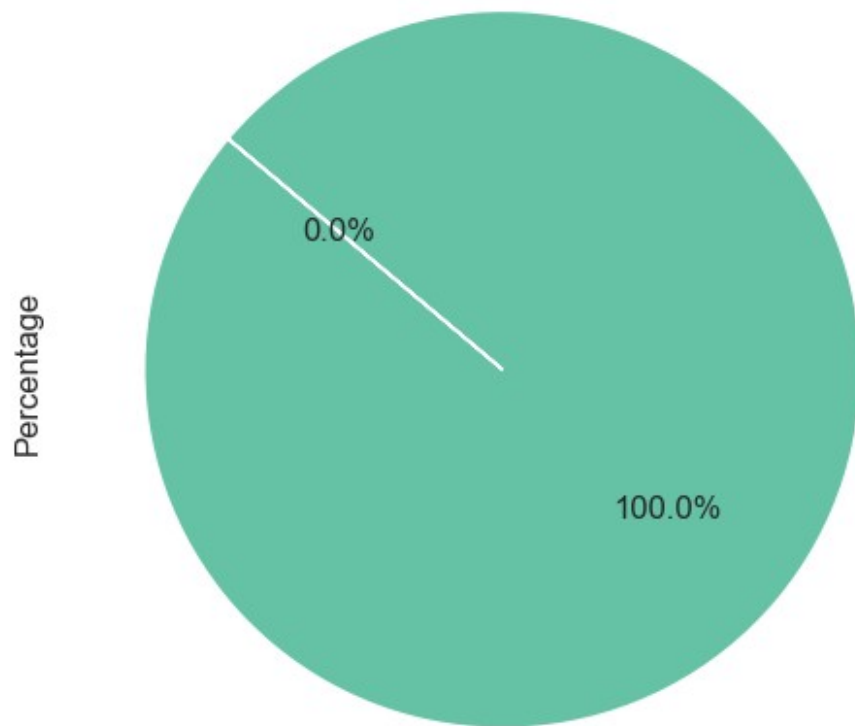
FLAG\_DOCUMENT\_2

```
1    35612
0    14387
Name: FLAG_DOCUMENT_3, dtype: int64
[71. 29.]
```



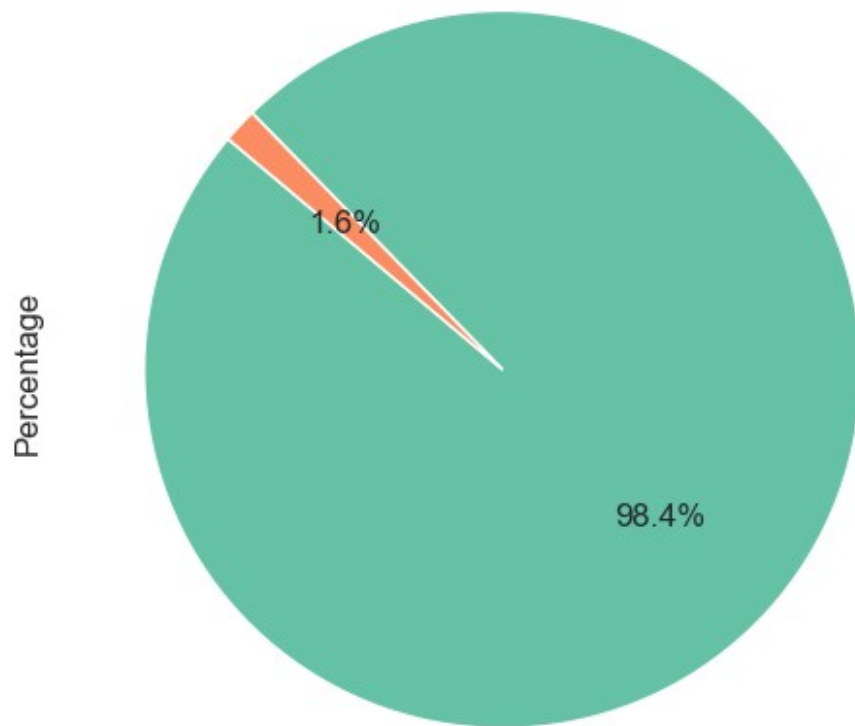
FLAG\_DOCUMENT\_3

```
0    49990
1         9
Name: FLAG_DOCUMENT_4, dtype: int64
[100.    0.]
```



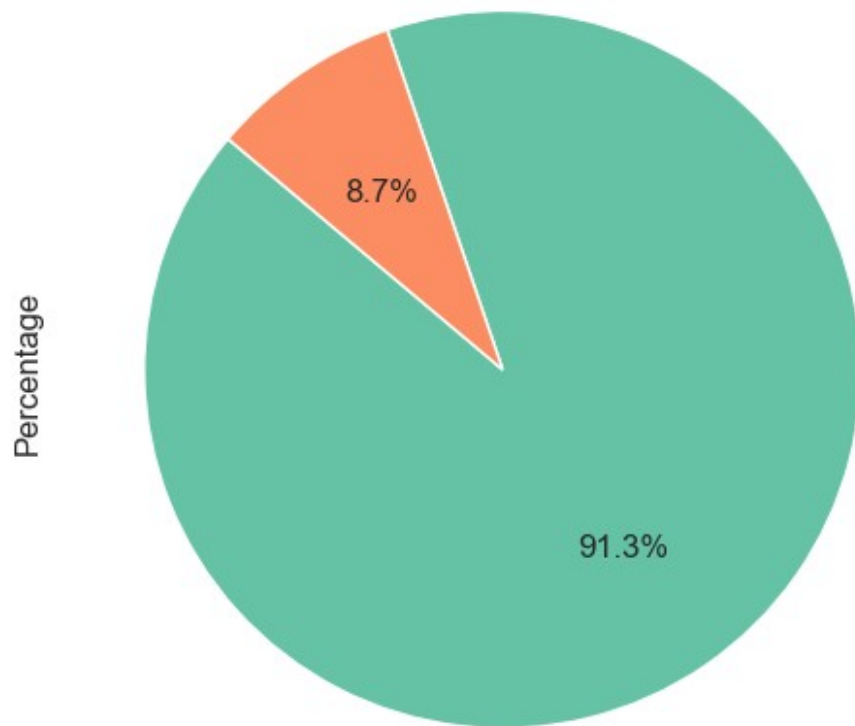
FLAG\_DOCUMENT\_4

```
0    49214
1      785
Name: FLAG_DOCUMENT_5, dtype: int64
[98.  2.]
```



FLAG\_DOCUMENT\_5

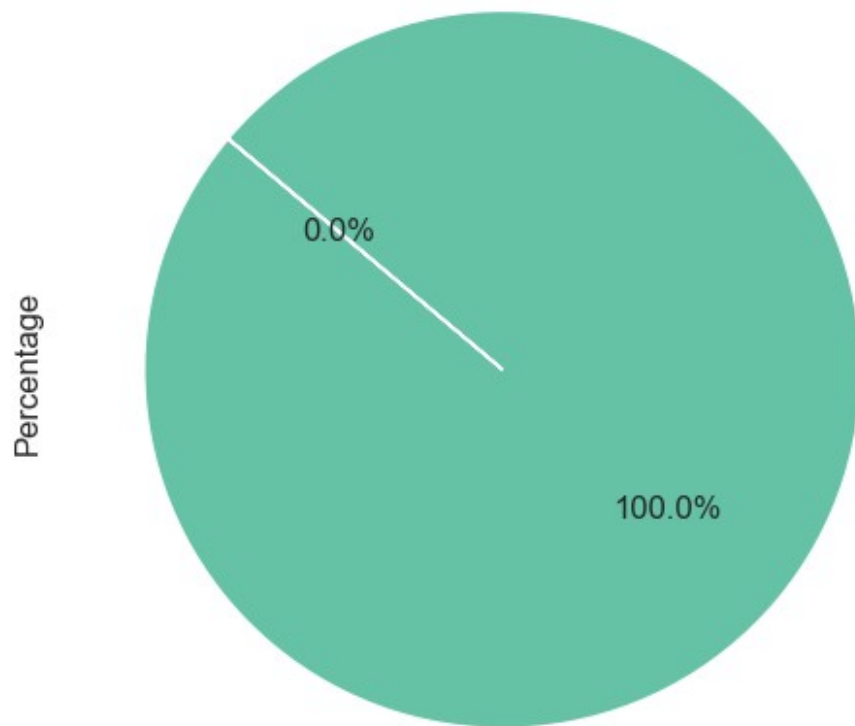
```
0    45664
1     4335
Name: FLAG_DOCUMENT_6, dtype: int64
[91.  9.]
```



FLAG\_DOCUMENT\_6

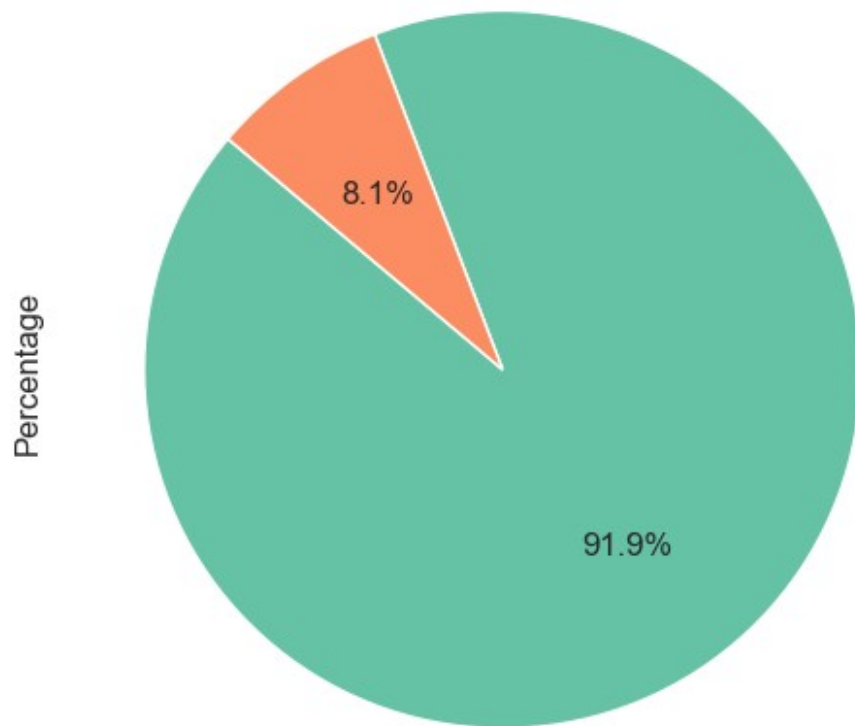
```
0    49988
1         11
Name: FLAG_DOCUMENT_7, dtype: int64
[100.    0.]
```





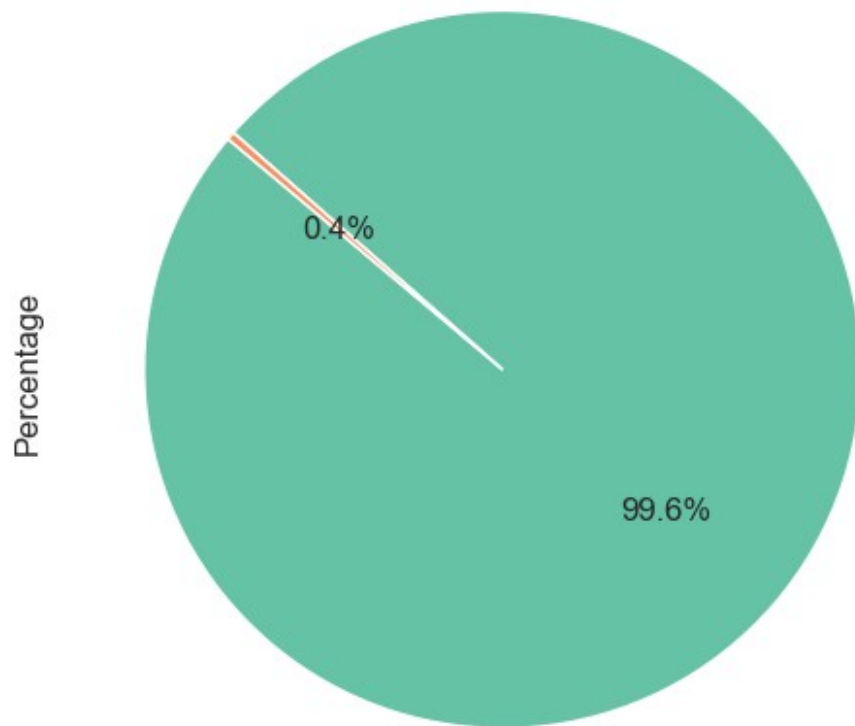
FLAG\_DOCUMENT\_7

```
0    45961
1     4038
Name: FLAG_DOCUMENT_8, dtype: int64
[92.  8.]
```



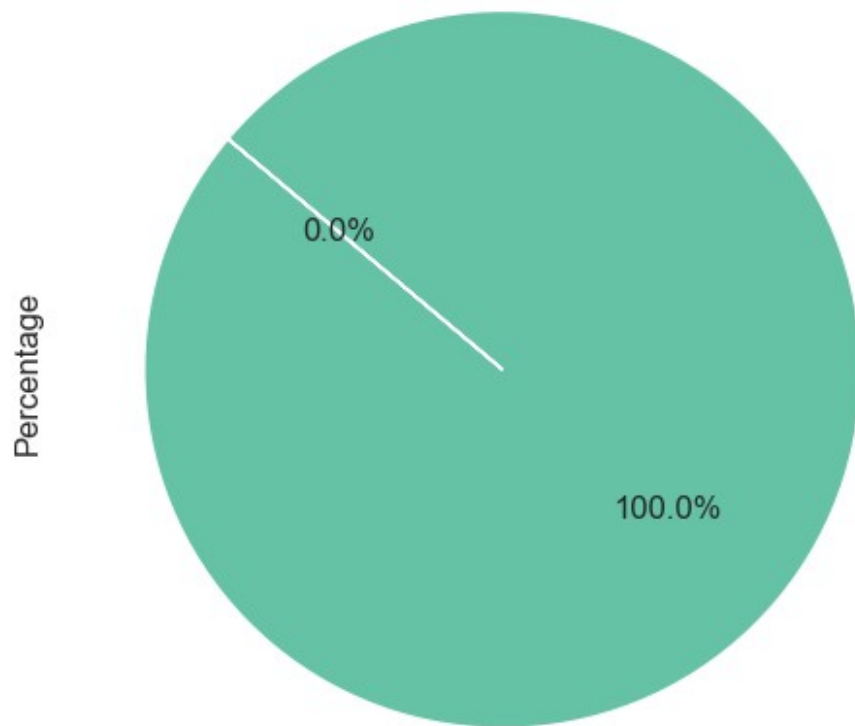
FLAG\_DOCUMENT\_8

```
0    49815
1      184
Name: FLAG_DOCUMENT_9, dtype: int64
[100.    0.]
```



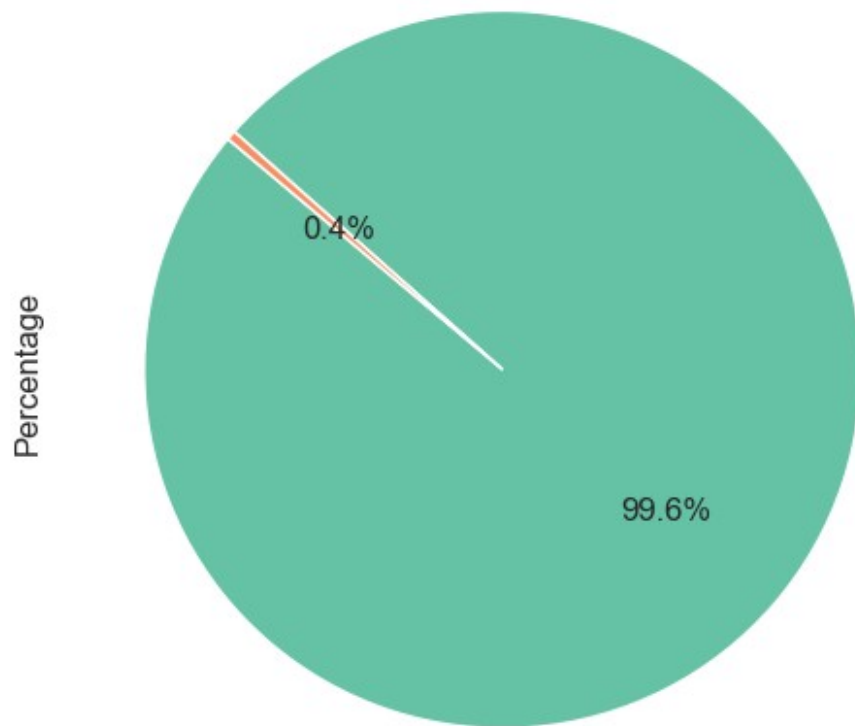
FLAG\_DOCUMENT\_9

```
0    49998
1         1
Name: FLAG_DOCUMENT_10, dtype: int64
[100.    0.]
```



FLAG\_DOCUMENT\_10

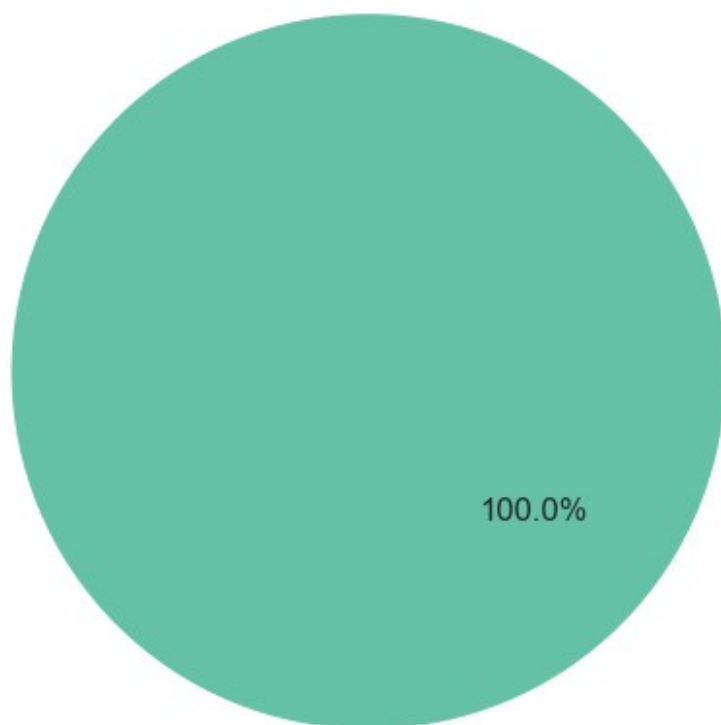
```
0    49786
1      213
Name: FLAG_DOCUMENT_11, dtype: int64
[100.    0.]
```



FLAG\_DOCUMENT\_11

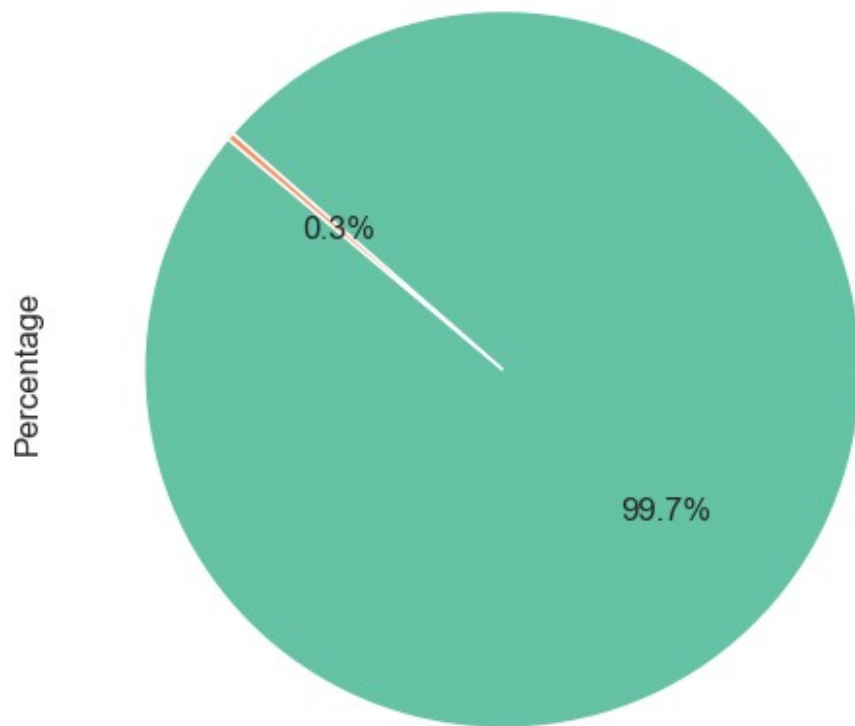
```
0      49999  
Name: FLAG_DOCUMENT_12, dtype: int64  
[100.]
```

Percentage



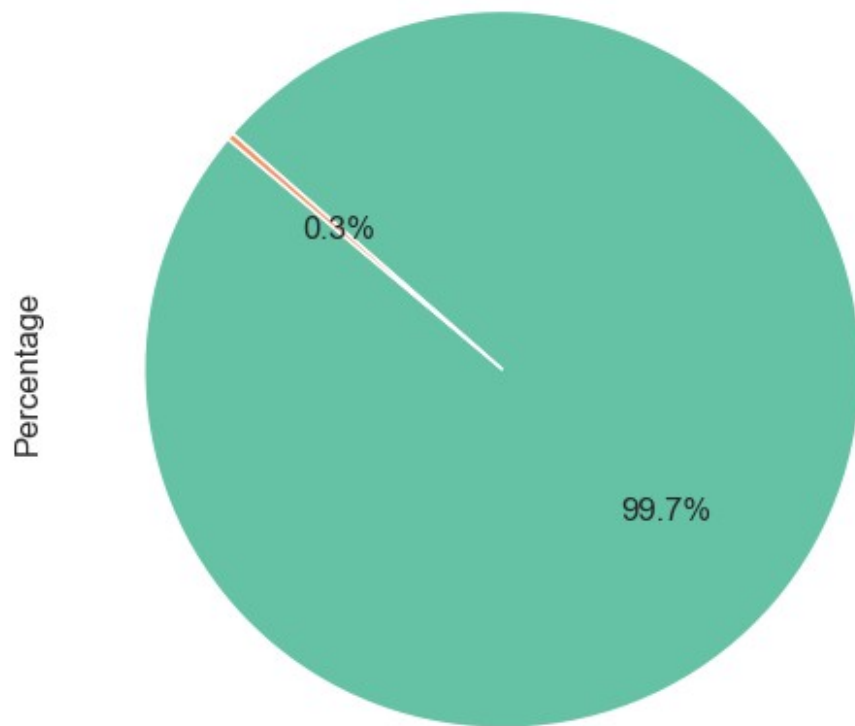
FLAG\_DOCUMENT\_12

```
0    49838
1      161
Name: FLAG_DOCUMENT_13, dtype: int64
[100.    0.]
```



FLAG\_DOCUMENT\_13

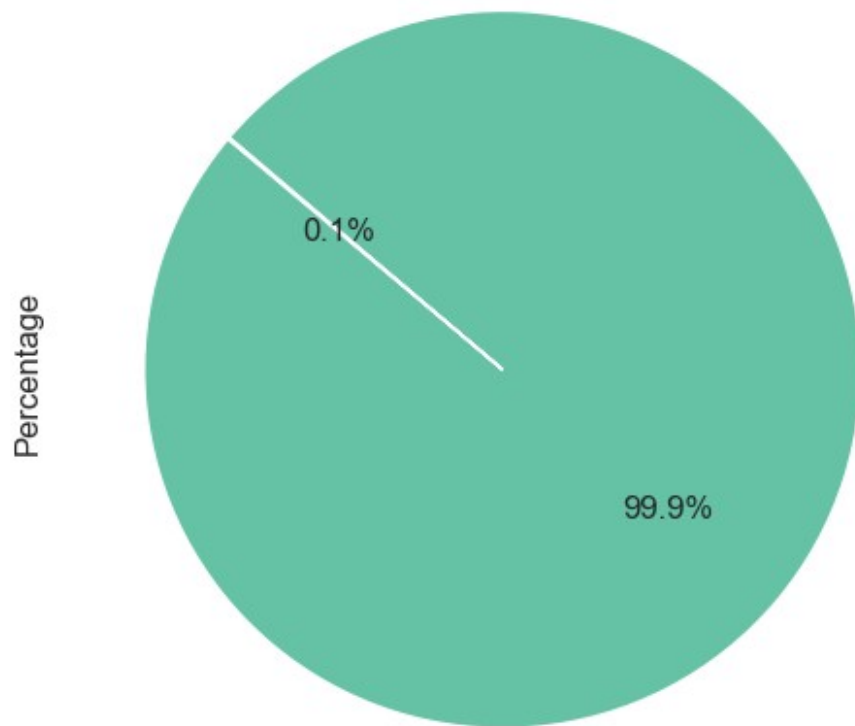
```
0    49841
1      158
Name: FLAG_DOCUMENT_14, dtype: int64
[100.    0.]
```



FLAG\_DOCUMENT\_14

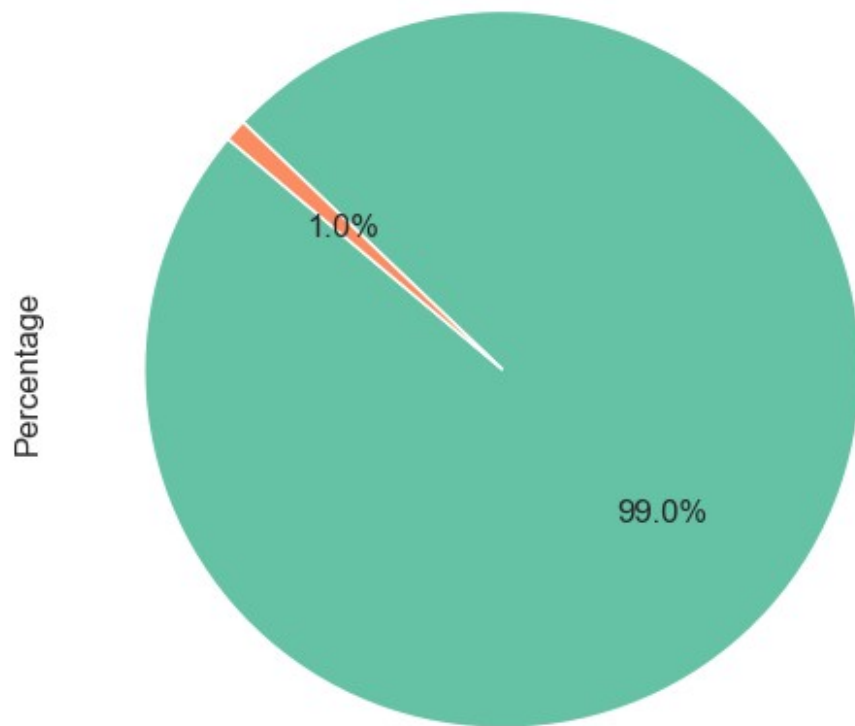
```
0    49958
1         41
Name: FLAG_DOCUMENT_15, dtype: int64
[100.    0.]
```





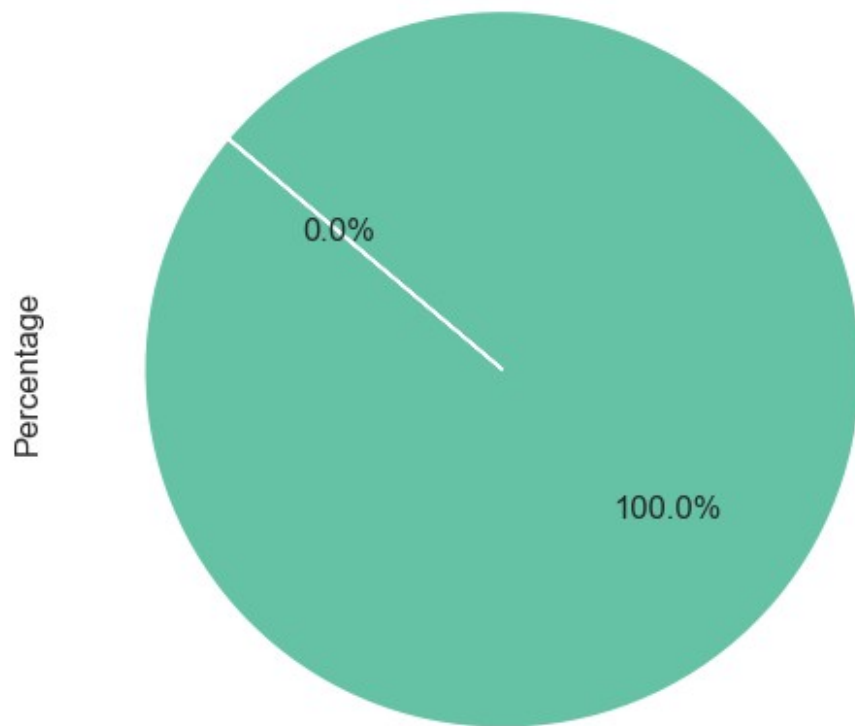
FLAG\_DOCUMENT\_15

```
0    49498
1      501
Name: FLAG_DOCUMENT_16, dtype: int64
[99.  1.]
```



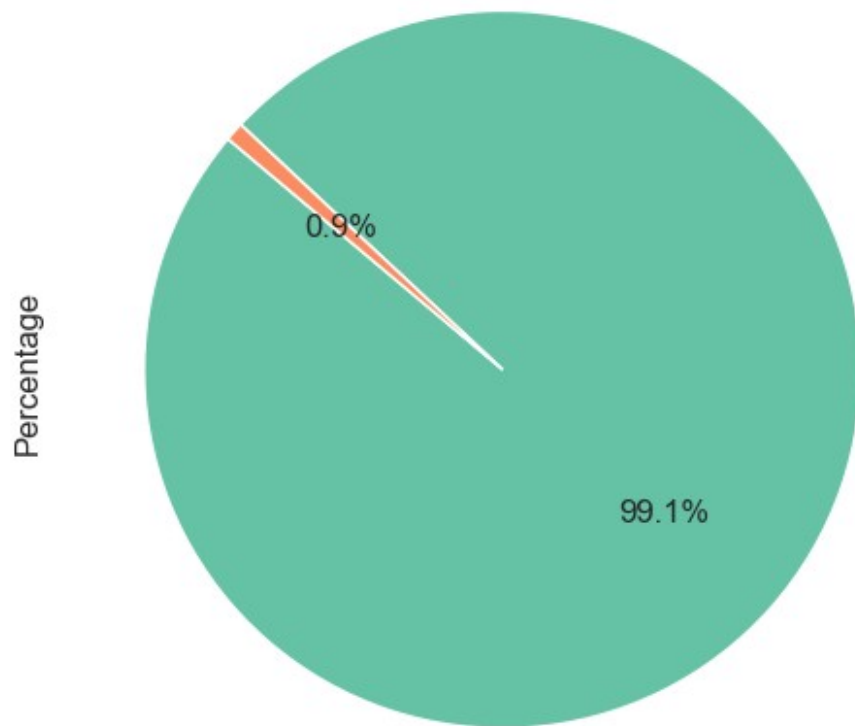
FLAG\_DOCUMENT\_16

```
0    49984
1      15
Name: FLAG_DOCUMENT_17, dtype: int64
[100.    0.]
```



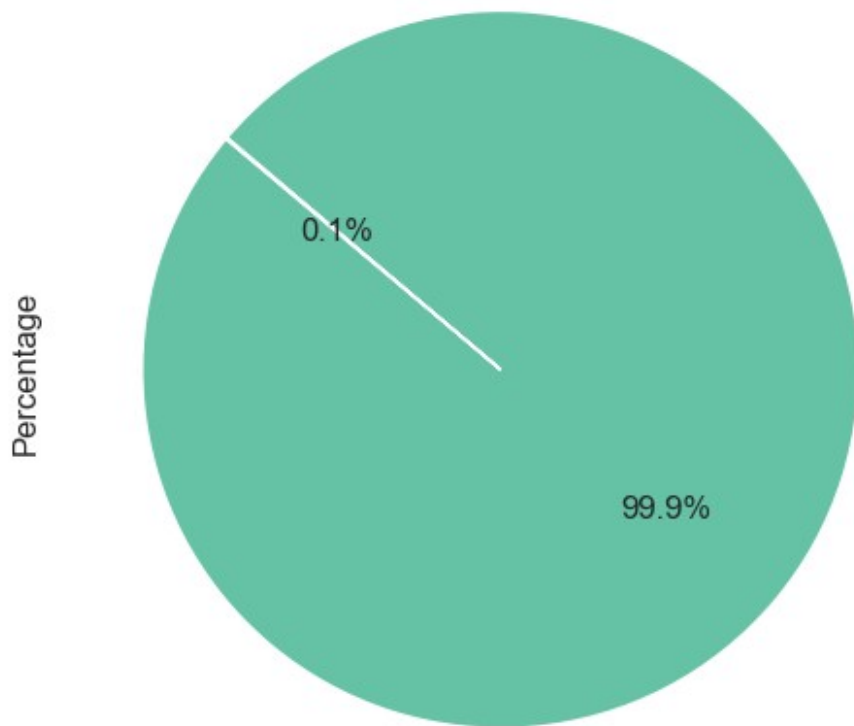
FLAG\_DOCUMENT\_17

```
0    49574
1      425
Name: FLAG_DOCUMENT_18, dtype: int64
[99.  1.]
```



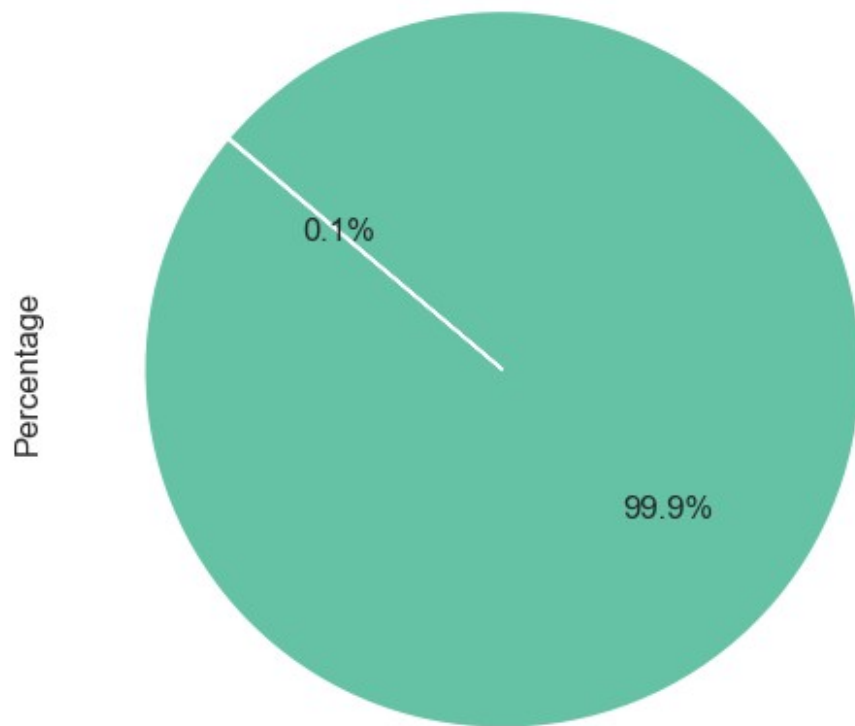
FLAG\_DOCUMENT\_18

```
0    49964
1         35
Name: FLAG_DOCUMENT_19, dtype: int64
[100.    0.]
```



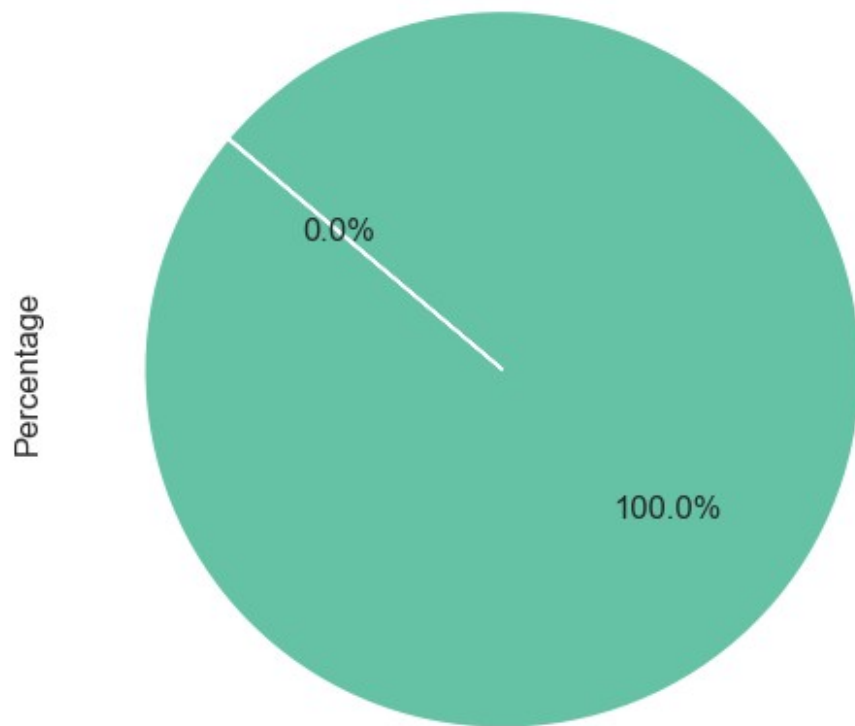
FLAG\_DOCUMENT\_19

```
0    49973
1      26
Name: FLAG_DOCUMENT_20, dtype: int64
[100.    0.]
```



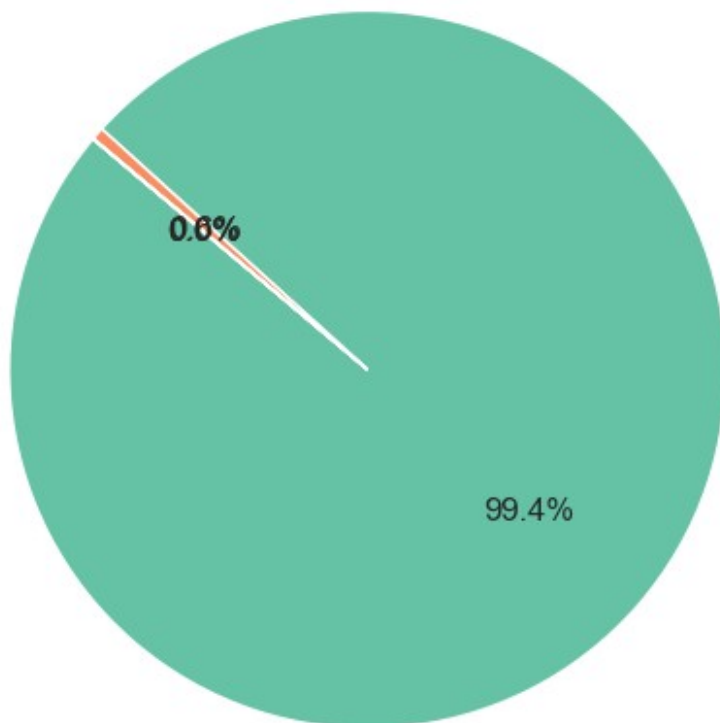
FLAG\_DOCUMENT\_20

```
0    49980
1      19
Name: FLAG_DOCUMENT_21, dtype: int64
[100.    0.]
```



```
0.0    49704
1.0      285
2.0         8
3.0         2
Name: AMT_REQ_CREDIT_BUREAU_HOUR, dtype: int64
[99.  1.  0.  0.]
```

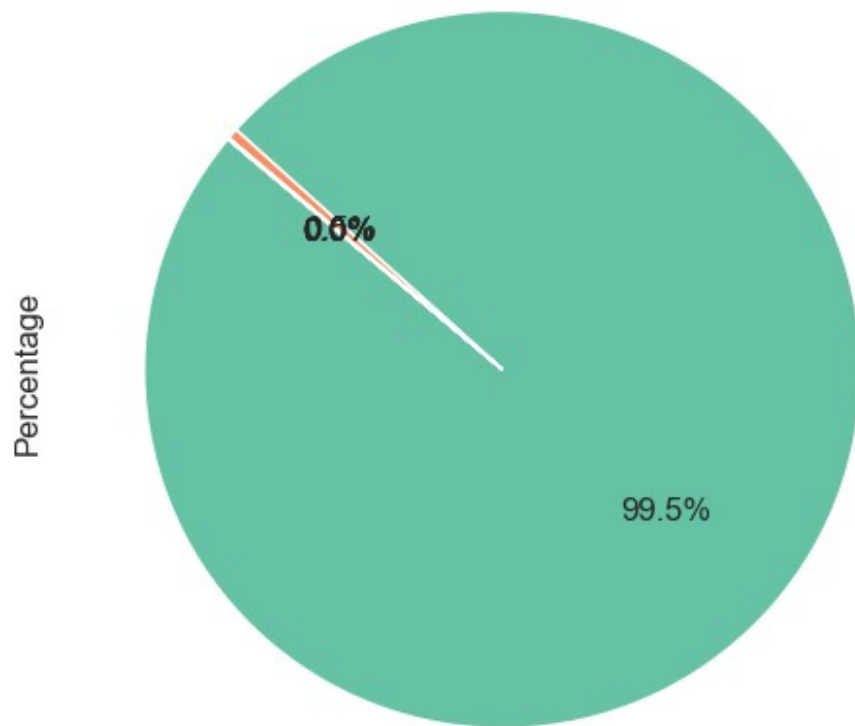
Percentage



AMT\_REQ\_CREDIT\_BUREAU\_HOUR

```
0.0    49727
1.0      242
2.0       17
3.0        7
4.0        3
5.0        2
6.0        1
Name: AMT_REQ_CREDIT_BUREAU_DAY, dtype: int64
[99.  0.  0.  0.  0.  0.  0.]
```

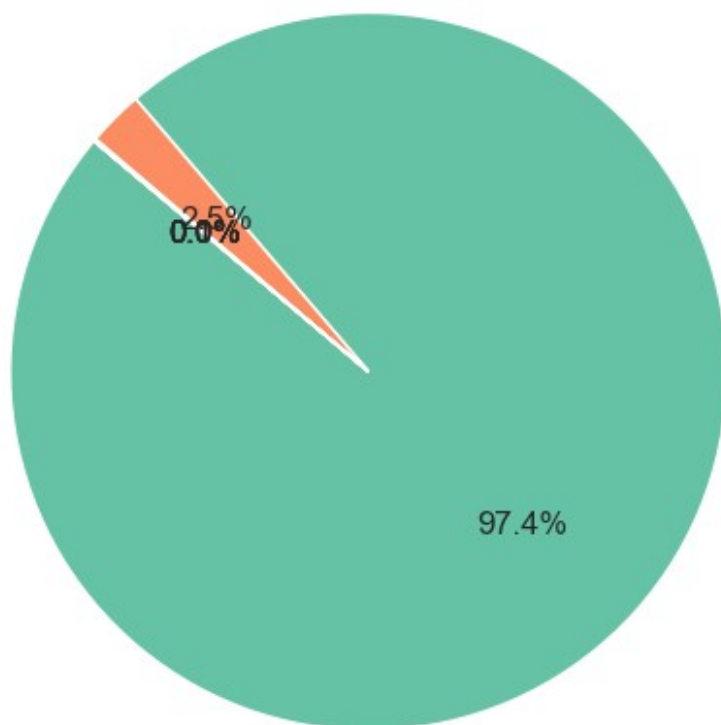




AMT\_REQ\_CREDIT\_BUREAU\_DAY

```
0.0    48685
1.0     1259
2.0        36
3.0        10
4.0         6
5.0         2
6.0         1
Name: AMT_REQ_CREDIT_BUREAU_WEEK, dtype: int64
[97.  3.  0.  0.  0.  0.  0.]
```

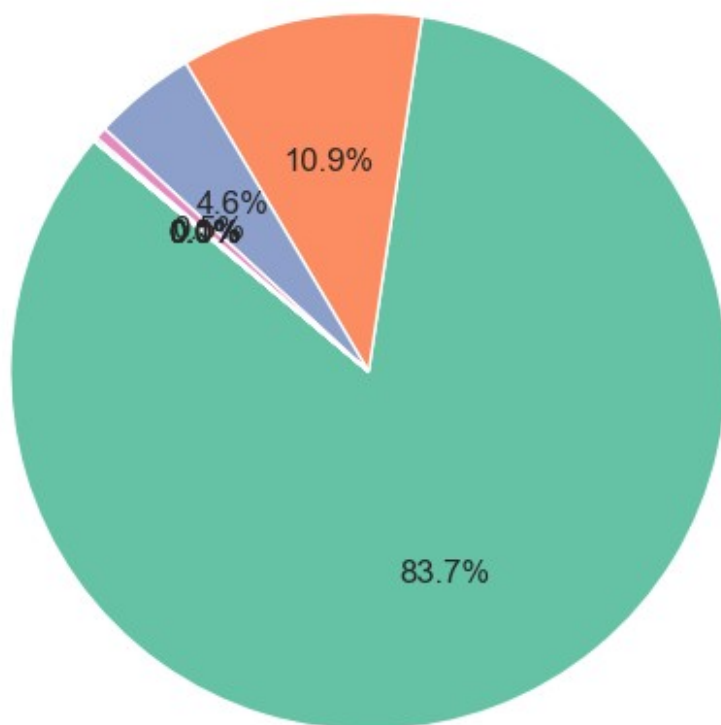
Percentage



AMT\_REQ\_CREDIT\_BUREAU\_WEEK

```
0.0    41865
1.0     5452
2.0     2324
3.0       269
4.0        74
5.0         8
6.0         3
7.0         2
8.0         2
Name: AMT_REQ_CREDIT_BUREAU_QRT, dtype: int64
[84. 11.  5.  1.  0.  0.  0.  0.  0.]
```

Percentage



AMT\_REQ\_CREDIT\_BUREAU\_QRT

# Inferences

target variable shows us that 92% percent people have the value 1 i.e. client with payment difficulties

NAME\_CONTRACT\_TYPE has the 91% of loans of Cash Loans type.

CODE\_GENDER univariate analysis shows us that there are 66% female applicants and 34% male applicants

FLAG\_OWN\_CAR univariate analysis shows us that 66% applicants don't own car.

FLAG\_OWN\_REALTY univariate analysis shows us that 69% applicants own house.

CNT\_CHILDREN univariate analysis shows us that 70% applicants don't have childrens.

NAME\_TYPE\_SUITE univariate analysis shows us that 81% of the applicants are unaccompanied

NAME\_INCOME\_TYPE univariate analysis shows us that 52% applicants are working.

NAME\_FAMILY\_STATUS univariate analysis shows us that 64% applicants are married.

NAME\_HOUSINGIN\_TYPE univariate analysis shows us that 52% applicants are live in House/Apartment.

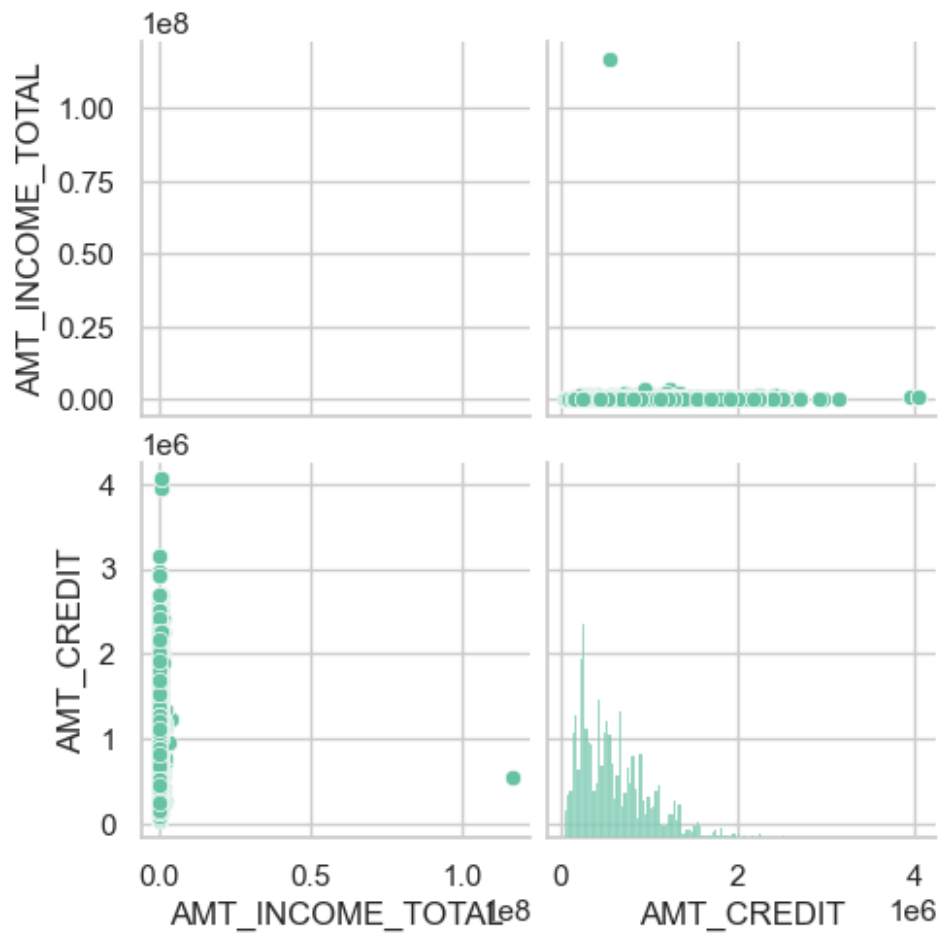
CNT\_FAM\_MEMBERS univariate analysis shows us that 52% applicants have 2 family members and 22%, 17% applicants have 1 & 3 family members respectively

```
from scipy.stats import chi2_contingency

# Bivariate Analysis: Numeric vs. Numeric Variables
numeric_vars = ['AMT_INCOME_TOTAL', 'AMT_CREDIT']
numeric_df = application_data[numeric_vars]

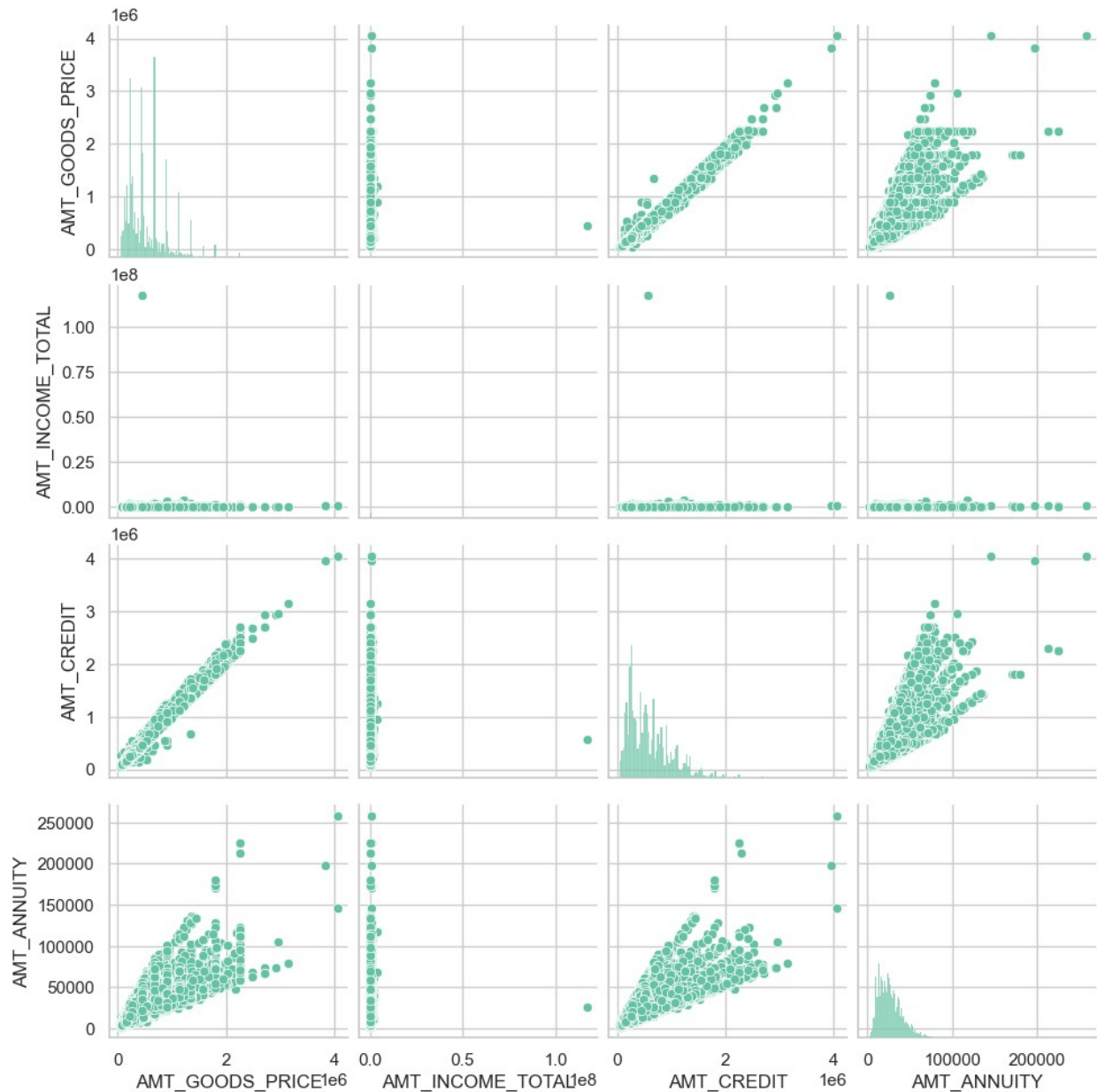
# Calculate correlation coefficient
correlation_matrix = numeric_df.corr()

# Create scatter plots
sns.pairplot(numeric_df)
plt.show()
```



```
plt.figure(figsize=[20,8])
sns.pairplot(application_data[['AMT_GOODS_PRICE', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY']])
plt.show()
```

<Figure size 2000x800 with 0 Axes>

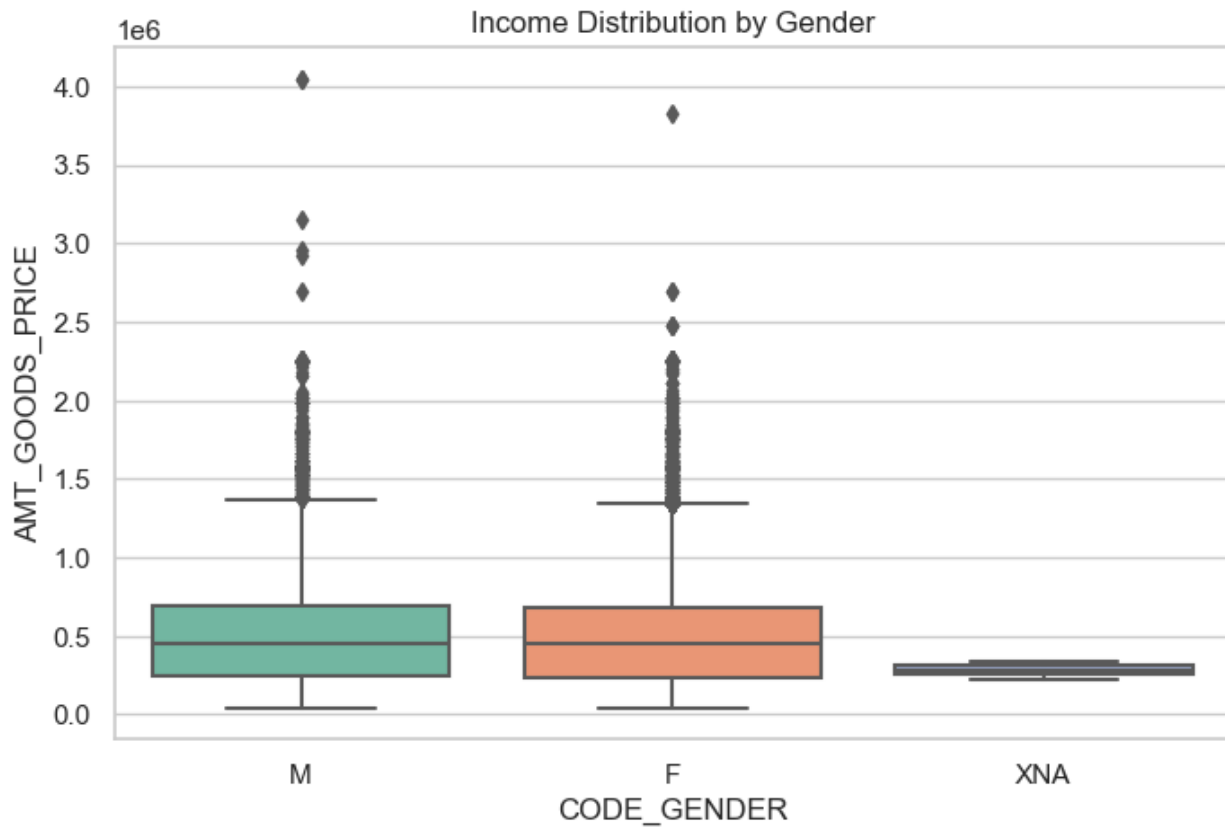


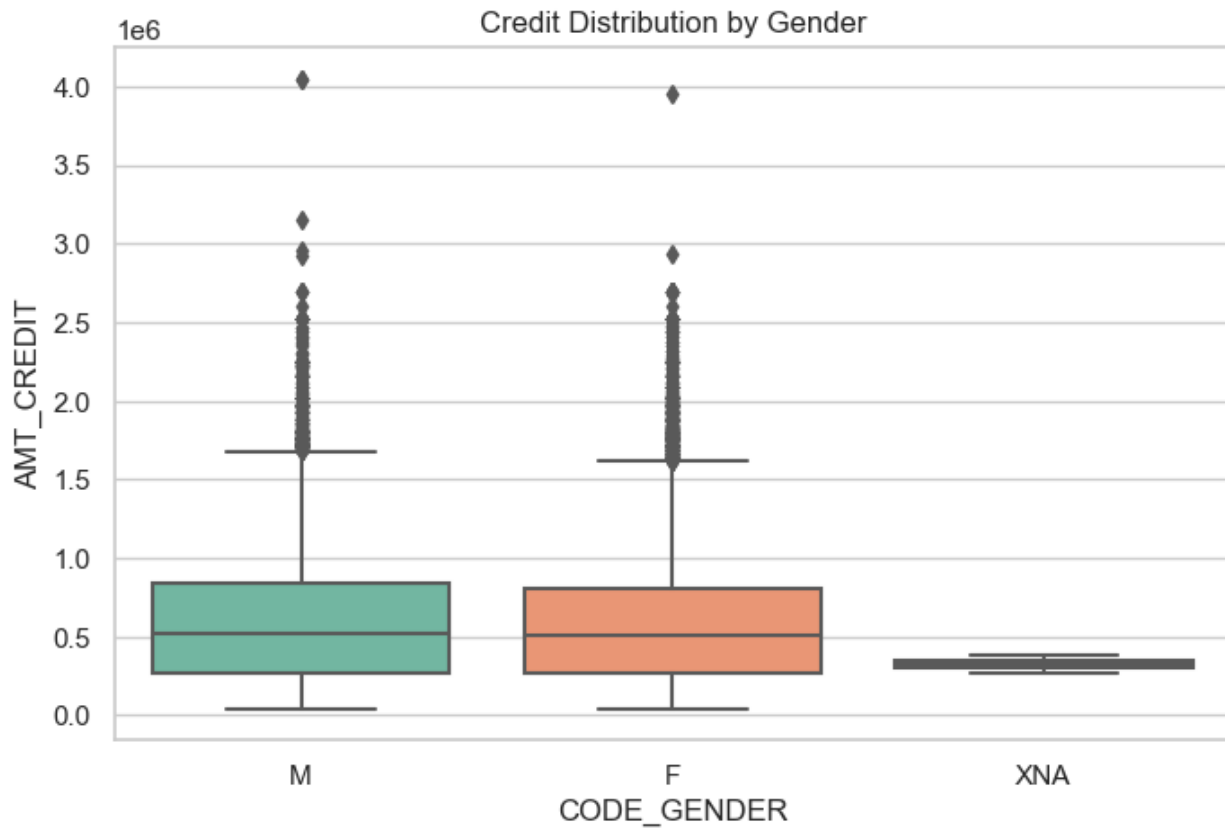
## Inference

The variables AMT\_GOODS\_PRICE, AMT\_ANNUITY, and AMT\_CREDIT show a good positive correlation, which is expected due to the higher cost of goods leading to larger loan amounts and subsequent annuity payments.

```
# To find Income Distribution by Gender
plt.figure(figsize=(8, 5))
sns.boxplot(x='CODE_GENDER', y='AMT_GOODS_PRICE',
data=application_data)
plt.title('Income Distribution by Gender')
plt.show()
```

```
# To find Credit Distribution by Gender
plt.figure(figsize=(8, 5))
sns.boxplot(x='CODE_GENDER', y='AMT_CREDIT', data=application_data)
plt.title('Credit Distribution by Gender')
plt.show()
```

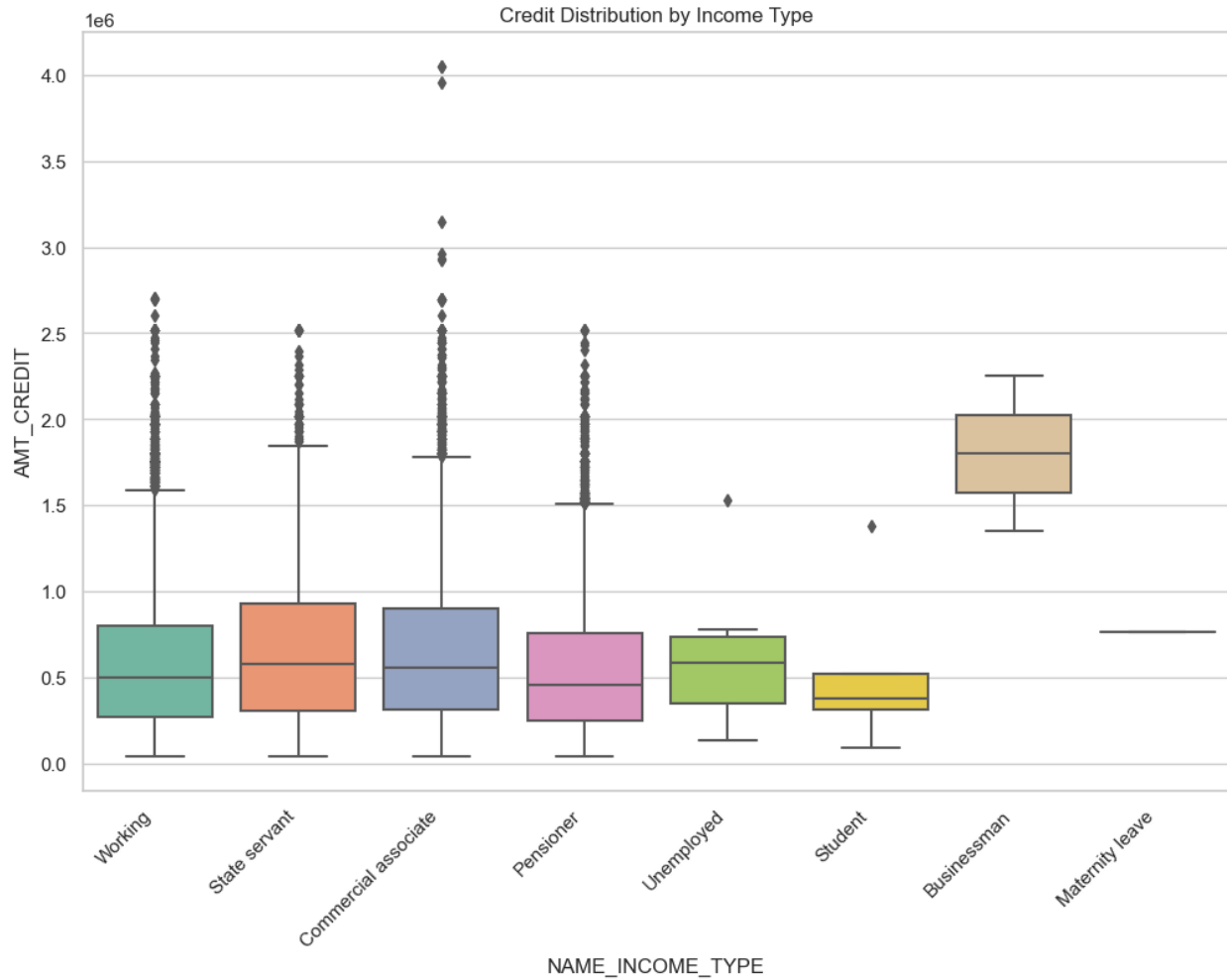




*# To find Credit Distribution by Income Type*

```
plt.figure(figsize=(12, 8))
sns.boxplot(x='NAME_INCOME_TYPE', y='AMT_CREDIT',
data=application_data)
plt.xticks(rotation=45, ha='right')
plt.title('Credit Distribution by Income Type')
plt.show()
```





## Inference

\_Bivariate analysis between AMT\_GOODS\_PRICE and AMT\_CREDIT through box plots segmented by CODE\_GENDER shows that both male and female applicants tend to receive similar loan amounts.

\_Bivariate analysis of AMT\_CREDIT through box plots segmented by NAME\_INCOME\_TYPE shows that Businessman get more Credit amount than that of other income types.

## E. Identify Top Correlations for Different Scenarios:

# Top Correlations for Different Scenarios

```
# Select numerical columns for Univariate Analysis
```

```
numerical_columns =  
application_data.select_dtypes(include=[np.number])
```

```
numerical_columns =  
numerical_columns.drop(columns=["FLAG_DOCUMENT_3", "FLAG_DOCUMENT_5", "FLAG_DOCUMENT_7", "FLAG_DOCUMENT_9", "FLAG_DOCUMENT_11", "FLAG_DOCUMENT_13", "FLAG_DOCUMENT_15", "FLAG_DOCUMENT_17", "FLAG_DOCUMENT_19", "FLAG_DOCUMENT_21", "FLAG_DOCUMENT_4", "FLAG_DOCUMENT_2", "FLAG_DOCUMENT_6", "FLAG_DOCUMENT_8", "FLAG_DOCUMENT_10", "FLAG_DOCUMENT_12", "FLAG_DOCUMENT_14", "FLAG_DOCUMENT_16", "FLAG_DOCUMENT_18", "FLAG_DOCUMENT_20"])
```

```
print(numerical_columns.shape)  
numerical_columns.columns
```

```
(49999, 43)
```

```
Index(['SK_ID_CURR', 'TARGET', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',  
       'AMT_CREDIT', 'AMT_ANNUITY', 'AMT_GOODS_PRICE',  
       'REGION_POPULATION_RELATIVE', 'DAYS_BIRTH', 'DAYS_EMPLOYED',  
       'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH', 'OWN_CAR_AGE',  
       'FLAG_MOBIL',  
       'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE',  
       'FLAG_PHONE',  
       'FLAG_EMAIL', 'CNT_FAM_MEMBERS', 'REGION_RATING_CLIENT',  
       'REGION_RATING_CLIENT_W_CITY', 'HOUR_APPR_PROCESS_START',  
       'REG_REGION_NOT_LIVE_REGION', 'REG_REGION_NOT_WORK_REGION',  
       'LIVE_REGION_NOT_WORK_REGION', 'REG_CITY_NOT_LIVE_CITY',  
       'REG_CITY_NOT_WORK_CITY', 'LIVE_CITY_NOT_WORK_CITY',  
       'EXT_SOURCE_1',  
       'EXT_SOURCE_2', 'EXT_SOURCE_3', 'OBS_30_CNT_SOCIAL_CIRCLE',  
       'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCIAL_CIRCLE',  
       'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE',  
       'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',
```

```
'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON',
'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR'],
dtype='object')
```

```
# Generate heatmap
```

```
correlation = numerical_columns.corr()
print(correlation)
correlation.to_clipboard(index=True)
```

	SK_ID_CURR	TARGET	CNT_CHILDREN	\
SK_ID_CURR	1.000000	0.003295	0.005538	
TARGET	0.003295	1.000000	0.026364	
CNT_CHILDREN	0.005538	0.026364	1.000000	
AMT_INCOME_TOTAL	-0.003014	0.010894	0.009589	
AMT_CREDIT	-0.000732	-0.032428	0.004972	
AMT_ANNUITY	-0.002084	-0.012399	0.026179	
AMT_GOODS_PRICE	-0.000743	-0.041307	0.000253	
REGION_POPULATION_RELATIVE	0.001979	-0.040799	-0.025556	
DAYS_BIRTH	-0.001324	-0.076788	-0.329264	
DAYS_EMPLOYED	-0.004393	-0.042472	-0.241540	
DAYS_REGISTRATION	0.003709	-0.042343	-0.181217	
DAYS_ID_PUBLISH	0.008738	-0.046927	0.032116	
OWN_CAR_AGE	0.002485	0.039534	0.017437	
FLAG_MOBIL	0.002863	0.001323	0.002593	
FLAG_EMP_PHONE	0.004449	0.041408	0.240678	
FLAG_WORK_PHONE	-0.003127	0.021302	0.055881	
FLAG_CONT_MOBILE	0.001012	0.006766	-0.002827	
FLAG_PHONE	-0.004005	-0.032679	-0.030654	
FLAG_EMAIL	0.002436	-0.001312	0.026816	
CNT_FAM_MEMBERS	0.001898	0.013006	0.880430	
REGION_RATING_CLIENT	0.004509	0.066130	0.025914	
REGION_RATING_CLIENT_W_CITY	0.003209	0.067079	0.022778	
HOUR_APPR_PROCESS_START	-0.007562	-0.032036	-0.006254	
REG_REGION_NOT_LIVE_REGION	-0.013077	0.009439	-0.010655	
REG_REGION_NOT_WORK_REGION	-0.001866	-0.001006	0.012057	
LIVE_REGION_NOT_WORK_REGION	0.003249	-0.005498	0.019659	
REG_CITY_NOT_LIVE_CITY	-0.005295	0.038773	0.019192	
REG_CITY_NOT_WORK_CITY	-0.003629	0.048451	0.070032	
LIVE_CITY_NOT_WORK_CITY	0.000143	0.032261	0.067751	
EXT_SOURCE_1	-0.006882	-0.156806	-0.146199	
EXT_SOURCE_2	-0.003865	-0.158424	-0.017641	
EXT_SOURCE_3	0.000215	-0.181276	-0.043791	
OBS_30_CNT_SOCIAL_CIRCLE	-0.003183	0.014180	0.016616	
DEF_30_CNT_SOCIAL_CIRCLE	-0.008408	0.041603	-0.002965	
OBS_60_CNT_SOCIAL_CIRCLE	-0.003520	0.013945	0.016500	
DEF_60_CNT_SOCIAL_CIRCLE	-0.007563	0.044260	-0.003955	
DAYS_LAST_PHONE_CHANGE	-0.003461	0.056137	-0.002023	
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003376	0.002053	0.002405	
AMT_REQ_CREDIT_BUREAU_DAY	-0.003983	0.010117	-0.001498	

AMT_REQ_CREDIT_BUREAU_WEEK	-0.005486	0.003328	0.001343
AMT_REQ_CREDIT_BUREAU_MON	-0.001118	-0.013591	-0.010548
AMT_REQ_CREDIT_BUREAU_QRT	-0.003482	-0.005551	-0.005485
AMT_REQ_CREDIT_BUREAU_YEAR	-0.004058	0.009493	-0.029619

	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY
\			
SK_ID_CURR	-0.003014	-0.000732	-0.002084
TARGET	0.010894	-0.032428	-0.012399
CNT_CHILDREN	0.009589	0.004972	0.026179
AMT_INCOME_TOTAL	1.000000	0.069316	0.083009
AMT_CREDIT	0.069316	1.000000	0.769499
AMT_ANNUITY	0.083009	0.769499	1.000000
AMT_GOODS_PRICE	0.069886	0.986944	0.774434
REGION_POPULATION_RELATIVE	0.029841	0.095111	0.115112
DAYS_BIRTH	-0.016003	0.059343	-0.007712
DAYS_EMPLOYED	-0.031510	-0.067739	-0.108710
DAYS_REGISTRATION	-0.009952	-0.003449	-0.033219
DAYS_ID_PUBLISH	-0.003507	0.012229	-0.006716
OWN_CAR_AGE	-0.142108	-0.092520	-0.096866
FLAG_MOBIL	0.000376	0.003568	0.000367
FLAG_EMP_PHONE	0.031568	0.069063	0.109570
FLAG_WORK_PHONE	-0.009181	-0.015115	-0.020965
FLAG_CONT_MOBILE	-0.003246	0.024481	0.023111
FLAG_PHONE	-0.002044	0.019460	0.005127
FLAG_EMAIL	0.015215	0.010812	0.065896
CNT_FAM_MEMBERS	0.011202	0.063985	0.077353
REGION_RATING_CLIENT	-0.038189	-0.100507	-0.125803
REGION_RATING_CLIENT_W_CITY	-0.040719	-0.109487	-0.139322

HOUR_APPR_PROCESS_START	0.018464	0.056677	0.053275
REG_REGION_NOT_LIVE_REGION	0.013773	0.025772	0.044803
REG_REGION_NOT_WORK_REGION	0.027597	0.053846	0.081295
LIVE_REGION_NOT_WORK_REGION	0.026152	0.053262	0.074849
REG_CITY_NOT_LIVE_CITY	0.000136	-0.024978	-0.006721
REG_CITY_NOT_WORK_CITY	-0.000021	-0.017377	0.001061
LIVE_CITY_NOT_WORK_CITY	0.001295	0.002136	0.010940
EXT_SOURCE_1	0.010034	0.170622	0.115437
EXT_SOURCE_2	0.019518	0.138125	0.128928
EXT_SOURCE_3	-0.021566	0.041746	0.023602
OBS_30_CNT_SOCIAL_CIRCLE	-0.008622	0.001806	-0.009325
DEF_30_CNT_SOCIAL_CIRCLE	-0.007629	-0.016197	-0.021819
OBS_60_CNT_SOCIAL_CIRCLE	-0.008591	0.002163	-0.009012
DEF_60_CNT_SOCIAL_CIRCLE	-0.007344	-0.021152	-0.025276
DAYS_LAST_PHONE_CHANGE	-0.004804	-0.076179	-0.067257
AMT_REQ_CREDIT_BUREAU_HOUR	0.001102	0.001224	0.012014
AMT_REQ_CREDIT_BUREAU_DAY	0.001311	0.011537	0.007011
AMT_REQ_CREDIT_BUREAU_WEEK	0.001057	0.004902	0.019918
AMT_REQ_CREDIT_BUREAU_MON	0.012808	0.065406	0.039915
AMT_REQ_CREDIT_BUREAU_QRT	0.001589	0.023708	0.009306
AMT_REQ_CREDIT_BUREAU_YEAR	0.006281	-0.019420	0.000027
REGION_POPULATION_RELATIVE	AMT_GOODS_PRICE		
SK_ID_CURR	\		
0.001979	-0.000743		
TARGET	-0.041307		-
0.040799			
CNT_CHILDREN	0.000253		-
0.025556			

AMT_INCOME_TOTAL	0.069886	
0.029841		
AMT_CREDIT	0.986944	
0.095111		
AMT_ANNUITY	0.774434	
0.115112		
AMT_GOODS_PRICE	1.000000	
0.099190		
REGION_POPULATION_RELATIVE	0.099190	
1.000000		
DAYS_BIRTH	0.057611	
0.032514		
DAYS_EMPLOYED	-0.065059	-
0.004158		
DAYS_REGISTRATION	-0.006101	
0.059322		
DAYS_ID_PUBLISH	0.013968	
0.004345		
OWN_CAR_AGE	-0.100465	-
0.083575		
FLAG_MOBIL	0.003472	
0.003301		
FLAG_EMP_PHONE	0.066428	
0.004186		
FLAG_WORK_PHONE	0.006491	-
0.016787		
FLAG_CONT_MOBILE	0.022094	-
0.005050		
FLAG_PHONE	0.035532	
0.094068		
FLAG_EMAIL	0.010534	
0.039508		
CNT_FAM_MEMBERS	0.061624	-
0.023018		
REGION_RATING_CLIENT	-0.103722	-
0.532667		
REGION_RATING_CLIENT_W_CITY	-0.111796	-
0.530439		
HOUR_APPR_PROCESS_START	0.066006	
0.167725		
REG_REGION_NOT_LIVE_REGION	0.028023	-
0.003552		
REG_REGION_NOT_WORK_REGION	0.055274	
0.060070		
LIVE_REGION_NOT_WORK_REGION	0.053566	
0.085697		
REG_CITY_NOT_LIVE_CITY	-0.024507	-
0.046482		
REG_CITY_NOT_WORK_CITY	-0.018651	-

0.040443		
LIVE_CITY_NOT_WORK_CITY	0.000333	-
0.013596		
EXT_SOURCE_1	0.176724	
0.102956		
EXT_SOURCE_2	0.146936	
0.201242		
EXT_SOURCE_3	0.045647	-
0.009622		
OBS_30_CNT_SOCIAL_CIRCLE	0.001504	-
0.018011		
DEF_30_CNT_SOCIAL_CIRCLE	-0.017494	
0.009276		
OBS_60_CNT_SOCIAL_CIRCLE	0.001794	-
0.016897		
DEF_60_CNT_SOCIAL_CIRCLE	-0.021743	
0.004000		
DAYS_LAST_PHONE_CHANGE	-0.079750	-
0.047752		
AMT_REQ_CREDIT_BUREAU_HOUR	0.001717	-
0.002315		
AMT_REQ_CREDIT_BUREAU_DAY	0.011749	-
0.001006		
AMT_REQ_CREDIT_BUREAU_WEEK	0.005279	
0.003154		
AMT_REQ_CREDIT_BUREAU_MON	0.066869	
0.071462		
AMT_REQ_CREDIT_BUREAU_QRT	0.024387	-
0.007684		
AMT_REQ_CREDIT_BUREAU_YEAR	-0.022805	
0.004505		

	DAYS_BIRTH	DAYS_EMPLOYED	...	\
SK_ID_CURR	-0.001324	-0.004393	...	
TARGET	-0.076788	-0.042472	...	
CNT_CHILDREN	-0.329264	-0.241540	...	
AMT_INCOME_TOTAL	-0.016003	-0.031510	...	
AMT_CREDIT	0.059343	-0.067739	...	
AMT_ANNUITY	-0.007712	-0.108710	...	
AMT_GOODS_PRICE	0.057611	-0.065059	...	
REGION_POPULATION_RELATIVE	0.032514	-0.004158	...	
DAYS_BIRTH	1.000000	0.621728	...	
DAYS_EMPLOYED	0.621728	1.000000	...	
DAYS_REGISTRATION	0.333633	0.209172	...	
DAYS_ID_PUBLISH	0.270825	0.272767	...	
OWN_CAR_AGE	-0.003714	0.026944	...	
FLAG_MOBIL	0.007637	0.002152	...	
FLAG_EMP_PHONE	-0.617703	-0.999746	...	
FLAG_WORK_PHONE	-0.175690	-0.232311	...	

FLAG_CONT_MOBILE	0.011900	0.015164	...
FLAG_PHONE	0.044219	0.024336	...
FLAG_EMAIL	-0.092150	-0.067357	...
CNT_FAM_MEMBERS	-0.277189	-0.230727	...
REGION_RATING_CLIENT	-0.016779	0.034559	...
REGION_RATING_CLIENT_W_CITY	-0.014552	0.036973	...
HOURL_APPR_PROCESS_START	-0.090589	-0.088523	...
REG_REGION_NOT_LIVE_REGION	-0.059105	-0.038080	...
REG_REGION_NOT_WORK_REGION	-0.093985	-0.108099	...
LIVE_REGION_NOT_WORK_REGION	-0.068120	-0.095692	...
REG_CITY_NOT_LIVE_CITY	-0.182109	-0.096498	...
REG_CITY_NOT_WORK_CITY	-0.237897	-0.258209	...
LIVE_CITY_NOT_WORK_CITY	-0.150552	-0.219286	...
EXT_SOURCE_1	0.600884	0.290723	...
EXT_SOURCE_2	0.093882	-0.023593	...
EXT_SOURCE_3	0.212215	0.118108	...
OBS_30_CNT_SOCIAL_CIRCLE	-0.011682	0.004930	...
DEF_30_CNT_SOCIAL_CIRCLE	-0.001899	0.015937	...
OBS_60_CNT_SOCIAL_CIRCLE	-0.011565	0.004869	...
DEF_60_CNT_SOCIAL_CIRCLE	-0.002842	0.014810	...
DAYS_LAST_PHONE_CHANGE	-0.080190	0.023612	...
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003514	-0.004418	...
AMT_REQ_CREDIT_BUREAU_DAY	-0.000736	0.004622	...
AMT_REQ_CREDIT_BUREAU_WEEK	0.002699	-0.004528	...
AMT_REQ_CREDIT_BUREAU_MON	0.003778	-0.031611	...
AMT_REQ_CREDIT_BUREAU_QRT	0.020875	0.015096	...
AMT_REQ_CREDIT_BUREAU_YEAR	0.074000	0.037550	...

# DEF\_30\_CNT\_SOCIAL\_CIRCLE \

SK_ID_CURR	-0.008408
TARGET	0.041603
CNT_CHILDREN	-0.002965
AMT_INCOME_TOTAL	-0.007629
AMT_CREDIT	-0.016197
AMT_ANNUITY	-0.021819
AMT_GOODS_PRICE	-0.017494
REGION_POPULATION_RELATIVE	0.009276
DAYS_BIRTH	-0.001899
DAYS_EMPLOYED	0.015937
DAYS_REGISTRATION	-0.004954
DAYS_ID_PUBLISH	-0.001267
OWN_CAR_AGE	0.014954
FLAG_MOBIL	0.001442
FLAG_EMP_PHONE	-0.016121
FLAG_WORK_PHONE	-0.014769
FLAG_CONT_MOBILE	0.000328
FLAG_PHONE	-0.028320
FLAG_EMAIL	-0.004021
CNT_FAM_MEMBERS	-0.002709



REGION_RATING_CLIENT	0.010547
REGION_RATING_CLIENT_W_CITY	0.008884
HOURL_APPR_PROCESS_START	-0.001399
REG_REGION_NOT_LIVE_REGION	-0.005975
REG_REGION_NOT_WORK_REGION	-0.007859
LIVE_REGION_NOT_WORK_REGION	-0.006901
REG_CITY_NOT_LIVE_CITY	0.006860
REG_CITY_NOT_WORK_CITY	0.001111
LIVE_CITY_NOT_WORK_CITY	-0.003794
EXT_SOURCE_1	-0.026880
EXT_SOURCE_2	-0.032851
EXT_SOURCE_3	-0.038033
OBS_30_CNT_SOCIAL_CIRCLE	0.311411
DEF_30_CNT_SOCIAL_CIRCLE	1.000000
OBS_60_CNT_SOCIAL_CIRCLE	0.313822
DEF_60_CNT_SOCIAL_CIRCLE	0.856223
DAYS_LAST_PHONE_CHANGE	0.005240
AMT_REQ_CREDIT_BUREAU_HOUR	-0.003421
AMT_REQ_CREDIT_BUREAU_DAY	0.004937
AMT_REQ_CREDIT_BUREAU_WEEK	-0.005671
AMT_REQ_CREDIT_BUREAU_MON	0.006967
AMT_REQ_CREDIT_BUREAU_QRT	0.006531
AMT_REQ_CREDIT_BUREAU_YEAR	0.014308

	OBS_60_CNT_SOCIAL_CIRCLE \
SK_ID_CURR	-0.003520
TARGET	0.013945
CNT_CHILDREN	0.016500
AMT_INCOME_TOTAL	-0.008591
AMT_CREDIT	0.002163
AMT_ANNUITY	-0.009012
AMT_GOODS_PRICE	0.001794
REGION_POPULATION_RELATIVE	-0.016897
DAYS_BIRTH	-0.011565
DAYS_EMPLOYED	0.004869
DAYS_REGISTRATION	-0.010552
DAYS_ID_PUBLISH	0.012464
OWN_CAR_AGE	0.004866
FLAG_MOBIL	0.002756
FLAG_EMP_PHONE	-0.004832
FLAG_WORK_PHONE	-0.020758
FLAG_CONT_MOBILE	0.006604
FLAG_PHONE	-0.034807
FLAG_EMAIL	-0.003188
CNT_FAM_MEMBERS	0.025812
REGION_RATING_CLIENT	0.034581
REGION_RATING_CLIENT_W_CITY	0.032125
HOURL_APPR_PROCESS_START	-0.008885
REG_REGION_NOT_LIVE_REGION	-0.016541

REG_REGION_NOT_WORK_REGION	-0.025874
LIVE_REGION_NOT_WORK_REGION	-0.020243
REG_CITY_NOT_LIVE_CITY	-0.009358
REG_CITY_NOT_WORK_CITY	-0.008722
LIVE_CITY_NOT_WORK_CITY	-0.006472
EXT_SOURCE_1	-0.024871
EXT_SOURCE_2	-0.017695
EXT_SOURCE_3	-0.000598
OBS_30_CNT_SOCIAL_CIRCLE	0.998331
DEF_30_CNT_SOCIAL_CIRCLE	0.313822
OBS_60_CNT_SOCIAL_CIRCLE	1.000000
DEF_60_CNT_SOCIAL_CIRCLE	0.237930
DAYS_LAST_PHONE_CHANGE	-0.014415
AMT_REQ_CREDIT_BUREAU_HOUR	0.001544
AMT_REQ_CREDIT_BUREAU_DAY	-0.000716
AMT_REQ_CREDIT_BUREAU_WEEK	-0.004231
AMT_REQ_CREDIT_BUREAU_MON	0.008277
AMT_REQ_CREDIT_BUREAU_QRT	0.010772
AMT_REQ_CREDIT_BUREAU_YEAR	0.036337

#### DEF\_60\_CNT\_SOCIAL\_CIRCLE

DAYS_LAST_PHONE_CHANGE \		
SK_ID_CURR	-0.007563	-
0.003461		
TARGET	0.044260	
0.056137		
CNT_CHILDREN	-0.003955	-
0.002023		
AMT_INCOME_TOTAL	-0.007344	-
0.004804		
AMT_CREDIT	-0.021152	-
0.076179		
AMT_ANNUITY	-0.025276	-
0.067257		
AMT_GOODS_PRICE	-0.021743	-
0.079750		
REGION_POPULATION_RELATIVE	0.004000	-
0.047752		
DAYS_BIRTH	-0.002842	-
0.080190		
DAYS_EMPLOYED	0.014810	
0.023612		
DAYS_REGISTRATION	-0.006863	-
0.052146		
DAYS_ID_PUBLISH	-0.001560	-
0.091375		
OWN_CAR_AGE	0.014948	-
0.000053		
FLAG_MOBIL	0.001233	

NaN		
FLAG_EMP_PHONE	-0.015011	-
0.025556		
FLAG_WORK_PHONE	-0.012288	-
0.041372		
FLAG_CONT_MOBILE	0.002412	-
0.024574		
FLAG_PHONE	-0.027020	-
0.067253		
FLAG_EMAIL	-0.003760	-
0.018054		
CNT_FAM_MEMBERS	-0.004528	-
0.022708		
REGION_RATING_CLIENT	0.012628	
0.027327		
REGION_RATING_CLIENT_W_CITY	0.010966	
0.026789		
HOUR_APPR_PROCESS_START	-0.004749	-
0.017873		
REG_REGION_NOT_LIVE_REGION	-0.007144	
0.031606		
REG_REGION_NOT_WORK_REGION	-0.011727	
0.034668		
LIVE_REGION_NOT_WORK_REGION	-0.010898	
0.024238		
REG_CITY_NOT_LIVE_CITY	0.006864	
0.053764		
REG_CITY_NOT_WORK_CITY	0.003419	
0.046866		
LIVE_CITY_NOT_WORK_CITY	-0.001646	
0.021903		
EXT_SOURCE_1	-0.028560	-
0.134245		
EXT_SOURCE_2	-0.036537	-
0.192592		
EXT_SOURCE_3	-0.035986	-
0.078136		
OBS_30_CNT_SOCIAL_CIRCLE	0.235737	-
0.013601		
DEF_30_CNT_SOCIAL_CIRCLE	0.856223	
0.005240		
OBS_60_CNT_SOCIAL_CIRCLE	0.237930	-
0.014415		
DEF_60_CNT_SOCIAL_CIRCLE	1.000000	
0.006231		
DAYS_LAST_PHONE_CHANGE	0.006231	
1.000000		
AMT_REQ_CREDIT_BUREAU_HOUR	-0.004067	-
0.000114		

AMT_REQ_CREDIT_BUREAU_DAY 0.000380	0.001698	-
AMT_REQ_CREDIT_BUREAU_WEEK 0.005433	-0.005479	-
AMT_REQ_CREDIT_BUREAU_MON 0.048532	0.003971	-
AMT_REQ_CREDIT_BUREAU_QRT 0.012134	0.009792	-
AMT_REQ_CREDIT_BUREAU_YEAR 0.121967	0.014640	-

	AMT_REQ_CREDIT_BUREAU_HOUR	\
SK_ID_CURR	-0.003376	
TARGET	0.002053	
CNT_CHILDREN	0.002405	
AMT_INCOME_TOTAL	0.001102	
AMT_CREDIT	0.001224	
AMT_ANNUITY	0.012014	
AMT_GOODS_PRICE	0.001717	
REGION_POPULATION_RELATIVE	-0.002315	
DAYS_BIRTH	-0.003514	
DAYS_EMPLOYED	-0.004418	
DAYS_REGISTRATION	0.002817	
DAYS_ID_PUBLISH	-0.003866	
OWN_CAR_AGE	0.007001	
FLAG_MOBIL	0.000336	
FLAG_EMP_PHONE	0.003715	
FLAG_WORK_PHONE	-0.008695	
FLAG_CONT_MOBILE	-0.002073	
FLAG_PHONE	-0.008897	
FLAG_EMAIL	0.006319	
CNT_FAM_MEMBERS	0.003822	
REGION_RATING_CLIENT	0.006821	
REGION_RATING_CLIENT_W_CITY	0.005644	
HOURL_APPR_PROCESS_START	-0.009653	
REG_REGION_NOT_LIVE_REGION	-0.003236	
REG_REGION_NOT_WORK_REGION	0.001884	
LIVE_REGION_NOT_WORK_REGION	0.004810	
REG_CITY_NOT_LIVE_CITY	0.000408	
REG_CITY_NOT_WORK_CITY	0.005644	
LIVE_CITY_NOT_WORK_CITY	0.004998	
EXT_SOURCE_1	0.001420	
EXT_SOURCE_2	-0.001662	
EXT_SOURCE_3	0.000435	
OBS_30_CNT_SOCIAL_CIRCLE	0.001294	
DEF_30_CNT_SOCIAL_CIRCLE	-0.003421	
OBS_60_CNT_SOCIAL_CIRCLE	0.001544	
DEF_60_CNT_SOCIAL_CIRCLE	-0.004067	
DAYS_LAST_PHONE_CHANGE	-0.000114	

AMT_REQ_CREDIT_BUREAU_HOUR	1.000000
AMT_REQ_CREDIT_BUREAU_DAY	0.241413
AMT_REQ_CREDIT_BUREAU_WEEK	0.012731
AMT_REQ_CREDIT_BUREAU_MON	0.008800
AMT_REQ_CREDIT_BUREAU_QRT	0.005861
AMT_REQ_CREDIT_BUREAU_YEAR	0.009576

	AMT_REQ_CREDIT_BUREAU_DAY \
SK_ID_CURR	-0.003983
TARGET	0.010117
CNT_CHILDREN	-0.001498
AMT_INCOME_TOTAL	0.001311
AMT_CREDIT	0.011537
AMT_ANNUITY	0.007011
AMT_GOODS_PRICE	0.011749
REGION_POPULATION_RELATIVE	-0.001006
DAYS_BIRTH	-0.000736
DAYS_EMPLOYED	0.004622
DAYS_REGISTRATION	0.002799
DAYS_ID_PUBLISH	-0.003129
OWN_CAR_AGE	0.004615
FLAG_MOBIL	0.000289
FLAG_EMP_PHONE	-0.004667
FLAG_WORK_PHONE	-0.005362
FLAG_CONT_MOBILE	-0.014821
FLAG_PHONE	0.000773
FLAG_EMAIL	0.003394
CNT_FAM_MEMBERS	-0.002324
REGION_RATING_CLIENT	0.004392
REGION_RATING_CLIENT_W_CITY	0.003573
HOUR_APPR_PROCESS_START	0.009235
REG_REGION_NOT_LIVE_REGION	-0.004708
REG_REGION_NOT_WORK_REGION	0.001623
LIVE_REGION_NOT_WORK_REGION	0.003179
REG_CITY_NOT_LIVE_CITY	-0.001458
REG_CITY_NOT_WORK_CITY	-0.000214
LIVE_CITY_NOT_WORK_CITY	-0.000728
EXT_SOURCE_1	0.000222
EXT_SOURCE_2	-0.003756
EXT_SOURCE_3	-0.004208
OBS_30_CNT_SOCIAL_CIRCLE	-0.000585
DEF_30_CNT_SOCIAL_CIRCLE	0.004937
OBS_60_CNT_SOCIAL_CIRCLE	-0.000716
DEF_60_CNT_SOCIAL_CIRCLE	0.001698
DAYS_LAST_PHONE_CHANGE	-0.000380
AMT_REQ_CREDIT_BUREAU_HOUR	0.241413
AMT_REQ_CREDIT_BUREAU_DAY	1.000000
AMT_REQ_CREDIT_BUREAU_WEEK	0.233164
AMT_REQ_CREDIT_BUREAU_MON	-0.001836
AMT_REQ_CREDIT_BUREAU_QRT	-0.005011

AMT_REQ_CREDIT_BUREAU_YEAR	0.006455
	AMT_REQ_CREDIT_BUREAU_WEEK \
SK_ID_CURR	-0.005486
TARGET	0.003328
CNT_CHILDREN	0.001343
AMT_INCOME_TOTAL	0.001057
AMT_CREDIT	0.004902
AMT_ANNUITY	0.019918
AMT_GOODS_PRICE	0.005279
REGION_POPULATION_RELATIVE	0.003154
DAYS_BIRTH	0.002699
DAYS_EMPLOYED	-0.004528
DAYS_REGISTRATION	0.000606
DAYS_ID_PUBLISH	0.002539
OWN_CAR_AGE	0.010364
FLAG_MOBIL	0.000693
FLAG_EMP_PHONE	0.004652
FLAG_WORK_PHONE	-0.004199
FLAG_CONT_MOBILE	-0.020121
FLAG_PHONE	0.002940
FLAG_EMAIL	0.024124
CNT_FAM_MEMBERS	0.003200
REGION_RATING_CLIENT	-0.000517
REGION_RATING_CLIENT_W_CITY	-0.003532
HOUS_APPR_PROCESS_START	-0.007025
REG_REGION_NOT_LIVE_REGION	-0.000924
REG_REGION_NOT_WORK_REGION	0.001554
LIVE_REGION_NOT_WORK_REGION	0.002529
REG_CITY_NOT_LIVE_CITY	-0.001234
REG_CITY_NOT_WORK_CITY	0.002550
LIVE_CITY_NOT_WORK_CITY	0.003236
EXT_SOURCE_1	-0.006674
EXT_SOURCE_2	0.006190
EXT_SOURCE_3	-0.023144
OBS_30_CNT_SOCIAL_CIRCLE	-0.003662
DEF_30_CNT_SOCIAL_CIRCLE	-0.005671
OBS_60_CNT_SOCIAL_CIRCLE	-0.004231
DEF_60_CNT_SOCIAL_CIRCLE	-0.005479
DAYS_LAST_PHONE_CHANGE	-0.005433
AMT_REQ_CREDIT_BUREAU_HOUR	0.012731
AMT_REQ_CREDIT_BUREAU_DAY	0.233164
AMT_REQ_CREDIT_BUREAU_WEEK	1.000000
AMT_REQ_CREDIT_BUREAU_MON	-0.010014
AMT_REQ_CREDIT_BUREAU_QRT	-0.012454
AMT_REQ_CREDIT_BUREAU_YEAR	0.035362
	AMT_REQ_CREDIT_BUREAU_MON \
SK_ID_CURR	-0.001118

TARGET	-0.013591
CNT_CHILDREN	-0.010548
AMT_INCOME_TOTAL	0.012808
AMT_CREDIT	0.065406
AMT_ANNUITY	0.039915
AMT_GOODS_PRICE	0.066869
REGION_POPULATION_RELATIVE	0.071462
DAYS_BIRTH	0.003778
DAYS_EMPLOYED	-0.031611
DAYS_REGISTRATION	0.010740
DAYS_ID_PUBLISH	0.015401
OWN_CAR_AGE	-0.014377
FLAG_MOBIL	0.001204
FLAG_EMP_PHONE	0.032024
FLAG_WORK_PHONE	-0.008081
FLAG_CONT_MOBILE	0.005447
FLAG_PHONE	0.042271
FLAG_EMAIL	0.020898
CNT_FAM_MEMBERS	-0.003239
REGION_RATING_CLIENT	-0.065410
REGION_RATING_CLIENT_W_CITY	-0.063231
HOURL_APPR_PROCESS_START	0.031588
REG_REGION_NOT_LIVE_REGION	-0.004435
REG_REGION_NOT_WORK_REGION	0.002984
LIVE_REGION_NOT_WORK_REGION	0.011852
REG_CITY_NOT_LIVE_CITY	-0.015625
REG_CITY_NOT_WORK_CITY	-0.015211
LIVE_CITY_NOT_WORK_CITY	-0.006084
EXT_SOURCE_1	0.032069
EXT_SOURCE_2	0.052304
EXT_SOURCE_3	-0.005081
OBS_30_CNT_SOCIAL_CIRCLE	0.008257
DEF_30_CNT_SOCIAL_CIRCLE	0.006967
OBS_60_CNT_SOCIAL_CIRCLE	0.008277
DEF_60_CNT_SOCIAL_CIRCLE	0.003971
DAYS_LAST_PHONE_CHANGE	-0.048532
AMT_REQ_CREDIT_BUREAU_HOUR	0.008800
AMT_REQ_CREDIT_BUREAU_DAY	-0.001836
AMT_REQ_CREDIT_BUREAU_WEEK	-0.010014
AMT_REQ_CREDIT_BUREAU_MON	1.000000
AMT_REQ_CREDIT_BUREAU_QRT	0.012454
AMT_REQ_CREDIT_BUREAU_YEAR	0.038940
AMT_REQ_CREDIT_BUREAU_QRT \	
SK_ID_CURR	-0.003482
TARGET	-0.005551
CNT_CHILDREN	-0.005485
AMT_INCOME_TOTAL	0.001589
AMT_CREDIT	0.023708

AMT_ANNUITY	0.009306
AMT_GOODS_PRICE	0.024387
REGION_POPULATION_RELATIVE	-0.007684
DAYS_BIRTH	0.020875
DAYS_EMPLOYED	0.015096
DAYS_REGISTRATION	-0.002168
DAYS_ID_PUBLISH	0.025493
OWN_CAR_AGE	-0.006915
FLAG_MOBIL	0.001767
FLAG_EMP_PHONE	-0.015193
FLAG_WORK_PHONE	-0.028020
FLAG_CONT_MOBILE	0.000630
FLAG_PHONE	-0.011156
FLAG_EMAIL	0.016410
CNT_FAM_MEMBERS	-0.003731
REGION_RATING_CLIENT	0.010586
REGION_RATING_CLIENT_W_CITY	0.008997
HOURL_APPR_PROCESS_START	-0.001253
REG_REGION_NOT_LIVE_REGION	-0.001257
REG_REGION_NOT_WORK_REGION	-0.008942
LIVE_REGION_NOT_WORK_REGION	-0.012478
REG_CITY_NOT_LIVE_CITY	-0.000238
REG_CITY_NOT_WORK_CITY	-0.008235
LIVE_CITY_NOT_WORK_CITY	-0.008296
EXT_SOURCE_1	0.004251
EXT_SOURCE_2	0.000290
EXT_SOURCE_3	-0.026090
OBS_30_CNT_SOCIAL_CIRCLE	0.010803
DEF_30_CNT_SOCIAL_CIRCLE	0.006531
OBS_60_CNT_SOCIAL_CIRCLE	0.010772
DEF_60_CNT_SOCIAL_CIRCLE	0.009792
DAYS_LAST_PHONE_CHANGE	-0.012134
AMT_REQ_CREDIT_BUREAU_HOUR	0.005861
AMT_REQ_CREDIT_BUREAU_DAY	-0.005011
AMT_REQ_CREDIT_BUREAU_WEEK	-0.012454
AMT_REQ_CREDIT_BUREAU_MON	0.012454
AMT_REQ_CREDIT_BUREAU_QRT	1.000000
AMT_REQ_CREDIT_BUREAU_YEAR	0.143058

	AMT_REQ_CREDIT_BUREAU_YEAR
SK_ID_CURR	-0.004058
TARGET	0.009493
CNT_CHILDREN	-0.029619
AMT_INCOME_TOTAL	0.006281
AMT_CREDIT	-0.019420
AMT_ANNUITY	0.000027
AMT_GOODS_PRICE	-0.022805
REGION_POPULATION_RELATIVE	0.004505
DAYS_BIRTH	0.074000



DAYS_EMPLOYED	0.037550
DAYS_REGISTRATION	0.022053
DAYS_ID_PUBLISH	0.061546
OWN_CAR_AGE	-0.021589
FLAG_MOBIL	0.003935
FLAG_EMP_PHONE	-0.037329
FLAG_WORK_PHONE	-0.066926
FLAG_CONT_MOBILE	0.021767
FLAG_PHONE	-0.012145
FLAG_EMAIL	0.045041
CNT_FAM_MEMBERS	-0.014805
REGION_RATING_CLIENT	0.008251
REGION_RATING_CLIENT_W_CITY	0.006391
HOURL_APPR_PROCESS_START	-0.022741
REG_REGION_NOT_LIVE_REGION	-0.022749
REG_REGION_NOT_WORK_REGION	-0.028481
LIVE_REGION_NOT_WORK_REGION	-0.022003
REG_CITY_NOT_LIVE_CITY	-0.012058
REG_CITY_NOT_WORK_CITY	-0.016600
LIVE_CITY_NOT_WORK_CITY	-0.013596
EXT_SOURCE_1	0.032711
EXT_SOURCE_2	0.000103
EXT_SOURCE_3	-0.070507
OBS_30_CNT_SOCIAL_CIRCLE	0.035988
DEF_30_CNT_SOCIAL_CIRCLE	0.014308
OBS_60_CNT_SOCIAL_CIRCLE	0.036337
DEF_60_CNT_SOCIAL_CIRCLE	0.014640
DAYS_LAST_PHONE_CHANGE	-0.121967
AMT_REQ_CREDIT_BUREAU_HOUR	0.009576
AMT_REQ_CREDIT_BUREAU_DAY	0.006455
AMT_REQ_CREDIT_BUREAU_WEEK	0.035362
AMT_REQ_CREDIT_BUREAU_MON	0.038940
AMT_REQ_CREDIT_BUREAU_QRT	0.143058
AMT_REQ_CREDIT_BUREAU_YEAR	1.000000

[43 rows x 43 columns]

```
print(correlation["AMT_ANNUITY"].sort_values(ascending = False), "\n")
```

AMT_ANNUITY	1.000000
AMT_GOODS_PRICE	0.774434
AMT_CREDIT	0.769499
EXT_SOURCE_2	0.128928
EXT_SOURCE_1	0.115437
REGION_POPULATION_RELATIVE	0.115112
FLAG_EMP_PHONE	0.109570
AMT_INCOME_TOTAL	0.083009
REG_REGION_NOT_WORK_REGION	0.081295
CNT_FAM_MEMBERS	0.077353
LIVE_REGION_NOT_WORK_REGION	0.074849

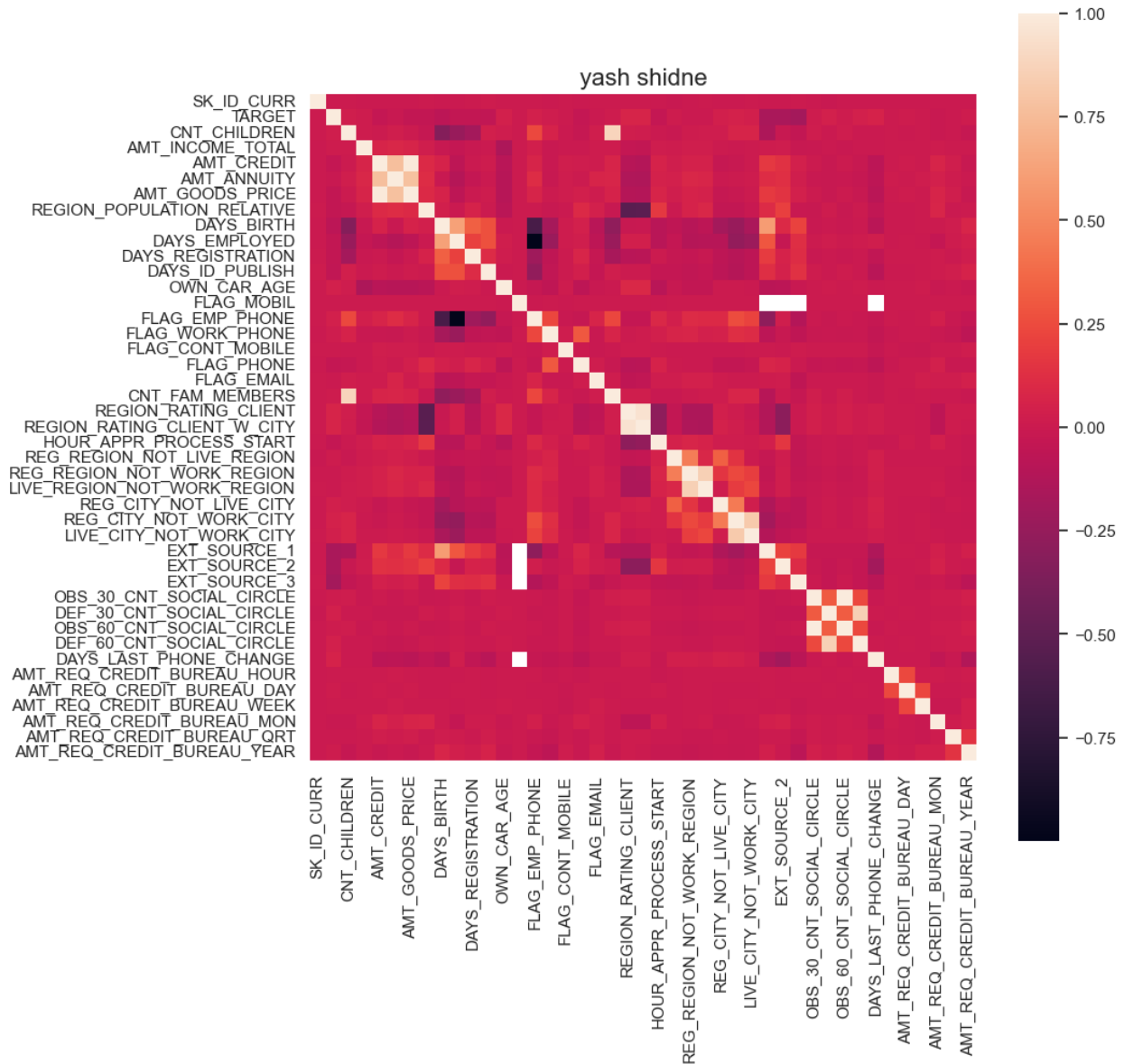
FLAG_EMAIL	0.065896
HOUR_APPR_PROCESS_START	0.053275
REG_REGION_NOT_LIVE_REGION	0.044803
AMT_REQ_CREDIT_BUREAU_MON	0.039915
CNT_CHILDREN	0.026179
EXT_SOURCE_3	0.023602
FLAG_CONT_MOBILE	0.023111
AMT_REQ_CREDIT_BUREAU_WEEK	0.019918
AMT_REQ_CREDIT_BUREAU_HOUR	0.012014
LIVE_CITY_NOT_WORK_CITY	0.010940
AMT_REQ_CREDIT_BUREAU_QRT	0.009306
AMT_REQ_CREDIT_BUREAU_DAY	0.007011
FLAG_PHONE	0.005127
REG_CITY_NOT_WORK_CITY	0.001061
FLAG_MOBIL	0.000367
AMT_REQ_CREDIT_BUREAU_YEAR	0.000027
SK_ID_CURR	-0.002084
DAYS_ID_PUBLISH	-0.006716
REG_CITY_NOT_LIVE_CITY	-0.006721
DAYS_BIRTH	-0.007712
OBS_60_CNT_SOCIAL_CIRCLE	-0.009012
OBS_30_CNT_SOCIAL_CIRCLE	-0.009325
TARGET	-0.012399
FLAG_WORK_PHONE	-0.020965
DEF_30_CNT_SOCIAL_CIRCLE	-0.021819
DEF_60_CNT_SOCIAL_CIRCLE	-0.025276
DAYS_REGISTRATION	-0.033219
DAYS_LAST_PHONE_CHANGE	-0.067257
OWN_CAR_AGE	-0.096866
DAYS_EMPLOYED	-0.108710
REGION_RATING_CLIENT	-0.125803
REGION_RATING_CLIENT_W_CITY	-0.139322

Name: AMT\_ANNUITY, dtype: float64

```
f, ax = plt.subplots(figsize=(10, 10))
plt.title("yash shidne", y=1, size=16)

sns.heatmap(correlation, square=True, vmax=1, linewidths=
0.000001)

<AxesSubplot:title={'center': 'yash shidne'}>
```



```
# Get the upper triangle of the correlation matrix so that there is no
same correlation values counted twice.
```

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

```
# Find the top 5 highest correlations
```

```
top_positive_correlations =
upper_triangle_values.unstack().sort_values(ascending=False).head(5)
```

```
# Find the top 5 lowest correlations
```

```
top_negative_correlations =
upper_triangle_values.unstack().sort_values(ascending=True).head(5)
```

```
print("Top 5 highest correlations:")
print(top_positive_correlations)
```

```
print("\nTop 5 lowest correlations:")
print(top_negative_correlations)
```

Top 5 highest correlations:

OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.998331
AMT_GOODS_PRICE	AMT_CREDIT	0.986944
REGION_RATING_CLIENT_W_CITY	REGION_RATING_CLIENT	0.950710
CNT_FAM_MEMBERS	CNT_CHILDREN	0.880430
LIVE_REGION_NOT_WORK_REGION	REG_REGION_NOT_WORK_REGION	0.857142

dtype: float64

Top 5 lowest correlations:

FLAG_EMP_PHONE	DAYS_EMPLOYED	-0.999746
	DAYS_BIRTH	-0.617703
REGION_RATING_CLIENT	REGION_POPULATION_RELATIVE	-0.532667
REGION_RATING_CLIENT_W_CITY	REGION_POPULATION_RELATIVE	-0.530439
DAYS_BIRTH	CNT_CHILDREN	-0.329264

dtype: float64

```
C:\Users\Yash\AppData\Local\Temp\ipykernel_8388\2900829348.py:2:
DeprecationWarning: `np.bool` is a deprecated alias for the builtin
`bool`. To silence this warning, use `bool` by itself. Doing this will
not modify any behavior and is safe. If you specifically wanted the
numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
    upper_triangle_values =
correlation.where(np.triu(np.ones(correlation.shape),
k=1).astype(np.bool))
```