```python
# Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```python
# In order to view all columns and rows
pd.set_option('display.max_columns', None)
pd.set_option("display.max_rows",None)
```

```python
# Importing the data and store in variable df
df=pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/application_data.csv")
df.head(3)
```

{"type":"dataframe","variable_name":"df"}

```python
# Size of the data
print(df.shape)
print("Number of Rows in the data   :",df.shape[0])
print("Number of columns in the data: ",df.shape[1])
```

```
(307511, 122)
Number of Rows in the data   : 307511
Number of columns in the data:  122
```

```python
# Size of the data
print(df.shape)
print("Number of Rows in the data   :",df.shape[0])
print("Number of columns in the data: ",df.shape[1])
```

```
(307511, 122)
Number of Rows in the data   : 307511
Number of columns in the data:  122
```

```python
df.info(verbose=True)
# dtypes: float64(65), int64(41), object(16)
# there are 65 columns with data type float64
# there are 41 columns with data type int64
# there are 16 columns with data type categorical
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
```

```
Data columns (total 122 columns):
 #    Column                        Dtype
---   ------                        -----
 0    SK_ID_CURR                    int64
 1    TARGET                        int64
 2    NAME_CONTRACT_TYPE            object
 3    CODE_GENDER                   object
 4    FLAG_OWN_CAR                  object
 5    FLAG_OWN_REALTY               object
 6    CNT_CHILDREN                  int64
 7    AMT_INCOME_TOTAL              float64
 8    AMT_CREDIT                    float64
 9    AMT_ANNUITY                   float64
 10   AMT_GOODS_PRICE               float64
 11   NAME_TYPE_SUITE               object
 12   NAME_INCOME_TYPE              object
 13   NAME_EDUCATION_TYPE           object
 14   NAME_FAMILY_STATUS            object
 15   NAME_HOUSING_TYPE             object
 16   REGION_POPULATION_RELATIVE    float64
 17   DAYS_BIRTH                    int64
 18   DAYS_EMPLOYED                 int64
 19   DAYS_REGISTRATION             float64
 20   DAYS_ID_PUBLISH               int64
 21   OWN_CAR_AGE                   float64
 22   FLAG_MOBIL                    int64
 23   FLAG_EMP_PHONE                int64
 24   FLAG_WORK_PHONE               int64
 25   FLAG_CONT_MOBILE              int64
 26   FLAG_PHONE                    int64
 27   FLAG_EMAIL                    int64
 28   OCCUPATION_TYPE               object
 29   CNT_FAM_MEMBERS               float64
 30   REGION_RATING_CLIENT          int64
 31   REGION_RATING_CLIENT_W_CITY   int64
 32   WEEKDAY_APPR_PROCESS_START    object
 33   HOUR_APPR_PROCESS_START       int64
 34   REG_REGION_NOT_LIVE_REGION    int64
 35   REG_REGION_NOT_WORK_REGION    int64
 36   LIVE_REGION_NOT_WORK_REGION   int64
 37   REG_CITY_NOT_LIVE_CITY        int64
 38   REG_CITY_NOT_WORK_CITY        int64
 39   LIVE_CITY_NOT_WORK_CITY       int64
 40   ORGANIZATION_TYPE             object
 41   EXT_SOURCE_1                  float64
 42   EXT_SOURCE_2                  float64
 43   EXT_SOURCE_3                  float64
 44   APARTMENTS_AVG                float64
 45   BASEMENTAREA_AVG              float64
```

```
46   YEARS_BEGINEXPLUATATION_AVG   float64
47   YEARS_BUILD_AVG               float64
48   COMMONAREA_AVG                float64
49   ELEVATORS_AVG                 float64
50   ENTRANCES_AVG                 float64
51   FLOORSMAX_AVG                 float64
52   FLOORSMIN_AVG                 float64
53   LANDAREA_AVG                  float64
54   LIVINGAPARTMENTS_AVG          float64
55   LIVINGAREA_AVG                float64
56   NONLIVINGAPARTMENTS_AVG       float64
57   NONLIVINGAREA_AVG             float64
58   APARTMENTS_MODE               float64
59   BASEMENTAREA_MODE             float64
60   YEARS_BEGINEXPLUATATION_MODE  float64
61   YEARS_BUILD_MODE              float64
62   COMMONAREA_MODE               float64
63   ELEVATORS_MODE                float64
64   ENTRANCES_MODE                float64
65   FLOORSMAX_MODE                float64
66   FLOORSMIN_MODE                float64
67   LANDAREA_MODE                 float64
68   LIVINGAPARTMENTS_MODE         float64
69   LIVINGAREA_MODE               float64
70   NONLIVINGAPARTMENTS_MODE      float64
71   NONLIVINGAREA_MODE            float64
72   APARTMENTS_MEDI               float64
73   BASEMENTAREA_MEDI             float64
74   YEARS_BEGINEXPLUATATION_MEDI  float64
75   YEARS_BUILD_MEDI              float64
76   COMMONAREA_MEDI               float64
77   ELEVATORS_MEDI                float64
78   ENTRANCES_MEDI                float64
79   FLOORSMAX_MEDI                float64
80   FLOORSMIN_MEDI                float64
81   LANDAREA_MEDI                 float64
82   LIVINGAPARTMENTS_MEDI         float64
83   LIVINGAREA_MEDI               float64
84   NONLIVINGAPARTMENTS_MEDI      float64
85   NONLIVINGAREA_MEDI            float64
86   FONDKAPREMONT_MODE            object
87   HOUSETYPE_MODE                object
88   TOTALAREA_MODE                float64
89   WALLSMATERIAL_MODE            object
90   EMERGENCYSTATE_MODE           object
91   OBS_30_CNT_SOCIAL_CIRCLE      float64
92   DEF_30_CNT_SOCIAL_CIRCLE      float64
93   OBS_60_CNT_SOCIAL_CIRCLE      float64
94   DEF_60_CNT_SOCIAL_CIRCLE      float64
```

```
 95   DAYS_LAST_PHONE_CHANGE        float64
 96   FLAG_DOCUMENT_2               int64
 97   FLAG_DOCUMENT_3               int64
 98   FLAG_DOCUMENT_4               int64
 99   FLAG_DOCUMENT_5               int64
 100  FLAG_DOCUMENT_6               int64
 101  FLAG_DOCUMENT_7               int64
 102  FLAG_DOCUMENT_8               int64
 103  FLAG_DOCUMENT_9               int64
 104  FLAG_DOCUMENT_10              int64
 105  FLAG_DOCUMENT_11              int64
 106  FLAG_DOCUMENT_12              int64
 107  FLAG_DOCUMENT_13              int64
 108  FLAG_DOCUMENT_14              int64
 109  FLAG_DOCUMENT_15              int64
 110  FLAG_DOCUMENT_16              int64
 111  FLAG_DOCUMENT_17              int64
 112  FLAG_DOCUMENT_18              int64
 113  FLAG_DOCUMENT_19              int64
 114  FLAG_DOCUMENT_20              int64
 115  FLAG_DOCUMENT_21              int64
 116  AMT_REQ_CREDIT_BUREAU_HOUR    float64
 117  AMT_REQ_CREDIT_BUREAU_DAY     float64
 118  AMT_REQ_CREDIT_BUREAU_WEEK    float64
 119  AMT_REQ_CREDIT_BUREAU_MON     float64
 120  AMT_REQ_CREDIT_BUREAU_QRT     float64
 121  AMT_REQ_CREDIT_BUREAU_YEAR    float64
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

Data Cleaning

```
## 5 point summary
# Check the summary for the numeric columns
df.describe().round(1)
```

{"type":"dataframe"}

Data Cleaning

```
# Check for missing values in percentage

round(100 * df.isnull().mean(),2)
```

```
SK_ID_CURR                      0.00
TARGET                          0.00
NAME_CONTRACT_TYPE              0.00
CODE_GENDER                     0.00
```

```
FLAG_OWN_CAR                      0.00
FLAG_OWN_REALTY                   0.00
CNT_CHILDREN                      0.00
AMT_INCOME_TOTAL                  0.00
AMT_CREDIT                        0.00
AMT_ANNUITY                       0.00
AMT_GOODS_PRICE                   0.09
NAME_TYPE_SUITE                   0.42
NAME_INCOME_TYPE                  0.00
NAME_EDUCATION_TYPE               0.00
NAME_FAMILY_STATUS                0.00
NAME_HOUSING_TYPE                 0.00
REGION_POPULATION_RELATIVE        0.00
DAYS_BIRTH                        0.00
DAYS_EMPLOYED                     0.00
DAYS_REGISTRATION                 0.00
DAYS_ID_PUBLISH                   0.00
OWN_CAR_AGE                      65.99
FLAG_MOBIL                        0.00
FLAG_EMP_PHONE                    0.00
FLAG_WORK_PHONE                   0.00
FLAG_CONT_MOBILE                  0.00
FLAG_PHONE                        0.00
FLAG_EMAIL                        0.00
OCCUPATION_TYPE                  31.35
CNT_FAM_MEMBERS                   0.00
REGION_RATING_CLIENT              0.00
REGION_RATING_CLIENT_W_CITY       0.00
WEEKDAY_APPR_PROCESS_START        0.00
HOUR_APPR_PROCESS_START           0.00
REG_REGION_NOT_LIVE_REGION        0.00
REG_REGION_NOT_WORK_REGION        0.00
LIVE_REGION_NOT_WORK_REGION       0.00
REG_CITY_NOT_LIVE_CITY            0.00
REG_CITY_NOT_WORK_CITY            0.00
LIVE_CITY_NOT_WORK_CITY           0.00
ORGANIZATION_TYPE                 0.00
EXT_SOURCE_1                     56.38
EXT_SOURCE_2                      0.21
EXT_SOURCE_3                     19.83
APARTMENTS_AVG                   50.75
BASEMENTAREA_AVG                 58.52
YEARS_BEGINEXPLUATATION_AVG      48.78
YEARS_BUILD_AVG                  66.50
COMMONAREA_AVG                   69.87
ELEVATORS_AVG                    53.30
ENTRANCES_AVG                    50.35
FLOORSMAX_AVG                    49.76
FLOORSMIN_AVG                    67.85
```

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

```
FLAG_DOCUMENT_8                   0.00
FLAG_DOCUMENT_9                   0.00
FLAG_DOCUMENT_10                  0.00
FLAG_DOCUMENT_11                  0.00
FLAG_DOCUMENT_12                  0.00
FLAG_DOCUMENT_13                  0.00
FLAG_DOCUMENT_14                  0.00
FLAG_DOCUMENT_15                  0.00
FLAG_DOCUMENT_16                  0.00
FLAG_DOCUMENT_17                  0.00
FLAG_DOCUMENT_18                  0.00
FLAG_DOCUMENT_19                  0.00
FLAG_DOCUMENT_20                  0.00
FLAG_DOCUMENT_21                  0.00
AMT_REQ_CREDIT_BUREAU_HOUR       13.50
AMT_REQ_CREDIT_BUREAU_DAY        13.50
AMT_REQ_CREDIT_BUREAU_WEEK       13.50
AMT_REQ_CREDIT_BUREAU_MON        13.50
AMT_REQ_CREDIT_BUREAU_QRT        13.50
AMT_REQ_CREDIT_BUREAU_YEAR       13.50
dtype: float64
```

```
# Columns with more then 40 percent null values

col_with_null_40=(df.isnull().sum()*100/df.shape[0])
[(df.isnull().sum()*100/df.shape[0])>40]
col_with_null_40.shape # there are 49 columns which have more than 40
% null values
```

```
(49,)
```

```
# Dropping null values with more than 40 percent of null values
df1=df.drop(columns=col_with_null_40.index)
```

```
df1.shape # After removing the columns with more than
```

```
(307511, 73)
```

```
df1.describe().round(0)
```

```
{"type":"dataframe"}
```

- CNT_FAM_MEMBERS-Majority of customers are having 3 members in their family
- REGION_RATING_CLIENT-25 % of the customers are living in the region which is having higher risk
- REGION_RATING_CLIENT_W_CITY-on average the client applies loan at noon
- Most of the customers gave their permanent adress is same as contact adress

- Most of the customers gave their permanent adress is same as work adress
- Most of the customers contact adress is same as their work adress
- Most of the customers has the registered city is the same as the current living city
- most of the client lives in city where they work
- most of the customers have higher value in DAYS_LAST_PHONE_CHANGE indicates that the client has had the same phone number for a longer time, potentially indicating stability.
- most of the documents were not provided by the customers
- 4 is the maximun Number of inquiries in the last hour before application.
- most people enquired before 1 year of application
- OBS_30_CNT_SOCIAL_CIRCLE:
- Interpretation: This represents the number of observations of the client's social surroundings with a 30-day past due default (DPD).
- The data suggests that most clients have low to moderate numbers of such observations, with some outliers having significantly more.
- DEF_30_CNT_SOCIAL_CIRCLE:
- Interpretation: This represents how many of the client's social surroundings have defaulted on a 30-day DPD.

The five-point summary shows that defaults are generally rare, with most clients having no defaults in their social circles.

- OBS_60_CNT_SOCIAL_CIRCLE:
- Interpretation: This captures the number of observations of the client's social surroundings with a 60-day DPD default.
- The distribution seems similar to the 30-day observation count, with a few outliers having a higher number of such observations.
- DEF_60_CNT_SOCIAL_CIRCLE:
- Interpretation: This variable represents defaults on a 60-day DPD within the client's social circle.
- Similar to the 30-day default count, defaults remain rare, with most individuals having zero defaults, but with outliers having up to 24 defaults.
- EXT_SOURCE_2 and EXT_SOURCE_3: These could be external score sources (e.g., credit scores, risk factors, etc.)

- higher score might suggest lower risk, while a lower score might indicate higher risk.
- NAME_CONTRACT_TYPE: Type of contract (e.g., Cash loans, Consumer loans). Most frequent is "Cash loans" (278,232 cases).
- CODE_GENDER: Gender of the client (e.g., F, M). Most frequent is "F" (202,448 cases).
- FLAG_OWN_CAR: Whether the client owns a car (Y/N). Most frequent is "Y" (202,924 cases).
- FLAG_OWN_REALTY: Whether the client owns real estate (Y/N). Most frequent is "Y" (213,312 cases).
- NAME_TYPE_SUITE: Type of suite the client lives in (e.g., Unaccompanied, Family). Most frequent is "Unaccompanied" (248,526 cases).
- NAME_INCOME_TYPE: Type of income (e.g., Working, Commercial associate). Most frequent is "Working" (158,774 cases).
- NAME_EDUCATION_TYPE: Education level (e.g., Secondary / secondary special, Higher education). Most frequent is "Secondary / secondary special" (218,391 cases).
- NAME_FAMILY_STATUS: Family status (e.g., Married, Single / not married). Most frequent is "Married" (196,432 cases).
- NAME_HOUSING_TYPE: Type of housing (e.g., House / apartment, Rented apartment). Most frequent is "House / apartment" (272,868 cases).
- OCCUPATION_TYPE: Type of occupation (e.g., Laborers, Managers). Most frequent is "Laborers" (55,186 cases).
- WEEKDAY_APPR_PROCESS_START: Weekday when application process starts (e.g., Monday, Tuesday). Most frequent is "Tuesday" (53,901 cases).
- ORGANIZATION_TYPE: Type of organization (e.g., Business Entity Type 3, State owned). Most frequent is "Business Entity Type 3" (67,992 cases).
- FONDKAPREMONT_MODE: Fund repair mode (e.g., Reg oper account, Money transfer). Most frequent is "Reg oper account" (73,830 cases).
- HOUSETYPE_MODE: House type (e.g., Block of flats, Detached house). Most frequent is "Block of flats" (150,503 cases).
- WALLSMATERIAL_MODE: Wall material of the house (e.g., Panel, Monolithic). Most frequent is "Panel" (66,040 cases).
- EMERGENCYSTATE_MODE: Emergency state (e.g., No, Yes). Most frequent is "No" (159,428 cases).

```
# Check for % missing values for remaining columns
round(100 * df1.isnull().sum() / df1.shape[0],2)
```

```
SK_ID_CURR                      0.00
TARGET                          0.00
NAME_CONTRACT_TYPE              0.00
CODE_GENDER                     0.00
FLAG_OWN_CAR                    0.00
FLAG_OWN_REALTY                 0.00
CNT_CHILDREN                    0.00
AMT_INCOME_TOTAL                0.00
AMT_CREDIT                      0.00
AMT_ANNUITY                     0.00
AMT_GOODS_PRICE                 0.09
```

```
NAME_TYPE_SUITE                  0.42
NAME_INCOME_TYPE                 0.00
NAME_EDUCATION_TYPE              0.00
NAME_FAMILY_STATUS               0.00
NAME_HOUSING_TYPE                0.00
REGION_POPULATION_RELATIVE       0.00
DAYS_BIRTH                       0.00
DAYS_EMPLOYED                    0.00
DAYS_REGISTRATION                0.00
DAYS_ID_PUBLISH                  0.00
FLAG_MOBIL                       0.00
FLAG_EMP_PHONE                   0.00
FLAG_WORK_PHONE                  0.00
FLAG_CONT_MOBILE                 0.00
FLAG_PHONE                       0.00
FLAG_EMAIL                       0.00
OCCUPATION_TYPE                 31.35
CNT_FAM_MEMBERS                  0.00
REGION_RATING_CLIENT             0.00
REGION_RATING_CLIENT_W_CITY      0.00
WEEKDAY_APPR_PROCESS_START       0.00
HOUR_APPR_PROCESS_START          0.00
REG_REGION_NOT_LIVE_REGION       0.00
REG_REGION_NOT_WORK_REGION       0.00
LIVE_REGION_NOT_WORK_REGION      0.00
REG_CITY_NOT_LIVE_CITY           0.00
REG_CITY_NOT_WORK_CITY           0.00
LIVE_CITY_NOT_WORK_CITY          0.00
ORGANIZATION_TYPE                0.00
EXT_SOURCE_2                     0.21
EXT_SOURCE_3                    19.83
OBS_30_CNT_SOCIAL_CIRCLE         0.33
DEF_30_CNT_SOCIAL_CIRCLE         0.33
OBS_60_CNT_SOCIAL_CIRCLE         0.33
DEF_60_CNT_SOCIAL_CIRCLE         0.33
DAYS_LAST_PHONE_CHANGE           0.00
FLAG_DOCUMENT_2                  0.00
FLAG_DOCUMENT_3                  0.00
FLAG_DOCUMENT_4                  0.00
FLAG_DOCUMENT_5                  0.00
FLAG_DOCUMENT_6                  0.00
FLAG_DOCUMENT_7                  0.00
FLAG_DOCUMENT_8                  0.00
FLAG_DOCUMENT_9                  0.00
FLAG_DOCUMENT_10                 0.00
FLAG_DOCUMENT_11                 0.00
FLAG_DOCUMENT_12                 0.00
FLAG_DOCUMENT_13                 0.00
FLAG_DOCUMENT_14                 0.00
```

```
FLAG_DOCUMENT_15                 0.00
FLAG_DOCUMENT_16                 0.00
FLAG_DOCUMENT_17                 0.00
FLAG_DOCUMENT_18                 0.00
FLAG_DOCUMENT_19                 0.00
FLAG_DOCUMENT_20                 0.00
FLAG_DOCUMENT_21                 0.00
AMT_REQ_CREDIT_BUREAU_HOUR      13.50
AMT_REQ_CREDIT_BUREAU_DAY       13.50
AMT_REQ_CREDIT_BUREAU_WEEK      13.50
AMT_REQ_CREDIT_BUREAU_MON       13.50
AMT_REQ_CREDIT_BUREAU_QRT       13.50
AMT_REQ_CREDIT_BUREAU_YEAR      13.50
dtype: float64
```

```
# We dropped columns with more than 40 percent of null values since
imputing this columns will lead to biased dataset
# and will not be able to draw proper insights

# After removing columns we left with 73 columns

# In OCCUPATION_TYPE column we have 31.35 percent of null values and
if we impute it with mode dataset will be higly biased so we impute it
with unknown
```

columns with missing values other than occupation type

AMT_REQ_CREDIT_BUREAU_HOUR 13.50 AMT_REQ_CREDIT_BUREAU_DAY 13.50 AMT_REQ_CREDIT_BUREAU_WEEK 13.50 AMT_REQ_CREDIT_BUREAU_MON 13.50 AMT_REQ_CREDIT_BUREAU_QRT 13.50 AMT_REQ_CREDIT_BUREAU_YEAR 13.50 EXT_SOURCE_3 OBS_30_CNT_SOCIAL_CIRCLE 0.33 DEF_30_CNT_SOCIAL_CIRCLE 0.33 OBS_60_CNT_SOCIAL_CIRCLE 0.33 DEF_60_CNT_SOCIAL_CIRCLE

```
df1[['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_CREDI
T_BUREAU_YEAR']].info()

## these columns are number of inquiries made to credit bureau in the
last hour, day, week, month, quarter
## So we need to impute with median since if we impute with mean it
takes float value and will not be having any meaning
## we need to make this columns integer from float variables
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 6 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   AMT_REQ_CREDIT_BUREAU_HOUR  265992 non-null  float64
 1   AMT_REQ_CREDIT_BUREAU_DAY   265992 non-null  float64
 2   AMT_REQ_CREDIT_BUREAU_WEEK  265992 non-null  float64
 3   AMT_REQ_CREDIT_BUREAU_MON   265992 non-null  float64
 4   AMT_REQ_CREDIT_BUREAU_QRT   265992 non-null  float64
 5   AMT_REQ_CREDIT_BUREAU_YEAR  265992 non-null  float64
dtypes: float64(6)
memory usage: 14.1 MB
```

```
columns=['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_CREDI
T_BUREAU_YEAR']
for i in columns:
  # Impute NaN with median and then convert to integer
  df1[i] = df1[i].fillna(df1[i].median()).astype(int)
df1[['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_CREDI
T_BUREAU_YEAR']].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 6 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   AMT_REQ_CREDIT_BUREAU_HOUR  307511 non-null  int64
 1   AMT_REQ_CREDIT_BUREAU_DAY   307511 non-null  int64
 2   AMT_REQ_CREDIT_BUREAU_WEEK  307511 non-null  int64
 3   AMT_REQ_CREDIT_BUREAU_MON   307511 non-null  int64
 4   AMT_REQ_CREDIT_BUREAU_QRT   307511 non-null  int64
 5   AMT_REQ_CREDIT_BUREAU_YEAR  307511 non-null  int64
dtypes: int64(6)
memory usage: 14.1 MB
```

```
col1=["OBS_30_CNT_SOCIAL_CIRCLE","DEF_30_CNT_SOCIAL_CIRCLE",
     "OBS_60_CNT_SOCIAL_CIRCLE","DEF_60_CNT_SOCIAL_CIRCLE"]
for i in col1:
  df1[i] = df1[i].fillna(df1[i].median()).astype(int)
##  these columns are Number of observations of people in the client's
##   social circle with 30 days past due on defaults it shoul be in
integer
## we filled null values with median
```

```
df1["EXT_SOURCE_3"].info()
# It likely represents a risk assessment score from a third-party
source,
# used to evaluate a client's creditworthiness.
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 307511 entries, 0 to 307510
Series name: EXT_SOURCE_3
Non-Null Count   Dtype
--------------   -----
246546 non-null  float64
dtypes: float64(1)
memory usage: 2.3 MB
```

```
df1["EXT_SOURCE_3"].skew()
```

```
-0.4093904596160267
```

```
#we need to impute it with median since it is skewed so we cant rely
on mean

df1["EXT_SOURCE_3"] =
df1["EXT_SOURCE_3"].fillna(df1["EXT_SOURCE_3"].median())
df1["EXT_SOURCE_2"] =
df1["EXT_SOURCE_2"].fillna(df1["EXT_SOURCE_2"].median())
```

```
df1[["AMT_ANNUITY","AMT_GOODS_PRICE","NAME_TYPE_SUITE","OCCUPATION_TYP
E","CNT_FAM_MEMBERS","DAYS_LAST_PHONE_CHANGE"]].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 6 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   AMT_ANNUITY             307499 non-null  float64
 1   AMT_GOODS_PRICE         307233 non-null  float64
 2   NAME_TYPE_SUITE         306219 non-null  object
 3   OCCUPATION_TYPE         211120 non-null  object
 4   CNT_FAM_MEMBERS         307509 non-null  float64
 5   DAYS_LAST_PHONE_CHANGE  307510 non-null  float64
dtypes: float64(4), object(2)
memory usage: 14.1+ MB
```

```
for i in
["AMT_ANNUITY","AMT_GOODS_PRICE","CNT_FAM_MEMBERS","DAYS_LAST_PHONE_CH
ANGE"]:
  df1[i] = df1[i].fillna(df1[i].median()) #we need to impute with
median since columns are skewed we need to impute it with median
df1["OCCUPATION_TYPE"] = df1["OCCUPATION_TYPE"].fillna("Unknown") # as
said earlier we impute this column with unknown
df1["NAME_TYPE_SUITE"] =
```

```
df1["NAME_TYPE_SUITE"].fillna(df1["NAME_TYPE_SUITE"].mode()[0])# For
this column we impute null values with mode

df1.isnull().sum() # Null values are removed and treated
```

```
SK_ID_CURR                     0
TARGET                         0
NAME_CONTRACT_TYPE             0
CODE_GENDER                    0
FLAG_OWN_CAR                   0
FLAG_OWN_REALTY                0
CNT_CHILDREN                   0
AMT_INCOME_TOTAL               0
AMT_CREDIT                     0
AMT_ANNUITY                    0
AMT_GOODS_PRICE                0
NAME_TYPE_SUITE                0
NAME_INCOME_TYPE               0
NAME_EDUCATION_TYPE            0
NAME_FAMILY_STATUS             0
NAME_HOUSING_TYPE              0
REGION_POPULATION_RELATIVE     0
DAYS_BIRTH                     0
DAYS_EMPLOYED                  0
DAYS_REGISTRATION              0
DAYS_ID_PUBLISH                0
FLAG_MOBIL                     0
FLAG_EMP_PHONE                 0
FLAG_WORK_PHONE                0
FLAG_CONT_MOBILE               0
FLAG_PHONE                     0
FLAG_EMAIL                     0
OCCUPATION_TYPE                0
CNT_FAM_MEMBERS                0
REGION_RATING_CLIENT           0
REGION_RATING_CLIENT_W_CITY    0
WEEKDAY_APPR_PROCESS_START     0
HOUR_APPR_PROCESS_START        0
REG_REGION_NOT_LIVE_REGION     0
REG_REGION_NOT_WORK_REGION     0
LIVE_REGION_NOT_WORK_REGION    0
REG_CITY_NOT_LIVE_CITY         0
REG_CITY_NOT_WORK_CITY         0
LIVE_CITY_NOT_WORK_CITY        0
ORGANIZATION_TYPE              0
EXT_SOURCE_2                   0
EXT_SOURCE_3                   0
OBS_30_CNT_SOCIAL_CIRCLE       0
DEF_30_CNT_SOCIAL_CIRCLE       0
OBS_60_CNT_SOCIAL_CIRCLE       0
```

```
DEF_60_CNT_SOCIAL_CIRCLE       0
DAYS_LAST_PHONE_CHANGE         0
FLAG_DOCUMENT_2                0
FLAG_DOCUMENT_3                0
FLAG_DOCUMENT_4                0
FLAG_DOCUMENT_5                0
FLAG_DOCUMENT_6                0
FLAG_DOCUMENT_7                0
FLAG_DOCUMENT_8                0
FLAG_DOCUMENT_9                0
FLAG_DOCUMENT_10               0
FLAG_DOCUMENT_11               0
FLAG_DOCUMENT_12               0
FLAG_DOCUMENT_13               0
FLAG_DOCUMENT_14               0
FLAG_DOCUMENT_15               0
FLAG_DOCUMENT_16               0
FLAG_DOCUMENT_17               0
FLAG_DOCUMENT_18               0
FLAG_DOCUMENT_19               0
FLAG_DOCUMENT_20               0
FLAG_DOCUMENT_21               0
AMT_REQ_CREDIT_BUREAU_HOUR     0
AMT_REQ_CREDIT_BUREAU_DAY      0
AMT_REQ_CREDIT_BUREAU_WEEK     0
AMT_REQ_CREDIT_BUREAU_MON      0
AMT_REQ_CREDIT_BUREAU_QRT      0
AMT_REQ_CREDIT_BUREAU_YEAR     0
dtype: int64
```

Check for Duplicates

```
df1.duplicated().sum() #there are no duplicated in the dataset
```

```
0
```

```
# In these columns we can see the negative values in the DAYS columns

df1[['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH
','DAYS_LAST_PHONE_CHANGE']].describe()
```


```
{"summary":"{\n  \"name\": \"df1[['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','DAYS_LAST_PHONE_CHANGE']]\",\n  \"rows\": 8,\n  \"fields\": [\n  {\n  \"column\": \"DAYS_BIRTH\",\n  \"properties\": {\n  \"dtype\": \"number\",\n  \"std\": 113721.74256664132,\n  \"min\": -25229.0,\n  \"max\": 307511.0,\n  \"num_unique_values\": 8,\n  \"samples\": [\n  -16036.995066843137,\n  -15750.0,\n  307511.0\n  ],\n  \"semantic_type\": \"\",\n
```

\"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_EMPLOYED\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 151565.6912219694,\n   \"min\": -17912.0,\n   \"max\": 365243.0,\n   \"num_unique_values\": 8,\n   \"samples\": [\n   63815.04590404896,\n   -1213.0,\n   307511.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_REGISTRATION\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 111067.93567402713,\n   \"min\": -24672.0,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n   \"samples\": [\n   -4986.120327538419,\n   -4504.0,\n   307511.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_ID_PUBLISH\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 109660.34010110334,\n   \"min\": -7197.0,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n   \"samples\": [\n   -2994.2023732484367,\n   -3254.0,\n   307511.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"DAYS_LAST_PHONE_CHANGE\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 109087.11125815548,\n   \"min\": -4292.0,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n   \"samples\": [\n   -962.8581188965597,\n   -757.0,\n   307511.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
# We need to convert it into absolute values '
# Make a list of all DAYS columns
col_list = ['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','DAYS_LAST_PHONE_CHANGE']

# Replace the values with their respective absolute values
for i in col_list:
    df1[i] = abs(df1[i])

# Verify the changes
df1[['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','DAYS_LAST_PHONE_CHANGE']].describe()
```

{"summary":"{\n \"name\": \"df1[['DAYS_BIRTH','DAYS_EMPLOYED','DAYS_REGISTRATION','DAYS_ID_PUBLISH','DAYS_LAST_PHONE_CHANGE']]\",\n \"rows\": 8,\n \"fields\": [\n {\n   \"column\": \"DAYS_BIRTH\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 103830.13734330218,\n   \"min\": 4363.988631785526,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n   \"samples\": [\n   16036.995066843137,\n   15750.0,\n   307511.0\

n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_EMPLOYED\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 147983.32970123301,\n   \"min\":
0.0,\n   \"max\": 365243.0,\n   \"num_unique_values\": 8,\n
\"samples\": [\n   67724.74214906133,\n   2219.0,\n
307511.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_REGISTRATION\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 106612.80932614328,\n   \"min\":
0.0,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n
\"samples\": [\n   4986.120327538419,\n   4504.0,\n
307511.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_ID_PUBLISH\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 107683.60602472254,\n   \"min\":
0.0,\n   \"max\": 307511.0,\n   \"num_unique_values\": 8,\n
\"samples\": [\n   2994.2023732484367,\n   3254.0,\n
307511.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_LAST_PHONE_CHANGE\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 108291.1788159357,\n
\"min\": 0.0,\n   \"max\": 307511.0,\n
\"num_unique_values\": 8,\n   \"samples\": [\n
962.8581188965597,\n   757.0,\n   307511.0\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   }\n]\n}","type":"dataframe"}

```
df1['CODE_GENDER'].value_counts() # there are 4 records with XNA which
is to be treated
df1['CODE_GENDER'] = df1['CODE_GENDER'].replace('XNA',np.nan)
```

```
df1['CODE_GENDER'].value_counts()
```

```
CODE_GENDER
F    202448
M    105059
Name: count, dtype: int64
```

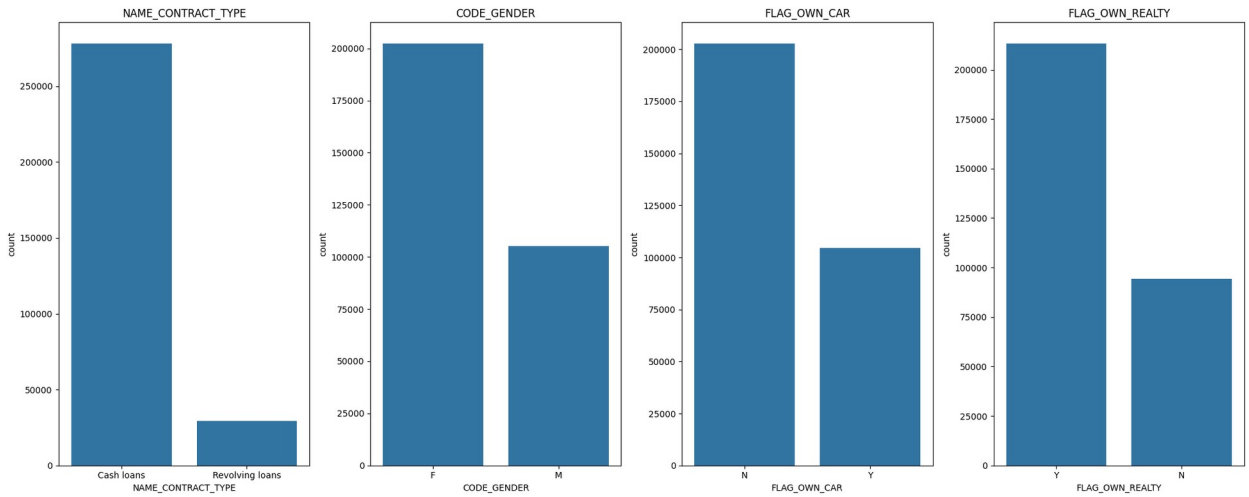
```
df1['CODE_GENDER']=df1['CODE_GENDER'].fillna(df1['CODE_GENDER'].mode()
[0])
```

```
plt.rcParams["figure.figsize"] = (5, 5)
```

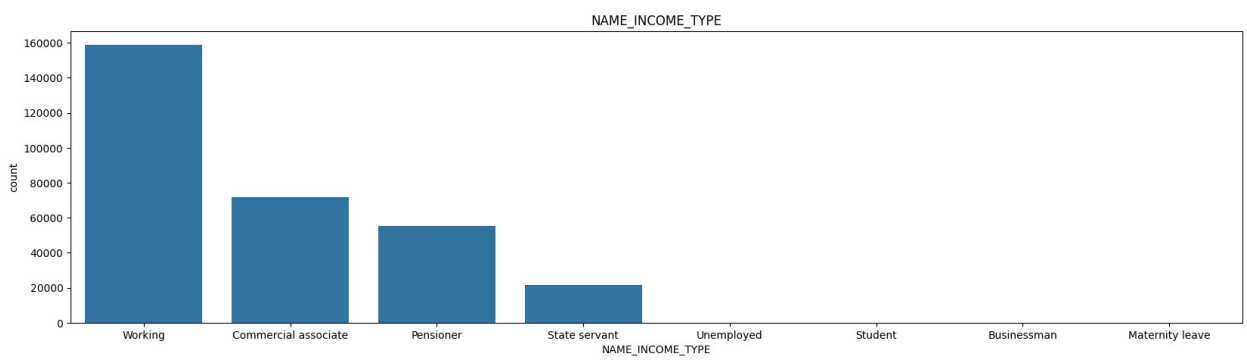
Univariate Analysis

```
plt.figure(figsize =[20,8])
j=1
for i in df1[['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY']]:
```

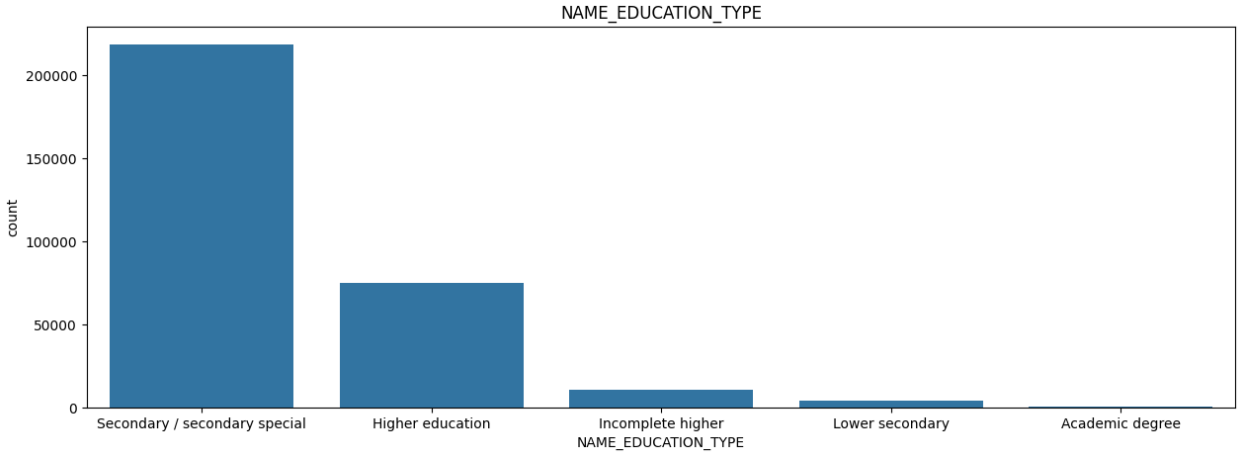
```
    plt.subplot(1,4,j)
    sns.barplot(df1[i].value_counts())
    plt.title(i)
    plt.xticks(rotation=0)
    j += 1
plt.tight_layout()
```



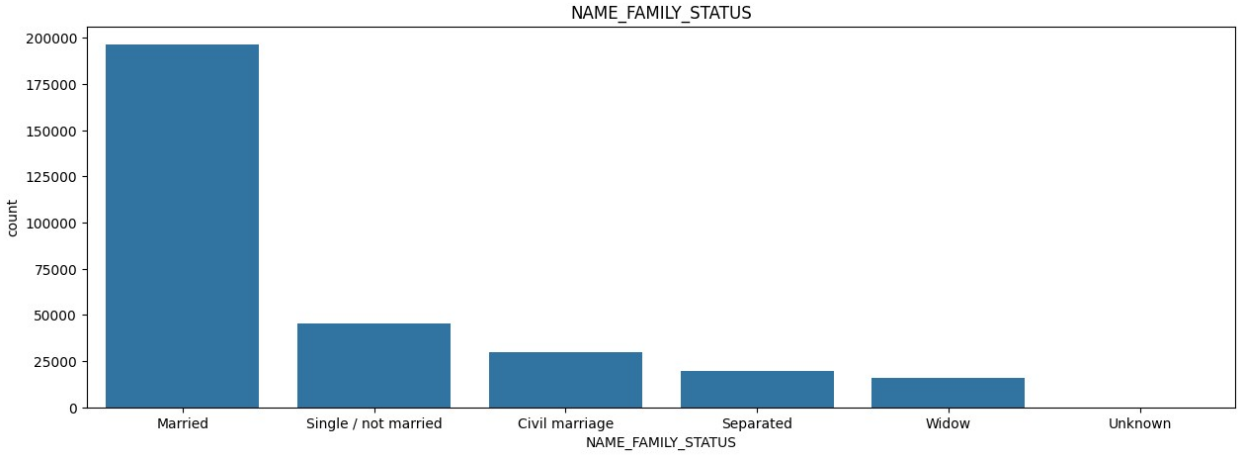

```
plt.figure(figsize =[20,5])
sns.barplot(df1['NAME_INCOME_TYPE'].value_counts())
plt.title('NAME_INCOME_TYPE')
plt.show()# Most clients income is by working
```



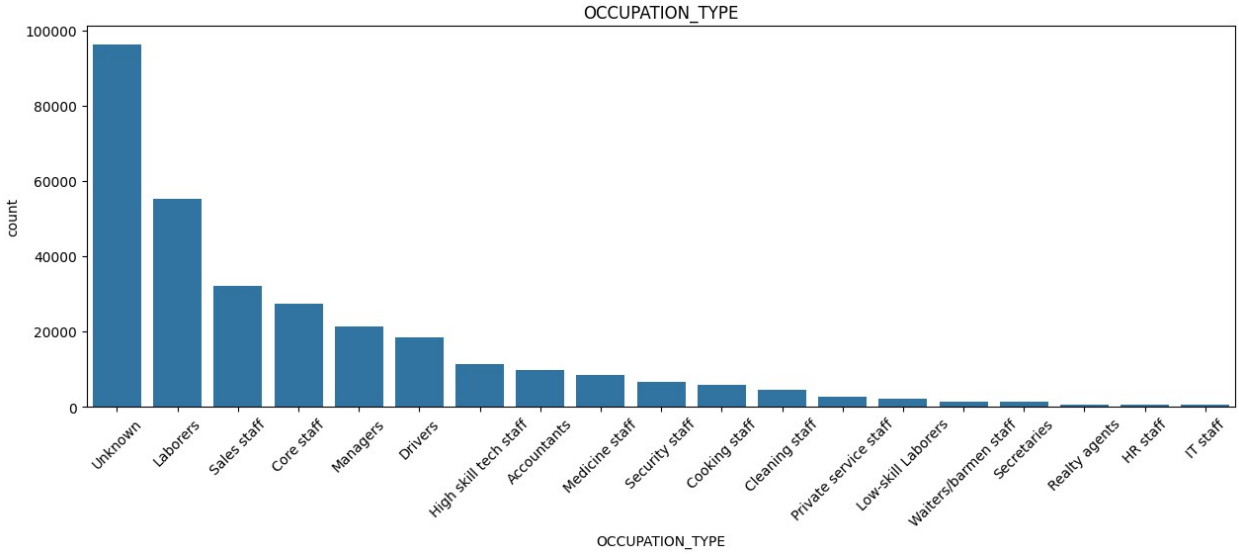

```
plt.figure(figsize =[15,5])
sns.barplot(df1['NAME_EDUCATION_TYPE'].value_counts())
plt.title('NAME_EDUCATION_TYPE')
plt.show()# Most clients education is secondary
```



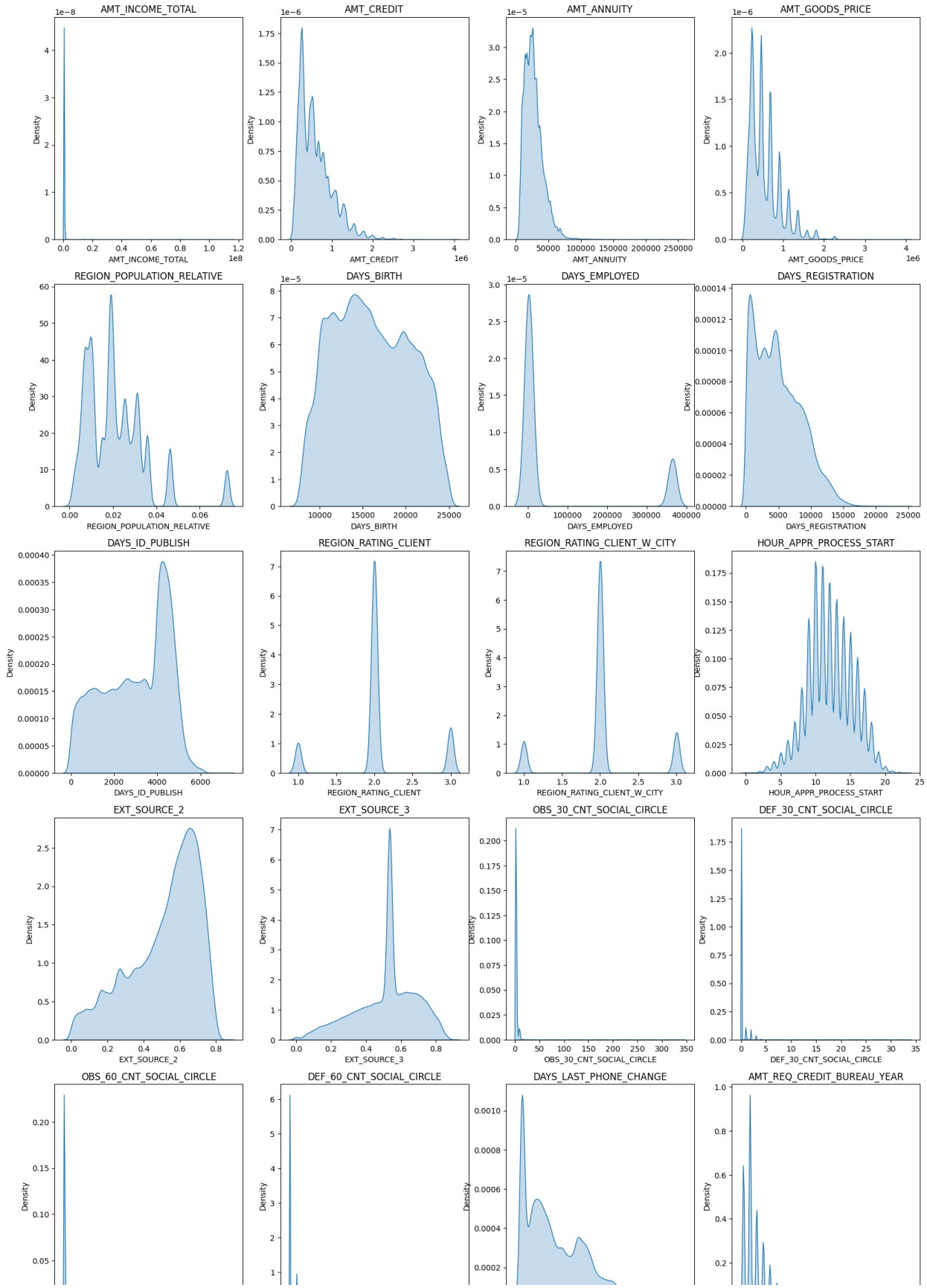

```
plt.figure(figsize =[15,5])
sns.barplot(df1['NAME_FAMILY_STATUS'].value_counts())
plt.title('NAME_FAMILY_STATUS')
plt.show()# Most clients are married
```



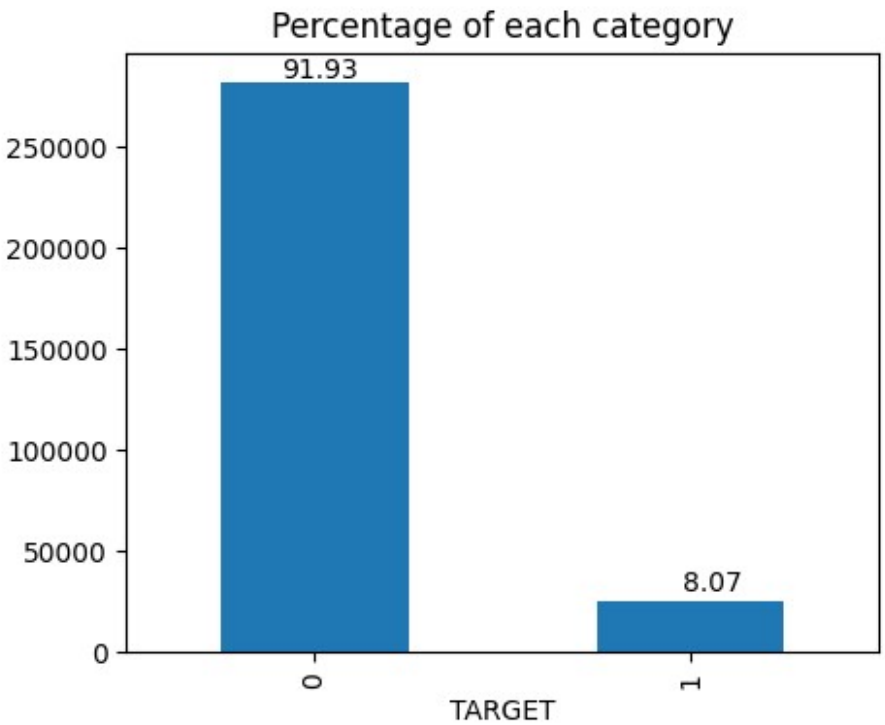

```
plt.figure(figsize =[15,5])
sns.barplot(df1['OCCUPATION_TYPE'].value_counts())
plt.title('OCCUPATION_TYPE')
plt.xticks(rotation=45)
plt.show()# most clients occupation type is labores
```




```
col=["AMT_INCOME_TOTAL","AMT_CREDIT","AMT_ANNUITY","AMT_GOODS_PRICE","
REGION_POPULATION_RELATIVE","DAYS_BIRTH",

"DAYS_EMPLOYED","DAYS_REGISTRATION","DAYS_ID_PUBLISH","REGION_RATING_C
LIENT",
     "REGION_RATING_CLIENT_W_CITY",   "HOUR_APPR_PROCESS_START",
     "EXT_SOURCE_2", "EXT_SOURCE_3",

"OBS_30_CNT_SOCIAL_CIRCLE","DEF_30_CNT_SOCIAL_CIRCLE","OBS_60_CNT_SOCI
AL_CIRCLE","DEF_60_CNT_SOCIAL_CIRCLE","DAYS_LAST_PHONE_CHANGE","AMT_RE
Q_CREDIT_BUREAU_YEAR"]
plt.figure(figsize =[20,30])
j=1
for i in col:
    plt.subplot(5,4,j)
    sns.kdeplot(df1[i],fill =True)
    plt.title(i)
    j+=1
# 1.AMT_INCOME_TOTAL column has high skewness. There is influence of
ouliers here
# 2.
"AMT_CREDIT","AMT_ANNUITY","AMT_GOODS_PRICE","REGION_POPULATION_RELATI
VE" columns are left skewed
# 3.
OBS_30_CNT_SOCIAL_CIRCLE,DEF_30_CNT_SOCIAL_CIRCLE,OBS_60_CNT_SOCIAL_CI
RCLE,DEF_60_CNT_SOCIAL_CIRCLE these columns are skewed highly which
indicates of outliers
# 4. remaing columns are having less skewness nearer to zero
```


AMT_INCOME_TOTAL
AMT_CREDIT
AMT_ANNUITY
AMT_GOODS_PRICE
REGION_POPULATION_RELATIVE
DAYS_BIRTH
DAYS_EMPLOYED
DAYS_REGISTRATION
DAYS_ID_PUBLISH
REGION_RATING_CLIENT
REGION_RATING_CLIENT_W_CITY
HOUR_APPR_PROCESS_START
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_YEAR
Density

```
plt.figure(figsize=[5,4])
df1["TARGET"].value_counts().plot(kind="bar",)
plt.text(x=-0.087, y=285000,s=round(df1["TARGET"].value_counts()
[0]*100/df1["TARGET"].shape[0],2))
plt.text(x=0.98, y=30000,s=round(df1["TARGET"].value_counts()
[1]*100/df1["TARGET"].shape[0],2))
plt.title("Percentage of each category")
plt.show()

# # There is imbalance in the data'
# need to treat imbalance data
```

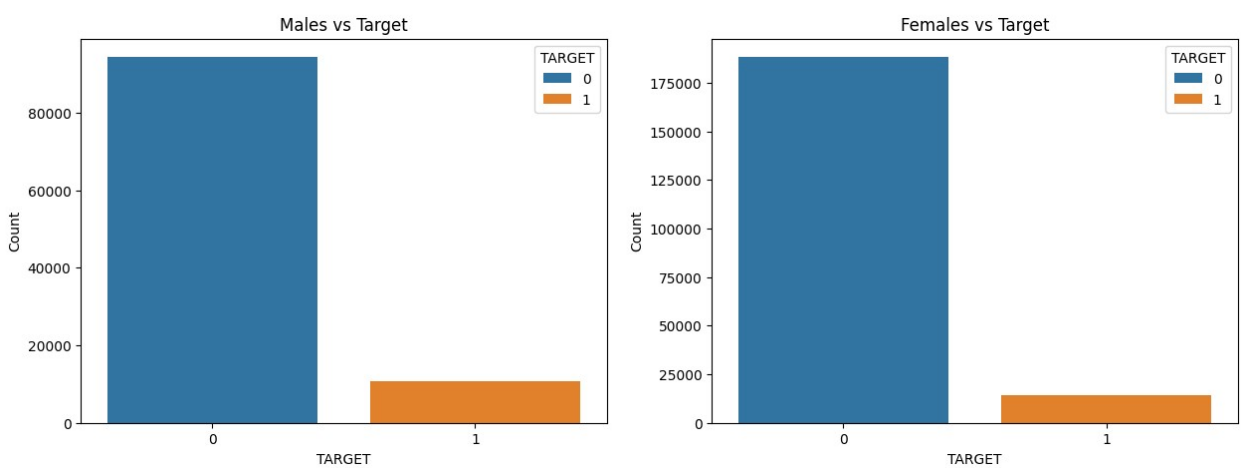


Bivariate Analysis

```
# Code-gender vs Target
import seaborn as sns
import matplotlib.pyplot as plt

# Code-gender vs Target
plt.figure(figsize=[15, 5])

plt.subplot(1, 2, 1)
# Create a DataFrame for male data
male_data = df1[df1["CODE_GENDER"] == "M"]
["TARGET"].value_counts().reset_index()
male_data.columns = ['TARGET', 'Count']
```

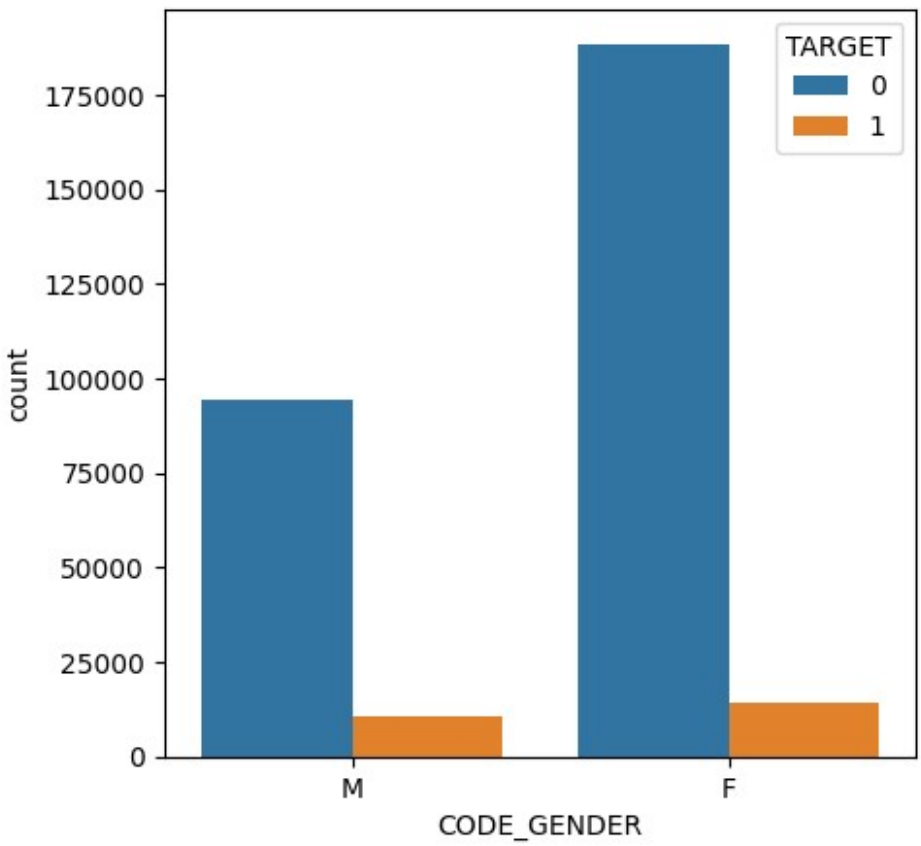
```
sns.barplot(x='TARGET', y='Count', data=male_data, hue='TARGET')
plt.title("Males vs Target")

plt.subplot(1, 2, 2)
Female_data = df1[df1["CODE_GENDER"] == "F"]
["TARGET"].value_counts().reset_index()
Female_data.columns = ['TARGET', 'Count']
sns.barplot(x='TARGET', y='Count', data=Female_data, hue='TARGET')
plt.title("Females vs Target")
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)

Text(0.5, 1.0, 'Females vs Target')
```

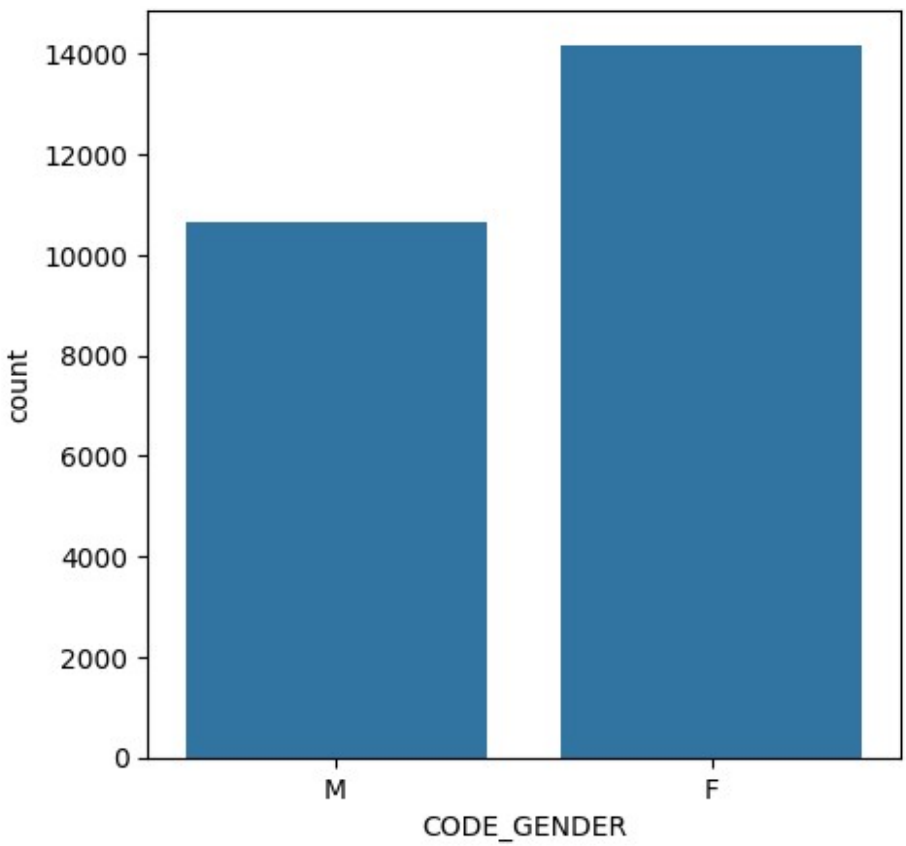



```
sns.countplot(x="CODE_GENDER",hue="TARGET",data=df1)
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949:
FutureWarning: When grouping with a length-1 list-like, you will need
to pass a length-1 tuple to get_group in a future version of pandas.
Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)

<Axes: xlabel='CODE_GENDER', ylabel='count'>
```

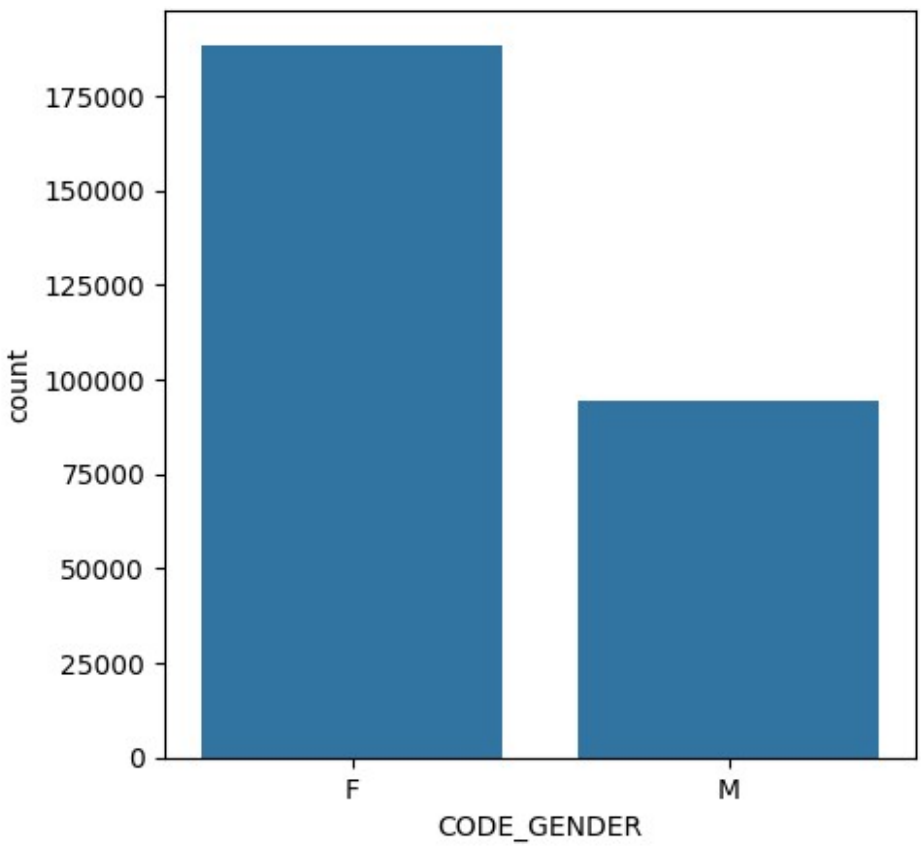



```
defaults=df1[df1["TARGET"]==1]
others=df1[df1["TARGET"]==0]
sns.countplot(data=defaults,x="CODE_GENDER")

<Axes: xlabel='CODE_GENDER', ylabel='count'>
```

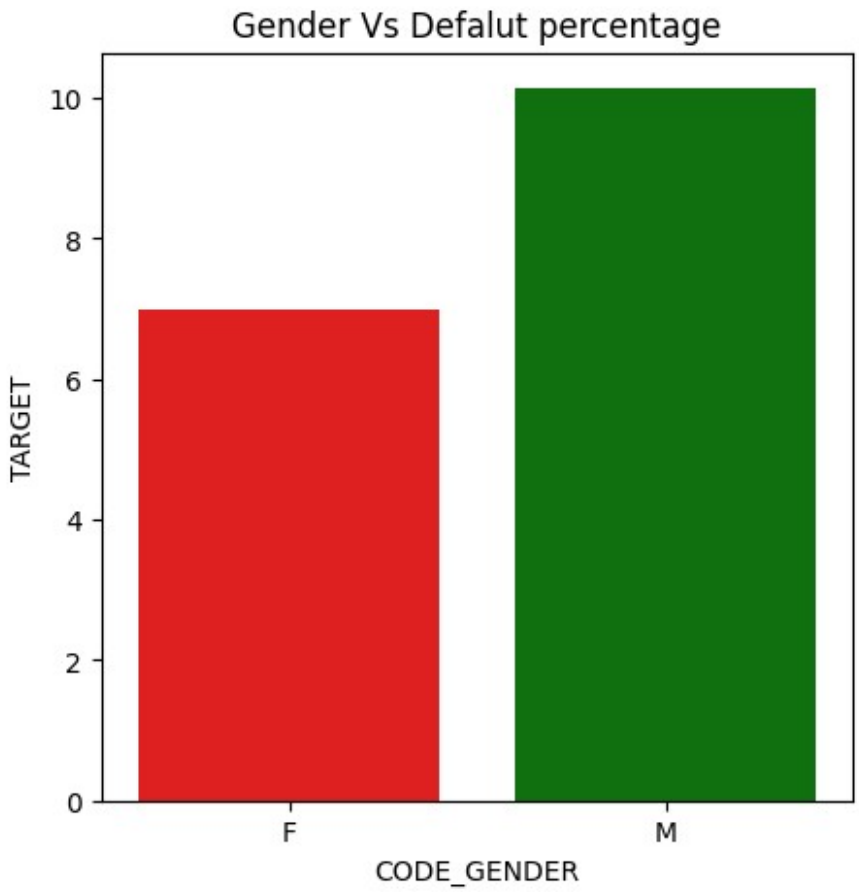



```
sns.countplot(data=others,x="CODE_GENDER")
```

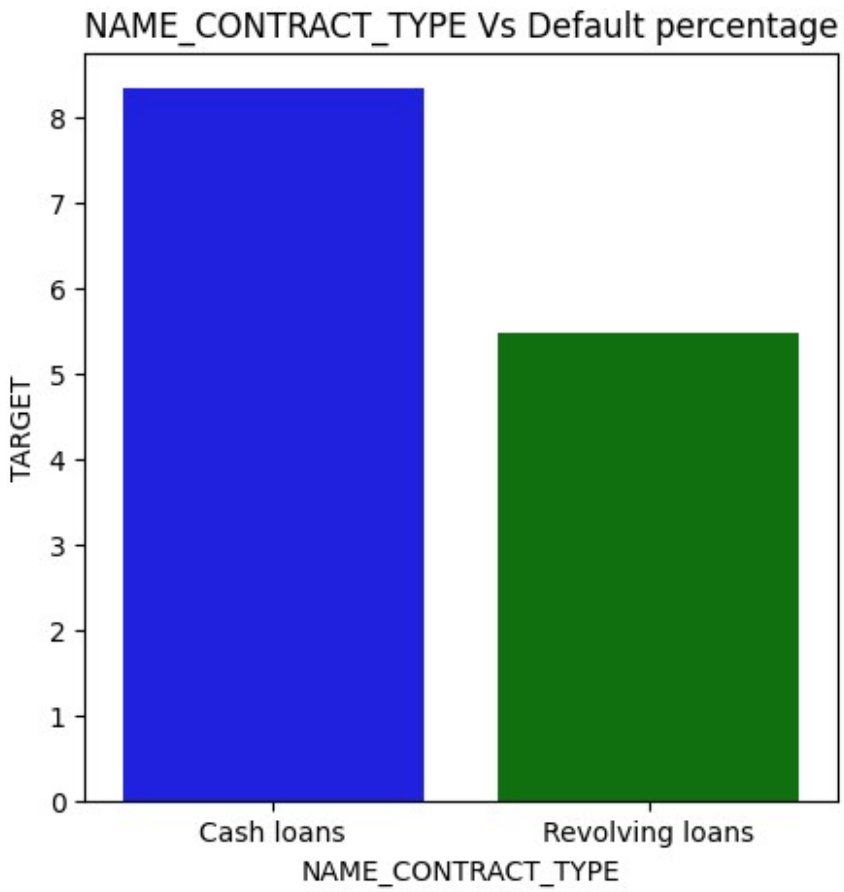
```
<Axes: xlabel='CODE_GENDER', ylabel='count'>
```



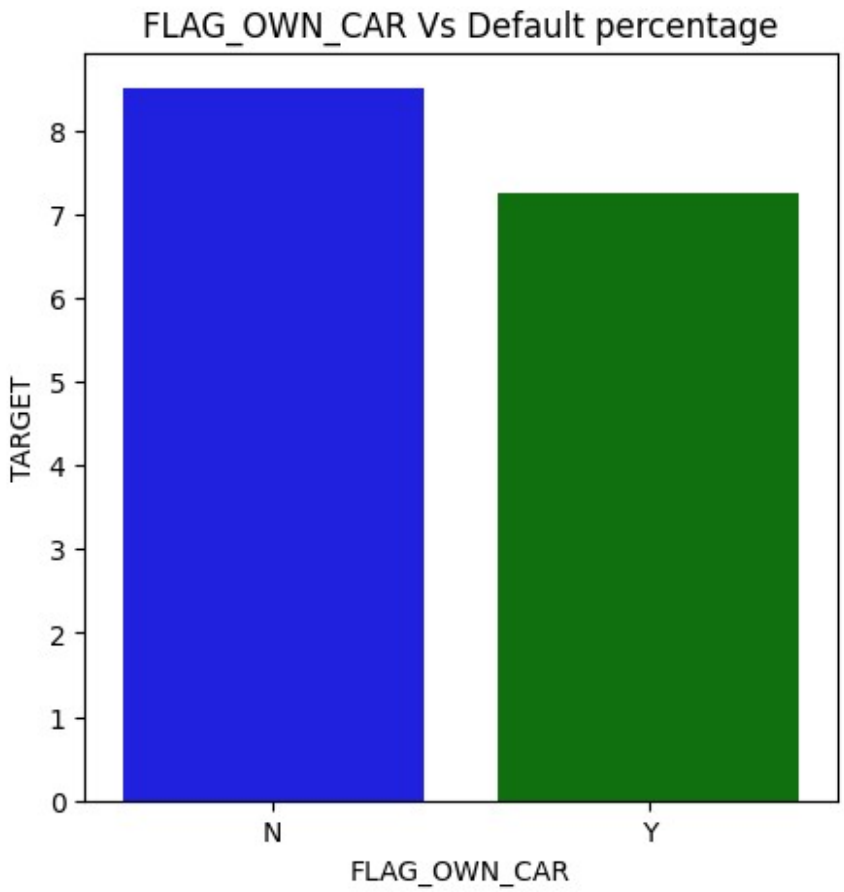

```
import warnings
warnings.filterwarnings("ignore")

tempdf = df1[["TARGET","CODE_GENDER"]].groupby(["CODE_GENDER"],
as_index=False).mean()
tempdf["TARGET"] = tempdf["TARGET"]*100
sns.barplot(x="CODE_GENDER", y = "TARGET", data = tempdf,palette=["r",
"g"])
plt.title("Gender Vs Defalut percentage")
plt.show()
#As seen from the above diagram, males have comparatively higher
percentage of being defaulters than females.
```



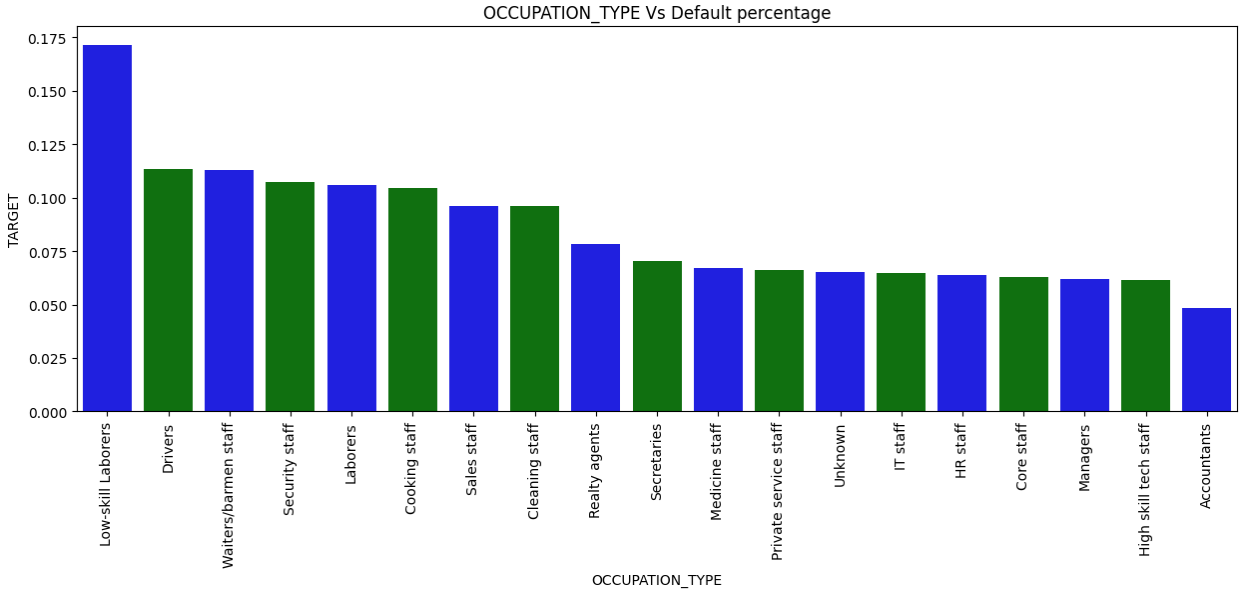

```
df1.select_dtypes(include="object").columns

Index(['NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
'FLAG_OWN_REALTY',
       'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE',
       'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
       'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE'],
      dtype='object')

tempdf =
df1[["TARGET","NAME_CONTRACT_TYPE"]].groupby(["NAME_CONTRACT_TYPE"],
as_index=False).mean()
tempdf["TARGET"] = tempdf["TARGET"]*100
sns.barplot(x="NAME_CONTRACT_TYPE", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("NAME_CONTRACT_TYPE Vs Default percentage")
plt.show()
#As seen from the below diagram, cash loans have comparatively higher
percentage of being defaulters than Revovling loans.
```



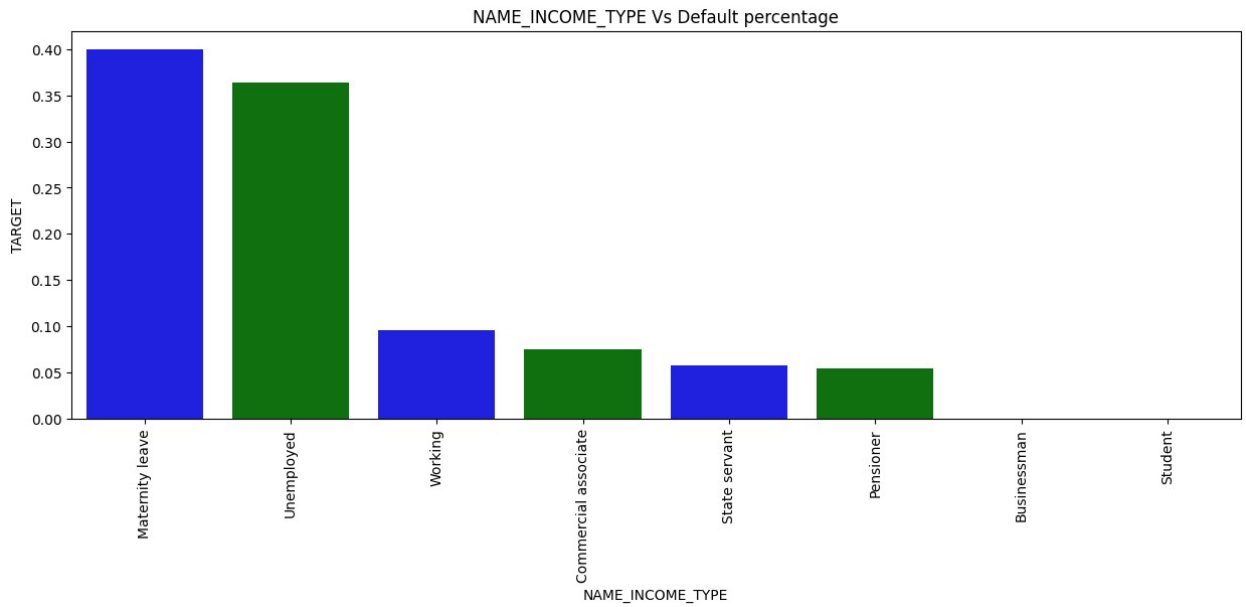

```
tempdf = df1[["TARGET","FLAG_OWN_CAR"]].groupby(["FLAG_OWN_CAR"],
as_index=False).mean()
tempdf["TARGET"] = tempdf["TARGET"]*100
sns.barplot(x="FLAG_OWN_CAR", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("FLAG_OWN_CAR Vs Default percentage")
plt.show()
#As seen from the below diagram, clients with no car have
comparatively higher percentage of being defaulters than the clients
who have car.
```



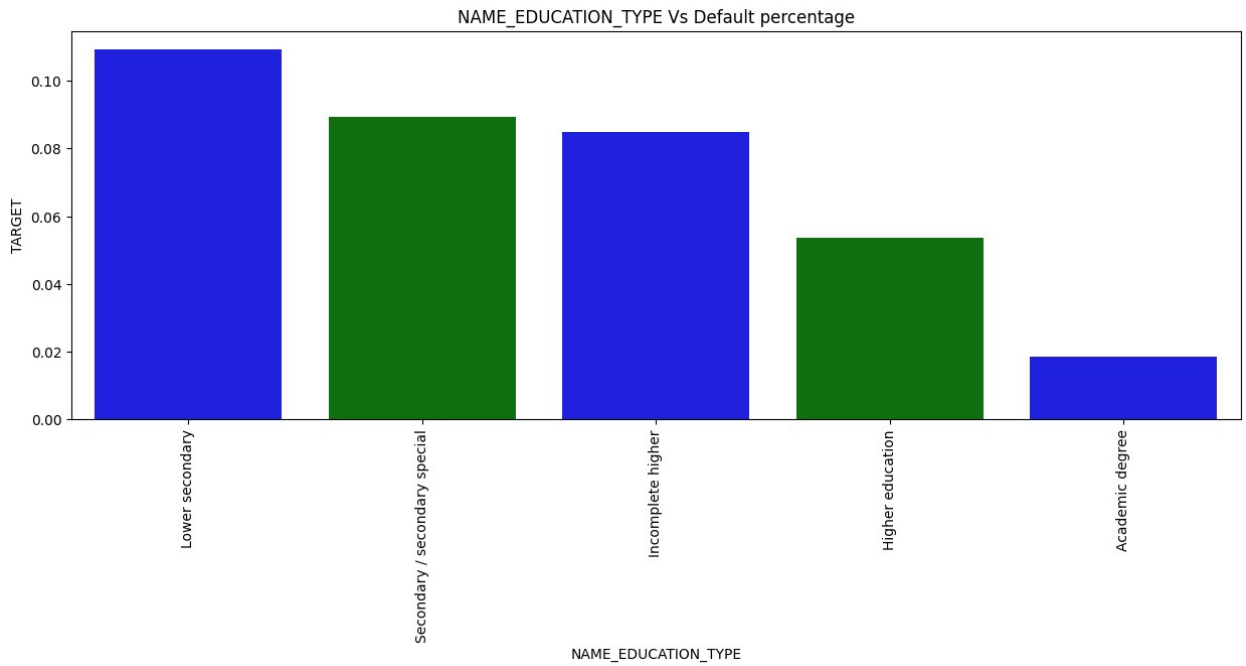

```
plt.figure(figsize=[15, 5])
tempdf =
df1[["TARGET","OCCUPATION_TYPE"]].groupby(["OCCUPATION_TYPE"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="OCCUPATION_TYPE", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("OCCUPATION_TYPE Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
#As seen from the below diagram we can say that low skill labors are
high chance of being defaulters.
```



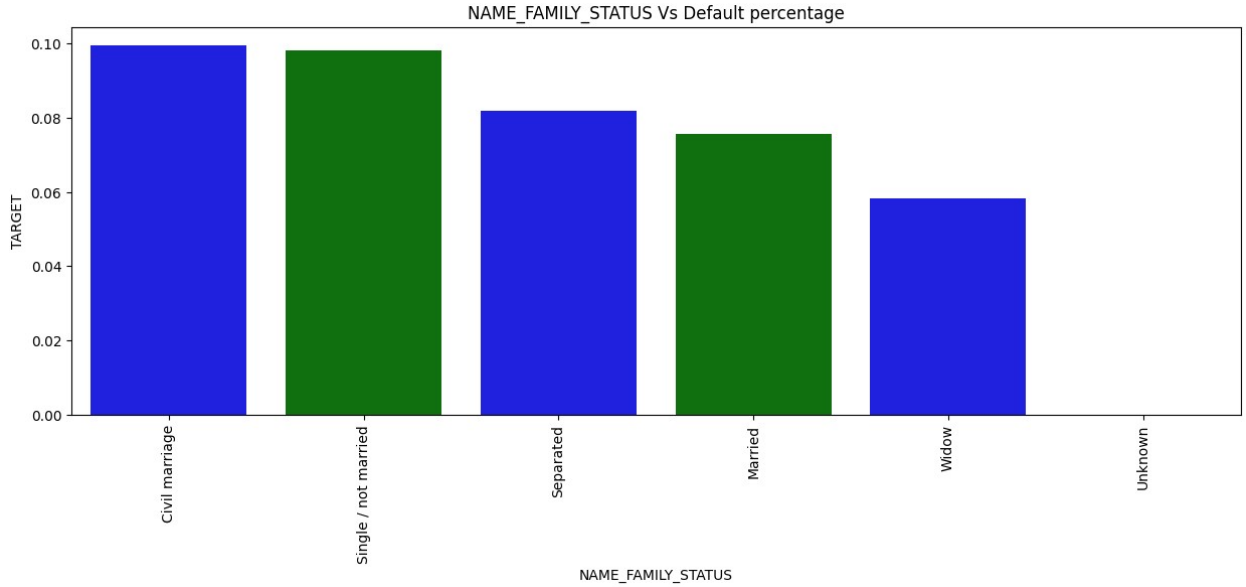

```
plt.figure(figsize=[15, 5])
tempdf =
df1[["TARGET","NAME_INCOME_TYPE"]].groupby(["NAME_INCOME_TYPE"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="NAME_INCOME_TYPE", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("NAME_INCOME_TYPE Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
# The people on Maternity leave and unemployed categories are more
likely to fail to repay.
# Businessman and Students have the lowest chances of defaulting.
```



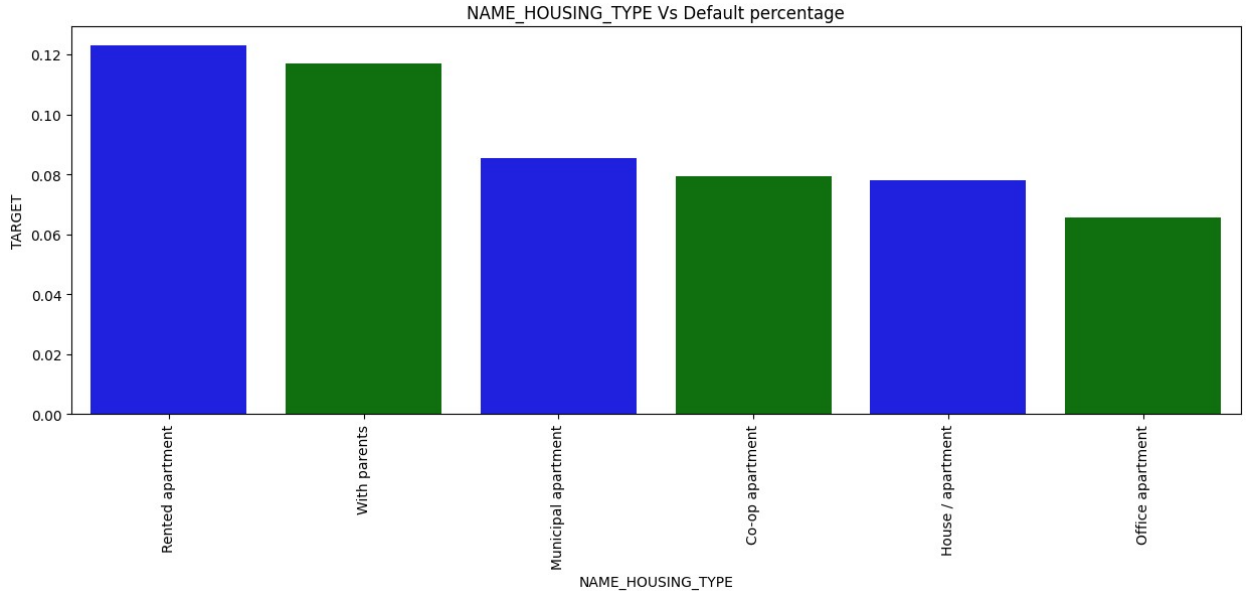

```
plt.figure(figsize=[15, 5])
tempdf =
df1[["TARGET","NAME_EDUCATION_TYPE"]].groupby(["NAME_EDUCATION_TYPE"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="NAME_EDUCATION_TYPE", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("NAME_EDUCATION_TYPE Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
# People with lower secondary education level are more likely to fail
repayment.
# People with academic degree or higher education, however, are mostly
able to repay on time.
```



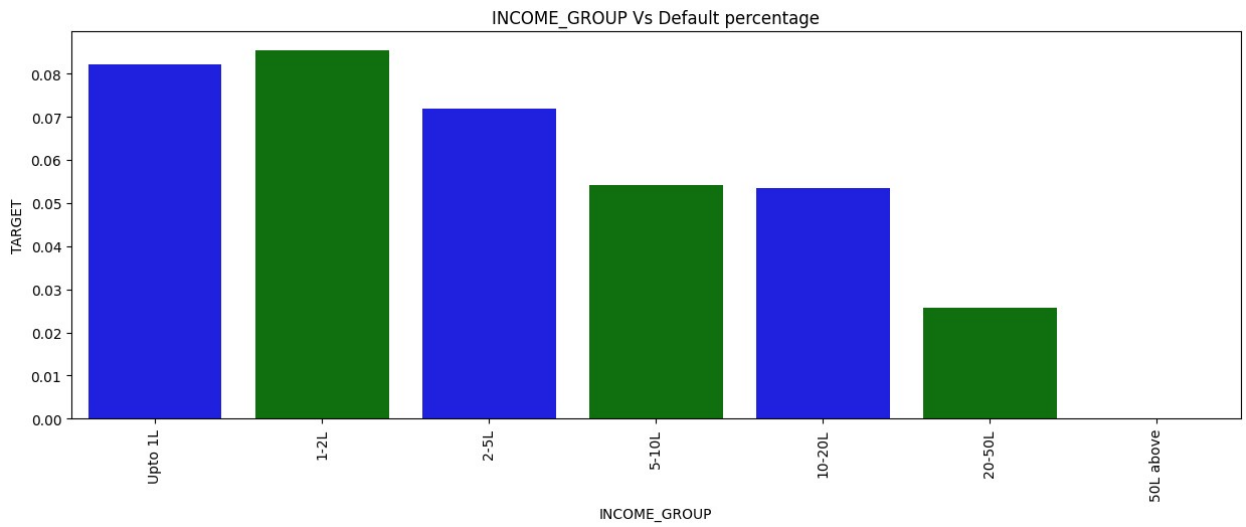

```
plt.figure(figsize=[15, 5])
tempdf =
df1[["TARGET","NAME_FAMILY_STATUS"]].groupby(["NAME_FAMILY_STATUS"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="NAME_FAMILY_STATUS", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("NAME_FAMILY_STATUS Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
# People in a civil marriage or those who are singles, are more likely
to default.
```



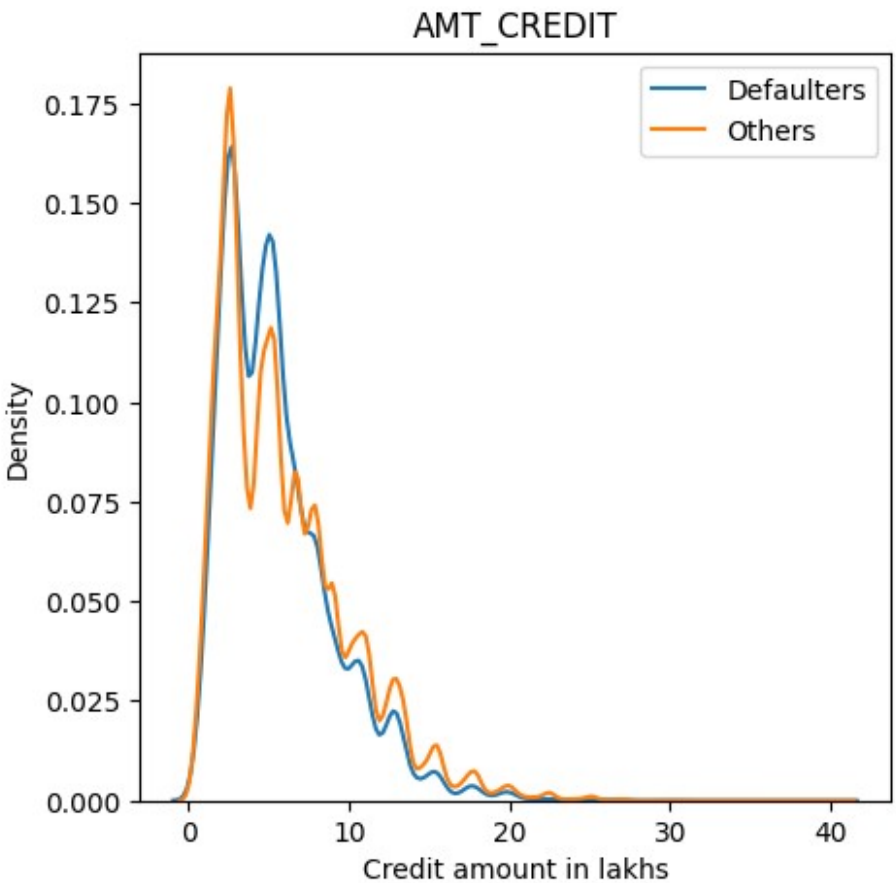

```
plt.figure(figsize=[15, 5])
tempdf =
df1[["TARGET","NAME_HOUSING_TYPE"]].groupby(["NAME_HOUSING_TYPE"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="NAME_HOUSING_TYPE", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("NAME_HOUSING_TYPE Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
#Most of the applicants who are likely to default are either staying
in a rented apartment or with parents compared to other housing types
```



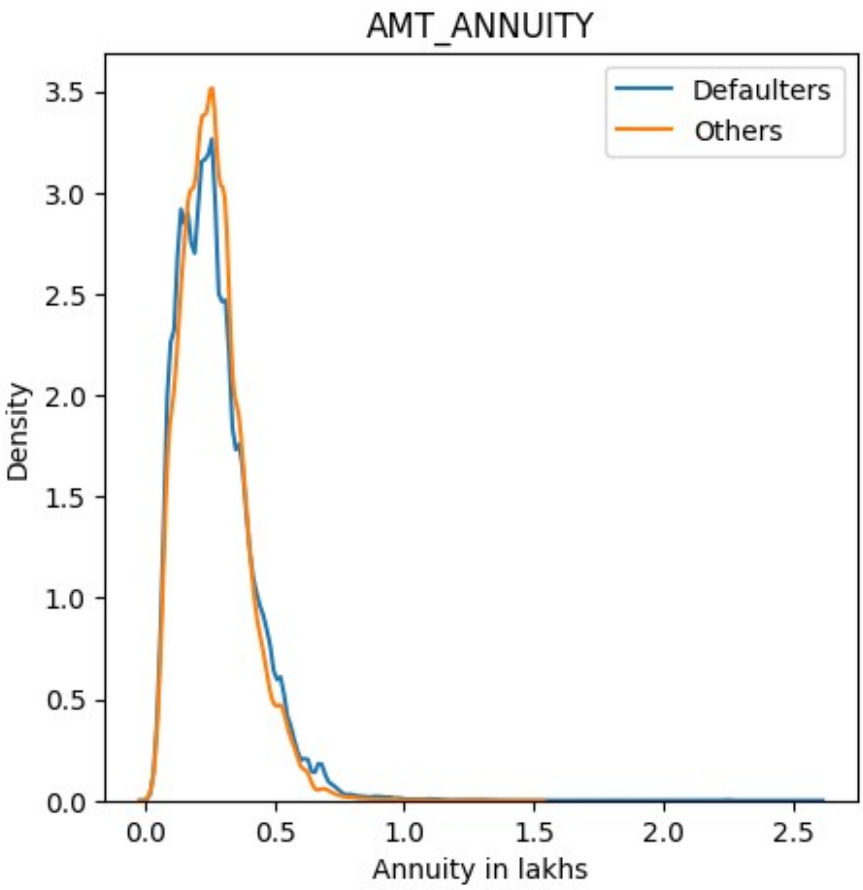
```
bins = [0,1,2,5,10,20,50,1000]
labels = ['Upto 1L','1-2L','2-5L','5-10L','10-20L','20-50L','50L
above']
df1['INCOME_GROUP'] = pd.cut(df1['AMT_INCOME_TOTAL'] / 100000, bins =
bins, labels = labels )

plt.figure(figsize=[15, 5])
tempdf = df1[["TARGET","INCOME_GROUP"]].groupby(["INCOME_GROUP"],
as_index=False).mean()
tempdf.sort_values(by="TARGET", ascending=False, inplace=True)
sns.barplot(x="INCOME_GROUP", y = "TARGET", data =
tempdf,palette=["b", "g"])
plt.title("INCOME_GROUP Vs Default percentage")
plt.xticks(rotation=90)
plt.show()
```



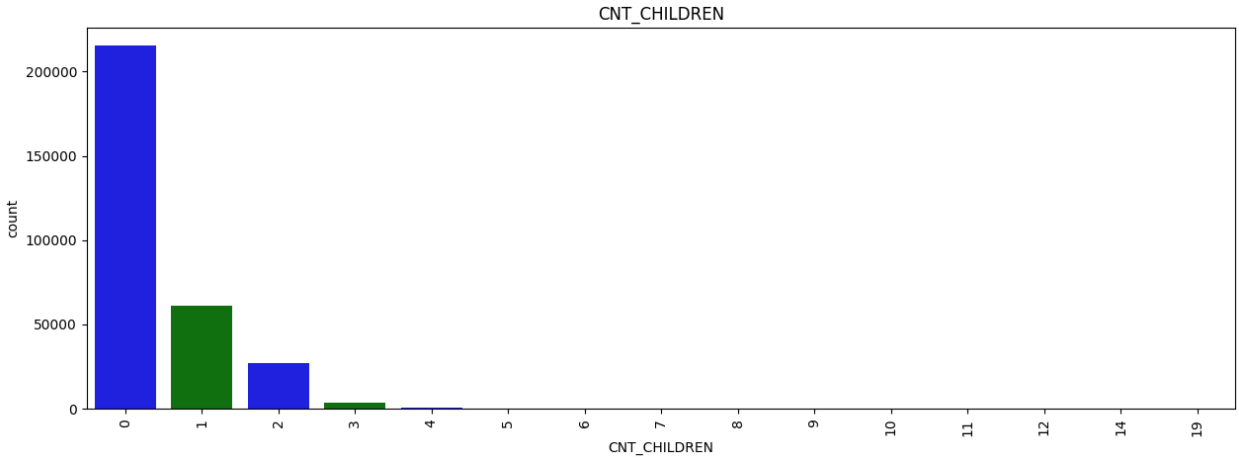

```
## Clients having less income are high likely defaulters

c1=df1[df1["TARGET"]==1]["AMT_CREDIT"]/100000
c2=df1[df1["TARGET"]==0]["AMT_CREDIT"]/100000
sns.kdeplot(c1 , label='Defaulters')
sns.kdeplot(c2 , label='Others')
plt.title("AMT_CREDIT")
plt.xlabel('Credit amount in lakhs')
plt.legend()
plt.show()
```



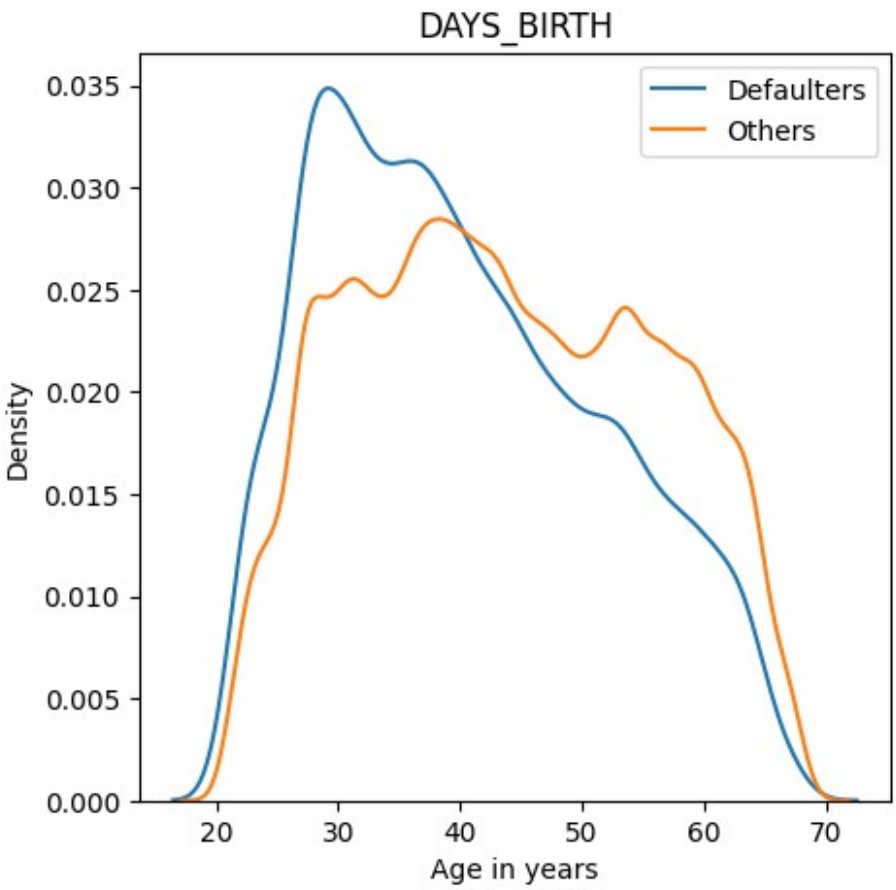

```
#Most of the loans are given with credit amount less than 10 lakhs.

c1=df1[df1["TARGET"]==0]["AMT_ANNUITY"]/100000
c2=df1[df1["TARGET"]==1]["AMT_ANNUITY"]/100000
sns.kdeplot(c1 , label='Defaulters')
sns.kdeplot(c2 , label='Others')
plt.title("AMT_ANNUITY")
plt.xlabel('Annuity in lakhs')
plt.legend()
plt.show()
#Most of the loan annuity is less than 75, 000.
```




```
plt.figure(figsize=[15, 5])
sns.countplot(x="CNT_CHILDREN", data = df1,palette=["b", "g"])
plt.title("CNT_CHILDREN")
plt.xticks(rotation=90)
plt.show()
#Majority of the applicants are having no children. Mostly they have 3
or less children.
```



```
col1 = df1[df1["TARGET"]==1]['DAYS_BIRTH']//365
col2 = df1[df1["TARGET"]==0]['DAYS_BIRTH']//365

sns.kdeplot(col1 , label='Defaulters')
sns.kdeplot(col2 , label='Others')
plt.title("DAYS_BIRTH")
plt.xlabel('Age in years')
plt.legend()
plt.show()
```

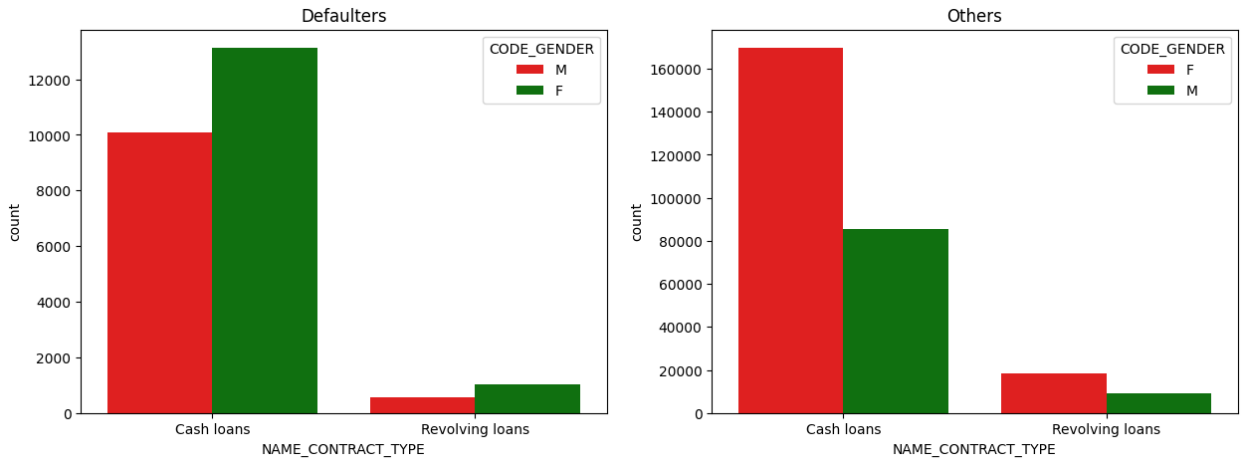



```
#Defaulters are more in 25-40 age group. Above 40, the number of
defaulters tends to decrease.
```

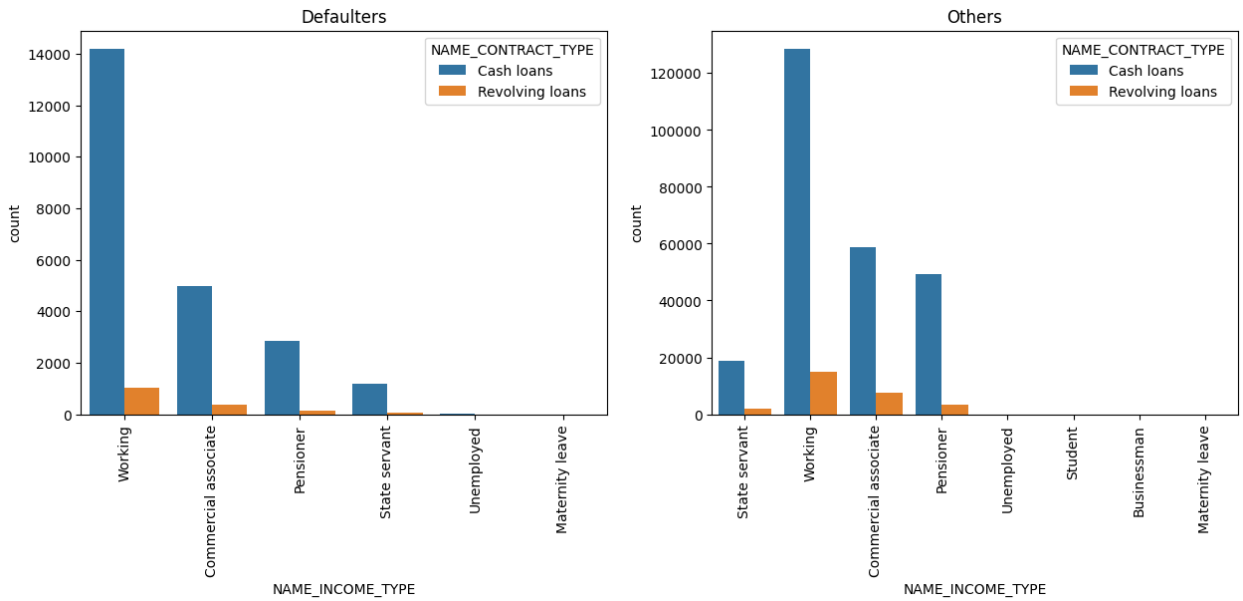
Bivariate Analysis

```
defaults=df1[df1["TARGET"]==1]
others=df1[df1["TARGET"]==0]

# NAME_CONTRACT_TYPE - CODE_GENDER
plt.figure(figsize=[15, 5])
plt.subplot(1,2,1)
```

```
sns.countplot(data=defaults,x="NAME_CONTRACT_TYPE",hue="CODE_GENDER",p
alette=("red","green"))
plt.title("Defaulters")
plt.subplot(1,2,2)
sns.countplot(data=others,x="NAME_CONTRACT_TYPE",hue="CODE_GENDER",pal
ette=("red","green"))
plt.title("Others")
plt.show()
```

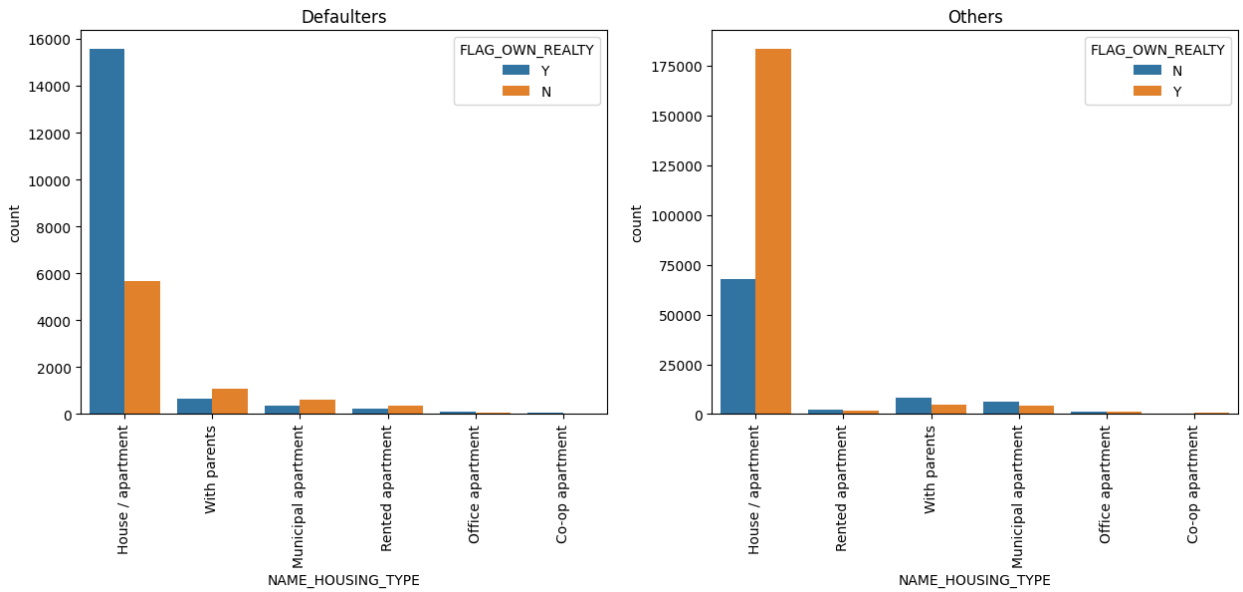



```
# Most of the applications have applied for cash loans.
# Female applicants are more than males.

#NAME_INCOME_TYPE - NAME_CONTRACT_TYPE
plt.figure(figsize=[15, 5])
plt.subplot(1,2,1)
sns.countplot(data=defaults,x="NAME_INCOME_TYPE",hue="NAME_CONTRACT_TY
PE")
plt.title("Defaulters")
plt.xticks(rotation=90)
plt.subplot(1,2,2)
sns.countplot(data=others,x="NAME_INCOME_TYPE",hue="NAME_CONTRACT_TYPE
")
plt.title("Others")
plt.xticks(rotation=90)
plt.show()
```



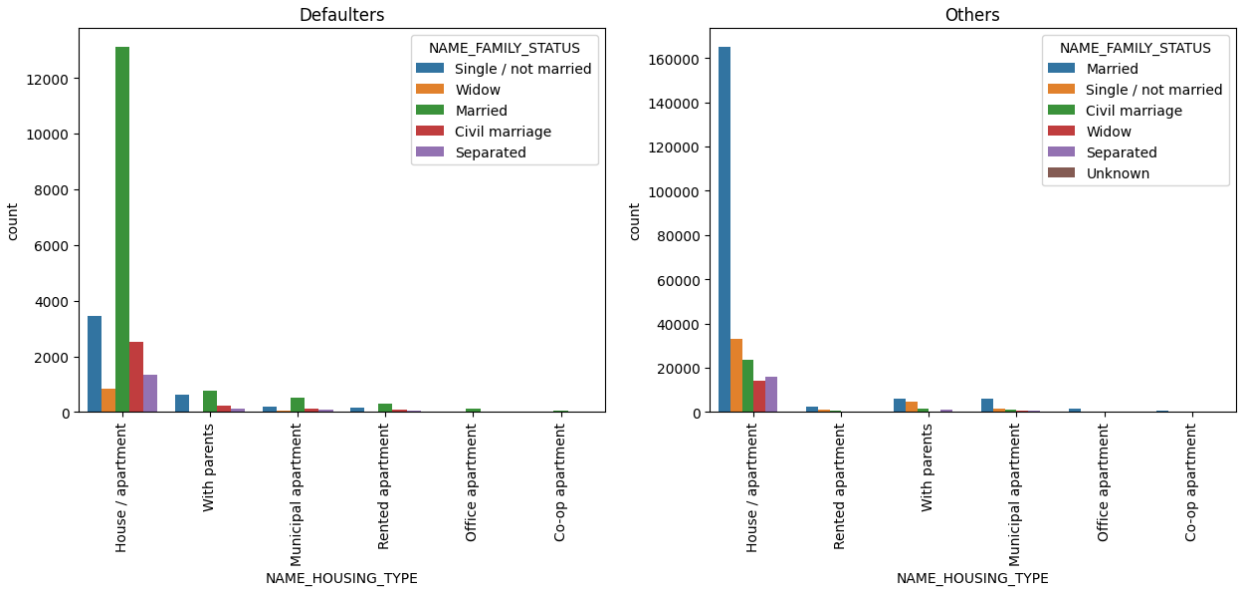
- Across income types, cash loan seems to be the popular contract type.
- Most of the people who have taken loans are working class and they have taken cash loans mostly compared to revolving loans.
- People who have taken cash loans are likely to default as well

```
# NAME_HOUSING_TYPE - FLAG_OWN_REALTY

plt.figure(figsize=[15, 5])
plt.subplot(1,2,1)
sns.countplot(data=defaults,x="NAME_HOUSING_TYPE",hue="FLAG_OWN_REALTY
")
plt.title("Defaulters")
plt.xticks(rotation=90)
plt.subplot(1,2,2)
sns.countplot(data=others,x="NAME_HOUSING_TYPE",hue="FLAG_OWN_REALTY")
plt.title("Others")
plt.xticks(rotation=90)
plt.show()
```



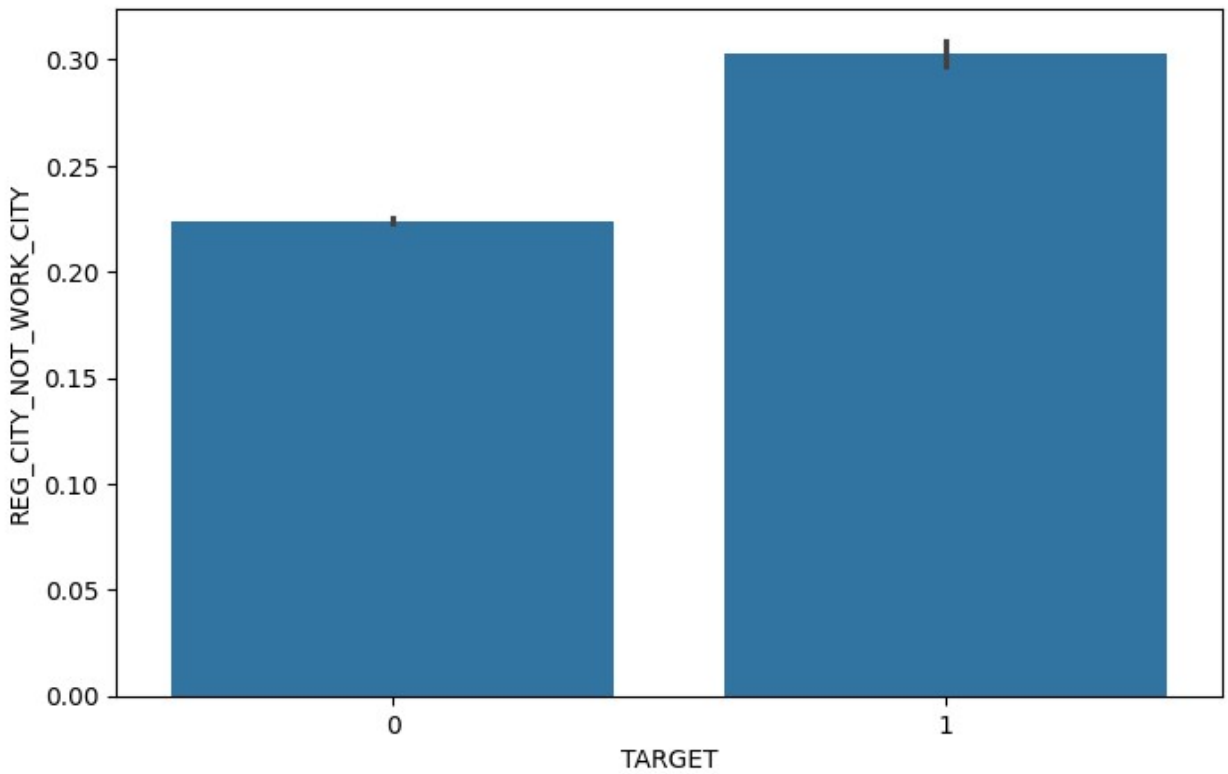
- People who own a house/flat and are staying in own property are likely to make repayments.

```
# NAME_HOUSING_TYPE - NAME_FAMILY_STATUS

plt.figure(figsize=[15, 5])
plt.subplot(1,2,1)
sns.countplot(data=defaults,x="NAME_HOUSING_TYPE",hue="NAME_FAMILY_STA
TUS")
plt.title("Defaulters")
plt.xticks(rotation=90)
plt.subplot(1,2,2)
sns.countplot(data=others,x="NAME_HOUSING_TYPE",hue="NAME_FAMILY_STATU
S",)
plt.title("Others")
plt.xticks(rotation=90)
plt.show()
```

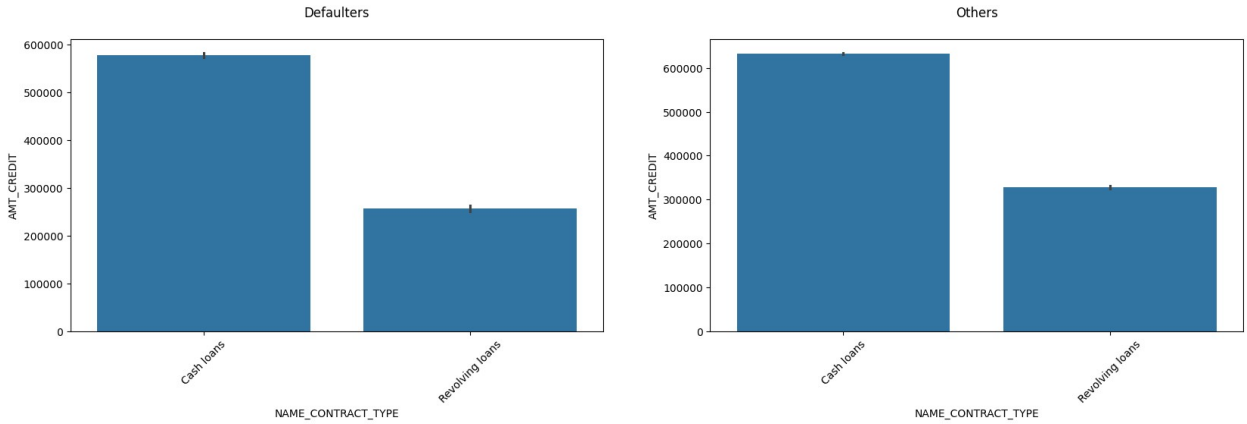


- Married loan applicants are mostly staying in house/apartment.
- Married people staying in house/apartments are the group with maximum number of loan applications.
- Single and civil marriage applicants are more likely to default.

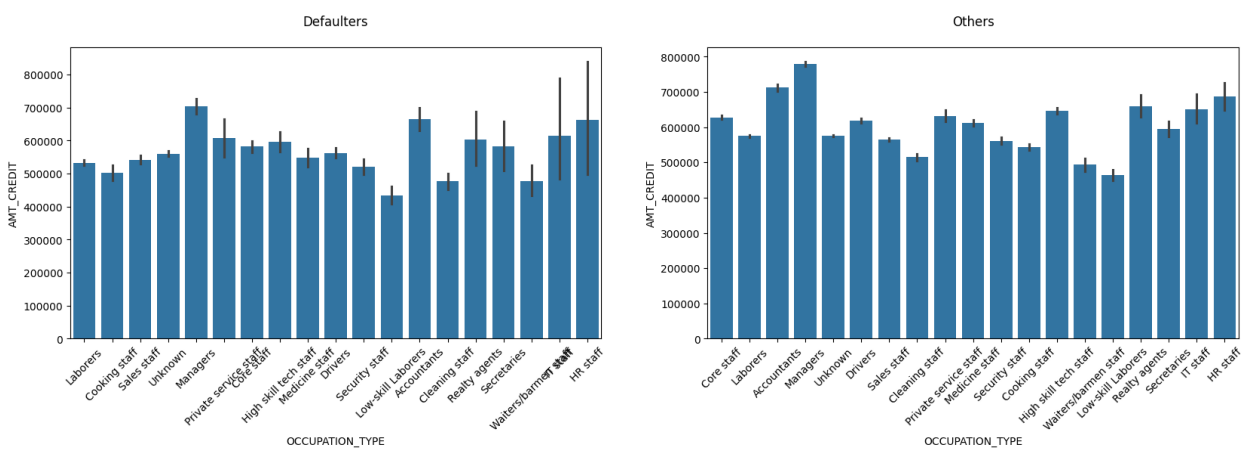
```
plt.figure(figsize=[8,5])
sns.barplot(data=df1,y='REG_CITY_NOT_WORK_CITY',x="TARGET")
plt.show()

# Number of people who have reg city differnet from their work city
has more defaulters than non defaulters.
```



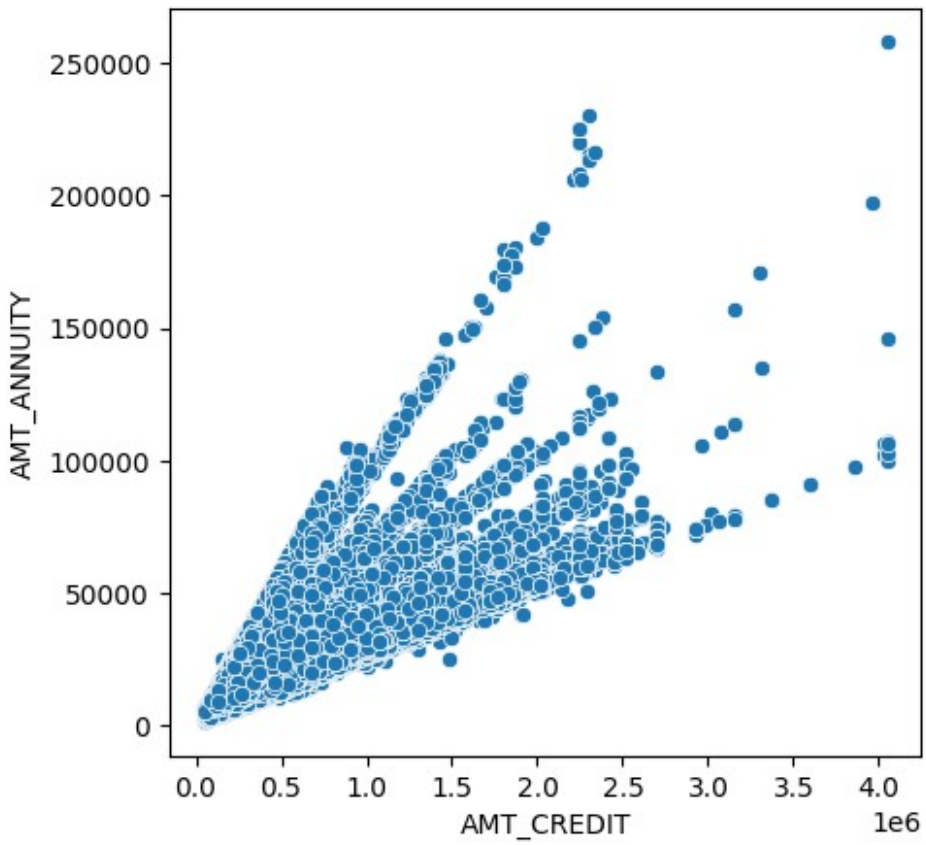

```
# NAME_CONTRACT_TYPE - AMT_CREDIT
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
plt.title('Defaulters\n')
sns.barplot(x="NAME_CONTRACT_TYPE",y="AMT_CREDIT", data=defaults)
plt.xlabel("NAME_CONTRACT_TYPE")
plt.ylabel("AMT_CREDIT")
plt.xticks(rotation=45)

plt.subplot(1,2,2)
plt.title('Others\n')
sns.barplot(x="NAME_CONTRACT_TYPE",y="AMT_CREDIT", data=others)
plt.xlabel("NAME_CONTRACT_TYPE")
plt.ylabel("AMT_CREDIT")
plt.xticks(rotation=45)
plt.show()
```



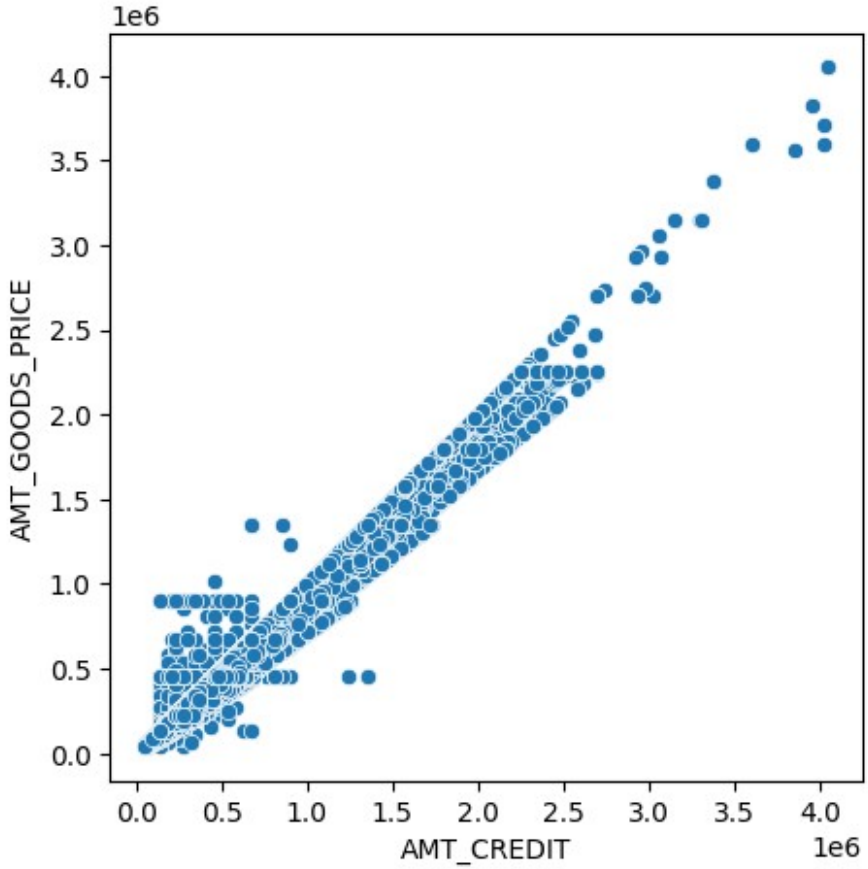

```
# Loan credit amount for cash loan is higher than that of revolving
loans.
# Cash loan is favourite among all genders.

# OCCUPATION_TYPE - AMT_CREDIT
plt.figure(figsize=(20,5))
plt.subplot(1,2,1)
plt.title('Defaulters\n')
sns.barplot(x="OCCUPATION_TYPE",y="AMT_CREDIT", data=defaults)
plt.xlabel("OCCUPATION_TYPE")
plt.ylabel("AMT_CREDIT")
plt.xticks(rotation=45)

plt.subplot(1,2,2)
plt.title('Others\n')
sns.barplot(x="OCCUPATION_TYPE",y="AMT_CREDIT", data=others)
plt.xlabel("OCCUPATION_TYPE")
plt.ylabel("AMT_CREDIT")
plt.xticks(rotation=45)
plt.show()
```



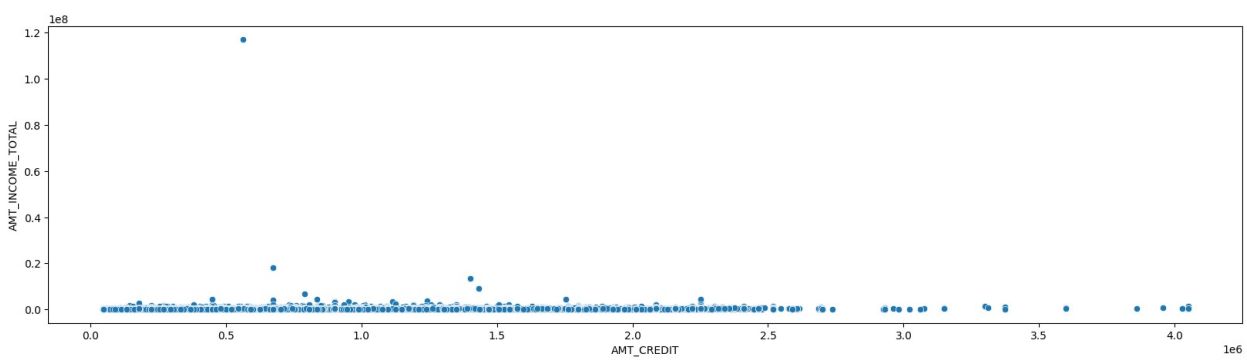
```
# Managers and Accountants have comparatively higher credit amount.
# Defaulters have high credit amount

# AMT_CREDIT-AMT_ANNUITY
sns.scatterplot(x = "AMT_CREDIT", y = "AMT_ANNUITY", data = df1)
plt.show()
```




```
# # AMT_CREDIT-AMT_GOODS_PRICE
sns.scatterplot(x = "AMT_CREDIT", y = "AMT_GOODS_PRICE", data = df1)
plt.show()
# AMT_CREDIT-AMT_GOODS_PRICE
```

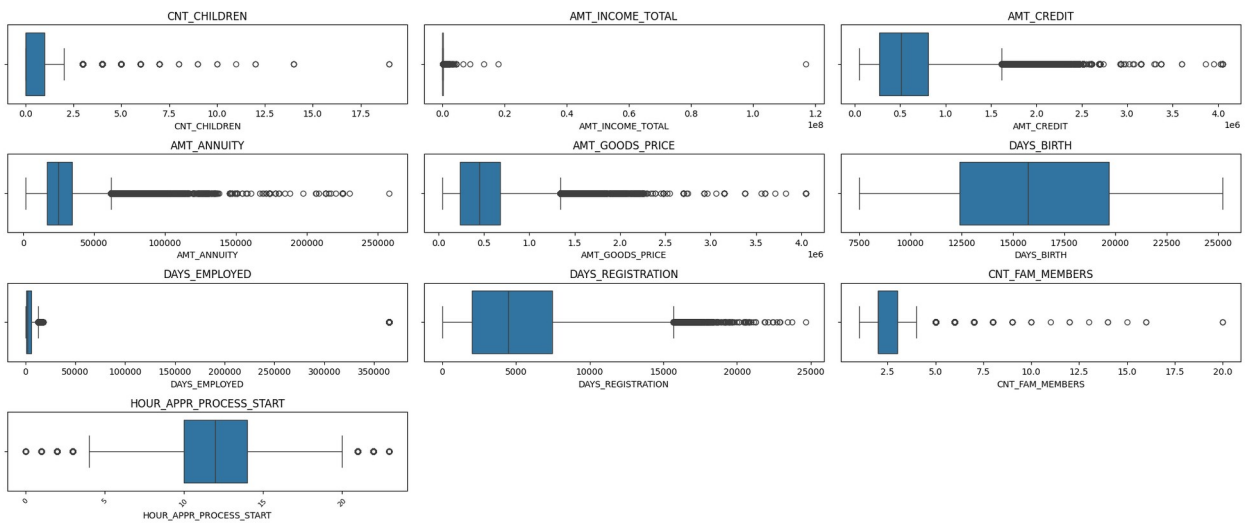



```
# # AMT_CREDIT-AMT_GOODS_PRICE
plt.figure(figsize=(20,5))
sns.scatterplot(x = "AMT_CREDIT", y = "AMT_INCOME_TOTAL", data = df1)
plt.show()
# AMT_CREDIT and AMT_INCOME_TOTAL does not seem to be correlated.
```




```
cols=['CNT_CHILDREN','AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AM
T_GOODS_PRICE','DAYS_BIRTH',

'DAYS_EMPLOYED','DAYS_REGISTRATION','CNT_FAM_MEMBERS','HOUR_APPR_PROCE
SS_START']
```

```
plt.figure(figsize=(20,10))
j = 1
for i in cols:
  plt.subplot(5, 3, j)
  sns.boxplot(x=df1.loc[:, i])
  plt.title(i)
  j += 1

plt.xticks(rotation=45, fontsize=8)
plt.tight_layout()
plt.show()

# All numerical columns are having outliers which might need
treatement
```




```
corr_df1 =
defaults[['AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AMT_GOODS_PRI
CE','DAYS_BIRTH','DAYS_EMPLOYED','CNT_CHILDREN']].corr()
corr_df1
```


```
{"summary":"{\n  \"name\": \"corr_df1\",\n  \"rows\": 7,\n
\"fields\": [\n  {\n  \"column\": \"AMT_INCOME_TOTAL\",\n
\"properties\": {\n  \"dtype\": \"number\",\n  \"std\":
0.37184769035509635,\n  \"min\": -0.014977396491471881,\n
\"max\": 1.0,\n  \"num_unique_values\": 7,\n  \"samples\":
[\n  1.0,\n  0.03813143463007386,\n  -
0.014977396491471881\n  ],\n  \"semantic_type\": \"\",\n
\"description\": \"\"\n  }\n  },\n  {\n  \"column\":
\"AMT_CREDIT\",\n  \"properties\": {\n  \"dtype\":
\"number\",\n  \"std\": 0.47307483573834835,\n  \"min\": -
0.0016749611094153205,\n  \"max\": 1.0,\n
\"num_unique_values\": 7,\n  \"samples\": [\n
0.03813143463007386,\n  1.0,\n  0.0019301832548641012\
```

n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_ANNUITY\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4542177710284441,\n   \"min\": -
0.08120712012550896,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n
0.046421056510901545,\n   0.7521947353758889,\n   -
0.08120712012550896\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_GOODS_PRICE\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.47338669530151983,\n   \"min\": -
0.008110740552729026,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n
0.03759087313053715,\n   0.9827833228776286,\n
0.006647516021066061\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_BIRTH\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.42325480146307637,\n   \"min\": -
0.259108666117443,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n   -
0.0030962446816019847,\n   0.13531636902889027,\n
0.5821851479036093\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_EMPLOYED\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4360689987181553,\n   \"min\": -
0.192863828031626,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n   -
0.014977396491471881,\n   0.0019301832548641012,\n
1.0\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"CNT_CHILDREN\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4199773820777796,\n   \"min\": -
0.259108666117443,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n
0.00479578732616832,\n   -0.0016749611094153205,\n   -
0.192863828031626\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   }\n]\
n}","type":"dataframe","variable_name":"corr_df1"}

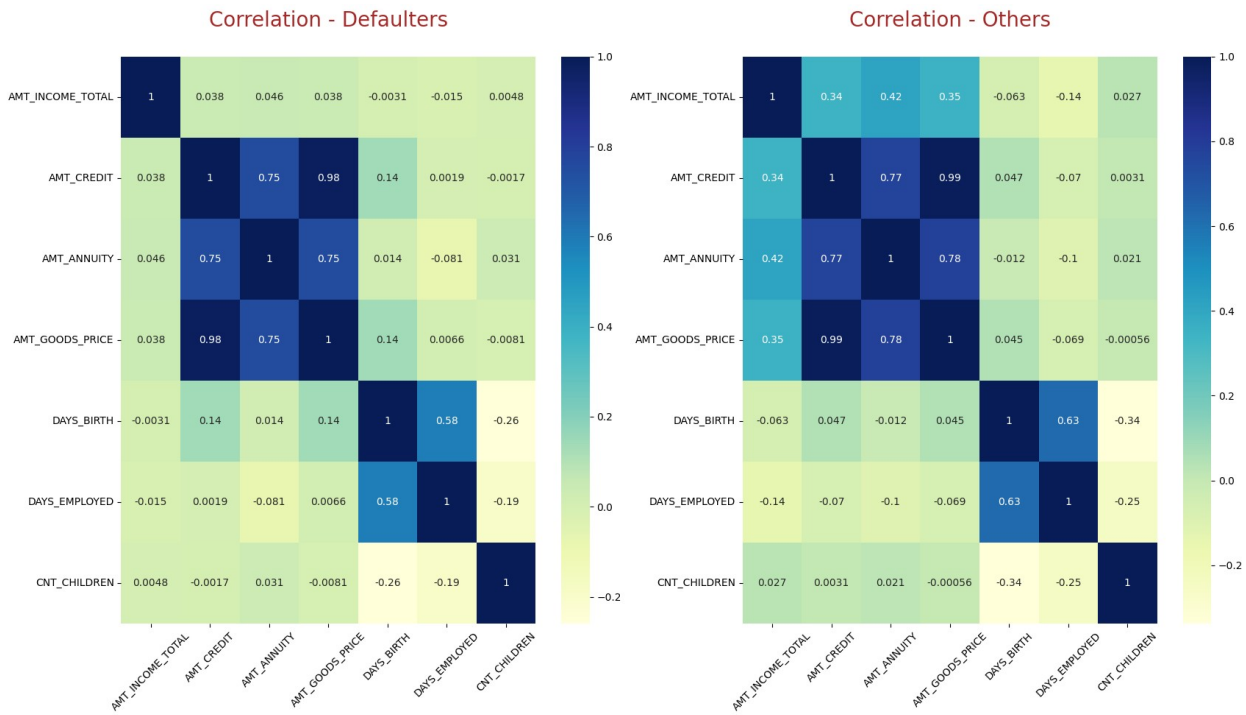
```
corr_df0 =
others[['AMT_INCOME_TOTAL','AMT_CREDIT','AMT_ANNUITY','AMT_GOODS_PRICE
','DAYS_BIRTH','DAYS_EMPLOYED','CNT_CHILDREN']].corr()
corr_df0
```

{"summary":"{\n \"name\": \"corr_df0\",\n \"rows\": 7,\n
\"fields\": [\n   {\n   \"column\": \"AMT_INCOME_TOTAL\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
0.388223325280255,\n   \"min\": -0.1403924655915397,\n
\"max\": 1.0,\n   \"num_unique_values\": 7,\n   \"samples\":
[\n   1.0,\n   0.3427994498748986,\n   -

0.1403924655915397\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_CREDIT\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.472104229635207,\n   \"min\": -
0.07010431389260673,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n
0.3427994498748986,\n   1.0,\n   -0.07010431389260673\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"AMT_ANNUITY\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
0.44867848298642565,\n   \"min\": -0.10497471490015325,\n
\"max\": 1.0,\n   \"num_unique_values\": 7,\n   \"samples\":
[\n   0.4189480860003718,\n   0.7712969450810268,\n
-0.10497471490015325\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"AMT_GOODS_PRICE\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4731452829781594,\n   \"min\": -
0.06852725590409603,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n
0.3494261146119611,\n   0.987021502499697,\n   -
0.06852725590409603\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_BIRTH\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4600900478792162,\n   \"min\": -
0.3369664839606809,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n   -
0.06260915814078147,\n   0.04737783126515827,\n
0.6261138779530819\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"DAYS_EMPLOYED\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.47442680282121086,\n   \"min\": -
0.24517406473567363,\n   \"max\": 1.0,\n
\"num_unique_values\": 7,\n   \"samples\": [\n   -
0.1403924655915397,\n   -0.07010431389260673,\n   1.0\n
],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n
}\n   },\n   {\n   \"column\": \"CNT_CHILDREN\",\n
\"properties\": {\n   \"dtype\": \"number\",\n   \"std\":
0.4365533752471343,\n   \"min\": -0.3369664839606809,\n
\"max\": 1.0,\n   \"num_unique_values\": 7,\n   \"samples\":
[\n   0.027397187930142647,\n   0.0030812246529976295,\n
-0.24517406473567363\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   }\n]\
n}","type":"dataframe","variable_name":"corr_df0"}

```
# Plot correlation heatmap for numerical variables

plt.figure(figsize=[20,10])

plt.subplot(1,2,1)
sns.heatmap(corr_df1, cmap="YlGnBu", annot = True)
```

```
plt.title('Correlation - Defaulters\n', fontdict={'fontsize': 20,
'fontweight' : 5, 'color' : 'Brown'})
plt.xticks(rotation=45)

plt.subplot(1,2,2)
sns.heatmap(corr_df0, cmap="YlGnBu", annot = True)
plt.title('Correlation - Others\n', fontdict={'fontsize': 20,
'fontweight' : 5, 'color' : 'Brown'})
plt.xticks(rotation=45)

plt.show()
```




```
 # AMT_CREDIT is strongly correlated to AMT_ANNUITY and
AMT_GOODS_PRICE in both cases
```

Statistical test

```
import statistics
from scipy import stats
from statsmodels.stats import weightstats as stests
from scipy.stats import shapiro
from statsmodels.stats import power

df1['TARGET']=df1['TARGET'].astype('O')

df1.drop(columns=['TARGET','AMT_ANNUITY','AMT_GOODS_PRICE','CNT_FAM_ME
MBERS','AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_R
```

```
EQ_CREDIT_BUREAU_WEEK','AMT_REQ_CREDIT_BUREAU_MON','AMT_REQ_CREDIT_BUR
EAU_QRT','AMT_REQ_CREDIT_BUREAU_YEAR']).select_dtypes(exclude=np.numbe
r).dtypes
```

```
NAME_CONTRACT_TYPE              object
CODE_GENDER                     object
FLAG_OWN_CAR                    object
FLAG_OWN_REALTY                 object
NAME_TYPE_SUITE                 object
NAME_INCOME_TYPE                object
NAME_EDUCATION_TYPE             object
NAME_FAMILY_STATUS              object
NAME_HOUSING_TYPE               object
OCCUPATION_TYPE                 object
WEEKDAY_APPR_PROCESS_START      object
ORGANIZATION_TYPE               object
INCOME_GROUP                  category
dtype: object
```

```
for i in df1.select_dtypes(exclude=np.number):
    a=pd.crosstab(df1[i],df1["TARGET"])
    print(i,":",stats.chi2_contingency(a))
# Null Hypothesis (H₀): The variables are independent (no association
between them).
# Alternative Hypothesis (H₁): The variables are not independent
(there is an association between them).
# his is the p-value associated with the test. Since this p-value is
extremely small (much smaller than a typical significance level like
0.05),
#you would reject the null hypothesis, indicating that the variables
are not independent, meaning there is a significant association
between them.
```

```
TARGET : Chi2ContingencyResult(statistic=307497.52517928014,
pvalue=0.0, dof=1, expected_freq=array([[259865.09294302,
22820.90705698],
       [ 22820.90705698,   2004.09294302]]))
NAME_CONTRACT_TYPE :
Chi2ContingencyResult(statistic=293.15054219964554,
pvalue=1.0235150721172847e-65, dof=1,
expected_freq=array([[255770.65910488,  22461.34089512],
       [ 26915.34089512,   2363.65910488]]))
CODE_GENDER : Chi2ContingencyResult(statistic=920.1038473528081,
pvalue=4.183493188620687e-202, dof=1,
expected_freq=array([[186108.28904332,  16343.71095668],
       [ 96577.71095668,   8481.28904332]]))
FLAG_OWN_CAR : Chi2ContingencyResult(statistic=146.65601825576024,
pvalue=9.330994431109667e-34, dof=1,
expected_freq=array([[186542.18504054,  16381.81495946],
       [ 96143.81495946,   8443.18504054]]))
```

```
FLAG_OWN_REALTY : Chi2ContingencyResult(statistic=11.57582729808418,
pvalue=0.0006681470317545887, dof=1,
expected_freq=array([[ 86594.42593598,   7604.57406402],
       [196091.57406402,  17220.42593598]]))
NAME_TYPE_SUITE : Chi2ContingencyResult(statistic=31.947946557874488,
pvalue=1.669680344640335e-05, dof=6,
expected_freq=array([[3.00325895e+03, 2.63741053e+02],
       [3.69078186e+04, 3.24118137e+03],
       [2.49122490e+02, 2.18775101e+01],
       [7.96088842e+02, 6.99111576e+01],
       [1.62710999e+03, 1.42890010e+02],
       [1.04521133e+04, 9.17886677e+02],
       [2.29650488e+05, 2.01675122e+04]]))
NAME_INCOME_TYPE : Chi2ContingencyResult(statistic=1253.4708080924986,
pvalue=1.9281456056861122e-266, dof=7,
expected_freq=array([[9.19271181e+00, 8.07288195e-01],
       [6.58354441e+04, 5.78155586e+03],
       [4.59635590e+00, 4.03644097e-01],
       [5.08926911e+04, 4.46930890e+03],
       [1.99509424e+04, 1.75205757e+03],
       [1.65468812e+01, 1.45311875e+00],
       [2.02239660e+01, 1.77603403e+00],
       [1.45956362e+05, 1.28176376e+04]]))
NAME_EDUCATION_TYPE :
Chi2ContingencyResult(statistic=1019.2131873088356,
pvalue=2.4476812052198174e-219, dof=4,
expected_freq=array([[1.50760474e+02, 1.32395264e+01],
       [6.88193984e+04, 6.04360161e+03],
       [9.44734992e+03, 8.29650078e+02],
       [3.50793882e+03, 3.08061175e+02],
       [2.00760552e+05, 1.76304476e+04]]))
NAME_FAMILY_STATUS :
Chi2ContingencyResult(statistic=504.6940825563211,
pvalue=7.744841561414037e-107, dof=5,
expected_freq=array([[2.73712994e+04, 2.40370060e+03],
       [1.80574277e+05, 1.58577235e+04],
       [1.81739912e+04, 1.59600876e+03],
       [4.17753595e+04, 3.66864047e+03],
       [1.83854236e+00, 1.61457639e-01],
       [1.47892348e+04, 1.29876525e+03]]))
NAME_HOUSING_TYPE :
Chi2ContingencyResult(statistic=420.55618983894664,
pvalue=1.0990890032617707e-88, dof=5,
expected_freq=array([[1.03142226e+03, 9.05777354e+01],
       [2.50839688e+05, 2.20283115e+04],
       [1.02802096e+04, 9.02790388e+02],
       [2.40573268e+03, 2.11267321e+02],
       [4.48696263e+03, 3.94037368e+02],
       [1.36419843e+04, 1.19801568e+03]]))
```

```
OCCUPATION_TYPE : Chi2ContingencyResult(statistic=1975.0827518430256,
pvalue=0.0, dof=18, expected_freq=array([[9.02080809e+03,
7.92191905e+02],
       [4.27736880e+03, 3.75631197e+02],
       [5.46598644e+03, 4.80013560e+02],
       [2.53443064e+04, 2.22569355e+03],
       [1.71012018e+04, 1.50179823e+03],
       [5.17549675e+02, 4.54503254e+01],
       [1.04613060e+04, 9.18693965e+02],
       [4.83536641e+02, 4.24633590e+01],
       [5.07308994e+04, 4.45510063e+03],
       [1.92403458e+03, 1.68965419e+02],
       [1.96457444e+04, 1.72525560e+03],
       [7.84781807e+03, 6.89181932e+02],
       [2.43790717e+03, 2.14092829e+02],
       [6.90372657e+02, 6.06273434e+01],
       [2.95104434e+04, 2.59155656e+03],
       [1.19964889e+03, 1.05351109e+02],
       [6.17842160e+03, 5.42578396e+02],
       [8.86094684e+04, 7.78153164e+03],
       [1.23917755e+03, 1.08822449e+02]]))
WEEKDAY_APPR_PROCESS_START :
Chi2ContingencyResult(statistic=15.387556913044653,
pvalue=0.01744736931389504, dof=6,
expected_freq=array([[46274.27268618,  4063.72731382],
       [46619.91865006,  4094.08134994],
       [31119.16800375,  2732.83199625],
       [14874.72697237,  1306.27302763],
       [46506.84829486,  4084.15170514],
       [49549.63590246,  4351.36409754],
       [47741.42949033,  4192.57050967]]))
ORGANIZATION_TYPE :
Chi2ContingencyResult(statistic=1609.2406359645206,
pvalue=5.224541090300172e-299, dof=57,
expected_freq=array([[3.94367336e+02, 3.46326635e+01],
       [2.25589148e+03, 1.98108523e+02],
       [2.30461285e+03, 2.02387150e+02],
       [5.50091874e+03, 4.83081256e+02],
       [9.70106877e+03, 8.51931232e+02],
       [6.25030861e+04, 5.48891389e+03],
       [2.39010507e+02, 2.09894931e+01],
       [6.17842160e+03, 5.42578396e+02],
       [3.48403777e+02, 3.05962226e+01],
       [8.73307622e+02, 7.66923785e+01],
       [5.14791861e+02, 4.52081389e+01],
       [9.56409736e+03, 8.39902638e+02],
       [8.88015960e+02, 7.79840396e+01],
       [2.71920415e+03, 2.38795848e+02],
       [9.55122757e+02, 8.38772434e+01],
```

```
       [1.00200559e+02, 8.79944132e+00],
       [2.48570927e+03, 2.18290728e+02],
       [3.39211066e+02, 2.97889344e+01],
       [6.15911691e+01, 5.40883090e+00],
       [4.21026201e+02, 3.69737993e+01],
       [3.01337093e+03, 2.64629070e+02],
       [8.06200825e+02, 7.07991747e+01],
       [5.50643437e+02, 4.83565629e+01],
       [1.02958372e+02, 9.04162778e+00],
       [1.20148743e+03, 1.05512567e+02],
       [2.20625083e+01, 1.93749167e+00],
       [3.09610534e+03, 2.71894664e+02],
       [5.48804895e+02, 4.81951052e+01],
       [6.32458572e+03, 5.55414278e+02],
       [2.80377710e+02, 2.46222899e+01],
       [1.02894023e+04, 9.03597676e+02],
       [2.42136029e+03, 2.12639710e+02],
       [2.91408964e+02, 2.55910358e+01],
       [1.53362011e+04, 1.34679889e+03],
       [2.15201383e+03, 1.88986166e+02],
       [1.98286794e+03, 1.74132064e+02],
       [3.64031387e+02, 3.19686125e+01],
       [7.81380503e+01, 6.86194965e+00],
       [1.66480011e+03, 1.46199892e+02],
       [8.17507861e+03, 7.17921391e+02],
       [2.98487352e+03, 2.62126477e+02],
       [1.81464131e+03, 1.59358690e+02],
       [3.53110446e+04, 3.10095541e+03],
       [1.44785211e+03, 1.27147891e+02],
       [5.30419471e+02, 4.65805288e+01],
       [3.19906371e+02, 2.80936292e+01],
       [1.74661524e+03, 1.53384757e+02],
       [3.21009496e+03, 2.81905038e+02],
       [5.88333556e+01, 5.16664445e+00],
       [4.50442878e+01, 3.95571215e+00],
       [5.80060115e+02, 5.09398851e+01],
       [7.19881261e+03, 6.32187385e+02],
       [1.84773507e+02, 1.62264927e+01],
       [2.02607368e+03, 1.77926318e+02],
       [1.09117489e+03, 9.58251087e+01],
       [4.96222583e+03, 4.35774167e+02],
       [1.21987286e+03, 1.07127143e+02],
       [5.09037224e+04, 4.47027765e+03]]))
INCOME_GROUP : Chi2ContingencyResult(statistic=165.27574873290746,
pvalue=4.5150776508532995e-33, dof=6,
expected_freq=array([[5.85559261e+04, 5.14207392e+03],
       [1.43313005e+05, 1.25849955e+04],
       [7.83341098e+04, 6.87889016e+03],
       [2.25406026e+03, 1.97939735e+02],
       [1.89370479e+02, 1.66295210e+01],
```

```
       [3.58516926e+01, 3.14830737e+00],
       [3.67709668e+00, 3.22903320e-01]]))
```

```
from scipy.stats import shapiro
col=["AMT_INCOME_TOTAL","AMT_CREDIT","AMT_ANNUITY","AMT_GOODS_PRICE","
REGION_POPULATION_RELATIVE","DAYS_BIRTH",

"DAYS_EMPLOYED","DAYS_REGISTRATION","DAYS_ID_PUBLISH","REGION_RATING_C
LIENT",
     "REGION_RATING_CLIENT_W_CITY",   "HOUR_APPR_PROCESS_START",
     "EXT_SOURCE_2", "EXT_SOURCE_3",

"OBS_30_CNT_SOCIAL_CIRCLE","DEF_30_CNT_SOCIAL_CIRCLE","OBS_60_CNT_SOCI
AL_CIRCLE","DEF_60_CNT_SOCIAL_CIRCLE","DAYS_LAST_PHONE_CHANGE","AMT_RE
Q_CREDIT_BUREAU_YEAR"]
for i in col:
    g1=df1[df1["TARGET"]==1][i]
    g2=df1[df1["TARGET"]==0][i]
    print(i,stats.shapiro(g1),stats.shapiro(g2))
```

```
AMT_INCOME_TOTAL ShapiroResult(statistic=0.01677782971852504,
pvalue=6.662375322133307e-142)
ShapiroResult(statistic=0.6192600058599327, pvalue=2.347277203672878e-
177)
AMT_CREDIT ShapiroResult(statistic=0.9049141805327058,
pvalue=2.5634663814507962e-80)
ShapiroResult(statistic=0.906051406373492, pvalue=6.906539376853772e-
132)
AMT_ANNUITY ShapiroResult(statistic=0.950335616967387,
pvalue=2.4323014446805237e-66)
ShapiroResult(statistic=0.9103069513528247, pvalue=1.694215084066444e-
130)
AMT_GOODS_PRICE ShapiroResult(statistic=0.8820380162995517,
pvalue=2.931472402851972e-85)
ShapiroResult(statistic=0.8903838302919731,
pvalue=1.4503528520418792e-136)
REGION_POPULATION_RELATIVE ShapiroResult(statistic=0.8964173270912867,
pvalue=2.916808606630239e-82)
ShapiroResult(statistic=0.8760926768509598,
pvalue=2.4311089073991435e-140)
DAYS_BIRTH ShapiroResult(statistic=0.962374384665713,
pvalue=8.769366684236648e-61)
ShapiroResult(statistic=0.970101969383913, pvalue=9.548528103092476e-
100)
DAYS_EMPLOYED ShapiroResult(statistic=0.3907498014316627,
pvalue=7.651324535820128e-128)
ShapiroResult(statistic=0.4846139205864164, pvalue=4.326184382825252e-
188)
DAYS_REGISTRATION ShapiroResult(statistic=0.9456712868471129,
pvalue=3.4332256903263684e-68)
```

```
ShapiroResult(statistic=0.954175613281937, pvalue=3.351416663784814e-
111)
DAYS_ID_PUBLISH ShapiroResult(statistic=0.950711109801341,
pvalue=3.4774291383025534e-66)
ShapiroResult(statistic=0.9400183640778638, pvalue=9.504077743523667e-
119)
REGION_RATING_CLIENT ShapiroResult(statistic=0.6788179937173893,
pvalue=3.3806580768183284e-110)
ShapiroResult(statistic=0.686589838733871, pvalue=1.2622882328752519e-
170)
REGION_RATING_CLIENT_W_CITY
ShapiroResult(statistic=0.6740554011890485,
pvalue=1.3748551665575398e-110)
ShapiroResult(statistic=0.6800208116685726, pvalue=2.454710404469502e-
171)
HOUR_APPR_PROCESS_START ShapiroResult(statistic=0.9905443883531981,
pvalue=7.58019364975599e-37)
ShapiroResult(statistic=0.9887943911134505, pvalue=8.036296612176762e-
76)
EXT_SOURCE_2 ShapiroResult(statistic=0.953531729416534,
pvalue=5.4992940033749706e-65)
ShapiroResult(statistic=0.924782746956069, pvalue=2.7404932678457945e-
125)
EXT_SOURCE_3 ShapiroResult(statistic=0.9594879026265539,
pvalue=3.0743180895246348e-62)
ShapiroResult(statistic=0.9654503866927961,
pvalue=1.4857157720665516e-103)
OBS_30_CNT_SOCIAL_CIRCLE ShapiroResult(statistic=0.6784973279135061,
pvalue=3.1807772678083075e-110)
ShapiroResult(statistic=0.6177332695759722,
pvalue=1.7012679345230269e-177)
DEF_30_CNT_SOCIAL_CIRCLE ShapiroResult(statistic=0.41911427937352796,
pvalue=1.7521283116663653e-126)
ShapiroResult(statistic=0.3484517290518495,
pvalue=1.2772492041897993e-196)
OBS_60_CNT_SOCIAL_CIRCLE ShapiroResult(statistic=0.6772679272460036,
pvalue=2.5192534166018172e-110)
ShapiroResult(statistic=0.6164521245406203, pvalue=1.299736741123094e-
177)
DEF_60_CNT_SOCIAL_CIRCLE ShapiroResult(statistic=0.3588685602754883,
pvalue=2.6347662340004317e-129)
ShapiroResult(statistic=0.2910433683585099 7,
pvalue=9.706134089914555e-200)
DAYS_LAST_PHONE_CHANGE ShapiroResult(statistic=0.8960402174221515,
pvalue=2.40904978549676e-82)
ShapiroResult(statistic=0.9246218506064995, pvalue=2.372675591912799e-
125)
AMT_REQ_CREDIT_BUREAU_YEAR ShapiroResult(statistic=0.8346970869311088,
pvalue=2.6911989352416408e-93)
```

```
ShapiroResult(statistic=0.8377357208383164,
pvalue=7.8145700166249495e-149)
```

```python
# Given the p-value is extraordinarily small,
# you would reject the null hypothesis at any reasonable significance
level (e.g., 0.05, 0.01).
# This means there is strong evidence that the two groups do not come
from the same distribution, suggesting that there is a
# statistically significant difference between the two groups you
compared.

from scipy.stats import mannwhitneyu
for i in
df1[["AMT_CREDIT","AMT_ANNUITY","AMT_GOODS_PRICE","REGION_POPULATION_R
ELATIVE","DAYS_BIRTH","DAYS_EMPLOYED","DAYS_REGISTRATION","DAYS_ID_PUB
LISH","REGION_RATING_CLIENT",
     "REGION_RATING_CLIENT_W_CITY",   "HOUR_APPR_PROCESS_START",
      "EXT_SOURCE_2", "EXT_SOURCE_3",
"OBS_30_CNT_SOCIAL_CIRCLE","DEF_30_CNT_SOCIAL_CIRCLE","OBS_60_CNT_SOCI
AL_CIRCLE","DEF_60_CNT_SOCIAL_CIRCLE","DAYS_LAST_PHONE_CHANGE","AMT_RE
Q_CREDIT_BUREAU_YEAR"]]:
    g1=df1[df1["TARGET"]==1][i]
    g2=df1[df1["TARGET"]==0][i]
    stat, p_value = mannwhitneyu(g1, g2)
    print(i,"stats:",stat,"p_value:",p_value)
```

```
AMT_CREDIT stats: 3378434520.0 p_value: 2.36018881652632e-22
AMT_ANNUITY stats: 3508297762.0 p_value: 0.9677479203683577
AMT_GOODS_PRICE stats: 3274917364.5 p_value: 2.821334043506046e-68
REGION_POPULATION_RELATIVE stats: 3281647585.5 p_value:
1.9999665809732712e-64
DAYS_BIRTH stats: 2926354691.5 p_value: 0.0
DAYS_EMPLOYED stats: 2866924137.5 p_value: 0.0
DAYS_REGISTRATION stats: 3210111966.0 p_value: 6.304065912692224e-110
DAYS_ID_PUBLISH stats: 3118165526.0 p_value: 1.3917745563748238e-186
REGION_RATING_CLIENT stats: 3846132118.5 p_value: 4.555791548665177e-
234
REGION_RATING_CLIENT_W_CITY stats: 3853982907.5 p_value:
2.6798603110992284e-250
HOUR_APPR_PROCESS_START stats: 3339172571.5 p_value:
5.433090599121058e-37
EXT_SOURCE_2 stats: 2414683836.5 p_value: 0.0
EXT_SOURCE_3 stats: 2460886559.0 p_value: 0.0
OBS_30_CNT_SOCIAL_CIRCLE stats: 3575901262.0 p_value:
4.896756666134539e-08
DEF_30_CNT_SOCIAL_CIRCLE stats: 3641655396.5 p_value:
5.093631155153175e-72
OBS_60_CNT_SOCIAL_CIRCLE stats: 3574774897.0 p_value:
7.863423087584917e-08
DEF_60_CNT_SOCIAL_CIRCLE stats: 3619686965.5 p_value:
```

```
2.064553521295198e-66
DAYS_LAST_PHONE_CHANGE stats: 3109788371.0 p_value:
6.183497950494181e-195
AMT_REQ_CREDIT_BUREAU_YEAR stats: 3603082793.0 p_value:
4.3996169061348015e-13
```

```
# H₀: The two groups come from the same distribution (or have the same
median).
# H₁: The two groups come from different distributions (or have
different medians).
 #The p-value is extremely small (essentially 0 when considering
typical significance levels, like 0.05).
#This means that the result is statistically significant, and you can
reject the null hypothesis,
#which usually states that there is no difference between the two
groups.
```

```
df_p = pd.read_csv('/content/drive/MyDrive/Colab
Notebooks/previous_application.csv')
```

```
df_p.shape
```

```
(1670214, 37)
```

```
df_p.describe().T
```


```
{"summary":"{\n  \"name\": \"df_p\",\n  \"rows\": 21,\n  \"fields\":
[\n    {\n      \"column\": \"count\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 512237.10644422047,\n
\"min\": 5951.0,\n        \"max\": 1670214.0,\n
\"num_unique_values\": 8,\n        \"samples\": [\n
1297979.0,\n          5951.0,\n          1670214.0\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"mean\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 417552.0186896905,\n
\"min\": -880.6796679946402,\n        \"max\": 1923089.1353305625,\n
\"num_unique_values\": 21,\n        \"samples\": [\n
1923089.1353305625,\n          33767.77405382746,\n
342209.85503871535\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    },\n    {\n      \"column\":
\"std\",\n      \"properties\": {\n        \"dtype\": \"number\",\n
\"std\": 146016.87868102104,\n        \"min\": 0.05932963128712511,\n
\"max\": 532597.9586955433,\n        \"num_unique_values\": 21,\n
\"samples\": [\n          532597.9586955433,\n
106857.03478910643,\n          88916.11583368349\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"min\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 218429.7507997795,\n
\"min\": -2922.0,\n        \"max\": 1000001.0,\n
\"num_unique_values\": 13,\n        \"samples\": [\n          -
2889.0,\n          -2892.0,\n          1000001.0\n        ],\n
```

\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"25%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 323874.28943008685,\n   \"min\": -1628.0,\n   \"max\": 1461857.25,\n   \"num_unique_values\": 19,\n   \"samples\": [\n   1461857.25,\n   0.0,\n   -1300.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"50%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 421268.92450452177,\n   \"min\": -831.0,\n   \"max\": 1923110.5,\n   \"num_unique_values\": 20,\n   \"samples\": [\n   1923110.5,\n   -537.0,\n   -831.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"75%\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 520049.5579420275,\n   \"min\": -411.0,\n   \"max\": 2384279.75,\n   \"num_unique_values\": 20,\n   \"samples\": [\n   2384279.75,\n   129.0,\n   365243.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   },\n   {\n   \"column\": \"max\",\n   \"properties\": {\n   \"dtype\": \"number\",\n   \"std\": 2496808.87949573,\n   \"min\": -1.0,\n   \"max\": 6905160.0,\n   \"num_unique_values\": 11,\n   \"samples\": [\n   23.0,\n   2845382.0,\n   84.0\n   ],\n   \"semantic_type\": \"\",\n   \"description\": \"\"\n   }\n   }\n]\n}","type":"dataframe"}

```
df_null=(df_p.isnull().sum()/
df_p.shape[0]*100).reset_index().sort_values(by=0,ascending=False)
```

```
df_null=df_null[df_null[0]>40].set_index("index")
```

```
df_null.index
```

```
Index(['RATE_INTEREST_PRIVILEGED', 'RATE_INTEREST_PRIMARY',
'AMT_DOWN_PAYMENT',
       'RATE_DOWN_PAYMENT', 'NAME_TYPE_SUITE',
'NFLAG_INSURED_ON_APPROVAL',
       'DAYS_TERMINATION', 'DAYS_LAST_DUE',
'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_FIRST_DUE', 'DAYS_FIRST_DRAWING'],
      dtype='object', name='index')
```

```
col_with_40=['RATE_INTEREST_PRIVILEGED', 'RATE_INTEREST_PRIMARY',
'AMT_DOWN_PAYMENT',
       'RATE_DOWN_PAYMENT', 'NAME_TYPE_SUITE',
'NFLAG_INSURED_ON_APPROVAL',
       'DAYS_TERMINATION', 'DAYS_LAST_DUE',
'DAYS_LAST_DUE_1ST_VERSION',
       'DAYS_FIRST_DUE', 'DAYS_FIRST_DRAWING']
```

```
for i in col_with_40:
  df_p.drop(columns=i,inplace=True)
```

```
df_p.shape
```

```
(1670214, 26)
```

```
df_p.isnull().sum()/df_p.shape[0]*100
```

```
SK_ID_PREV                      0.000000
SK_ID_CURR                      0.000000
NAME_CONTRACT_TYPE              0.000000
AMT_ANNUITY                    22.286665
AMT_APPLICATION                 0.000000
AMT_CREDIT                      0.000060
AMT_GOODS_PRICE                23.081773
WEEKDAY_APPR_PROCESS_START      0.000000
HOUR_APPR_PROCESS_START         0.000000
FLAG_LAST_APPL_PER_CONTRACT     0.000000
NFLAG_LAST_APPL_IN_DAY          0.000000
NAME_CASH_LOAN_PURPOSE          0.000000
NAME_CONTRACT_STATUS            0.000000
DAYS_DECISION                   0.000000
NAME_PAYMENT_TYPE               0.000000
CODE_REJECT_REASON              0.000000
NAME_CLIENT_TYPE                0.000000
NAME_GOODS_CATEGORY             0.000000
NAME_PORTFOLIO                  0.000000
NAME_PRODUCT_TYPE               0.000000
CHANNEL_TYPE                    0.000000
SELLERPLACE_AREA                0.000000
NAME_SELLER_INDUSTRY            0.000000
CNT_PAYMENT                    22.286366
NAME_YIELD_GROUP                0.000000
PRODUCT_COMBINATION             0.020716
dtype: float64
```

```
df_p.select_dtypes(np.number).skew()

# all are skewed we can impute null values with medin
```

```
SK_ID_PREV                  -0.000573
SK_ID_CURR                  -0.003303
AMT_ANNUITY                  2.692572
AMT_APPLICATION              3.391442
AMT_CREDIT                   3.245815
AMT_GOODS_PRICE              3.073690
HOUR_APPR_PROCESS_START     -0.025629
NFLAG_LAST_APPL_IN_DAY     -16.735924
DAYS_DECISION               -1.053080
SELLERPLACE_AREA           529.620279
```

```
CNT_PAYMENT                  1.531403
dtype: float64
```

```
df_p.select_dtypes(exclude=np.number).describe()
```


```
{"summary":"{\n  \"name\": \"df_p\",\n  \"rows\": 4,\n  \"fields\": [\
n    {\n      \"column\": \"NAME_CONTRACT_TYPE\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          4,\n
\"747553\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"WEEKDAY_APPR_PROCESS_START\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          7,\n
\"255118\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"FLAG_LAST_APPL_PER_CONTRACT\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          2,\n
\"1661739\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"NAME_CASH_LOAN_PURPOSE\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          25,\n
\"922661\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"NAME_CONTRACT_STATUS\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          4,\n
\"1036781\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"NAME_PAYMENT_TYPE\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          4,\n
\"1033552\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"CODE_REJECT_REASON\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          9,\n
\"1353093\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"NAME_CLIENT_TYPE\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          4,\n
\"1231261\",\n          \"1670214\"\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"NAME_GOODS_CATEGORY\",\n
\"properties\": {\n        \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n        \"samples\": [\n          28,\n
\"950809\",\n          \"1670214\"\n        ],\n
```

\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"NAME_PORTFOLIO\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   5,\n
\"691011\",\n   \"1670214\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"NAME_PRODUCT_TYPE\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   3,\n
\"1063666\",\n   \"1670214\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"CHANNEL_TYPE\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   8,\n
\"719968\",\n   \"1670214\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"NAME_SELLER_INDUSTRY\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   11,\n
\"855720\",\n   \"1670214\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"NAME_YIELD_GROUP\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   5,\n
\"517215\",\n   \"1670214\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   },\n   {\n   \"column\": \"PRODUCT_COMBINATION\",\n
\"properties\": {\n   \"dtype\": \"string\",\n
\"num_unique_values\": 4,\n   \"samples\": [\n   17,\n
\"285990\",\n   \"1669868\"\n   ],\n
\"semantic_type\": \"\",\n   \"description\": \"\"\n   }\
n   }\n]\n}","type":"dataframe"}

```
df_p.select_dtypes(exclude=np.number).isnull().sum()
```

```
NAME_CONTRACT_TYPE               0
WEEKDAY_APPR_PROCESS_START       0
FLAG_LAST_APPL_PER_CONTRACT      0
NAME_CASH_LOAN_PURPOSE           0
NAME_CONTRACT_STATUS             0
NAME_PAYMENT_TYPE                0
CODE_REJECT_REASON               0
NAME_CLIENT_TYPE                 0
NAME_GOODS_CATEGORY              0
NAME_PORTFOLIO                   0
NAME_PRODUCT_TYPE                0
CHANNEL_TYPE                     0
NAME_SELLER_INDUSTRY             0
NAME_YIELD_GROUP                 0
```

```
PRODUCT_COMBINATION            346
dtype: int64
```

```
df_p["PRODUCT_COMBINATION"]=df_p["PRODUCT_COMBINATION"].fillna(df_p["P
RODUCT_COMBINATION"].mode()[0])
```

```
for i in df_p.select_dtypes(np.number):
  df_p[i]=df_p[i].fillna(df_p[i].median())
```

```
df_p.isnull().sum()
```

```
SK_ID_PREV                     0
SK_ID_CURR                     0
NAME_CONTRACT_TYPE             0
AMT_ANNUITY                    0
AMT_APPLICATION                0
AMT_CREDIT                     0
AMT_GOODS_PRICE                0
WEEKDAY_APPR_PROCESS_START     0
HOUR_APPR_PROCESS_START        0
FLAG_LAST_APPL_PER_CONTRACT    0
NFLAG_LAST_APPL_IN_DAY         0
NAME_CASH_LOAN_PURPOSE         0
NAME_CONTRACT_STATUS           0
DAYS_DECISION                  0
NAME_PAYMENT_TYPE              0
CODE_REJECT_REASON             0
NAME_CLIENT_TYPE               0
NAME_GOODS_CATEGORY            0
NAME_PORTFOLIO                 0
NAME_PRODUCT_TYPE              0
CHANNEL_TYPE                   0
SELLERPLACE_AREA               0
NAME_SELLER_INDUSTRY           0
CNT_PAYMENT                    0
NAME_YIELD_GROUP               0
PRODUCT_COMBINATION            0
dtype: int64
```

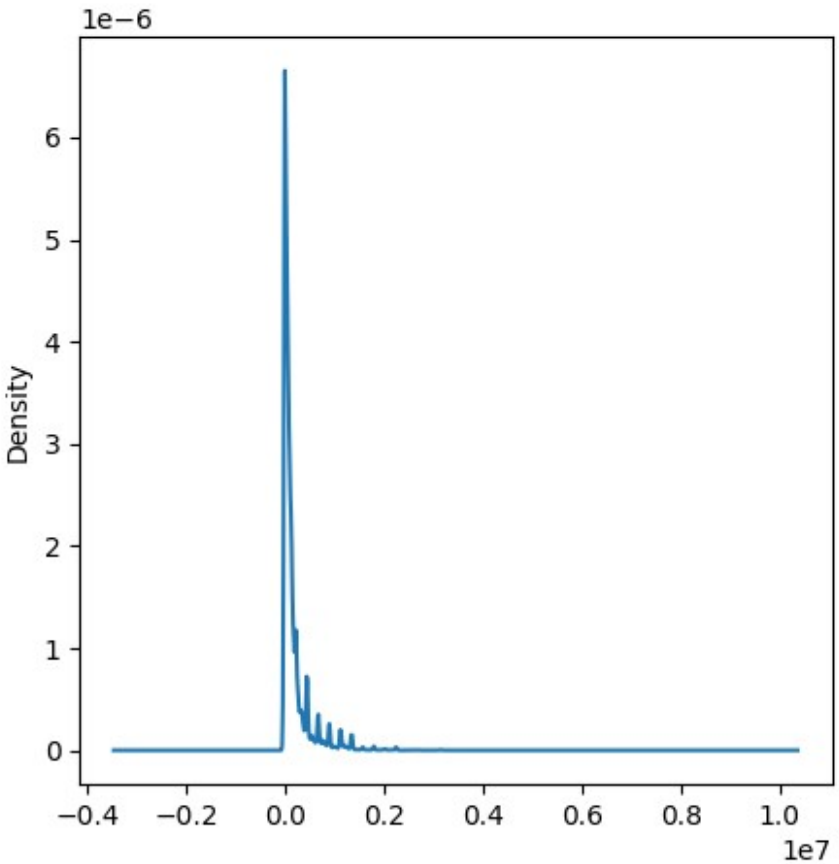
```
df_p.select_dtypes(np.number).columns
```

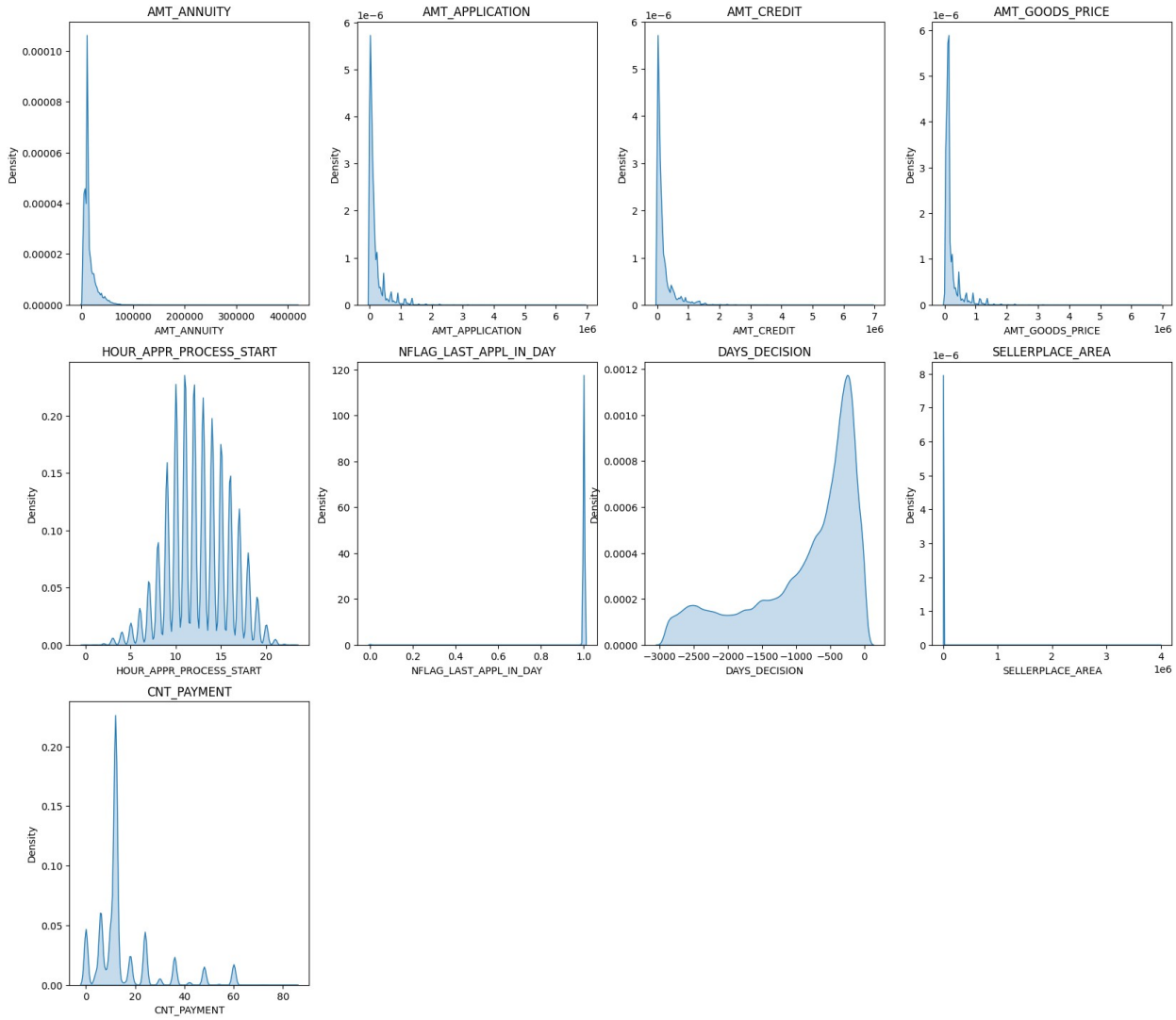
```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'AMT_ANNUITY', 'AMT_APPLICATION',
       'AMT_CREDIT', 'AMT_GOODS_PRICE', 'HOUR_APPR_PROCESS_START',
       'NFLAG_LAST_APPL_IN_DAY', 'DAYS_DECISION', 'SELLERPLACE_AREA',
       'CNT_PAYMENT'],
      dtype='object')
```

```
df_p['AMT_APPLICATION'].plot(kind='kde')
```

```
cols=df_p.select_dtypes(np.number).drop(columns=["SK_ID_PREV","SK_ID_C
URR"]).columns
```

```
plt.figure(figsize =[20,30])
j=1
for i in cols:
    plt.subplot(5,4,j)
    sns.kdeplot(df_p[i],fill =True)
    plt.title(i)
    j+=1
```






```
pd.set_option('display.max_columns',None)


df_p.head()
```

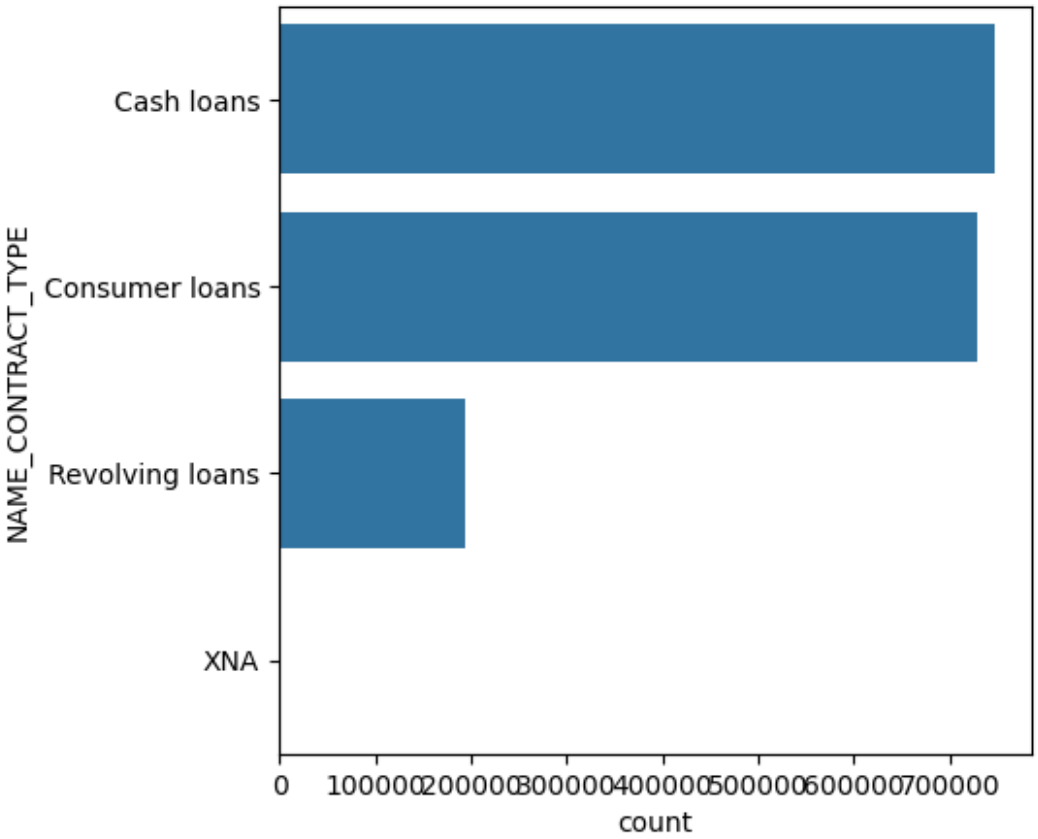
{"type":"dataframe","variable_name":"df_p"}

```
df_p.select_dtypes(exclude=np.number).columns
```

```
Index(['NAME_CONTRACT_TYPE', 'WEEKDAY_APPR_PROCESS_START',
       'FLAG_LAST_APPL_PER_CONTRACT', 'NAME_CASH_LOAN_PURPOSE',
       'NAME_CONTRACT_STATUS', 'NAME_PAYMENT_TYPE',
'CODE_REJECT_REASON',
       'NAME_CLIENT_TYPE', 'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO',
       'NAME_PRODUCT_TYPE', 'CHANNEL_TYPE', 'NAME_SELLER_INDUSTRY',
       'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION'],
      dtype='object')
```

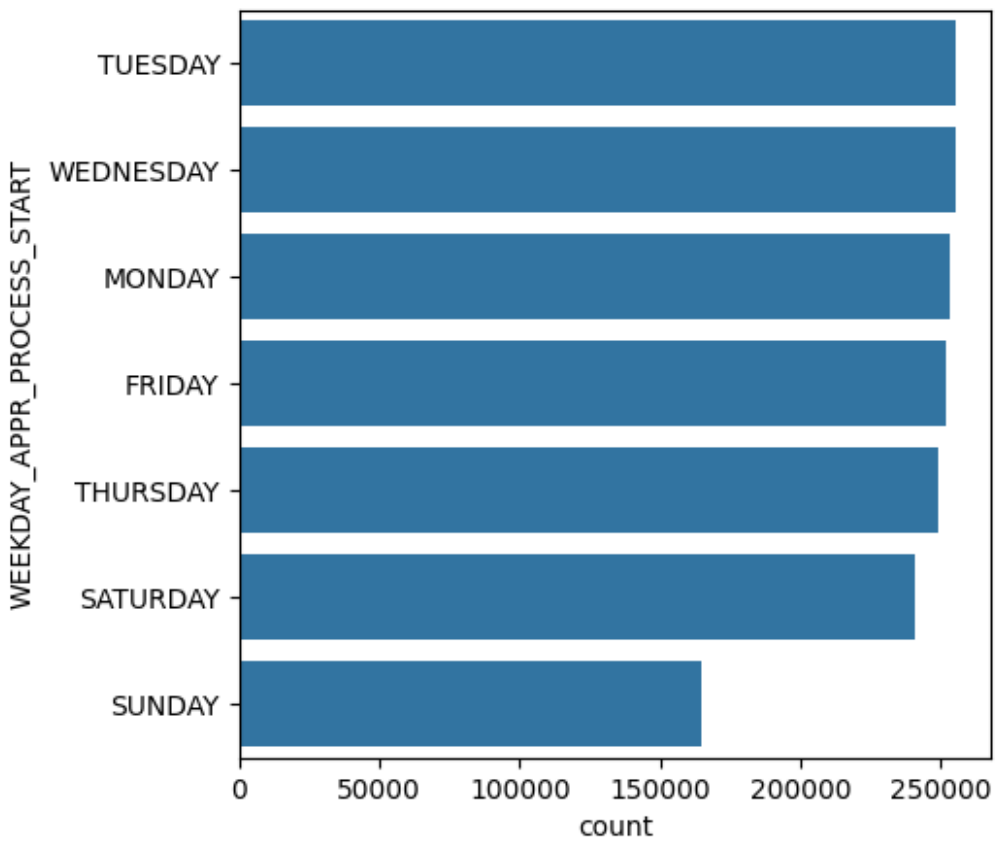
```
sns.countplot(df_p['NAME_CONTRACT_TYPE'],order=df_p['NAME_CONTRACT_TYPE'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_CONTRACT_TYPE'>
```



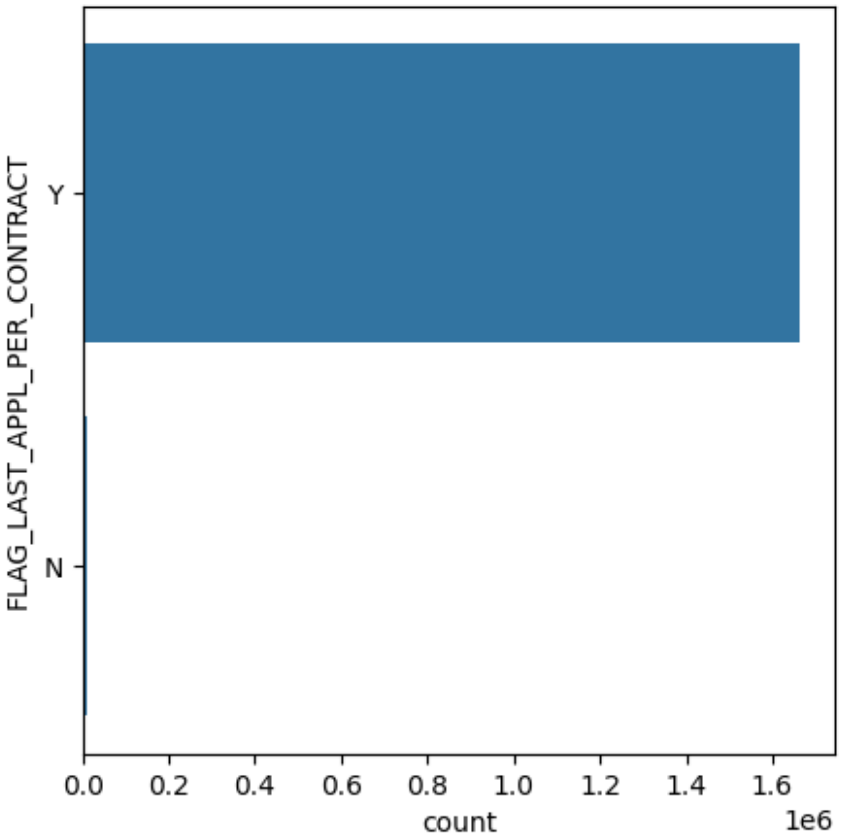

```
sns.countplot(df_p['WEEKDAY_APPR_PROCESS_START'],order=df_p['WEEKDAY_APPR_PROCESS_START'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='WEEKDAY_APPR_PROCESS_START'>
```



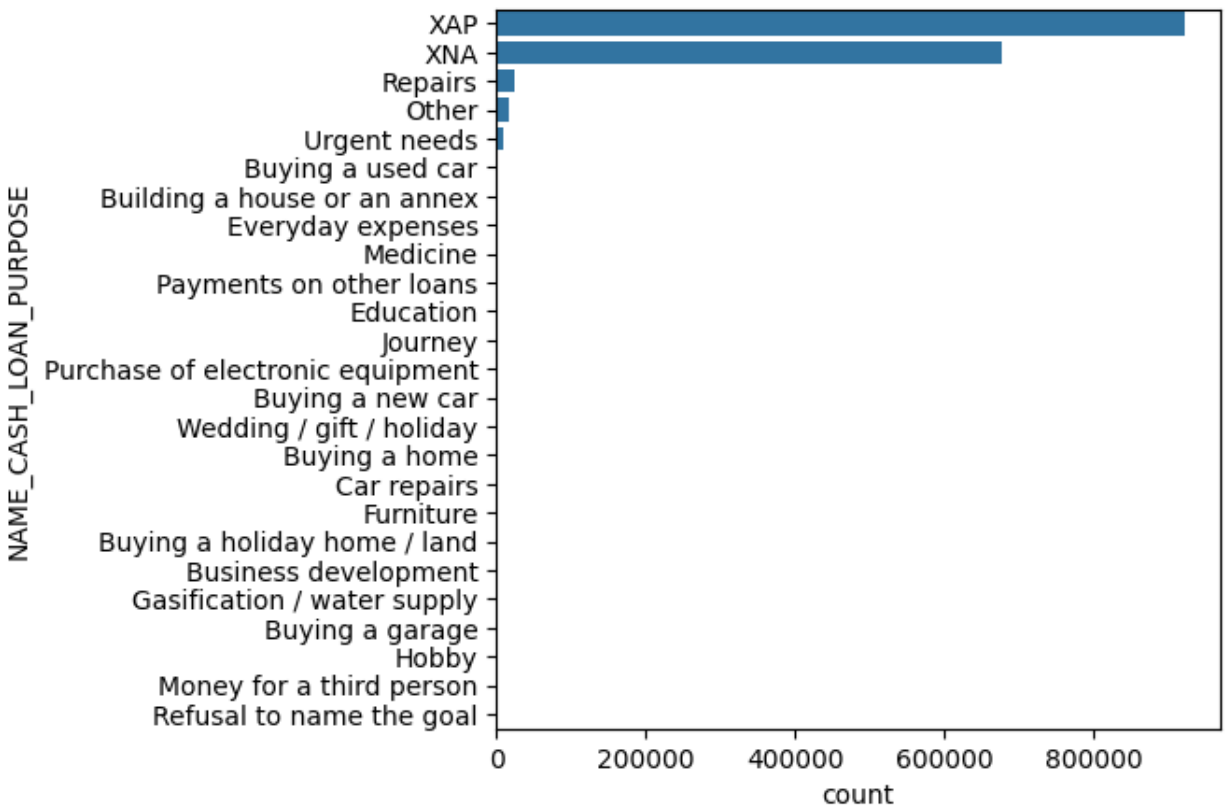

```
sns.countplot(df_p['FLAG_LAST_APPL_PER_CONTRACT'],order=df_p['FLAG_LAS
T_APPL_PER_CONTRACT'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='FLAG_LAST_APPL_PER_CONTRACT'>
```



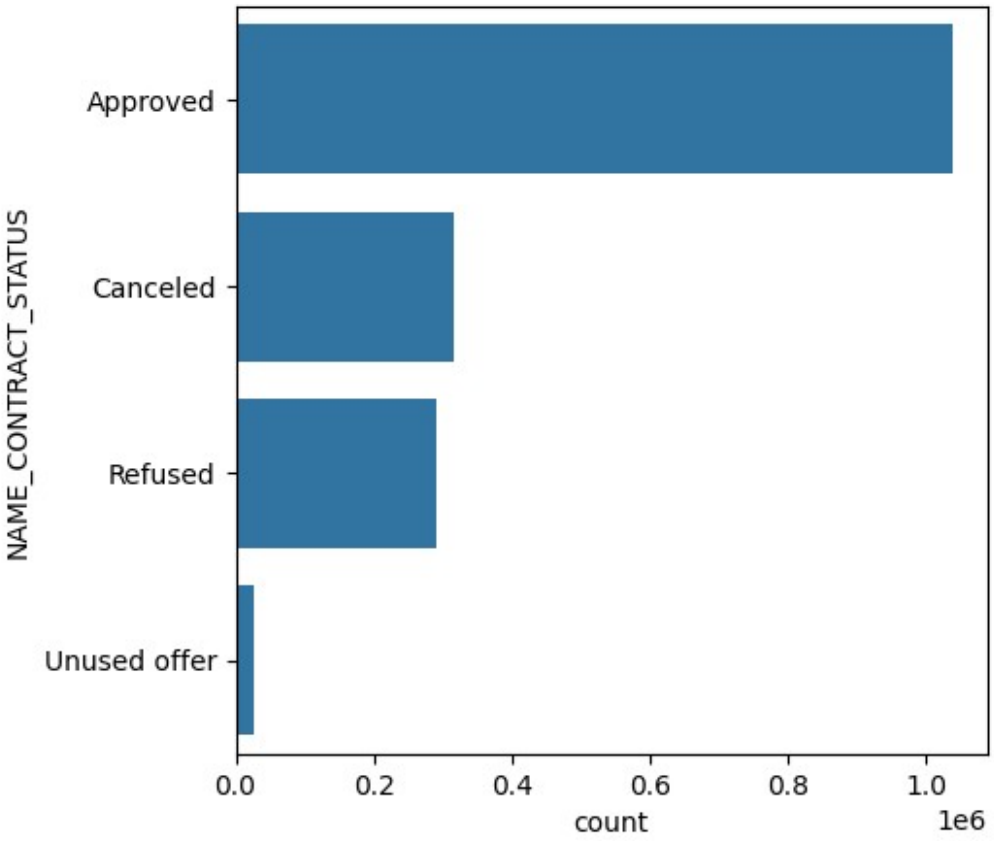

```
sns.countplot(df_p['NAME_CASH_LOAN_PURPOSE'],order=df_p['NAME_CASH_LOA
N_PURPOSE'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_CASH_LOAN_PURPOSE'>
```



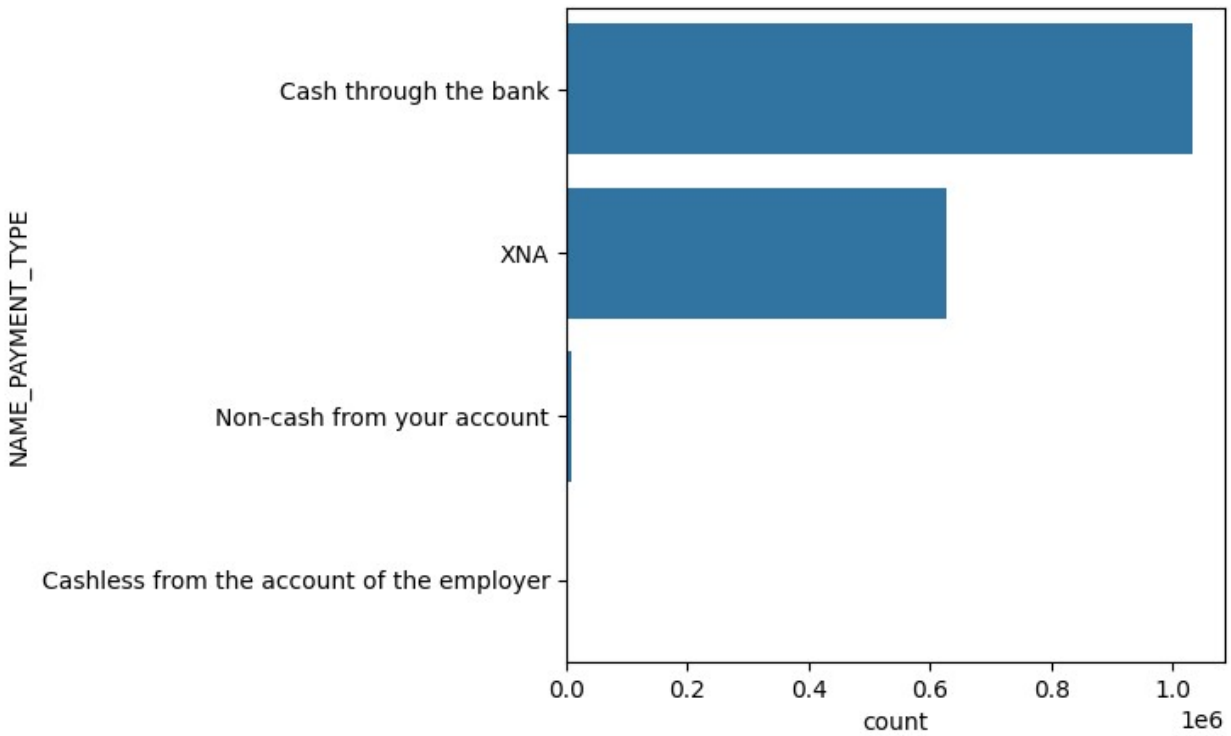

```
sns.countplot(df_p['NAME_CONTRACT_STATUS'],order=df_p['NAME_CONTRACT_S
TATUS'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_CONTRACT_STATUS'>
```



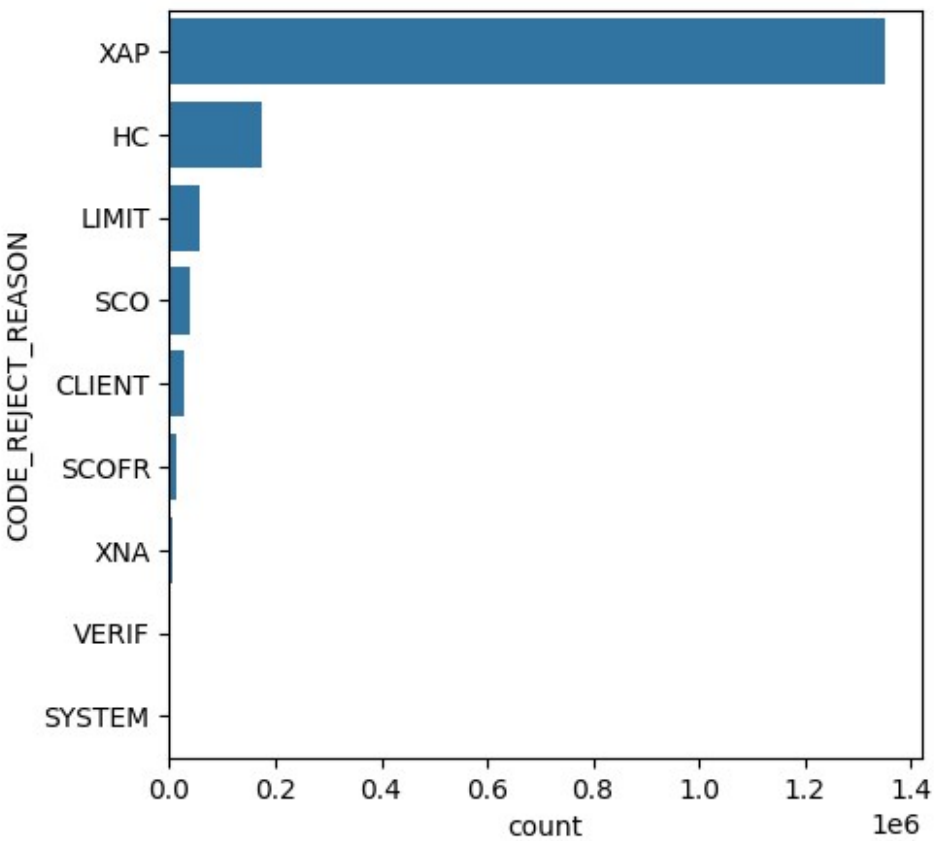

```
sns.countplot(df_p['NAME_PAYMENT_TYPE'],order=df_p['NAME_PAYMENT_TYPE'
].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_PAYMENT_TYPE'>
```



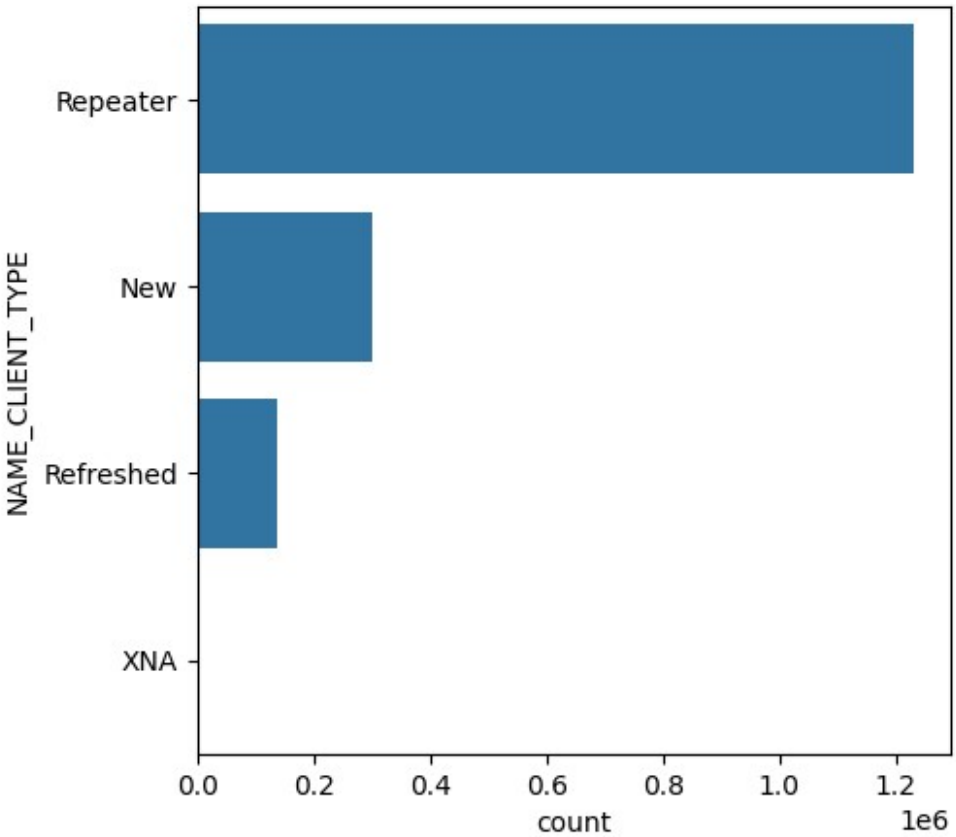

```
sns.countplot(df_p['CODE_REJECT_REASON'],order=df_p['CODE_REJECT_REASO
N'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='CODE_REJECT_REASON'>
```



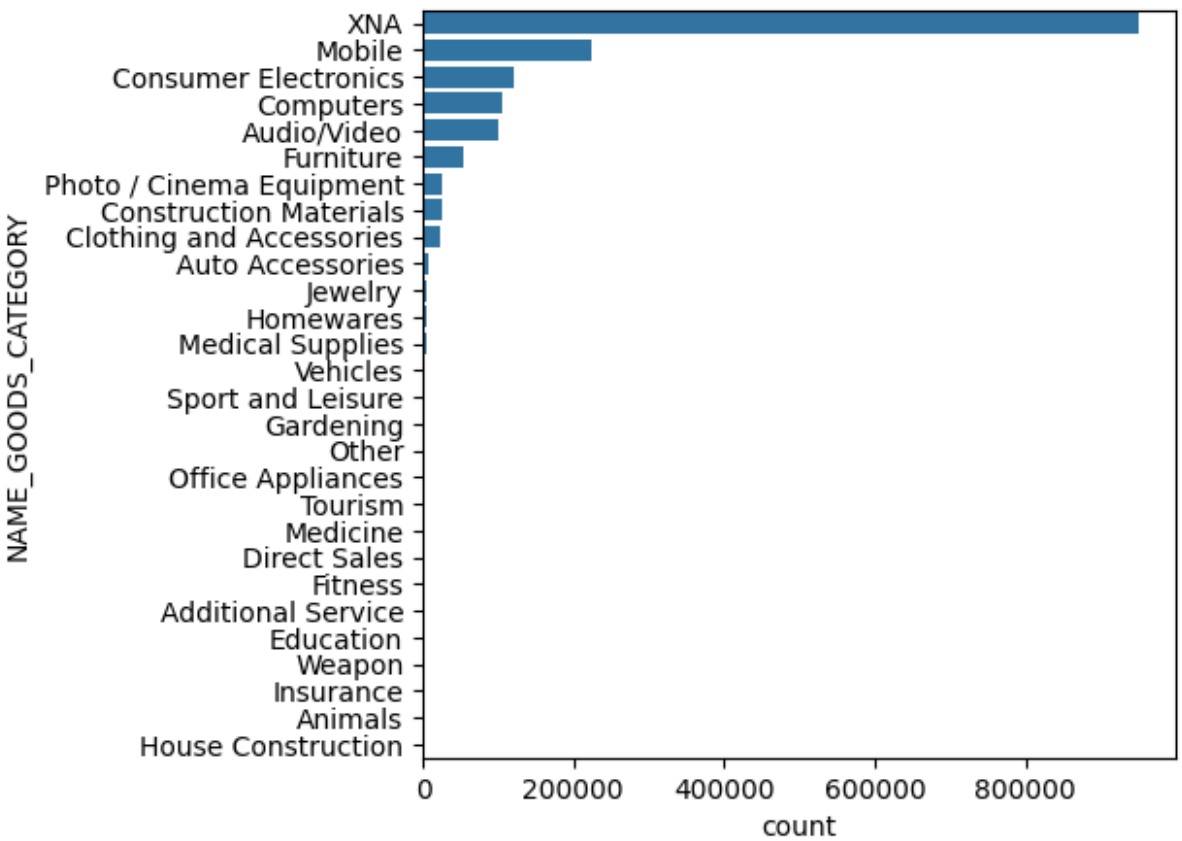

```
sns.countplot(df_p['NAME_CLIENT_TYPE'],order=df_p['NAME_CLIENT_TYPE'].
value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_CLIENT_TYPE'>
```



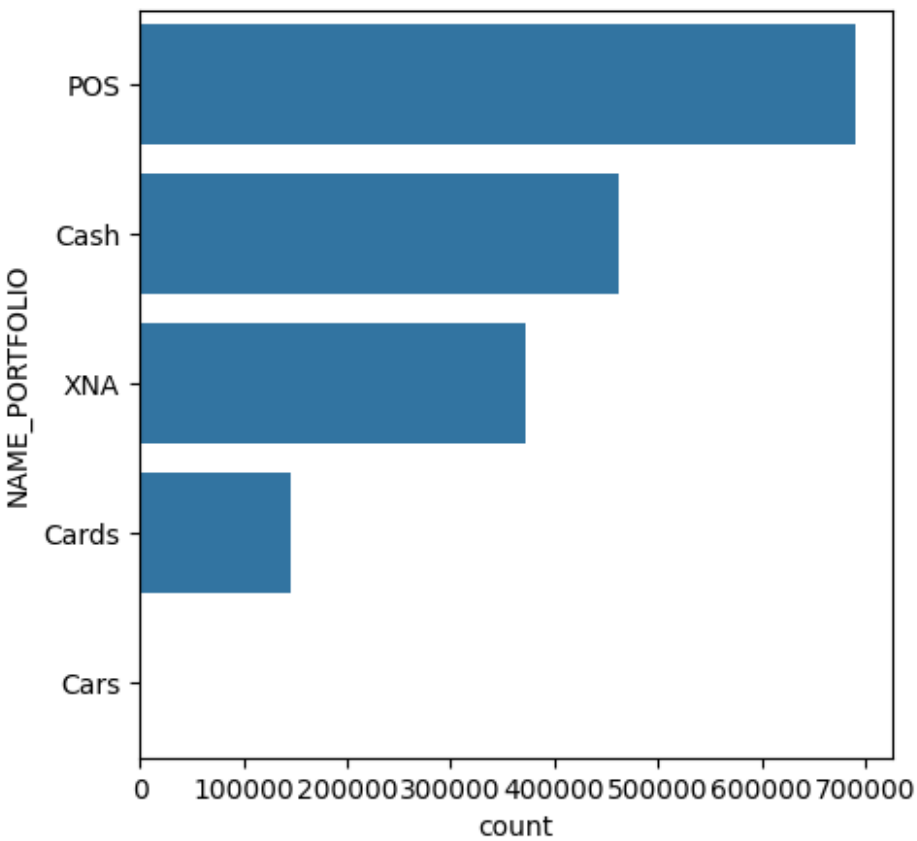

```
sns.countplot(df_p['NAME_GOODS_CATEGORY'],order=df_p['NAME_GOODS_CATEG
ORY'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_GOODS_CATEGORY'>
```



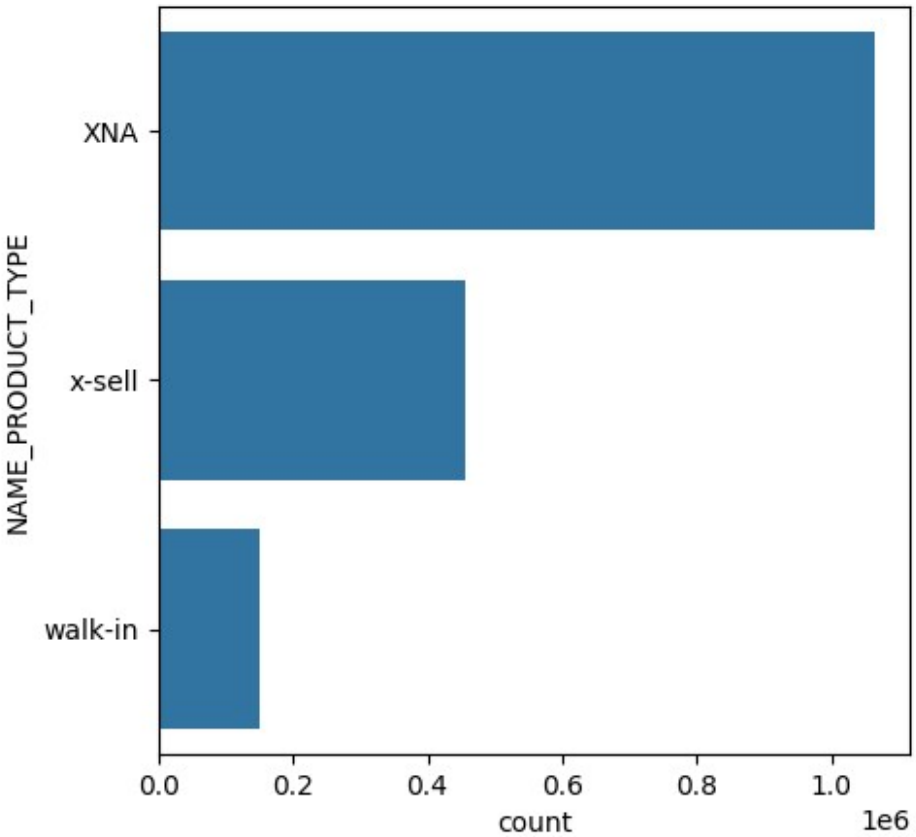

```
sns.countplot(df_p['NAME_PORTFOLIO'],order=df_p['NAME_PORTFOLIO'].valu
e_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_PORTFOLIO'>
```



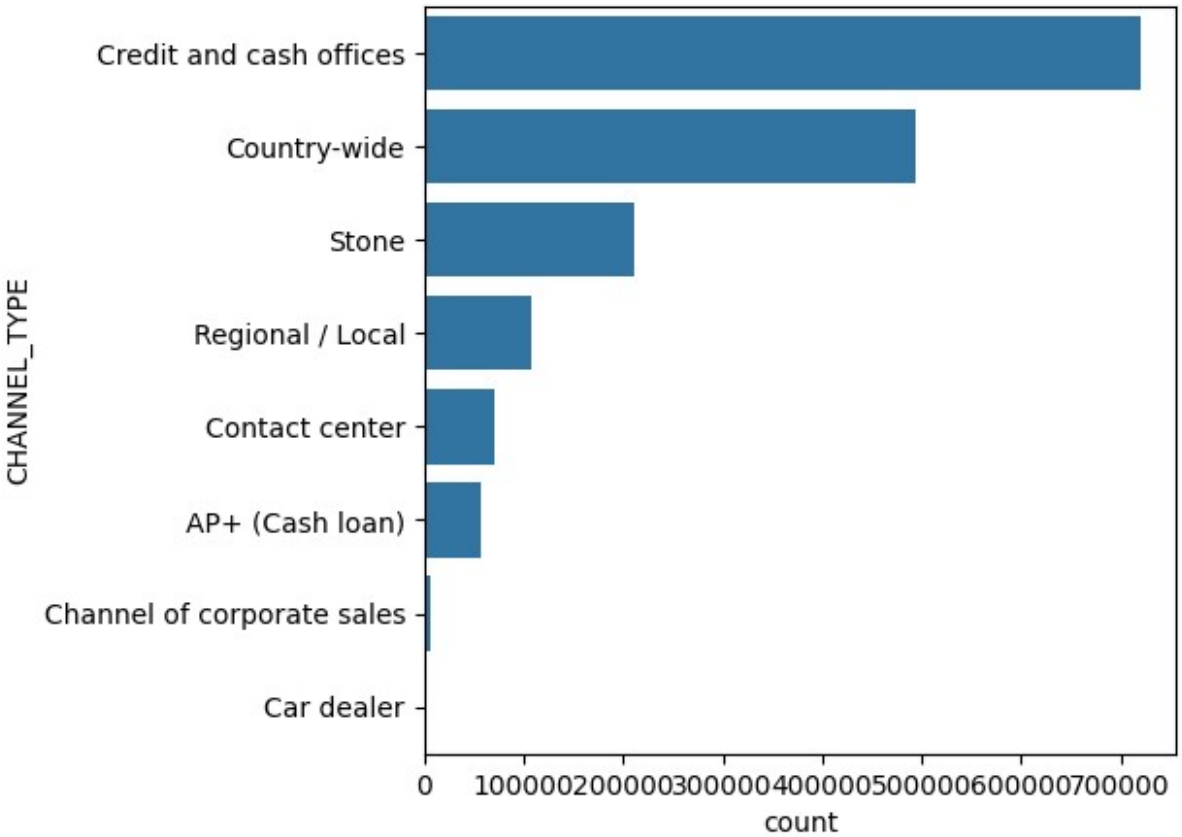

```
sns.countplot(df_p['NAME_PRODUCT_TYPE'],order=df_p['NAME_PRODUCT_TYPE'
].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_PRODUCT_TYPE'>
```



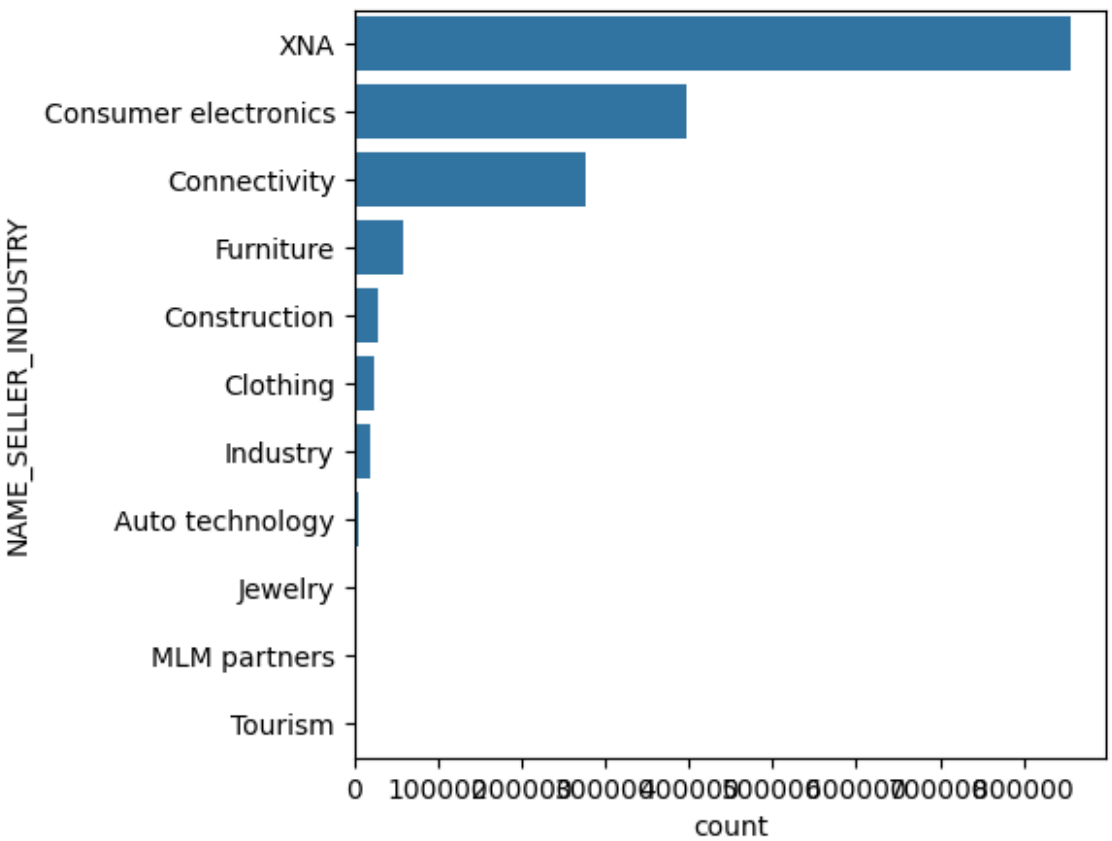

```
sns.countplot(df_p['CHANNEL_TYPE'],order=df_p['CHANNEL_TYPE'].value_co
unts().index)
```

```
<Axes: xlabel='count', ylabel='CHANNEL_TYPE'>
```



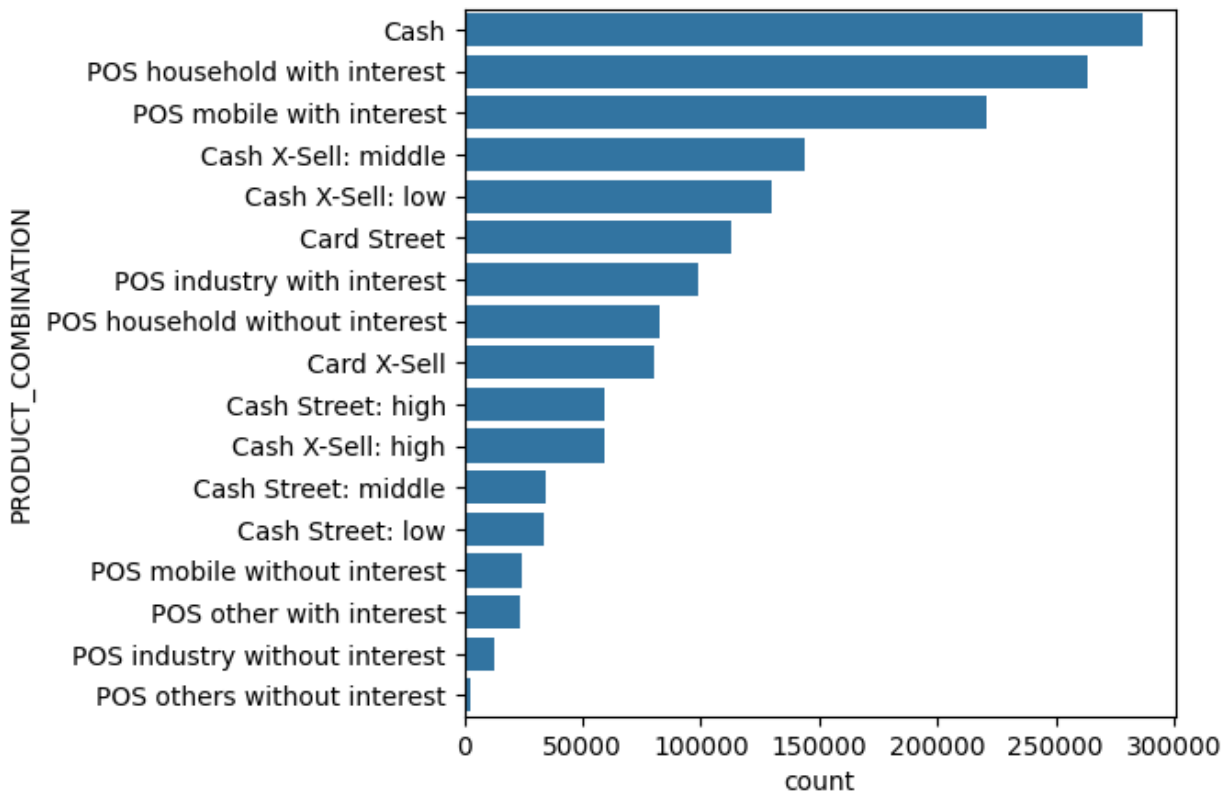

```
sns.countplot(df_p['NAME_SELLER_INDUSTRY'],order=df_p['NAME_SELLER_IND
USTRY'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='NAME_SELLER_INDUSTRY'>
```




```
sns.countplot(df_p['PRODUCT_COMBINATION'],order=df_p['PRODUCT_COMBINAT
ION'].value_counts().index)
```

```
<Axes: xlabel='count', ylabel='PRODUCT_COMBINATION'>
```




```
df_p['CODE_REJECT_REASON'].value_counts()
```

```
CODE_REJECT_REASON
XAP       1353093
HC         175231
LIMIT       55680
SCO         37467
CLIENT      26436
SCOFR       12811
XNA          5244
VERIF        3535
SYSTEM        717
Name: count, dtype: int64
```

XAP (1353093): This could refer to a rejection related to an application processing error, such as missing or incorrect information in the application.

HC (175231): This might indicate a health-related issue, potentially involving compliance with health regulations or requirements.

LIMIT (55680): This likely pertains to exceeding a predefined limit, such as financial thresholds or operational limits set by a regulatory body.

SCO (37467): This could refer to a score-related issue, possibly indicating that a score (like a credit score) fell below acceptable levels.

CLIENT (26436): This may relate to client-specific issues, such as account status or client eligibility.

SCOFR (12811): This could refer to a specific scoring framework or criteria that was not met.

XNA (5244): This might indicate a rejection due to an unknown or unspecified reason, often used when other codes do not apply.

VERIF (3535): This likely refers to verification issues, such as problems confirming identity or credentials.

cols=df_p.select_dtypes(np.number).drop(columns=["SK_ID_PREV","SK_ID_CURR"]).columns plt.figure(figsize=(20,10)) j = 1 for i in cols: plt.subplot(5, 3, j) sns.boxplot(x=df_p.loc[:, i]) plt.title(i) j += 1

plt.xticks(rotation=45, fontsize=8) plt.tight_layout() plt.show()

POS CASH BALANCE EDA

```
df=pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/POS_CASH_balance.csv")
df.head()
```

```
{"type":"dataframe","variable_name":"df"}
```

```
df.shape
```

```
(10001358, 8)
```

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

```
SK_ID_PREV                   0
SK_ID_CURR                   0
MONTHS_BALANCE               0
CNT_INSTALMENT           26071
CNT_INSTALMENT_FUTURE    26087
NAME_CONTRACT_STATUS         0
SK_DPD                       0
SK_DPD_DEF                   0
dtype: int64
```

```
df.isnull().sum()*100/df.shape[0]
```

```
SK_ID_PREV               0.000000
SK_ID_CURR               0.000000
MONTHS_BALANCE           0.000000
CNT_INSTALMENT           0.260675
CNT_INSTALMENT_FUTURE    0.260835
NAME_CONTRACT_STATUS     0.000000
SK_DPD                   0.000000
SK_DPD_DEF               0.000000
dtype: float64
```

```
df.select_dtypes(include=np.number).describe().round()
```

{"summary":"{\n \"name\": \"df\",\n \"rows\": 8,\n \"fields\": [\n {\n \"column\": \"SK_ID_PREV\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3020814.5656346893,\n \"min\": 535847.0,\n \"max\": 10001358.0,\n \"num_unique_values\": 8,\n \"samples\": [\n 1903217.0,\n 1896565.0,\n 10001358.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_ID_CURR\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3448651.3957597744,\n \"min\": 100001.0,\n \"max\": 10001358.0,\n \"num_unique_values\": 8,\n \"samples\": [\n 278404.0,\n 278654.0,\n 10001358.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"MONTHS_BALANCE\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3536024.1836563903,\n \"min\": -96.0,\n \"max\": 10001358.0,\n \"num_unique_values\": 8,\n \"samples\": [\n -35.0,\n -28.0,\n 10001358.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CNT_INSTALMENT\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3526788.055824791,\n \"min\": 1.0,\n \"max\": 9975287.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 9975287.0,\n 17.0,\n 24.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CNT_INSTALMENT_FUTURE\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3526784.3182522696,\n \"min\": 0.0,\n \"max\": 9975271.0,\n \"num_unique_values\": 8,\n \"samples\": [\n 10.0,\n 7.0,\n 9975271.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3535793.316792337,\n \"min\": 0.0,\n \"max\": 10001358.0,\n \"num_unique_values\": 5,\n \"samples\": [\n 12.0,\n 4231.0,\n 133.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD_DEF\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 3535830.9623564114,\n \"min\": 0.0,\n \"max\": 10001358.0,\n \"num_unique_values\": 5,\n \"samples\": [\n 1.0,\n 3595.0,\n 33.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\n}","type":"dataframe"}

```
df.select_dtypes(exclude=np.number).describe()
```

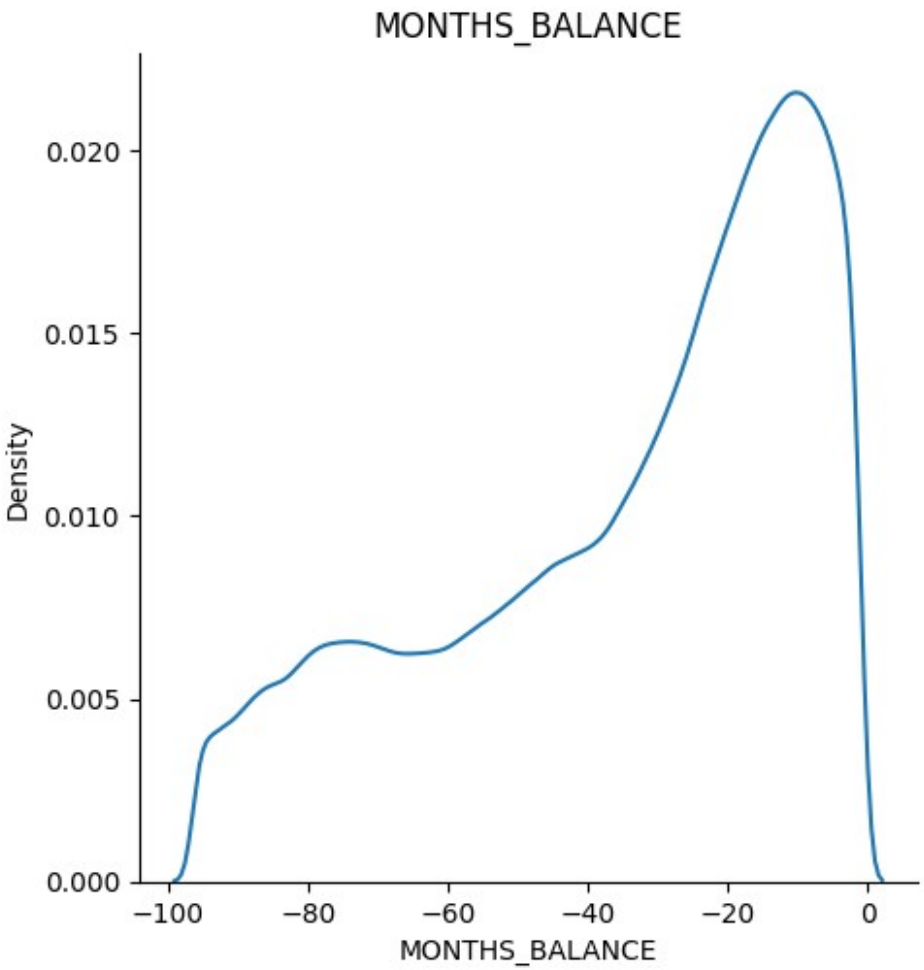
{"summary":"{\n \"name\": \"df\",\n \"rows\": 4,\n \"fields\": [\n {\n \"column\": \"NAME_CONTRACT_STATUS\",\n \"properties\": {\n \"dtype\": \"string\",\n \"num_unique_values\": 4,\n \"samples\": [\n 9,\n \"9151119\",\n \"10001358\"\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\n}","type":"dataframe"}

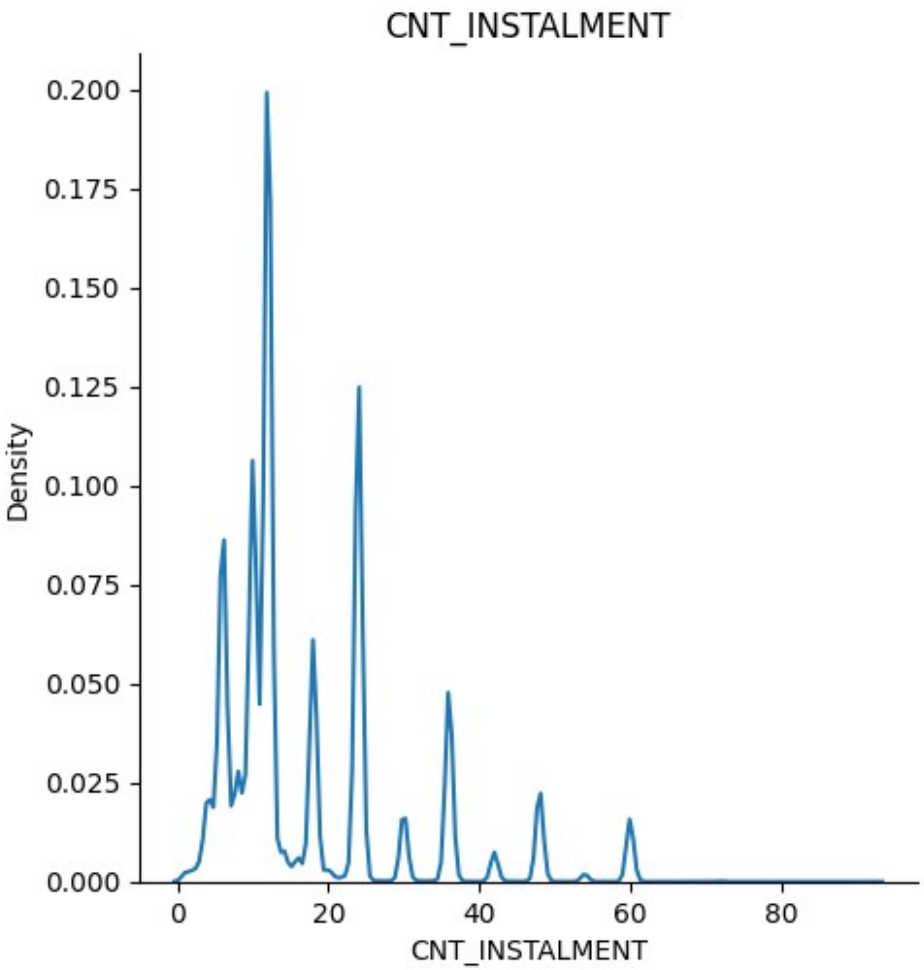
- SK_ID_PREV :ID of previous credit in Home Credit related to loan in our sample. (One loan in our sample can have 0,1,2 or more previous loans in Home Credit)
- SK_ID_CURR : ID of loan in our sample
- MONTHS_BALANCE : Month of balance relative to application date (-1 means the information to the freshest monthly snapshot, 0 means the information at application - often it will be the same as -1 as many banks are not updating the information to Credit Bureau regularly)
- CNT_INSTALMENT : Term of previous credit (can change over time)
- CNT_INSTALMENT_FUTURE : Installments left to pay on the previous credit
- NAME_CONTRACT_STATUS : Contract status during the month
- SK_DPD : DPD (days past due) during the month of previous credit
- SK_DPD_DEF : DPD during the month with tolerance (debts with low loan amounts are ignored) of the previous credit

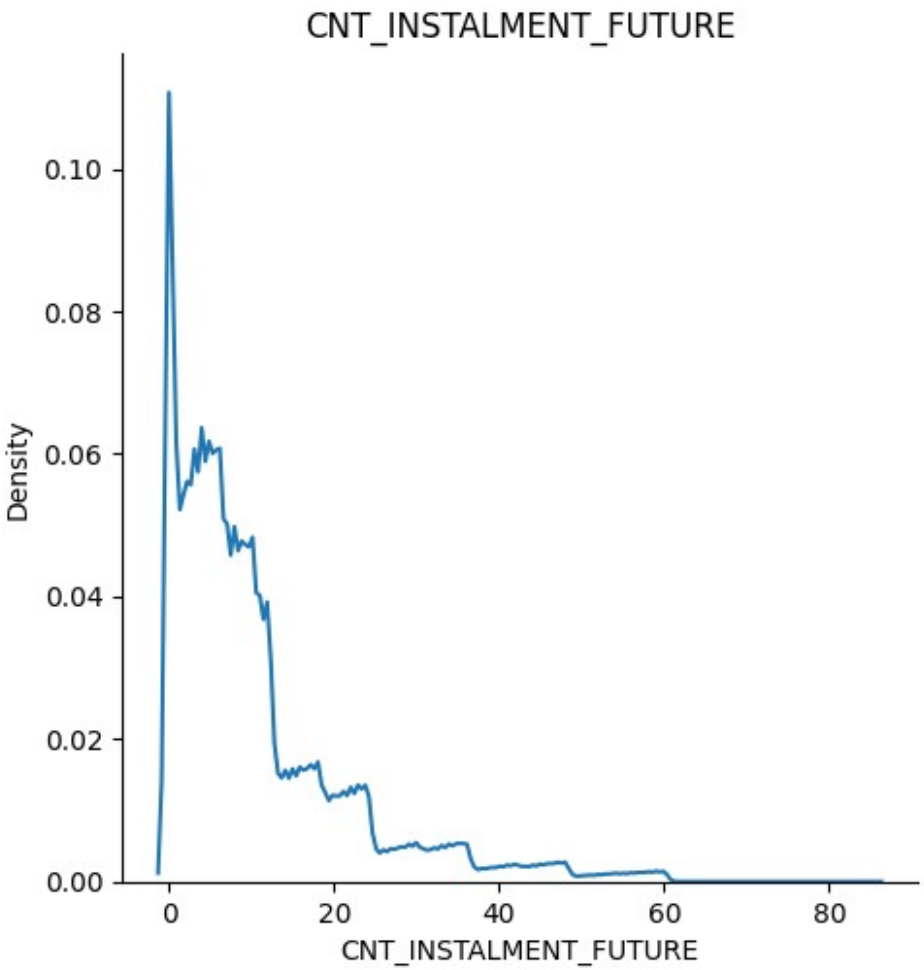
```
df.columns
```

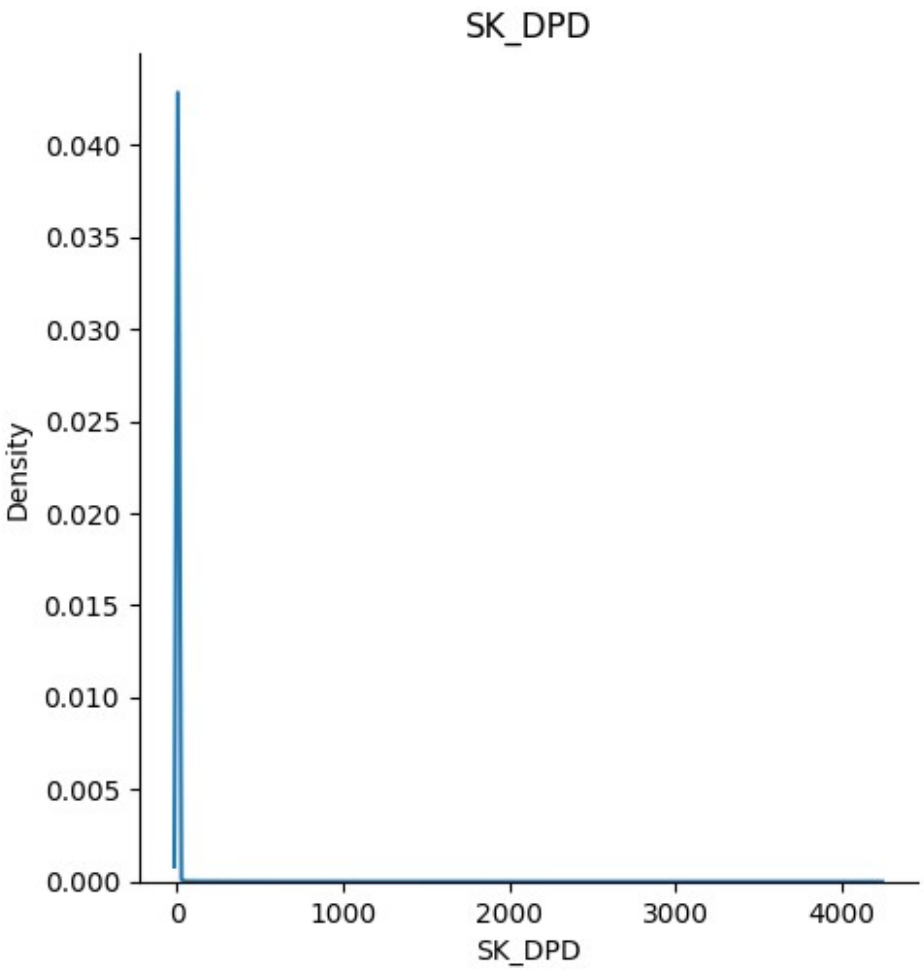
```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'MONTHS_BALANCE', 'CNT_INSTALMENT',
       'CNT_INSTALMENT_FUTURE', 'NAME_CONTRACT_STATUS', 'SK_DPD',
       'SK_DPD_DEF'],
      dtype='object')
```

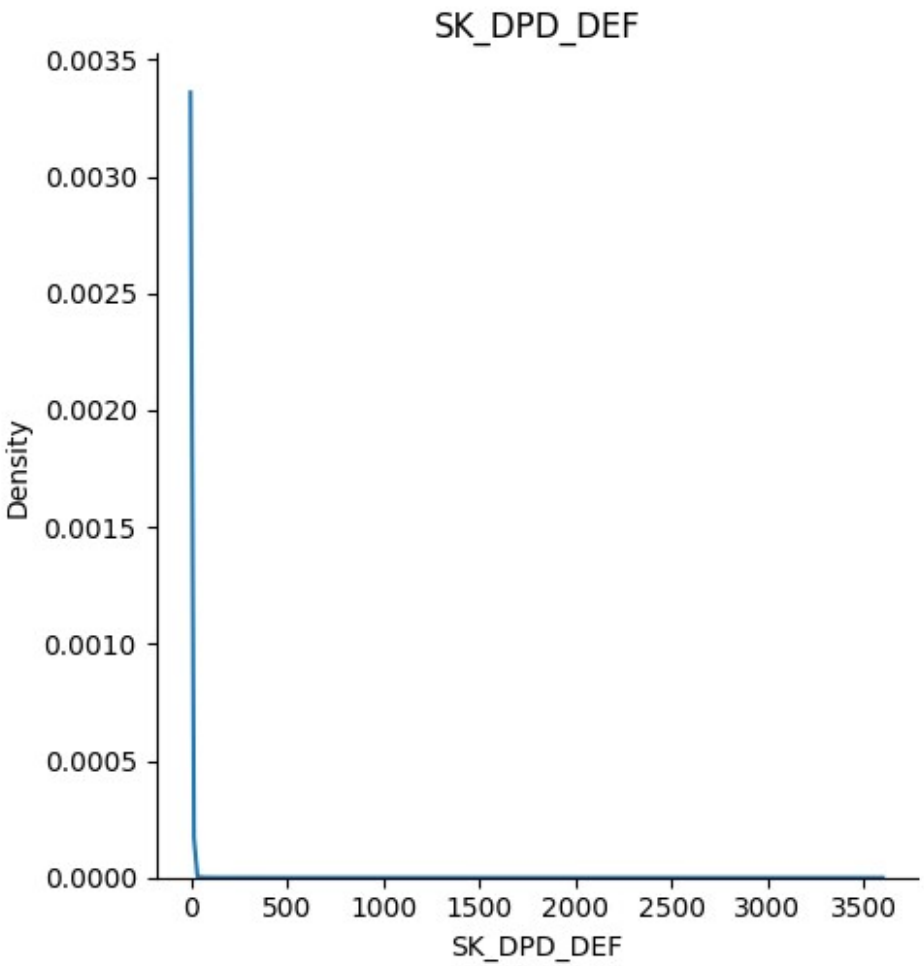
```
cols=['MONTHS_BALANCE','CNT_INSTALMENT','CNT_INSTALMENT_FUTURE','SK_DPD','SK_DPD_DEF']

for i in cols:
    sns.displot(df[i],kind='kde')
    plt.title(i)
    plt.show()
```


MONTHS_BALANCE
Density
0.020
0.015
0.010
0.005
0.000
−100
−80
−60
−40
−20
0
MONTHS_BALANCE

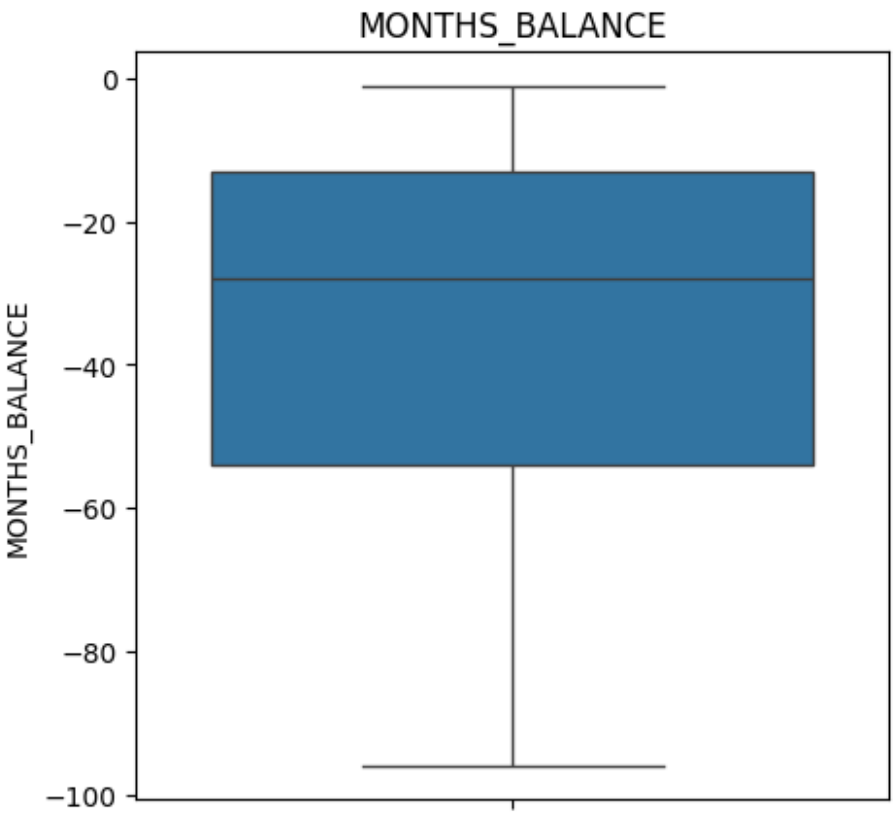

CNT_INSTALMENT
Density
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
20
40
60
80
CNT_INSTALMENT

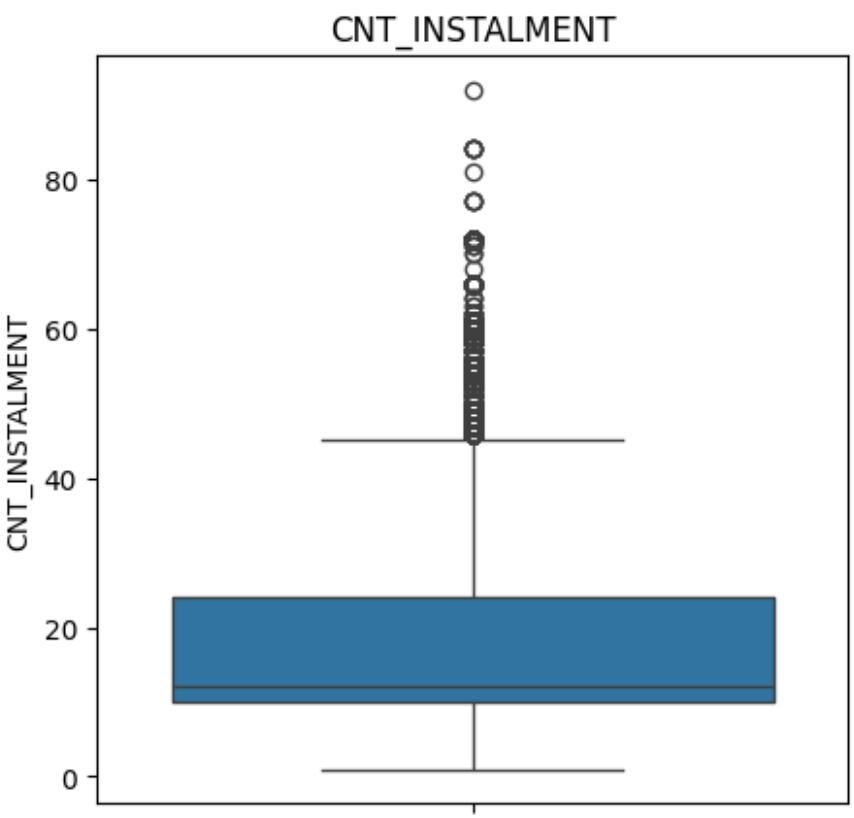

CNT_INSTALMENT_FUTURE
Density
0.10
0.08
0.06
0.04
0.02
0.00
0
20
40
60
80
CNT_INSTALMENT_FUTURE

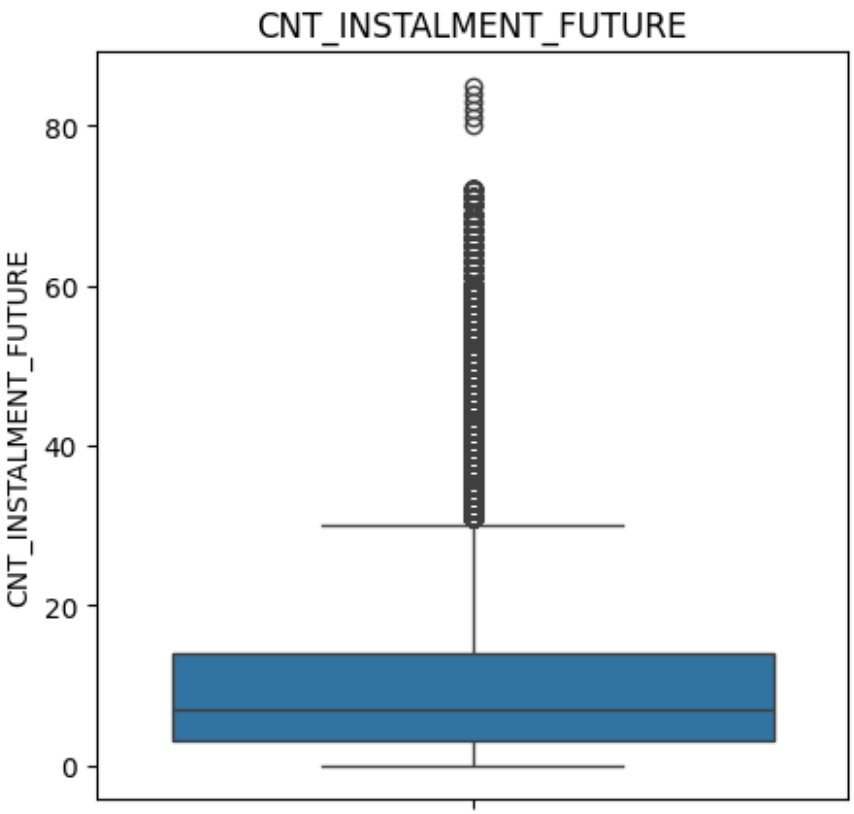

SK_DPD
Density
0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
0
1000
2000
3000
4000
SK_DPD

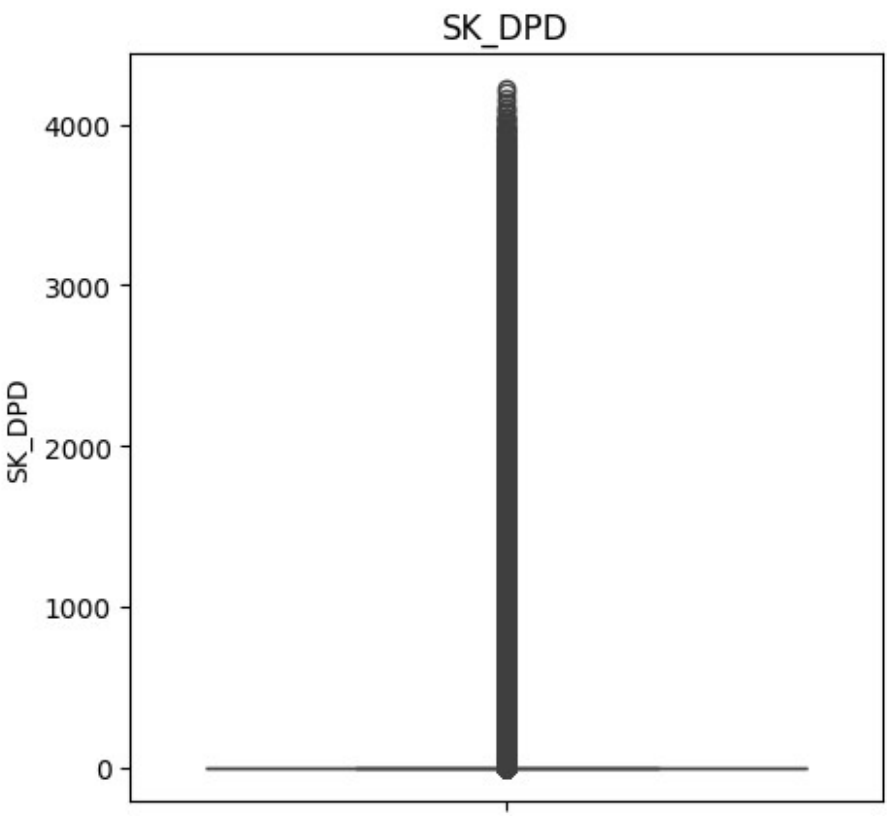


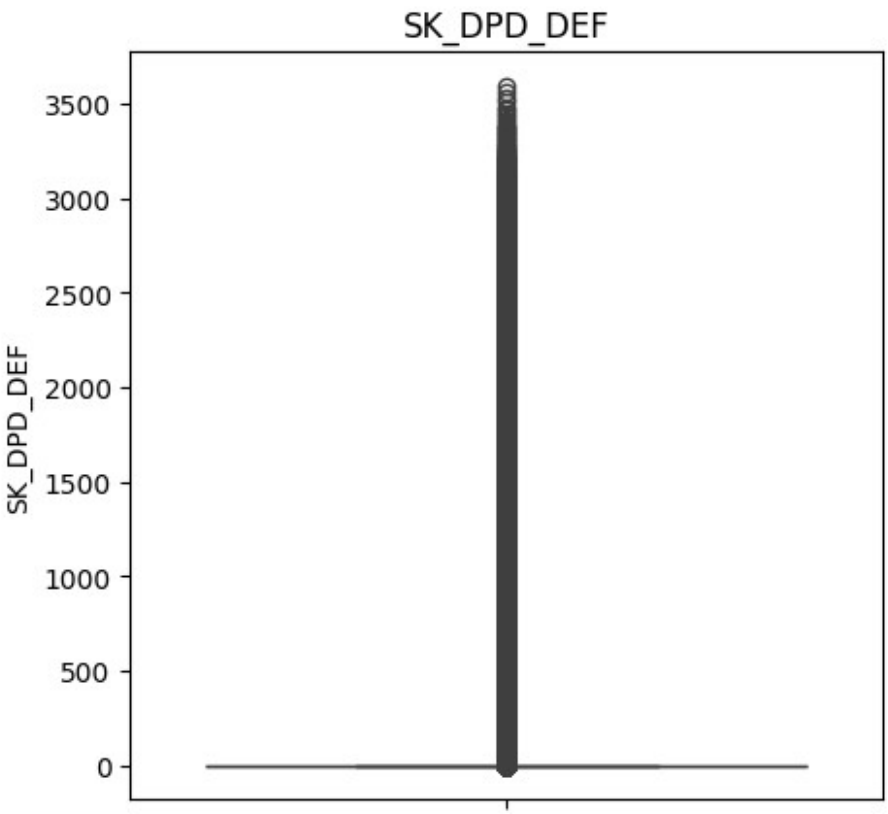

```
cols=['MONTHS_BALANCE','CNT_INSTALMENT','CNT_INSTALMENT_FUTURE','SK_DP
D','SK_DPD_DEF']

for i in cols:
    sns.boxplot(df[i])
    plt.title(i)
    plt.show()
```


MONTHS_BALANCE
MONTHS_BALANCE
0
−20
−40
−60
−80
−100


CNT_INSTALMENT
CNT_INSTALMENT
80
60
40
20
0


CNT_INSTALMENT_FUTURE
CNT_INSTALMENT_FUTURE
0
20
40
60
80


SK_DPD
SK_DPD
0
1000
2000
3000
4000




```
df['NAME_CONTRACT_STATUS'].unique()
```

```
array(['Active', 'Completed', 'Signed', 'Approved',
       'Returned to the store', 'Demand', 'Canceled', 'XNA',
       'Amortized debt'], dtype=object)
```

```
df['NAME_CONTRACT_STATUS'].value_counts()
```

```
NAME_CONTRACT_STATUS
Active                   9151119
Completed                 744883
Signed                     87260
Demand                      7065
Returned to the store       5461
Approved                    4917
Amortized debt               636
Canceled                      15
XNA                            2
Name: count, dtype: int64
```

```
df['SK_DPD'].value_counts()
```

```
SK_DPD
0       9706131
1         21872
2         17358
3         14403
4         12350
5         11046
6          9615
7          8332
8          7360
9          6668
10         6049
11         5392
12         4907
13         4468
14         3944
15         3438
16         3169
17         2980
18         2759
19         2532
20         2322
21         1996
22         1820
23         1586
24         1386
25         1258
26         1101
27          923
28          864
29          700
30          571
31          518
32          512
33          439
35          428
34          401
36          338
37          321
39          289
38          288
40          284
41          274
43          267
44          250
42          237
49          237
45          226
50          225
48          225
```

47	217
46	216
53	210
51	210
59	201
69	196
74	194
67	194
54	194
63	192
78	188
73	187
68	183
52	180
80	179
65	178
66	178
77	175
98	175
109	172
61	172
128	172
97	172
71	172
99	172
79	171
94	171
64	170
111	170
104	170
70	169
125	167
81	167
158	166
100	165
93	164
84	163
62	162
120	161
186	161
130	161
135	161
72	160
141	160
89	159
56	159
60	157
82	156
90	156
85	156

105	156
92	155
139	155
110	155
155	154
126	153
76	153
124	153
133	153
189	152
151	152
96	151
159	151
112	151
102	150
108	150
172	150
57	148
91	147
140	147
58	147
83	146
103	146
115	146
55	146
166	143
161	143
212	143
95	142
134	142
114	142
75	141
127	141
194	141
106	141
229	140
129	139
170	139
165	138
191	137
203	137
217	137
107	136
146	136
201	136
119	135
131	134
204	134
87	133
171	133

163	133
188	133
154	133
142	133
143	133
192	133
156	133
164	132
220	132
168	132
150	131
137	131
101	131
121	131
222	131
123	130
169	129
181	128
216	128
157	128
160	127
231	127
202	127
196	127
145	127
187	126
179	125
132	125
247	125
262	125
173	125
198	125
136	124
86	124
113	124
152	123
246	123
176	123
162	123
118	123
253	123
232	123
233	122
182	122
138	122
372	122
321	122
88	122
219	121
395	120

190	120
200	120
261	119
185	119
284	119
225	119
144	119
292	119
167	119
148	119
197	118
250	118
116	118
207	118
199	117
224	117
245	117
215	116
260	116
290	116
117	115
183	115
249	115
184	114
122	114
264	114
314	114
153	114
353	114
210	113
195	113
277	113
175	113
180	112
227	112
193	112
223	112
218	112
414	112
276	111
257	111
255	111
177	111
323	110
453	110
273	110
352	110
248	110
259	110
230	109

214	109
242	109
252	109
149	108
397	108
316	108
147	108
281	108
234	108
425	107
569	107
278	107
307	107
174	107
377	107
294	107
271	107
283	107
286	106
311	106
322	106
243	105
228	105
263	105
279	105
211	105
308	104
312	104
235	103
291	103
404	103
542	103
240	103
266	103
450	103
206	103
325	103
280	102
632	102
342	102
265	102
226	102
293	102
237	102
373	102
306	101
626	101
428	101
382	101
256	101

221	101
236	100
238	100
315	100
285	100
455	99
332	99
585	99
347	99
335	99
296	99
288	99
304	99
309	98
282	98
295	98
338	98
383	98
406	98
559	97
388	97
328	97
254	97
393	97
463	97
420	97
343	96
239	96
244	96
378	96
367	96
251	96
481	96
686	96
576	95
354	95
268	95
396	95
340	95
418	95
289	95
337	95
258	95
375	95
297	95
413	95
267	94
274	94
305	94
384	94

345	94
209	94
324	94
655	94
213	93
208	93
339	93
784	93
506	93
415	93
649	93
419	93
275	93
400	93
205	93
358	93
327	93
299	93
477	93
475	92
272	92
567	92
467	92
474	92
351	91
178	91
445	91
344	91
357	91
424	91
241	91
346	91
369	90
386	90
363	90
333	90
444	90
476	90
443	90
684	89
595	89
452	89
302	89
300	89
507	89
659	88
417	88
287	88
451	88
313	88

365	88
359	88
356	88
815	88
326	88
303	88
269	88
618	88
433	88
355	87
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3773	2
3836	2
3291	2
4050	2
3115	1
3506	1
4172	1
4078	1
3316	1
3377	1
2937	1
2980	1
3716	1

3126	1
3989	1
3337	1
3475	1
3247	1
3987	1
4200	1
4080	1
3865	1
3929	1
3277	1
3414	1
3225	1
3534	1
3381	1
3146	1
3275	1
3219	1
3118	1
3442	1
3357	1
3351	1
3259	1
3746	1
3149	1
3065	1
4108	1
4047	1
3236	1
3154	1
3371	1
3388	1
3203	1
3238	1
3231	1
3807	1
3595	1
3059	1
3267	1
3280	1
3244	1
3177	1
3315	1
3191	1
3329	1
3353	1
3444	1
4110	1
3352	1

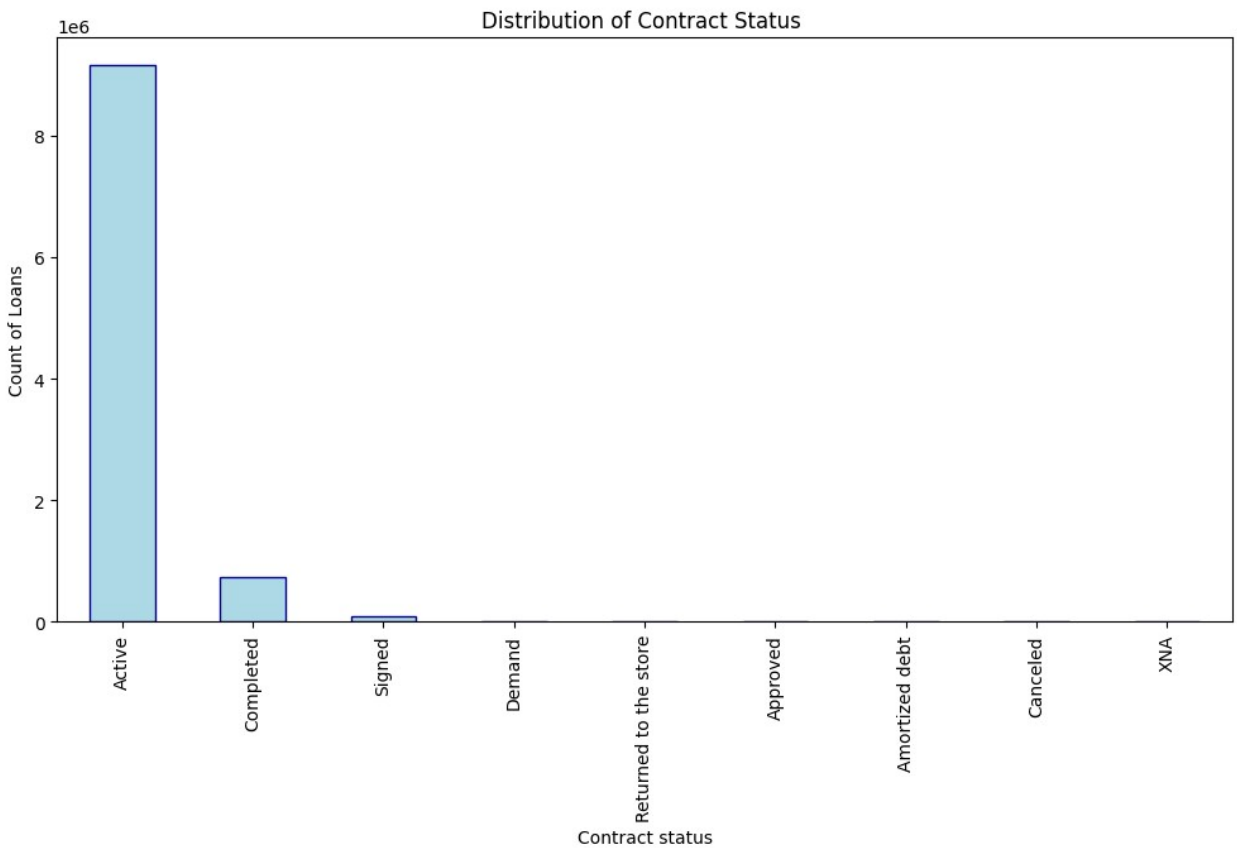
3142	1
2809	1
3396	1
3273	1
4049	1
3132	1
3113	1
2989	1
3163	1
4141	1
3054	1
2998	1
3235	1
3052	1
3071	1
3004	1
3144	1
3093	1
2870	1
3549	1
3731	1
3641	1
3580	1
3488	1
3335	1
3307	1
3383	1
3218	1
3264	1
3221	1
3246	1
3300	1
3330	1
3373	1
3342	1
3407	1
3361	1
3269	1
3468	1
3239	1
3025	1
3086	1
3178	1
3185	1
3298	1
3237	1
3048	1
3242	1
3310	1

4231	1
3565	1
3303	1
3284	1
3282	1
3427	1
3240	1
3125	1
3233	1
3309	1
3301	1
3253	1
3265	1
3272	1
3066	1
3087	1
3133	1
3457	1
3519	1
3610	1
3127	1
3292	1
3181	1
3101	1
3624	1
3120	1
3341	1
3192	1
3035	1
3296	1
3248	1
3222	1
3241	1
3278	1
3270	1
3429	1
3111	1
3143	1
3040	1
3179	1
3158	1
2995	1
3672	1
3700	1
2897	1
2958	1
3005	1
3366	1
3161	1

```
3217          1
3323          1
3399          1
3082          1
Name: count, dtype: int64
```

Distribution of Contract Status

```
df["NAME_CONTRACT_STATUS"].unique()

plt.figure(figsize=(12,6))
df['NAME_CONTRACT_STATUS'].value_counts().plot(kind='bar',color='light
blue',edgecolor='darkblue')
plt.title('Distribution of Contract Status ')
plt.xlabel('Contract status')
plt.ylabel('Count of Loans')
plt.show()
```



- Majority of the clients have "Active" status in NAME_CONTRACT_STATUS.

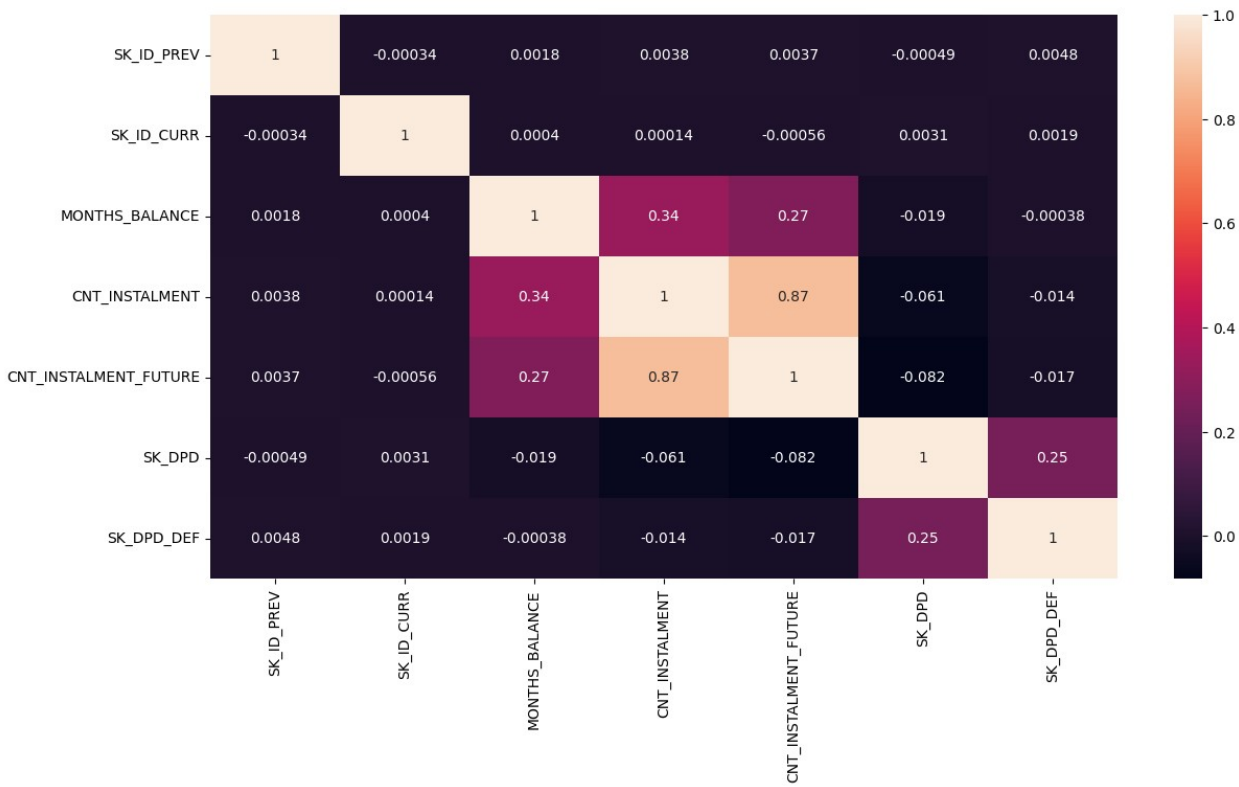
```
a=df.select_dtypes(include=np.number).corr()
a
```

{"summary":"{\n \"name\": \"a\",\n \"rows\": 7,\n \"fields\": [\n {\n \"column\": \"SK_ID_PREV\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.37712856641467885,\n \"min\": -0.00048650127831204997,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 1.0,\n -0.00033640186135633197,\n -0.00048650127831204997\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_ID_CURR\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.3776695599401592,\n \"min\": -0.000559450889491026,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n -0.00033640186135633197,\n 1.0,\n 0.003118111100230418\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"MONTHS_BALANCE\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.37095978975537525,\n \"min\": -0.018939226282118773,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 0.0018352433208916623,\n 0.00040396365483740015,\n -0.018939226282118773\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CNT_INSTALMENT\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.45166026788362235,\n \"min\": -0.06080313776025321,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 0.003819799424511613,\n 0.00014396700246291138,\n -0.06080313776025321\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CNT_INSTALMENT_FUTURE\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.45489741679065016,\n \"min\": -0.0820041344934497,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 0.003678917910923811,\n -0.000559450889491026,\n -0.0820041344934497\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.3878373776534058,\n \"min\": -0.0820041344934497,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n -0.00048650127831204997,\n 0.003118111100230418,\n 1.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD_DEF\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.37596546688745985,\n \"min\": -0.017436043627572374,\n \"max\": 1.0,\n \"num_unique_values\": 7,\n \"samples\": [\n 0.004848362321909511,\n 0.0019478986718724082,\n 0.2457822529945811\n],\n \"semantic_type\": \"\",\n

\"description\": \"\"\n   }\n   }\n]\
n}","type":"dataframe","variable_name":"a"}

```
plt.figure(figsize=(14,7))
sns.heatmap(a,annot=True)
```

```
<Axes: >
```



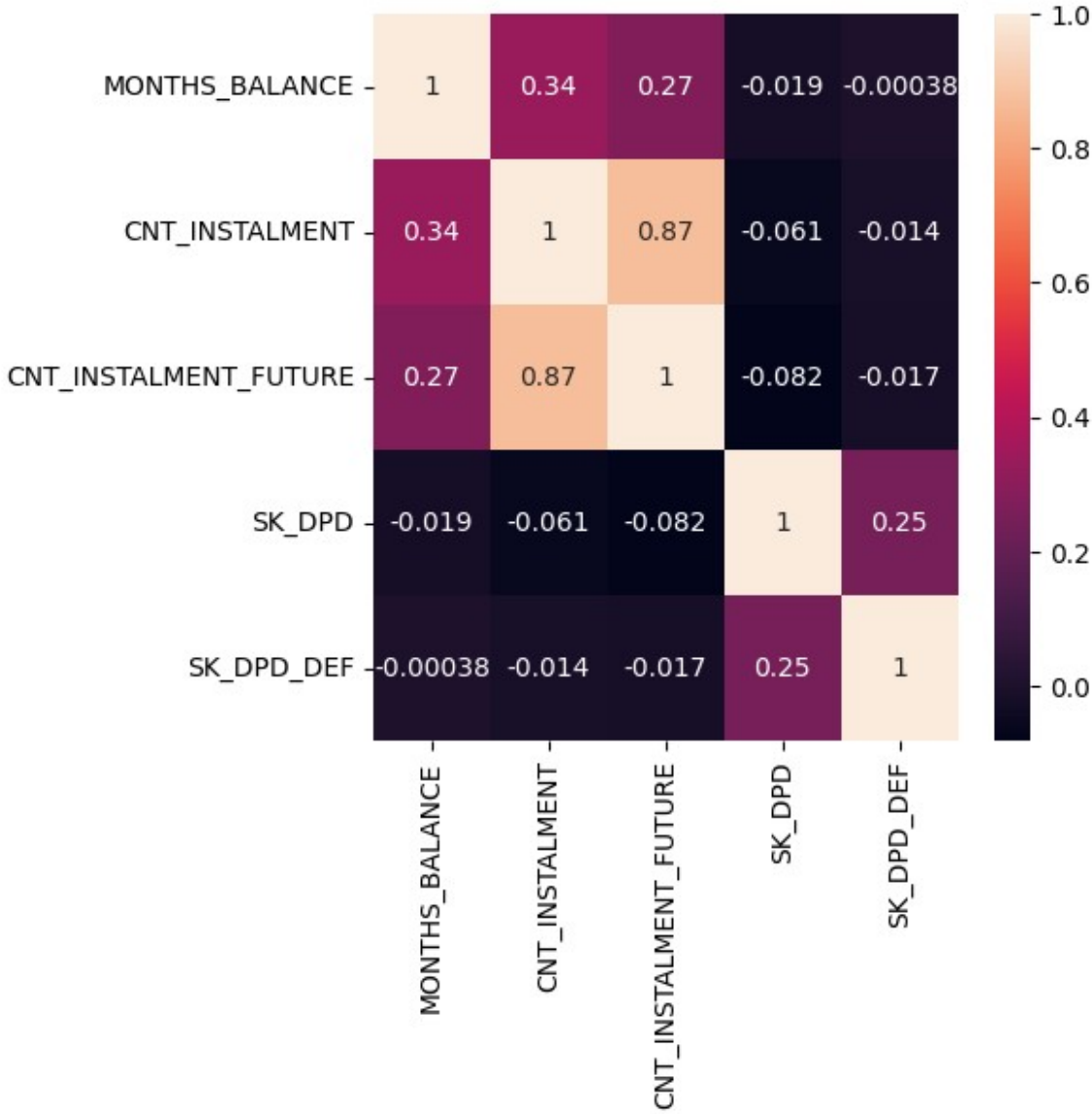

```
df.drop(columns=['SK_ID_PREV', 'SK_ID_CURR'], inplace=True)

b = df.select_dtypes(include=np.number).corr()

b
```

{"summary":"{\n \"name\": \"b\",\n \"rows\": 5,\n \"fields\": [\n
{\n   \"column\": \"MONTHS_BALANCE\",\n   \"properties\": {\n
\"dtype\": \"number\",\n   \"std\": 0.4130682128402052,\n
\"min\": -0.018939226282118773,\n   \"max\": 1.0,\n
\"num_unique_values\": 5,\n   \"samples\": [\n
0.33616300074310984,\n   -0.00038102329153132244,\n
0.27159451034013016\n   ],\n   \"semantic_type\": \"\",\n
\"description\": \"\"\n   }\n   },\n   {\n   \"column\":
\"CNT_INSTALMENT\",\n   \"properties\": {\n   \"dtype\":
\"number\",\n   \"std\": 0.4915609397447816,\n   \"min\": -
0.06080313776025321,\n   \"max\": 1.0,\n

\"num_unique_values\": 5,\n \"samples\": [\n 1.0,\n -0.014153584302564555,\n 0.8712759853337174\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"CNT_INSTALMENT_FUTURE\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.5011967233080064,\n \"min\": -0.0820041344934497,\n \"max\": 1.0,\n \"num_unique_values\": 5,\n \"samples\": [\n 0.8712759853337174,\n -0.017436043627572374,\n 1.0\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.45720963638843376,\n \"min\": -0.0820041344934497,\n \"max\": 1.0,\n \"num_unique_values\": 5,\n \"samples\": [\n -0.06080313776025321,\n 0.2457822529945811,\n -0.0820041344934497\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"SK_DPD_DEF\",\n \"properties\": {\n \"dtype\": \"number\",\n \"std\": 0.4376773011341028,\n \"min\": -0.017436043627572374,\n \"max\": 1.0,\n \"num_unique_values\": 5,\n \"samples\": [\n -0.014153584302564555,\n 1.0,\n -0.017436043627572374\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\n}","type":"dataframe","variable_name":"b"}

```
sns.heatmap(b,annot=True)
```

```
<Axes: >
```




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

```
MONTHS_BALANCE                0
CNT_INSTALMENT            26071
CNT_INSTALMENT_FUTURE     26087
NAME_CONTRACT_STATUS          0
SK_DPD                        0
SK_DPD_DEF                    0
dtype: int64
```

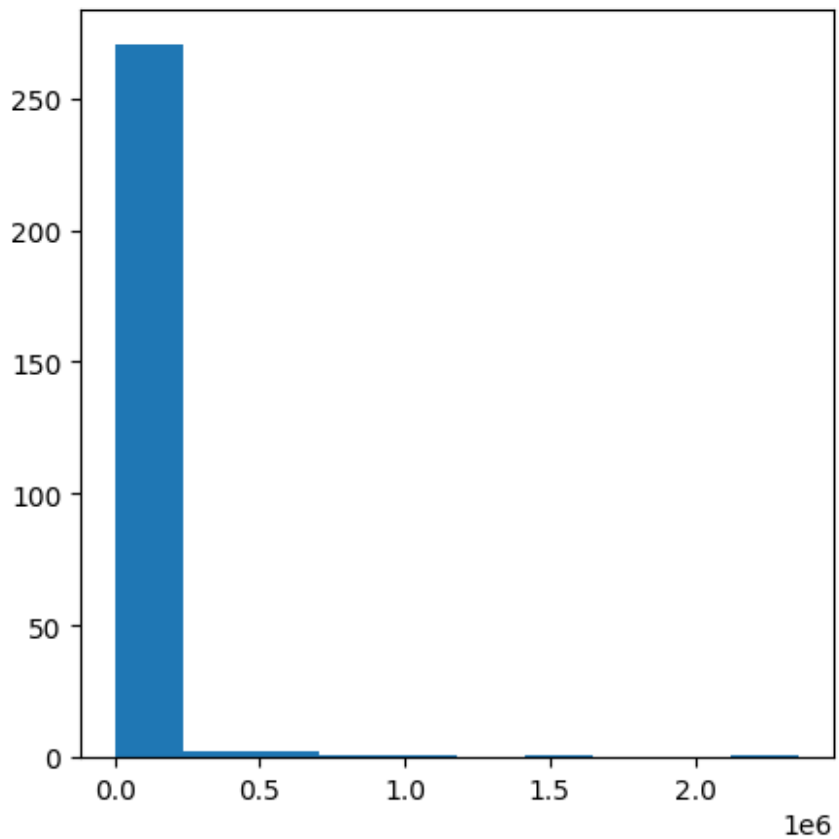
```
df["CNT_INSTALMENT"]=df["CNT_INSTALMENT"].fillna(df["CNT_INSTALMENT"].
median())
```

```
df["CNT_INSTALMENT_FUTURE"]=df["CNT_INSTALMENT_FUTURE"].fillna(df["CNT
_INSTALMENT_FUTURE"].median())

df.columns
```

```
Index(['MONTHS_BALANCE', 'CNT_INSTALMENT', 'CNT_INSTALMENT_FUTURE',
       'NAME_CONTRACT_STATUS', 'SK_DPD', 'SK_DPD_DEF'],
      dtype='object')
```

```
plt.hist(df.groupby('NAME_CONTRACT_STATUS')
["CNT_INSTALMENT"].value_counts())
```

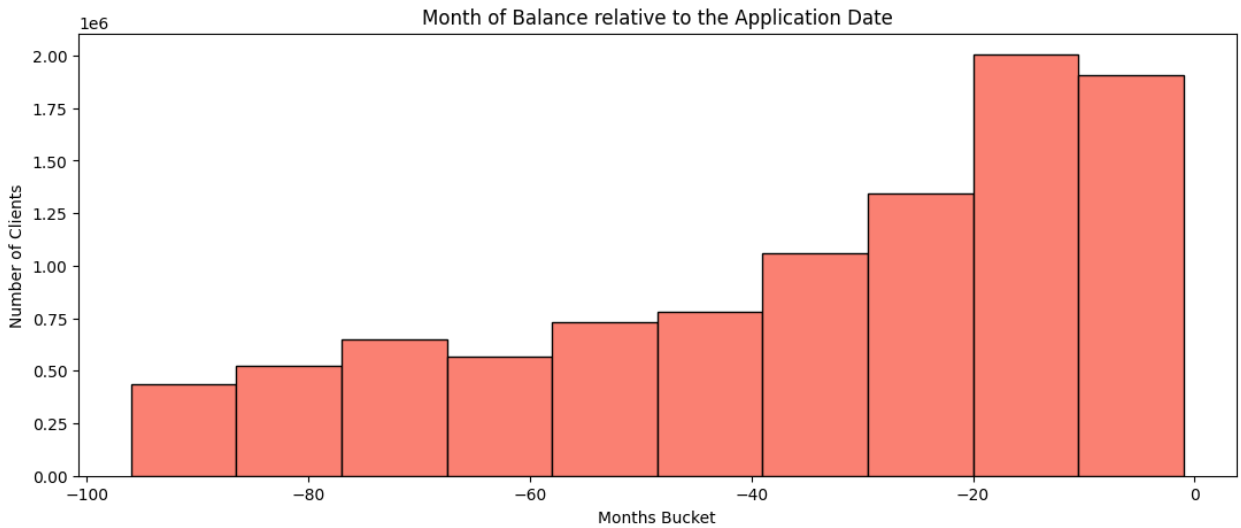
```
(array([270.,   2.,   2.,   1.,   1.,   0.,   1.,   0.,   0.,   1.]),
 array([1.000000e+00, 2.357040e+05, 4.714070e+05, 7.071100e+05,
        9.428130e+05, 1.178516e+06, 1.414219e+06, 1.649922e+06,
        1.885625e+06, 2.121328e+06, 2.357031e+06]),
 <BarContainer object of 10 artists>)
```



MONTHS_BALANCE

```
plt.figure(figsize=(13,5))
plt.hist((df['MONTHS_BALANCE']).values,edgecolor='black',color='salmon
')
```

```
plt.title('Month of Balance relative to the Application Date')
plt.xlabel('Months Bucket')
plt.ylabel('Number of Clients')
plt.show()
```



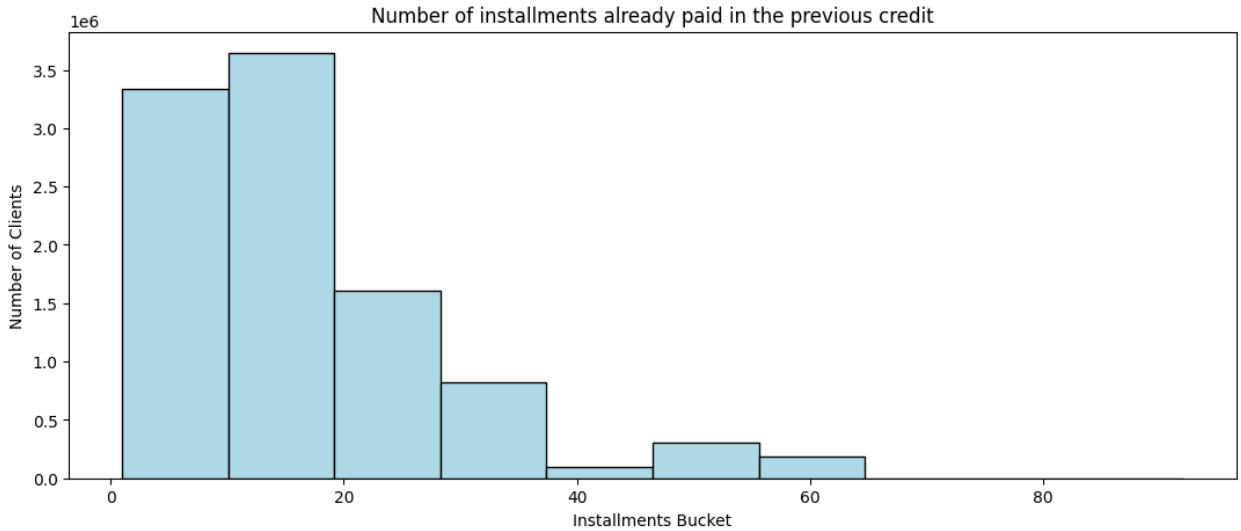
- MONTHS_BALANCE for majority of the clients is between 10 and 20 months before the date of application.

```
df.columns
```

```
Index(['MONTHS_BALANCE', 'CNT_INSTALMENT', 'CNT_INSTALMENT_FUTURE',
       'NAME_CONTRACT_STATUS', 'SK_DPD', 'SK_DPD_DEF'],
      dtype='object')
```

Number of installments already paid.

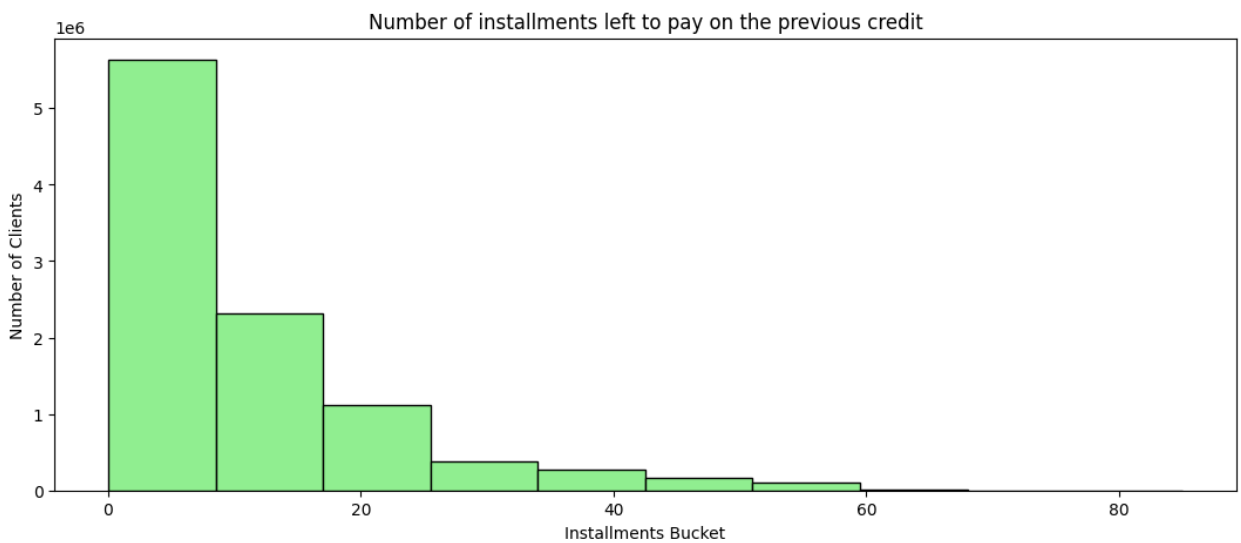
```
plt.figure(figsize=(13,5))
plt.hist((df['CNT_INSTALMENT']).values,edgecolor='black',color='lightb
lue')
plt.title('Number of installments already paid in the previous
credit')
plt.xlabel('Installments Bucket')
plt.ylabel('Number of Clients')
plt.show()
```



- Majority of the clients have number of installments less than equal 20

Number of installments left to pay

```
plt.figure(figsize=(13,5))
plt.hist((df['CNT_INSTALMENT_FUTURE']).values,edgecolor='black',color=
'lightgreen')
plt.title('Number of installments left to pay on the previous credit')
plt.xlabel('Installments Bucket')
plt.ylabel('Number of Clients')
plt.show()
```



- Majority of the the clients have less than 10 installments left to pay off.

Installments Balance

```
df_inst=pd.read_csv("/content/drive/MyDrive/Colab
Notebooks/installments_payments.csv")
df_inst.head()
```

{"type":"dataframe","variable_name":"df_inst"}

```
df_inst.columns
```

```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NUM_INSTALMENT_VERSION',
       'NUM_INSTALMENT_NUMBER', 'DAYS_INSTALMENT',
'DAYS_ENTRY_PAYMENT',
       'AMT_INSTALMENT', 'AMT_PAYMENT'],
      dtype='object')
```

```
df_inst.isnull().sum()
```

```
SK_ID_PREV                   0
SK_ID_CURR                   0
NUM_INSTALMENT_VERSION       0
NUM_INSTALMENT_NUMBER        0
DAYS_INSTALMENT              0
DAYS_ENTRY_PAYMENT        2905
AMT_INSTALMENT               0
AMT_PAYMENT               2905
dtype: int64
```

```
df_inst.isnull().sum()/df_inst.shape[0]*100
```

```
SK_ID_PREV                 0.000000
SK_ID_CURR                 0.000000
NUM_INSTALMENT_VERSION     0.000000
NUM_INSTALMENT_NUMBER      0.000000
DAYS_INSTALMENT            0.000000
DAYS_ENTRY_PAYMENT         0.021352
AMT_INSTALMENT             0.000000
AMT_PAYMENT                0.021352
dtype: float64
```

```
df_inst.shape
```

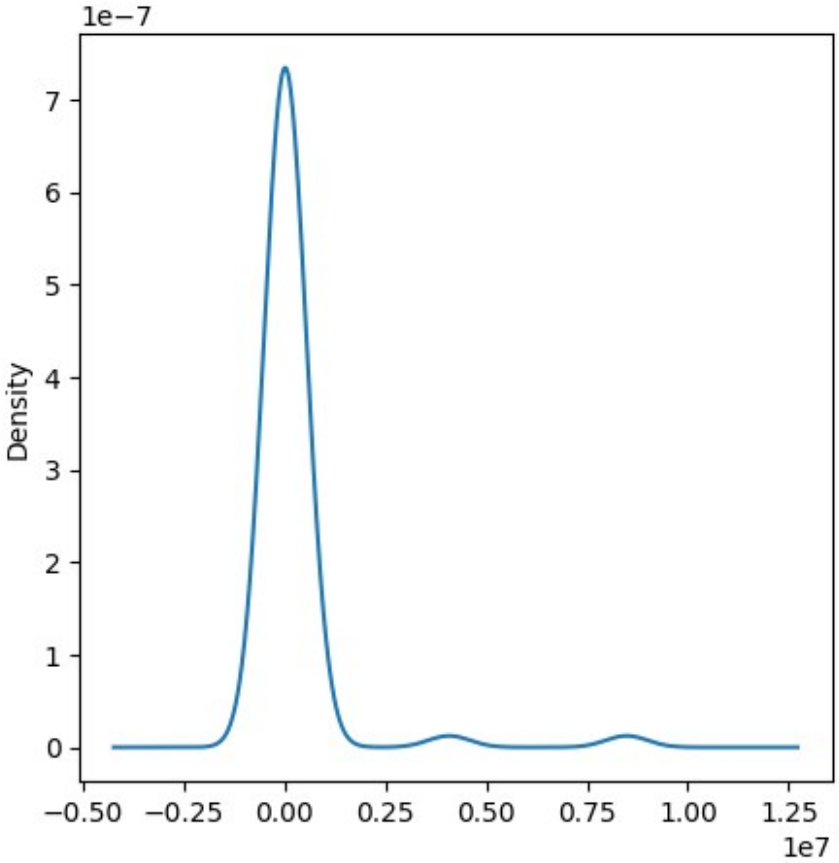
```
(13605401, 8)
```

```
df_inst.dropna(inplace=True)
df_inst.shape
```

```
(13602496, 8)
```

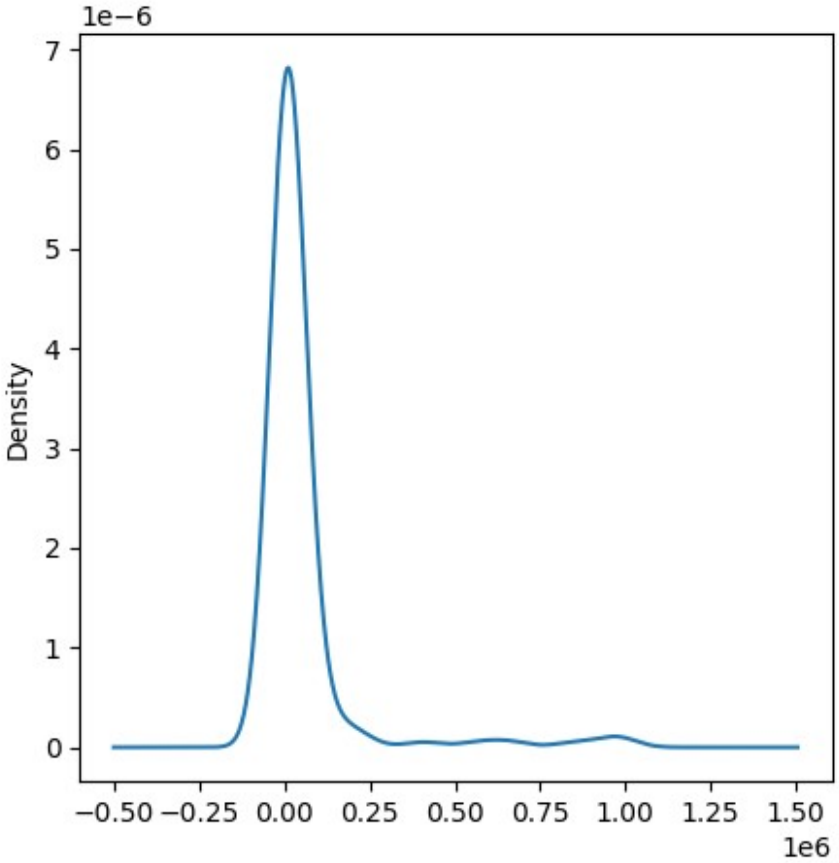
```
df_inst['NUM_INSTALMENT_VERSION'].value_counts().plot(kind='kde')
```

```
<Axes: ylabel='Density'>
```



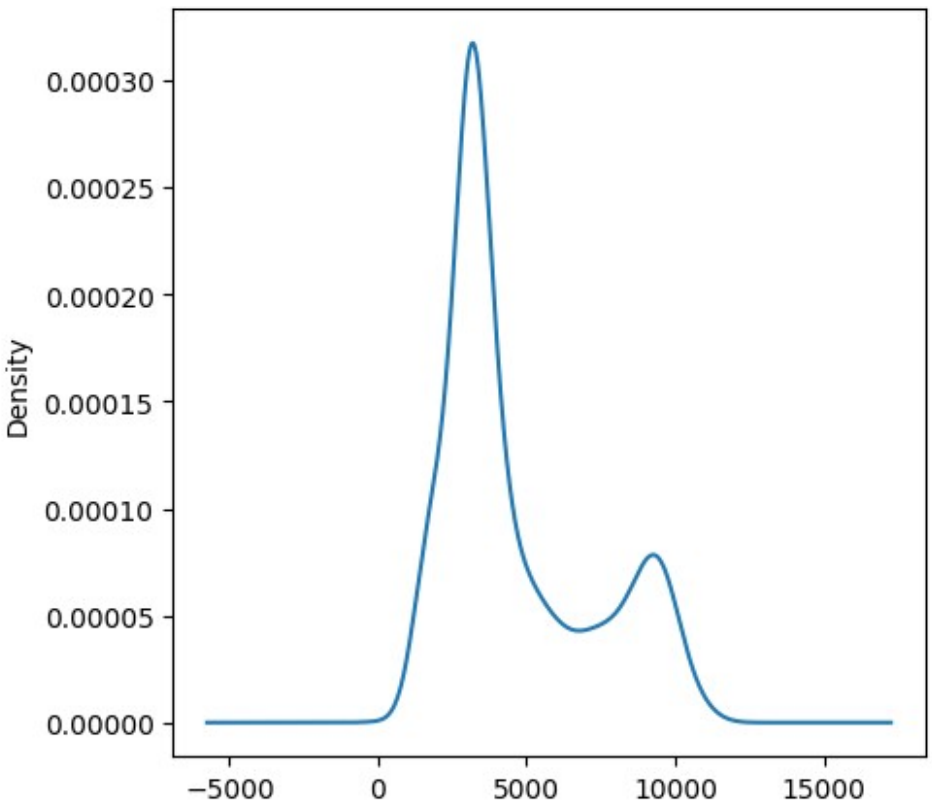

```
df_inst['NUM_INSTALMENT_NUMBER'].value_counts().plot(kind='kde')
```

```
<Axes: ylabel='Density'>
```



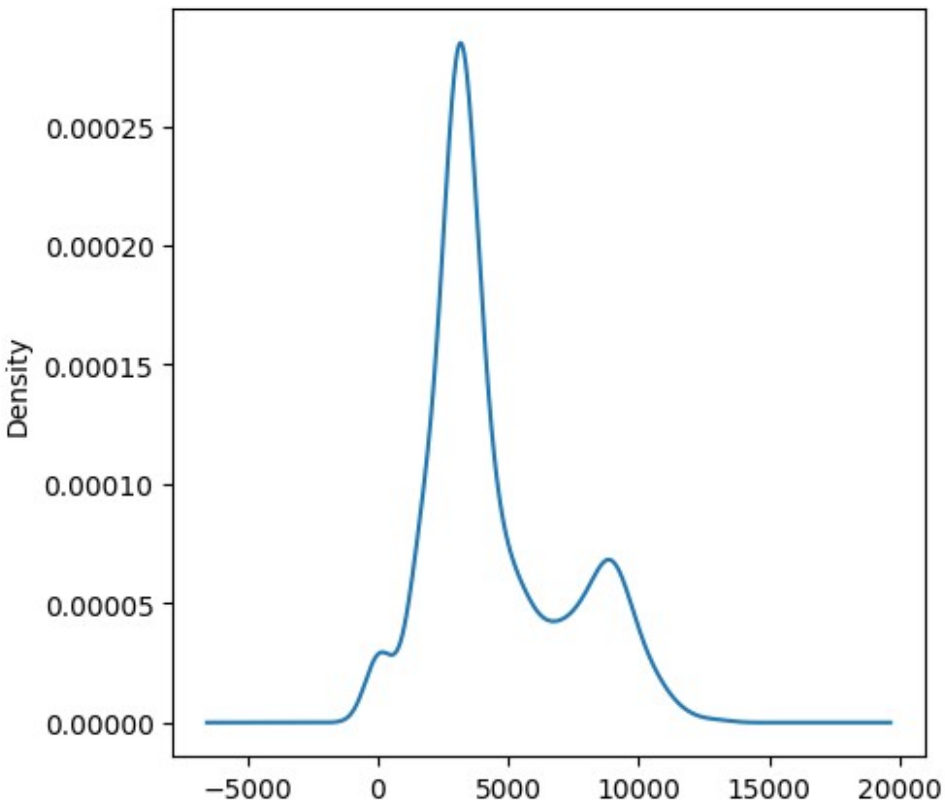

```
df_inst['DAYS_INSTALMENT'].value_counts().plot(kind='kde')
```

```
<Axes: ylabel='Density'>
```




```
df_inst['DAYS_ENTRY_PAYMENT'].value_counts().plot(kind='kde')
```

```
<Axes: ylabel='Density'>
```



CREDIT CARD BALANCE

```
credit_card_balance = pd.read_csv('/content/drive/MyDrive/Colab
Notebooks/credit_card_balance.csv')
credit_card_balance.head()
```

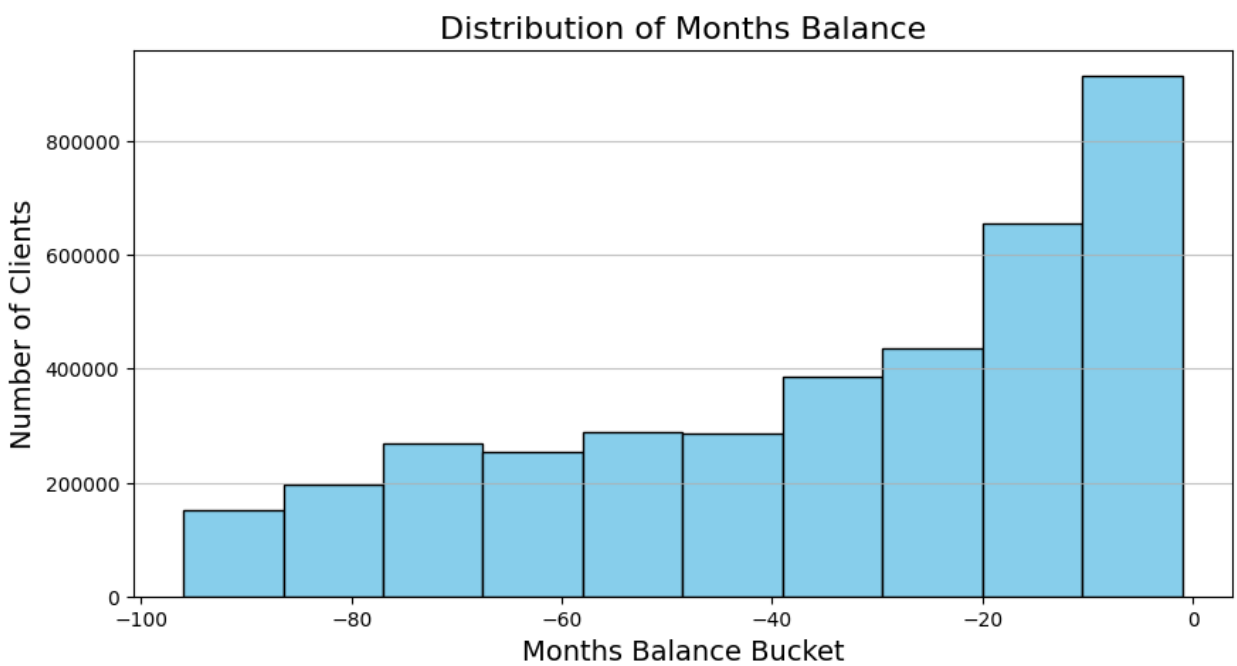
{"type":"dataframe","variable_name":"credit_card_balance"}

```
credit_card_balance.columns
```

```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'MONTHS_BALANCE', 'AMT_BALANCE',
       'AMT_CREDIT_LIMIT_ACTUAL', 'AMT_DRAWINGS_ATM_CURRENT',
       'AMT_DRAWINGS_CURRENT', 'AMT_DRAWINGS_OTHER_CURRENT',
       'AMT_DRAWINGS_POS_CURRENT', 'AMT_INST_MIN_REGULARITY',
       'AMT_PAYMENT_CURRENT', 'AMT_PAYMENT_TOTAL_CURRENT',
       'AMT_RECEIVABLE_PRINCIPAL', 'AMT_RECIVABLE',
'AMT_TOTAL_RECEIVABLE',
       'CNT_DRAWINGS_ATM_CURRENT', 'CNT_DRAWINGS_CURRENT',
       'CNT_DRAWINGS_OTHER_CURRENT', 'CNT_DRAWINGS_POS_CURRENT',
       'CNT_INSTALMENT_MATURE_CUM', 'NAME_CONTRACT_STATUS', 'SK_DPD',
       'SK_DPD_DEF'],
      dtype='object')
```

```
## UNIVARIATE ANALYSIS
```

```python
#### MONTH_BALANCE :

import matplotlib.pyplot as plt

# Set figure size
plt.figure(figsize=(10, 5))

# Create histogram
plt.hist(credit_card_balance['MONTHS_BALANCE'].values, bins=10,
edgecolor='black', color='skyblue')

# Add title and labels
plt.title('Distribution of Months Balance', fontsize=16)
plt.xlabel('Months Balance Bucket', fontsize=14)
plt.ylabel('Number of Clients', fontsize=14)

# Add grid for better readability
plt.grid(axis='y', alpha=0.75)

# Show plot
plt.show()
```



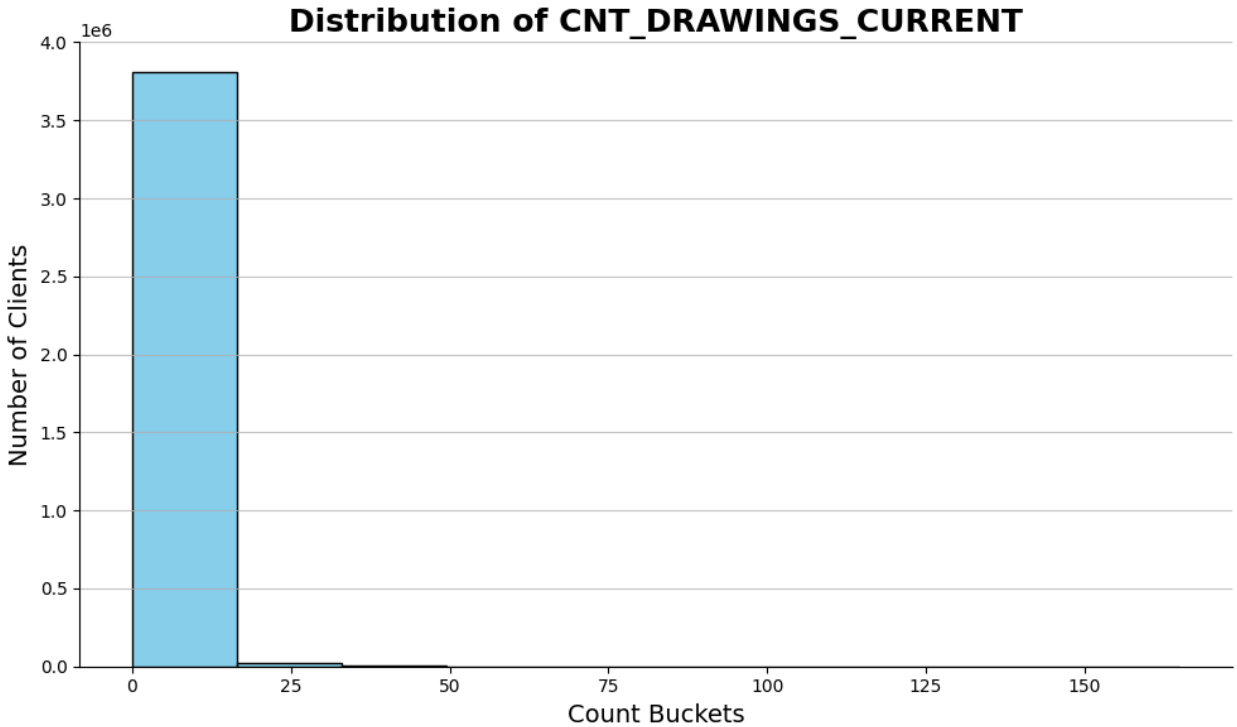
INFERENCES FOR THE ABOVE VISUALISATION:

New Application: Most clients have recent balances between 0 to -10 months from the application date, indicating active or recently closed credit accounts.

Fewer Long-Term Data: Fewer clients have balances older than 20 months, likely due to account closures or inactivity.

Data Recency Focus: The most relevant data for analysis is within the last 20 months, with a high density in the 0 to -10 months range.

```
#### CNT_DRAWINGS_CURRENT:

# Set figure size
plt.figure(figsize=(10, 6))

# Create histogram
plt.hist(credit_card_balance['CNT_DRAWINGS_CURRENT'].values, bins=10,
edgecolor='black', color='skyblue')

# Add title and labels with increased font sizes
plt.title('Distribution of CNT_DRAWINGS_CURRENT', fontsize=18,
fontweight='bold')
plt.xlabel('Count Buckets', fontsize=14)
plt.ylabel('Number of Clients', fontsize=14)

# Add grid lines for better readability
plt.grid(axis='y', alpha=0.75)

# Add a box around the plot for better definition
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

# Show plot
plt.tight_layout()  # Adjust layout to make room for labels
plt.show()
```



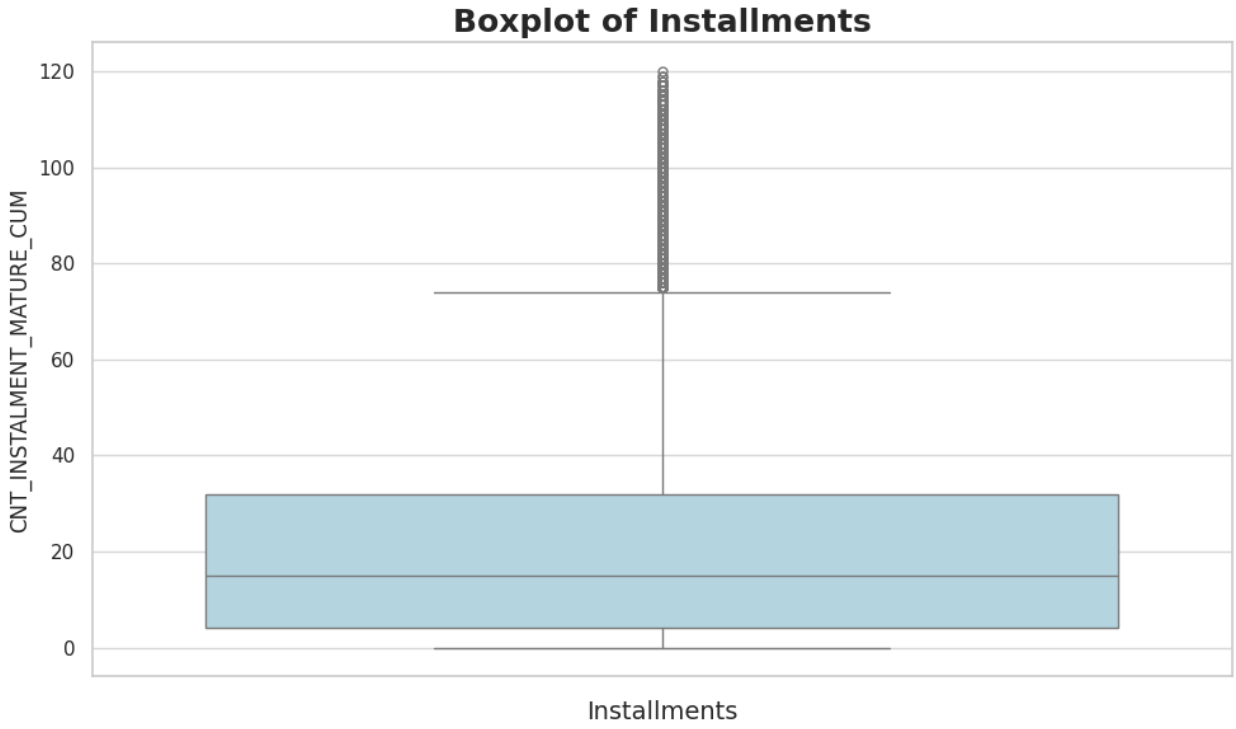
OBSERVATIONS:

Majority Low Usage: Most clients have fewer than 25 withdrawals in the current month on their credit accounts, indicating minimal drawing activity.

Rare Outliers: Only a small number of clients have high withdrawal counts, suggesting these are exceptions rather than the norm.

```
#### CNT_INSTALMENT_MATURE_CUM :


# Set the style for the plot
sns.set(style='whitegrid')

# Create the boxplot
plt.figure(figsize=(10, 6))
sns.boxplot(y='CNT_INSTALMENT_MATURE_CUM', data=credit_card_balance,
color='lightblue', fliersize=5)

# Add title and labels with increased font sizes
plt.title('Boxplot of Installments', fontsize=18, fontweight='bold')
plt.xlabel('Installments', fontsize=14)

# Add grid lines for better readability
plt.grid(axis='y', alpha=0.75)

# Show the plot
plt.tight_layout()  # Adjust layout to make room for labels
```

```
plt.show()
```



OBSERVATIONS

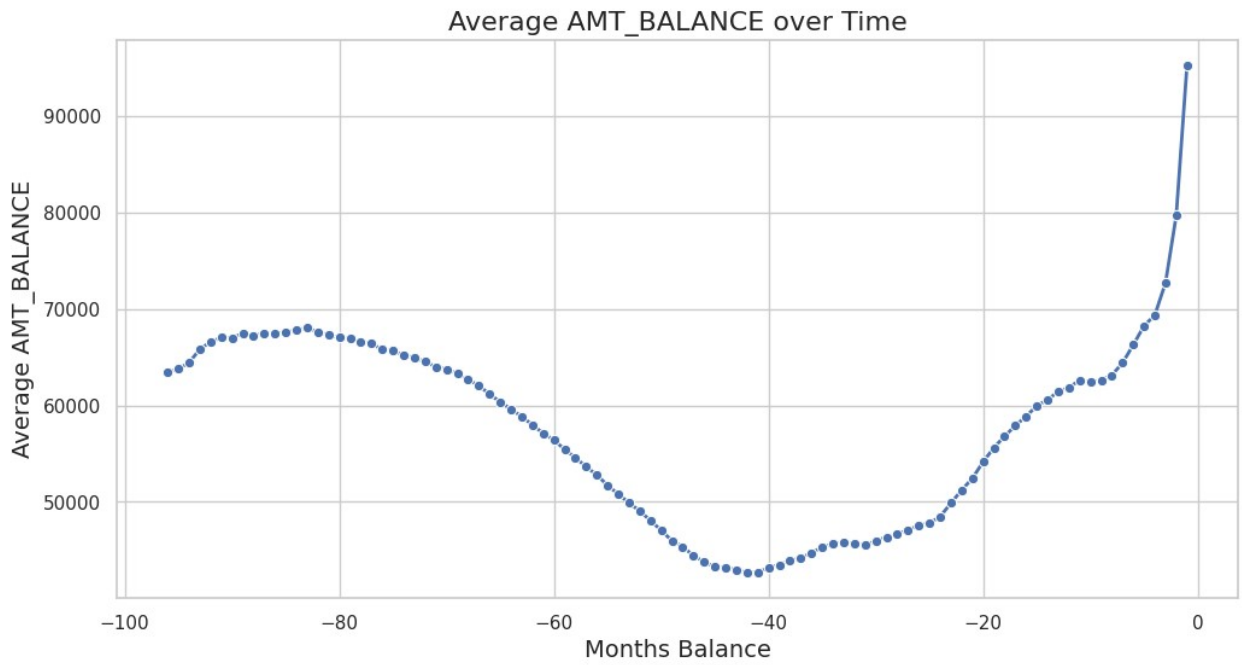
Installment Distribution: Most clients have fewer than 32 paid installments, with 50% having 15 or fewer.

A few clients (outliers) have made up to 120 installments, but this is uncommon.

Key Takeaway: The bulk of clients have relatively few installments, indicating shorter credit histories or less reliance on installment-based repayments.

BIVARIATE ANALYSIS

```
# Line plot showing AMT_BALANCE over time
df_time = credit_card_balance.groupby('MONTHS_BALANCE')
['AMT_BALANCE'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(x='MONTHS_BALANCE', y='AMT_BALANCE', data=df_time,
marker='o', color='b', linestyle='-', linewidth=2)
plt.title('Average AMT_BALANCE over Time', fontsize=16)
plt.xlabel('Months Balance', fontsize=14)
plt.ylabel('Average AMT_BALANCE', fontsize=14)
plt.grid(True)
plt.show()
```



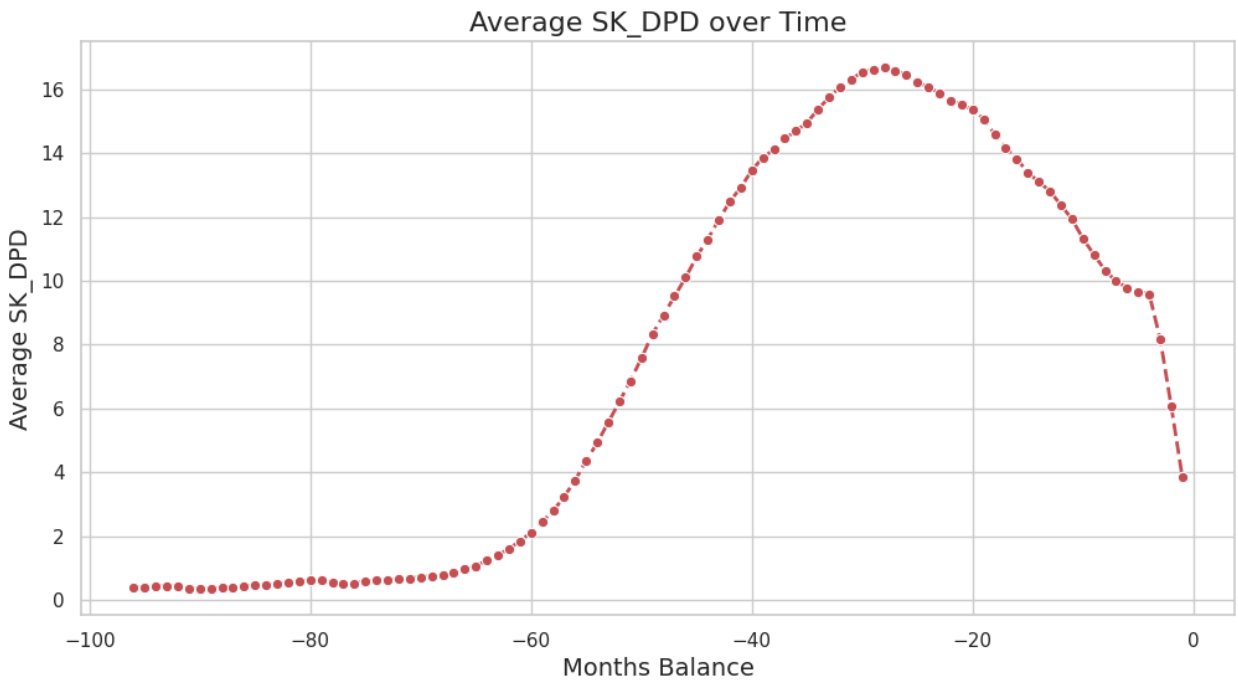
OBSERVATIONS

Initial Decline (-100 to -60 months): Average balance starts above BHD 60,000 and steadily decreases, possibly due to active repayment or reduced spending.

Lowest Point (-40 to -20 months): Balances hit a low of around BHD 45,000, likely indicating debt clearance or minimal credit usage.

Recent Spike (Last 20 months): A sharp rise to over BHD 90,000 suggests increased spending or unpaid balances, reflecting greater credit reliance or financial strain.

```
# Line plot showing SK_DPD over time
df_dpd_time = credit_card_balance.groupby('MONTHS_BALANCE')
['SK_DPD'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(x='MONTHS_BALANCE', y='SK_DPD', data=df_dpd_time,
marker='o', color='r', linestyle='--', linewidth=2)
plt.title('Average SK_DPD over Time', fontsize=16)
plt.xlabel('Months Balance', fontsize=14)
plt.ylabel('Average SK_DPD', fontsize=14)
plt.grid(True)
plt.show()
```



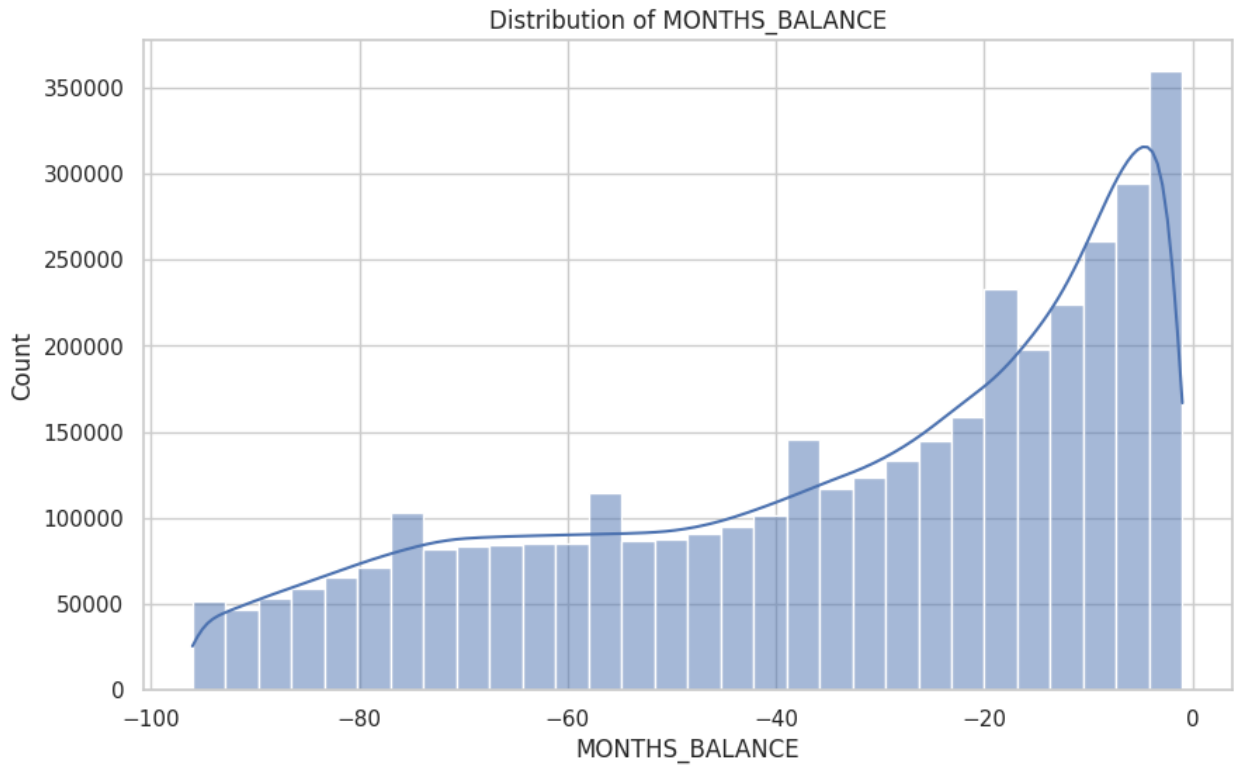
OBSERVATIONS

Correlation: As AMT_BALANCE rises, SK_DPD (delinquencies) may increase, indicating repayment difficulties.

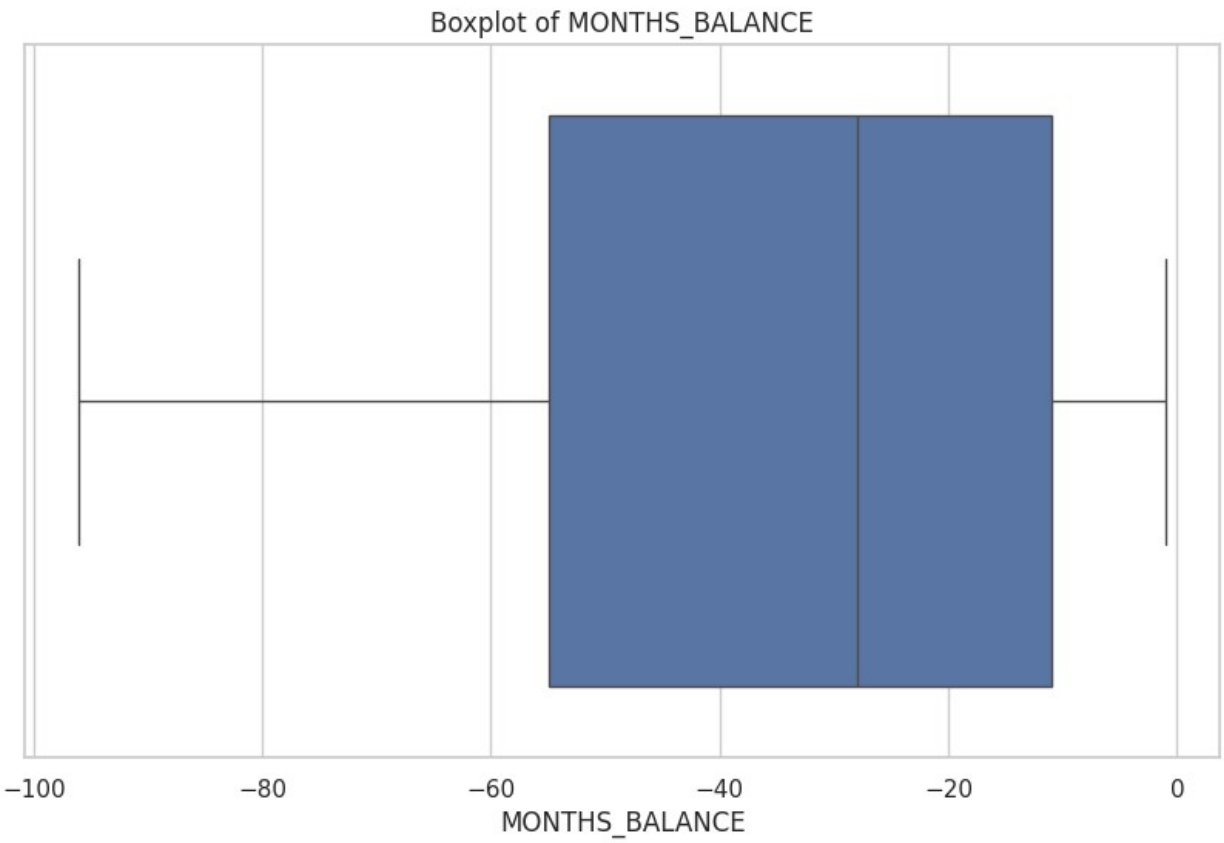
Minimal Delinquency (-40 to -20 months): During low balance periods, fewer overdue payments are expected.

Increase in Delinquencies (Recent months): As balances rise near the present, overdue payments likely increase, signaling financial stress.

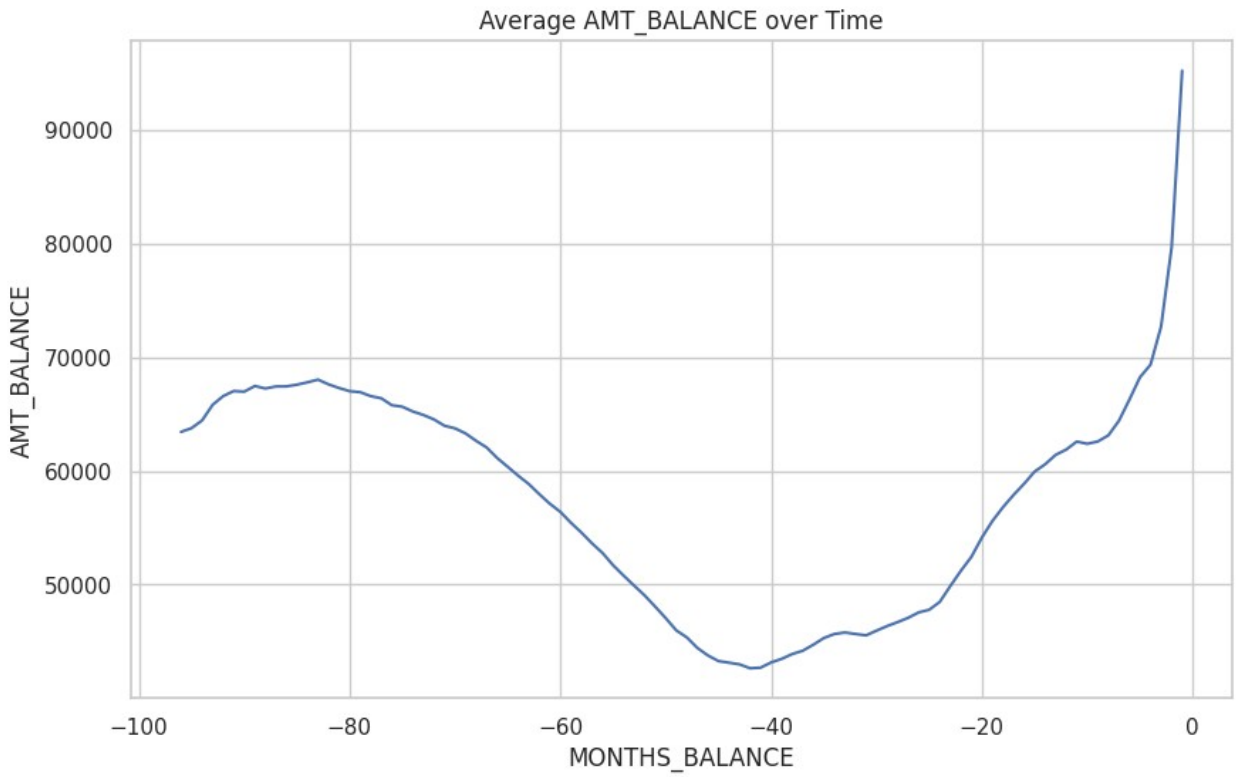
```
# Histogram for MONTHS_BALANCE
plt.figure(figsize=(10, 6))
sns.histplot(credit_card_balance['MONTHS_BALANCE'], bins=30, kde=True)
plt.title('Distribution of MONTHS_BALANCE')
plt.show()
```




```
# Boxplot for MONTHS_BALANCE
plt.figure(figsize=(10, 6))
sns.boxplot(x=credit_card_balance['MONTHS_BALANCE'])
plt.title('Boxplot of MONTHS_BALANCE')
plt.show()
```




```
# Line plot for MONTHS_BALANCE
df_time = credit_card_balance.groupby('MONTHS_BALANCE')
['AMT_BALANCE'].mean().reset_index()
plt.figure(figsize=(10, 6))
sns.lineplot(x='MONTHS_BALANCE', y='AMT_BALANCE', data=df_time)
plt.title('Average AMT_BALANCE over Time')
plt.show()
```



Machine Learning Model Building

```
df1.head()
```

{"type":"dataframe","variable_name":"df1"}

```
cat_cols=df1.select_dtypes(exclude=np.number).columns
cat_cols
```

```
Index(['TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
       'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE',
       'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
'NAME_HOUSING_TYPE',
       'OCCUPATION_TYPE', 'WEEKDAY_APPR_PROCESS_START',
'ORGANIZATION_TYPE',
       'INCOME_GROUP'],
      dtype='object')
```

```
for i in cat_cols:
  print(df1[i].value_counts())
  print()
```

```
TARGET
0    282686
1     24825
```

```
Name: count, dtype: int64

NAME_CONTRACT_TYPE
Cash loans         278232
Revolving loans     29279
Name: count, dtype: int64

CODE_GENDER
F    202452
M    105059
Name: count, dtype: int64

FLAG_OWN_CAR
N    202924
Y    104587
Name: count, dtype: int64

FLAG_OWN_REALTY
Y    213312
N     94199
Name: count, dtype: int64

NAME_TYPE_SUITE
Unaccompanied      249818
Family              40149
Spouse, partner     11370
Children             3267
Other_B              1770
Other_A               866
Group of people       271
Name: count, dtype: int64

NAME_INCOME_TYPE
Working                 158774
Commercial associate     71617
Pensioner                55362
State servant            21703
Unemployed                  22
Student                     18
Businessman                 10
Maternity leave              5
Name: count, dtype: int64

NAME_EDUCATION_TYPE
Secondary / secondary special    218391
Higher education                  74863
Incomplete higher                 10277
Lower secondary                    3816
Academic degree                     164
Name: count, dtype: int64
```

```
NAME_FAMILY_STATUS
Married                 196432
Single / not married     45444
Civil marriage           29775
Separated                19770
Widow                    16088
Unknown                      2
Name: count, dtype: int64

NAME_HOUSING_TYPE
House / apartment      272868
With parents            14840
Municipal apartment     11183
Rented apartment         4881
Office apartment         2617
Co-op apartment          1122
Name: count, dtype: int64

OCCUPATION_TYPE
Unknown                  96391
Laborers                 55186
Sales staff              32102
Core staff               27570
Managers                 21371
Drivers                  18603
High skill tech staff    11380
Accountants               9813
Medicine staff            8537
Security staff            6721
Cooking staff             5946
Cleaning staff            4653
Private service staff     2652
Low-skill Laborers        2093
Waiters/barmen staff      1348
Secretaries               1305
Realty agents              751
HR staff                   563
IT staff                   526
Name: count, dtype: int64

WEEKDAY_APPR_PROCESS_START
TUESDAY      53901
WEDNESDAY    51934
MONDAY       50714
THURSDAY     50591
FRIDAY       50338
SATURDAY     33852
SUNDAY       16181
Name: count, dtype: int64
```

```
ORGANIZATION_TYPE
Business Entity Type 3    67992
XNA                       55374
Self-employed             38412
Other                     16683
Medicine                  11193
Business Entity Type 2    10553
Government                10404
School                     8893
Trade: type 7              7831
Kindergarten               6880
Construction               6721
Business Entity Type 1     5984
Transport: type 4          5398
Trade: type 3              3492
Industry: type 9           3368
Industry: type 3           3278
Security                   3247
Housing                    2958
Industry: type 11          2704
Military                   2634
Bank                       2507
Agriculture                2454
Police                     2341
Transport: type 2          2204
Postal                     2157
Security Ministries        1974
Trade: type 2              1900
Restaurant                 1811
Services                   1575
University                 1327
Industry: type 7           1307
Transport: type 3          1187
Industry: type 1           1039
Hotel                       966
Electricity                 950
Industry: type 4            877
Trade: type 6               631
Industry: type 5            599
Insurance                   597
Telecom                     577
Emergency                   560
Industry: type 2            458
Advertising                 429
Realtor                     396
Culture                     379
Industry: type 12           369
Trade: type 1               348
```

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

INCOME_GROUP
1-2L         155898
2-5L          85213
Upto 1L       63698
5-10L          2452
10-20L          206
20-50L           39
50L above         4
Name: count, dtype: int64
```

```
df1["ORGANIZATION_TYPE"].nunique()
```

```
58
```

```
df1.to_csv('/content/drive/MyDrive/Colab
Notebooks/new_file.csv',index=False)
```

```
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# 1. Label Encoding for Ordinal Variables (if applicable)
# Assuming INCOME_GROUP is ordinal
income_order = ['Upto 1L', '1-2L', '2-5L', '5-10L', '10-20L', '20-
50L', '50L above']
df1['INCOME_GROUP'] = pd.Categorical(df1['INCOME_GROUP'],
categories=income_order, ordered=True).codes

# 2. One-Hot Encoding for Nominal Variables
# List of nominal variables to one-hot encode
nominal_vars = [
    'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
    'FLAG_OWN_REALTY', 'NAME_TYPE_SUITE', 'NAME_INCOME_TYPE',
    'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS',
    'NAME_HOUSING_TYPE', 'OCCUPATION_TYPE',
    'WEEKDAY_APPR_PROCESS_START', 'ORGANIZATION_TYPE'
]
```

```
# Apply one-hot encoding
df1 = pd.get_dummies(df1, columns=nominal_vars, drop_first=True)

# Display the encoded DataFrame
df1.head()
```

{"type":"dataframe","variable_name":"df1"}

```
df1.shape
```

```
(307511, 174)
```

```
bool_cols=df1.select_dtypes('bool').columns

df1[bool_cols]=df1[bool_cols].astype('int')

df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 174 entries, SK_ID_CURR to ORGANIZATION_TYPE_XNA
dtypes: float64(10), int64(162), int8(1), object(1)
memory usage: 406.2+ MB
```

```
df1.select_dtypes('object').columns
```

```
Index(['TARGET'], dtype='object')
```

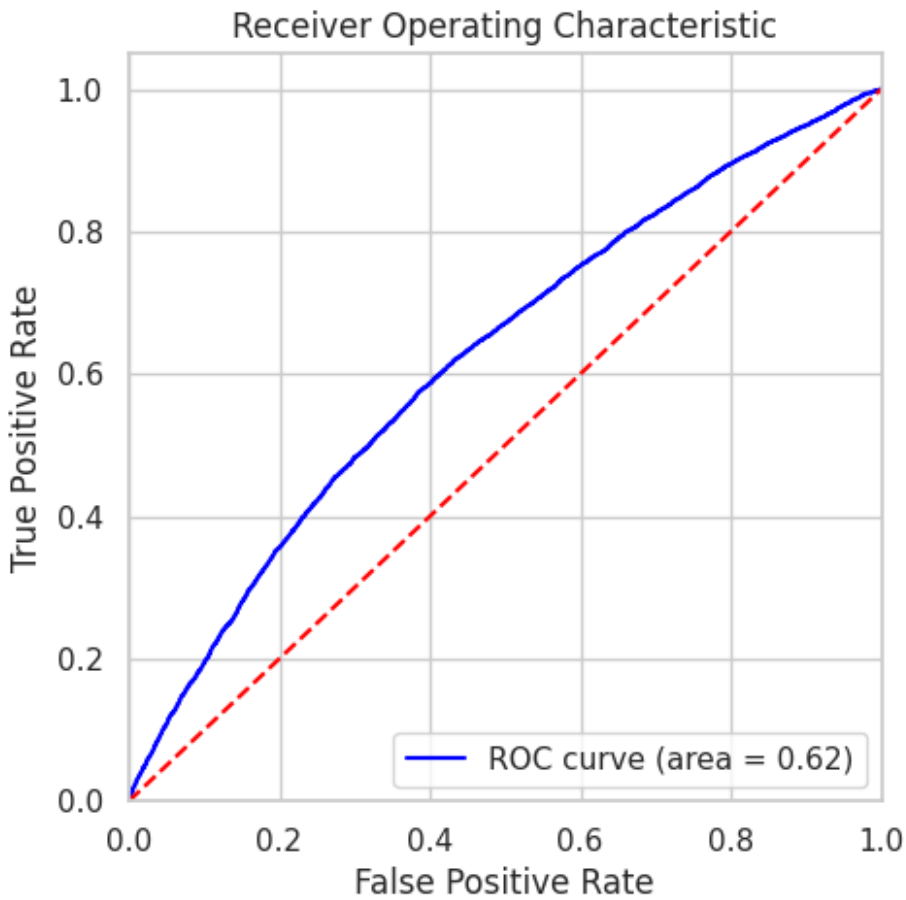
```
x=df1.drop(columns=['SK_ID_CURR','TARGET'])
y=df1['TARGET'].astype('int')

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score, roc_curve

xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_st
ate=42)

model = LogisticRegression()
model.fit(xtrain, ytrain)
```

```
LogisticRegression()
```

```
y_probs = model.predict_proba(xtest)[:, 1]

roc_auc = roc_auc_score(ytest, y_probs)
print(f"ROC-AUC: {roc_auc:.4f}")

# Optionally, plot the ROC curve
fpr, tpr, thresholds = roc_curve(ytest, y_probs)

plt.figure()
plt.plot(fpr, tpr, color='blue', label='ROC curve (area = %0.2f)' %
```

```
roc_auc)
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc='lower right')
plt.show()
```

```
ROC-AUC: 0.6231
```

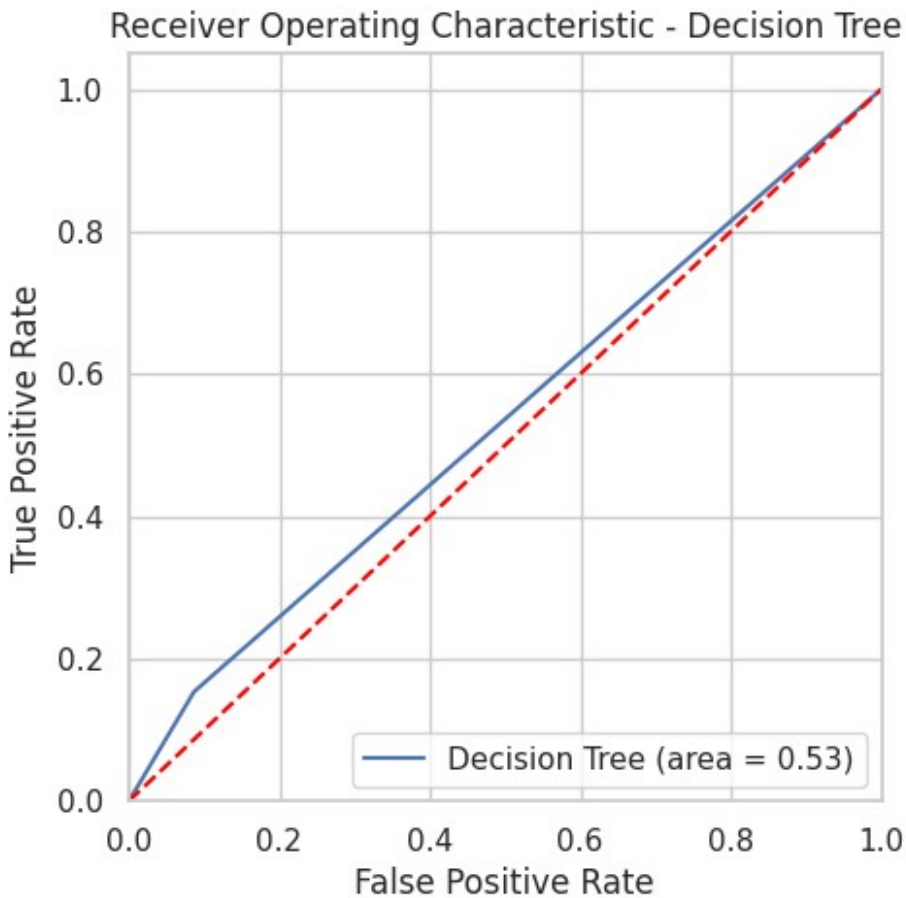



```
import tensorflow as tf

# Check if GPU is available
gpu_available = tf.config.list_physical_devices('GPU')
print("GPU Available:", gpu_available)
```

```
GPU Available: []
```

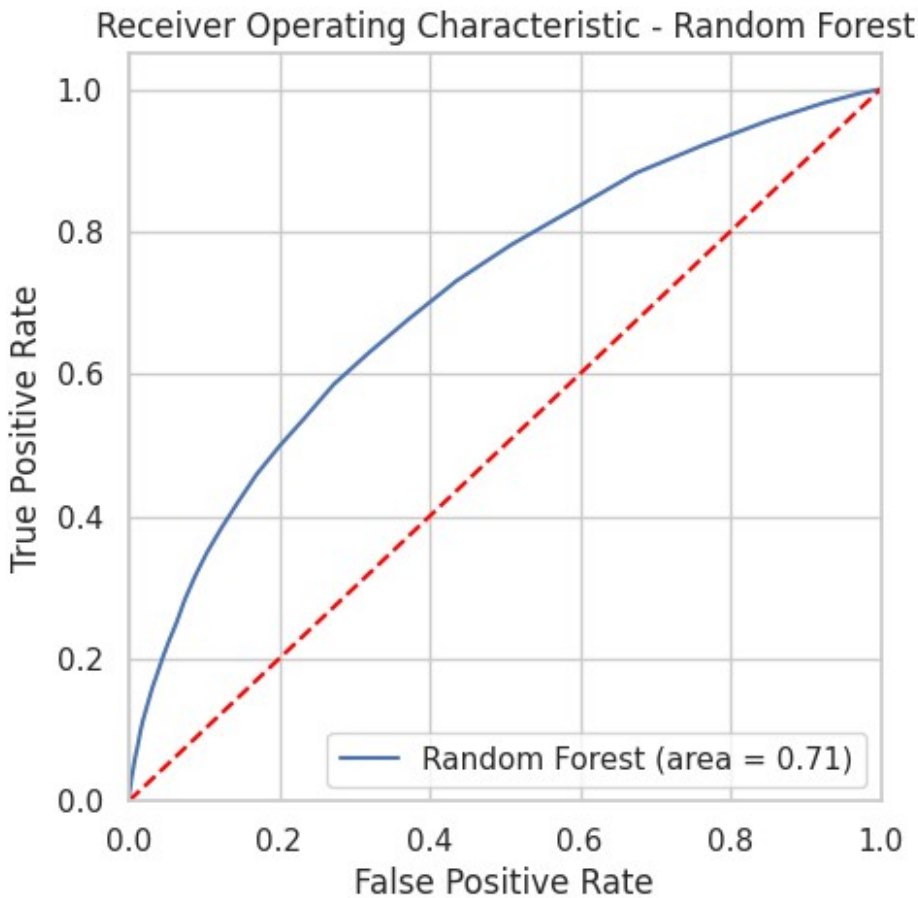
```
def plot_roc_auc(y_test, y_probs, model_name):
    """Function to plot ROC-AUC curve for a given model."""
```

```python
    roc_auc = roc_auc_score(y_test, y_probs)
    fpr, tpr, _ = roc_curve(y_test, y_probs)

    plt.plot(fpr, tpr, label=f'{model_name} (area = {roc_auc:.2f})')

    return roc_auc

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier

dt_model = DecisionTreeClassifier()
dt_model.fit(xtrain, ytrain)

# Predict probabilities
dt_y_probs = dt_model.predict_proba(xtest)[:, 1]

# Plot ROC-AUC curve
dt_roc_auc = plot_roc_auc(ytest, dt_y_probs, 'Decision Tree')

# Plot diagonal line for random classifier
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic - Decision Tree')
plt.legend(loc='lower right')
plt.show()

print(f"Decision Tree ROC-AUC: {dt_roc_auc:.4f}")
```



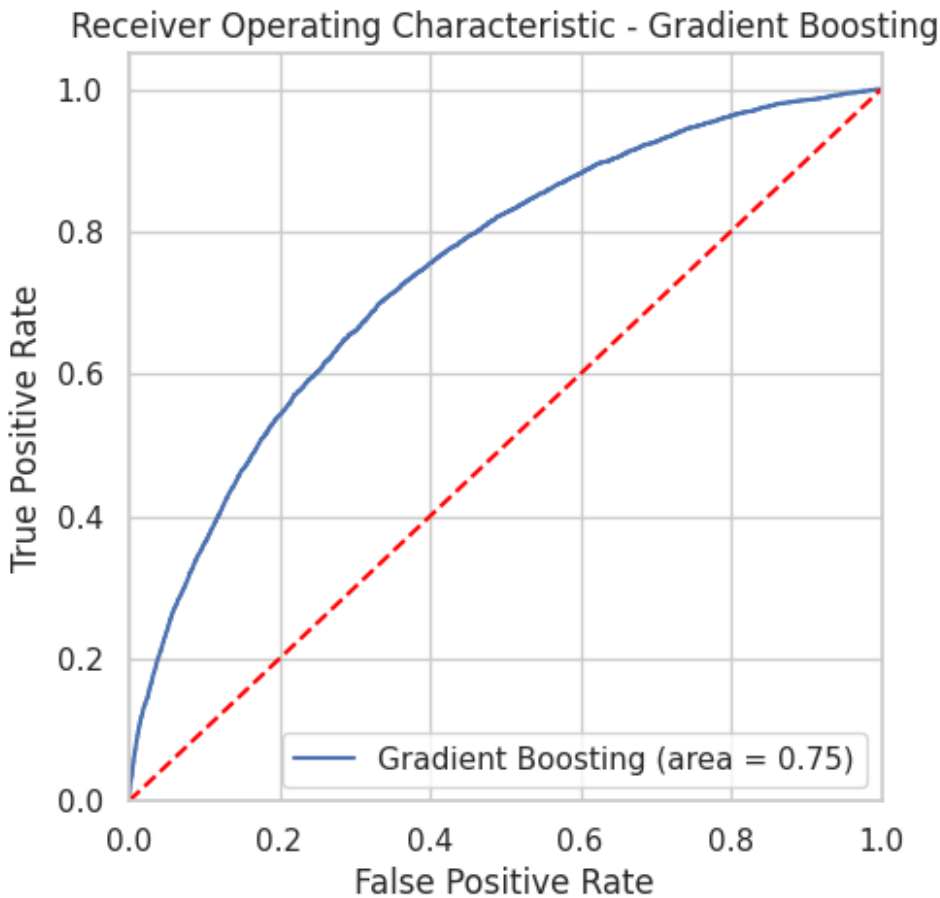

```
Decision Tree ROC-AUC: 0.5335
```

```
rf_model = RandomForestClassifier()
rf_model.fit(xtrain, ytrain)

# Predict probabilities
rf_y_probs = rf_model.predict_proba(xtest)[:, 1]

# Plot ROC-AUC curve
rf_roc_auc = plot_roc_auc(ytest, rf_y_probs, 'Random Forest')

# Plot diagonal line for random classifier
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic - Random Forest')
plt.legend(loc='lower right')
plt.show()

print(f"Random Forest ROC-AUC: {rf_roc_auc:.4f}")
```




```
Random Forest ROC-AUC: 0.7114
```

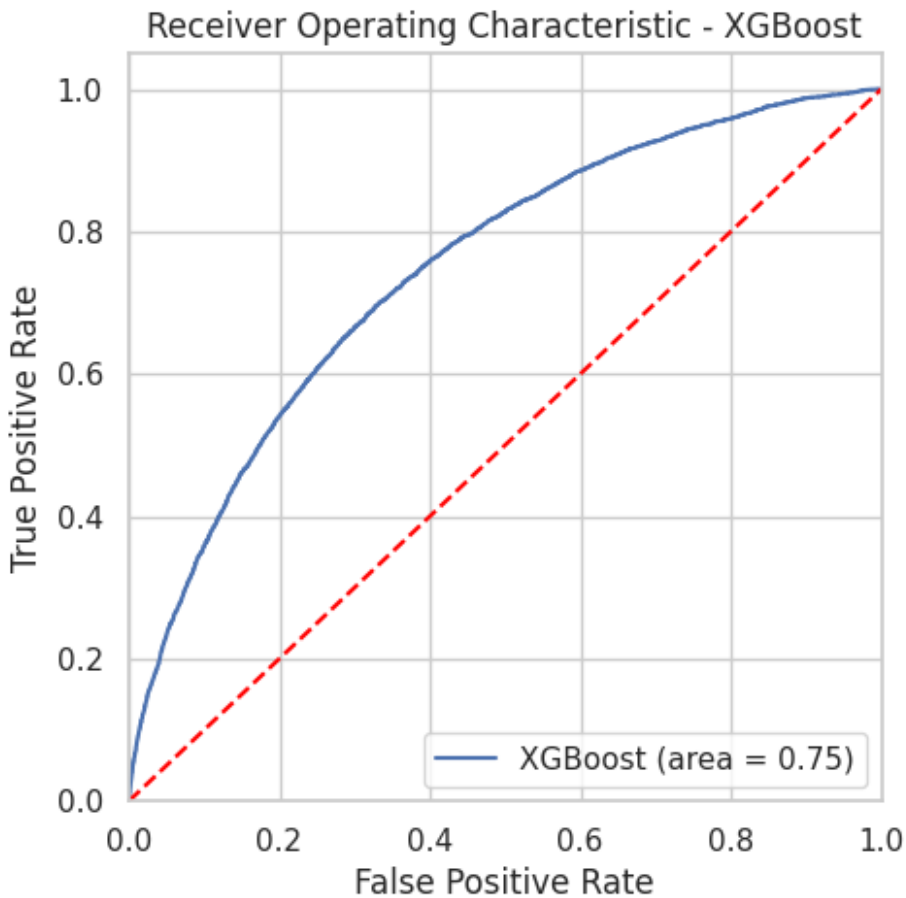
```
gb_model = GradientBoostingClassifier()
gb_model.fit(xtrain, ytrain)

# Predict probabilities
gb_y_probs = gb_model.predict_proba(xtest)[:, 1]

# Plot ROC-AUC curve
gb_roc_auc = plot_roc_auc(ytest, gb_y_probs, 'Gradient Boosting')

# Plot diagonal line for random classifier
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic - Gradient Boosting')
plt.legend(loc='lower right')
plt.show()

print(f"Gradient Boosting ROC-AUC: {gb_roc_auc:.4f}")
```




```
Gradient Boosting ROC-AUC: 0.7461
```

```
import xgboost as xgb

xgb_model = xgb.XGBClassifier(use_label_encoder=False,
eval_metric='auc')
xgb_model.fit(xtrain, ytrain)

# Predict probabilities
xgb_y_probs = xgb_model.predict_proba(xtest)[:, 1]

# Plot ROC-AUC curve
xgb_roc_auc = plot_roc_auc(ytest, xgb_y_probs, 'XGBoost')

# Plot diagonal line for random classifier
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic - XGBoost')
plt.legend(loc='lower right')
```

```
plt.show()

print(f"XGBoost ROC-AUC: {xgb_roc_auc:.4f}")
```

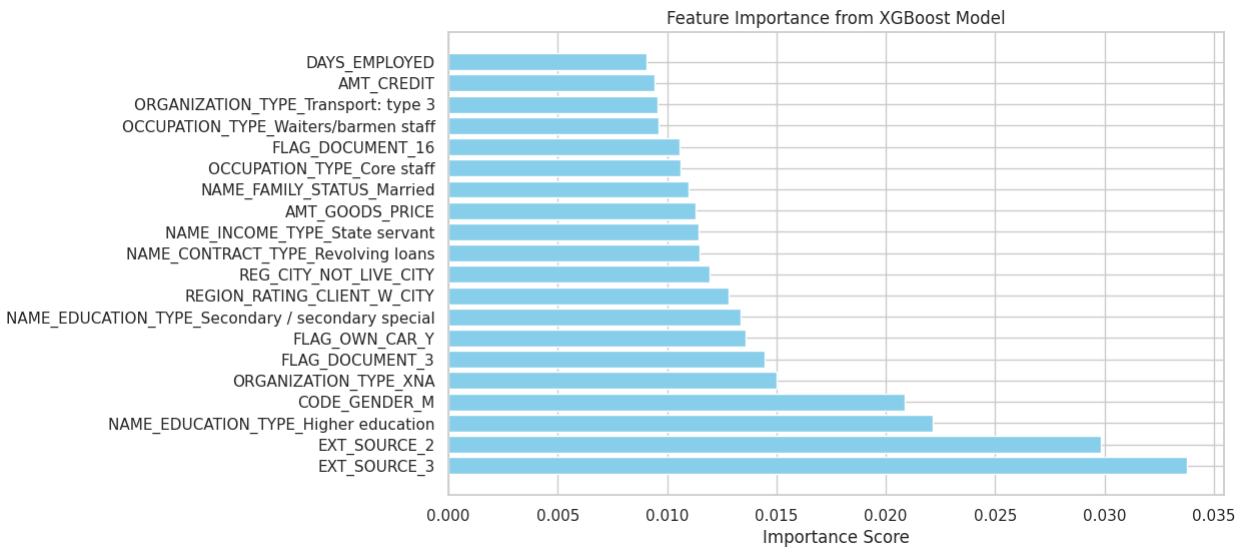



```
XGBoost ROC-AUC: 0.7464

# Get feature importance
importance = xgb_model.feature_importances_


feature_names = x.columns
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':
importance})
importance_df = importance_df.sort_values(by='Importance',
ascending=False)

importance_df.head(10)
```

{"summary":"{\n \"name\": \"importance_df\",\n \"rows\": 172,\n
\"fields\": [\n {\n \"column\": \"Feature\",\n
\"properties\": {\n \"dtype\": \"string\",\n
\"num_unique_values\": 172,\n \"samples\": [\n

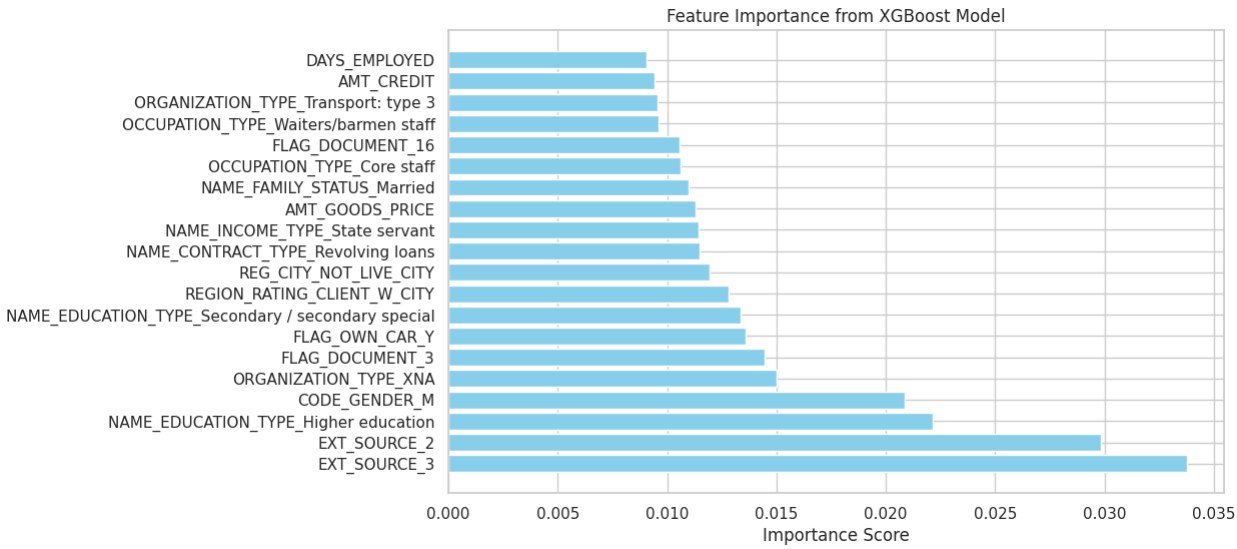
\"FLAG_OWN_REALTY_Y\",\n \"ORGANIZATION_TYPE_Hotel\",\n \"ORGANIZATION_TYPE_Services\"\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Importance\",\n \"properties\": {\n \"dtype\": \"float32\",\n \"num_unique_values\": 150,\n \"samples\": [\n 0.005802934523671865 5,\n 0.009425627067685127,\n 0.004412588197737932\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\n}","type":"dataframe","variable_name":"importance_df"}

```
# Plot feature importance
plt.figure(figsize=(10, 6))
plt.barh(importance_df.head(20)['Feature'], importance_df.head(20)
['Importance'], color='skyblue')
plt.xlabel('Importance Score')
plt.title('Feature Importance from XGBoost Model')
plt.show()
```




```
# RF feature importance
importance = rf_model.feature_importances_

# Create a DataFrame for better visualization
importance_rf = pd.DataFrame({'Feature': x.columns, 'Importance':
importance})
importance_rf = importance_df.sort_values(by='Importance',
ascending=False)

# Plot feature importance
plt.figure(figsize=(10, 6))
plt.barh(importance_rf.head(20)['Feature'], importance_rf.head(20)
['Importance'], color='skyblue')
plt.xlabel('Importance Score')
```

```
plt.title('Feature Importance from XGBoost Model')
plt.show()
```




```
importance_df
```

{"summary":"{\n \"name\": \"importance_df\",\n \"rows\": 172,\n \"fields\": [\n {\n \"column\": \"Feature\",\n \"properties\": {\n \"dtype\": \"string\",\n \"num_unique_values\": 172,\n \"samples\": [\n \"FLAG_OWN_REALTY_Y\",\n \"ORGANIZATION_TYPE_Hotel\",\n \"ORGANIZATION_TYPE_Services\"\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n },\n {\n \"column\": \"Importance\",\n \"properties\": {\n \"dtype\": \"float32\",\n \"num_unique_values\": 150,\n \"samples\": [\n 0.005802934523671865 5,\n 0.009425627067685127,\n 0.004412588197737932\n],\n \"semantic_type\": \"\",\n \"description\": \"\"\n }\n }\n]\n}","type":"dataframe","variable_name":"importance_df"}

```
from statsmodels.stats.outliers_influence import
variance_inflation_factor
import pandas as pd
# Calculate VIF for each feature
vif_data = pd.DataFrame()
vif_data["Feature"] = x.columns
vif_data["VIF"] = [variance_inflation_factor(x.values, i) for i in
range(x.shape[1])]

vif_data
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-199-f0e81c4a4c79> in <cell line: 6>()
      4 vif_data = pd.DataFrame()
      5 vif_data["Feature"] = x.columns
----> 6 vif_data["VIF"] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1])]
      7
      8 vif_data

<ipython-input-199-f0e81c4a4c79> in <listcomp>(.0)
      4 vif_data = pd.DataFrame()
      5 vif_data["Feature"] = x.columns
----> 6 vif_data["VIF"] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1])]
      7
      8 vif_data

/usr/local/lib/python3.10/dist-packages/statsmodels/stats/outliers_influence.py in variance_inflation_factor(exog, exog_idx)
    194     mask = np.arange(k_vars) != exog_idx
    195     x_noti = exog[:, mask]
--> 196     r_squared_i = OLS(x_i, x_noti).fit().rsquared
    197     vif = 1. / (1. - r_squared_i)
    198     return vif

/usr/local/lib/python3.10/dist-packages/statsmodels/regression/linear_model.py in __init__(self, endog, exog, missing, hasconst, **kwargs)
    919                     "An exception will be raised in the next version.")
    920             warnings.warn(msg, ValueWarning)
--> 921         super().__init__(endog, exog, missing=missing,
    922                          hasconst=hasconst, **kwargs)
    923         if "weights" in self._init_keys:

/usr/local/lib/python3.10/dist-packages/statsmodels/regression/linear_model.py in __init__(self, endog, exog, weights, missing, hasconst, **kwargs)
    744         else:
    745             weights = weights.squeeze()
--> 746         super().__init__(endog, exog, missing=missing,
    747                          weights=weights, hasconst=hasconst, **kwargs)
    748         nobs = self.exog.shape[0]

/usr/local/lib/python3.10/dist-packages/statsmodels/regression/linear_model.py in __init__(self, endog, exog, **kwargs)
    198     """
```

```
    199     def __init__(self, endog, exog, **kwargs):
--> 200         super().__init__(endog, exog, **kwargs)
    201         self.pinv_wexog: Float64Array | None = None
    202         self._data_attr.extend(['pinv_wexog', 'wendog',
'wexog', 'weights'])

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py in
__init__(self, endog, exog, **kwargs)
    268
    269     def __init__(self, endog, exog=None, **kwargs):
--> 270         super().__init__(endog, exog, **kwargs)
    271         self.initialize()
    272

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py in
__init__(self, endog, exog, **kwargs)
     93         missing = kwargs.pop('missing', 'none')
     94         hasconst = kwargs.pop('hasconst', None)
---> 95         self.data = self._handle_data(endog, exog, missing,
hasconst,
     96                                       **kwargs)
     97         self.k_constant = self.data.k_constant

/usr/local/lib/python3.10/dist-packages/statsmodels/base/model.py in
_handle_data(self, endog, exog, missing, hasconst, **kwargs)
    133
    134     def _handle_data(self, endog, exog, missing, hasconst,
**kwargs):
--> 135         data = handle_data(endog, exog, missing, hasconst,
**kwargs)
    136         # kwargs arrays could have changed, easier to just
attach here
    137         for key in kwargs:

/usr/local/lib/python3.10/dist-packages/statsmodels/base/data.py in
handle_data(endog, exog, missing, hasconst, **kwargs)
    673
    674     klass = handle_data_class_factory(endog, exog)
--> 675     return klass(endog, exog=exog, missing=missing,
hasconst=hasconst,
    676                  **kwargs)

/usr/local/lib/python3.10/dist-packages/statsmodels/base/data.py in
__init__(self, endog, exog, missing, hasconst, **kwargs)
     86         self.const_idx = None
     87         self.k_constant = 0
---> 88         self._handle_constant(hasconst)
     89         self._check_integrity()
     90         self._cache = {}
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/base/data.py in
_handle_constant(self, hasconst)
    176                              (np.ones(self.exog.shape[0]),
self.exog))
    177                 rank_augm =
np.linalg.matrix_rank(augmented_exog)
--> 178                 rank_orig = np.linalg.matrix_rank(self.exog)
    179                 self.k_constant = int(rank_orig == rank_augm)
    180                 self.const_idx = None

/usr/local/lib/python3.10/dist-packages/numpy/linalg/linalg.py in
matrix_rank(A, tol, hermitian)
   1920     if A.ndim < 2:
   1921         return int(not all(A==0))
-> 1922     S = svd(A, compute_uv=False, hermitian=hermitian)
   1923     if tol is None:
   1924         tol = S.max(axis=-1, keepdims=True) * max(A.shape[-
2:]) * finfo(S.dtype).eps

/usr/local/lib/python3.10/dist-packages/numpy/linalg/linalg.py in
svd(a, full_matrices, compute_uv, hermitian)
   1691
   1692         signature = 'D->d' if isComplexType(t) else 'd->d'
-> 1693         s = gufunc(a, signature=signature, extobj=extobj)
   1694         s = s.astype(_realType(result_t), copy=False)
   1695         return s

KeyboardInterrupt:
```

```
df1.to_csv('/content/drive/MyDrive/Colab
Notebooks/df1.csv',index=False)
```