

```

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from scipy import stats

prev = pd.read_csv('previous_application.csv')
post = pd.read_csv('application_data.csv')

```

```
prev.head()
```

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

```
post.head()
```

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

```
prev.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1670214 entries, 0 to 1670213
Data columns (total 37 columns):

```

#	Column	Non-Null	Count	Dtype
---	-----	-----	-----	-----
0	SK_ID_PREV	1670214	non-null	int64
1	SK_ID_CURR	1670214	non-null	int64
2	NAME_CONTRACT_TYPE	1670214	non-null	object
3	AMT_ANNUITY	1297979	non-null	float64
4	AMT_APPLICATION	1670214	non-null	float64
5	AMT_CREDIT	1670213	non-null	float64
6	AMT_DOWN_PAYMENT	774370	non-null	float64
7	AMT_GOODS_PRICE	1284699	non-null	float64
8	WEEKDAY_APPR_PROCESS_START	1670214	non-null	object
9	HOUR_APPR_PROCESS_START	1670214	non-null	int64
10	FLAG_LAST_APPL_PER_CONTRACT	1670214	non-null	object
11	NFLAG_LAST_APPL_IN_DAY	1670214	non-null	int64
12	RATE_DOWN_PAYMENT	774370	non-null	float64
13	RATE_INTEREST_PRIMARY	5951	non-null	float64
14	RATE_INTEREST_PRIVILEGED	5951	non-null	float64
15	NAME_CASH_LOAN_PURPOSE	1670214	non-null	object
16	NAME_CONTRACT_STATUS	1670214	non-null	object
17	DAYS_DECISION	1670214	non-null	int64
18	NAME_PAYMENT_TYPE	1670214	non-null	object
19	CODE_REJECT_REASON	1670214	non-null	object
20	NAME_TYPE_SUITE	849809	non-null	object
21	NAME_CLIENT_TYPE	1670214	non-null	object
22	NAME_GOODS_CATEGORY	1670214	non-null	object
23	NAME_PORTFOLIO	1670214	non-null	object
24	NAME_PRODUCT_TYPE	1670214	non-null	object
25	CHANNEL_TYPE	1670214	non-null	object

26	SELLERPLACE_AREA	1670214	non-null	int64
27	NAME_SELLER_INDUSTRY	1670214	non-null	object
28	CNT_PAYMENT	1297984	non-null	float64
29	NAME_YIELD_GROUP	1670214	non-null	object
30	PRODUCT_COMBINATION	1669868	non-null	object
31	DAYS_FIRST_DRAWING	997149	non-null	float64
32	DAYS_FIRST_DUE	997149	non-null	float64
33	DAYS_LAST_DUE_1ST_VERSION	997149	non-null	float64
34	DAYS_LAST_DUE	997149	non-null	float64
35	DAYS_TERMINATION	997149	non-null	float64
36	NFLAG_INSURED_ON_APPROVAL	997149	non-null	float64

dtypes: float64(15), int64(6), object(16)
memory usage: 471.5+ MB

post.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

prev.describe()

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

post.describe()

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

prev.dtypes

SK_ID_PREV	int64
SK_ID_CURR	int64
NAME_CONTRACT_TYPE	object
AMT_ANNUITY	float64
AMT_APPLICATION	float64
AMT_CREDIT	float64
AMT_DOWN_PAYMENT	float64
AMT_GOODS_PRICE	float64
WEEKDAY_APPR_PROCESS_START	object
HOUR_APPR_PROCESS_START	int64
FLAG_LAST_APPL_PER_CONTRACT	object
NFLAG_LAST_APPL_IN_DAY	int64
RATE_DOWN_PAYMENT	float64
RATE_INTEREST_PRIMARY	float64
RATE_INTEREST_PRIVILEGED	float64
NAME_CASH_LOAN_PURPOSE	object
NAME_CONTRACT_STATUS	object
DAYS_DECISION	int64
NAME_PAYMENT_TYPE	object

CODE_REJECT_REASON	object
NAME_TYPE_SUITE	object
NAME_CLIENT_TYPE	object
NAME_GOODS_CATEGORY	object
NAME_PORTFOLIO	object
NAME_PRODUCT_TYPE	object
CHANNEL_TYPE	object
SELLERPLACE_AREA	int64
NAME_SELLER_INDUSTRY	object
CNT_PAYMENT	float64
NAME_YIELD_GROUP	object
PRODUCT_COMBINATION	object
DAYS_FIRST_DRAWING	float64
DAYS_FIRST_DUE	float64
DAYS_LAST_DUE_1ST_VERSION	float64
DAYS_LAST_DUE	float64
DAYS_TERMINATION	float64
NFLAG_INSURED_ON_APPROVAL	float64

dtype: object

post.dtypes

SK_ID_CURR	int64
TARGET	int64
NAME_CONTRACT_TYPE	object
CODE_GENDER	object
FLAG_OWN_CAR	object
...	
AMT_REQ_CREDIT_BUREAU_DAY	float64
AMT_REQ_CREDIT_BUREAU_WEEK	float64
AMT_REQ_CREDIT_BUREAU_MON	float64
AMT_REQ_CREDIT_BUREAU_QRT	float64
AMT_REQ_CREDIT_BUREAU_YEAR	float64

Length: 122, dtype: object

prev.columns

```
Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE',
      'AMT_ANNUITY',
      'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
      'AMT_GOODS_PRICE',
      'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
      'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
      'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
      'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
      'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
      'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
      'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
      'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
      'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
```

```

        'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
        'DAYS_LAST_DUE_1ST_VERSION',
        'DAYS_LAST_DUE', 'DAYS_TERMINATION',
        'NFLAG_INSURED_ON_APPROVAL'],
        dtype='object')

post.columns

Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
        'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',
        'AMT_INCOME_TOTAL',
        'AMT_CREDIT', 'AMT_ANNUITY',
        ...,
        'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
        'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
        'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
        'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
        'AMT_REQ_CREDIT_BUREAU_YEAR'],
        dtype='object', length=122)

# check for missing data in each column
print(prev.isnull().sum())

```

SK_ID_PREV	0
SK_ID_CURR	0
NAME_CONTRACT_TYPE	0
AMT_ANNUITY	372235
AMT_APPLICATION	0
AMT_CREDIT	1
AMT_DOWN_PAYMENT	895844
AMT_GOODS_PRICE	385515
WEEKDAY_APPR_PROCESS_START	0
HOUR_APPR_PROCESS_START	0
FLAG_LAST_APPL_PER_CONTRACT	0
NFLAG_LAST_APPL_IN_DAY	0
RATE_DOWN_PAYMENT	895844
RATE_INTEREST_PRIMARY	1664263
RATE_INTEREST_PRIVILEGED	1664263
NAME_CASH_LOAN_PURPOSE	0
NAME_CONTRACT_STATUS	0
DAYS_DECISION	0
NAME_PAYMENT_TYPE	0
CODE_REJECT_REASON	0
NAME_TYPE_SUITE	820405
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	372230
NAME_YIELD_GROUP	0
PRODUCT_COMBINATION	346
DAYS_FIRST_DRAWING	673065
DAYS_FIRST_DUE	673065
DAYS_LAST_DUE_1ST_VERSION	673065
DAYS_LAST_DUE	673065
DAYS_TERMINATION	673065
NFLAG_INSURED_ON_APPROVAL	673065

dtype: int64

```
print(post.isnull().sum())
```

SK_ID_CURR	0
TARGET	0
NAME_CONTRACT_TYPE	0
CODE_GENDER	0
FLAG_OWN_CAR	0
...	
AMT_REQ_CREDIT_BUREAU_DAY	41519
AMT_REQ_CREDIT_BUREAU_WEEK	41519
AMT_REQ_CREDIT_BUREAU_MON	41519
AMT_REQ_CREDIT_BUREAU_QRT	41519
AMT_REQ_CREDIT_BUREAU_YEAR	41519

Length: 122, dtype: int64

```
missing_val_per_1 = (prev.isnull().sum() / len(prev)) * 100
missing_val_per_1
```

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_DOWN_PAYMENT	53.636480
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
RATE_DOWN_PAYMENT	53.636480
RATE_INTEREST_PRIMARY	99.643698
RATE_INTEREST_PRIVILEGED	99.643698
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_TYPE_SUITE	49.119754
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
DAYS_FIRST_DRAWING	40.298129
DAYS_FIRST_DUE	40.298129
DAYS_LAST_DUE_1ST_VERSION	40.298129
DAYS_LAST_DUE	40.298129
DAYS_TERMINATION	40.298129
NFLAG_INSURED_ON_APPROVAL	40.298129

dtype: float64

```
missing_val_per_2 = (post.isnull().sum() / len(post)) * 100
missing_val_per_2
```

SK_ID_CURR	0.000000
TARGET	0.000000
NAME_CONTRACT_TYPE	0.000000
CODE_GENDER	0.000000
FLAG_OWN_CAR	0.000000

...

AMT_REQ_CREDIT_BUREAU_DAY	13.501631
AMT_REQ_CREDIT_BUREAU_WEEK	13.501631
AMT_REQ_CREDIT_BUREAU_MON	13.501631
AMT_REQ_CREDIT_BUREAU_QRT	13.501631
AMT_REQ_CREDIT_BUREAU_YEAR	13.501631

Length: 122, dtype: float64

```
prev = prev.dropna()
prev.head()
```

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

```
prev.isnull().sum()
```

SK_ID_PREV	0
SK_ID_CURR	0
NAME_CONTRACT_TYPE	0
AMT_ANNUITY	0
AMT_APPLICATION	0
AMT_CREDIT	0
AMT_DOWN_PAYMENT	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
RATE_DOWN_PAYMENT	0
RATE_INTEREST_PRIMARY	0
RATE_INTEREST_PRIVILEGED	0
NAME_CASH_LOAN_PURPOSE	0
NAME_CONTRACT_STATUS	0
DAYS_DECISION	0
NAME_PAYMENT_TYPE	0
CODE_REJECT_REASON	0
NAME_TYPE_SUITE	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
DAYS_FIRST_DRAWING	0
DAYS_FIRST_DUE	0
DAYS_LAST_DUE_1ST_VERSION	0
DAYS_LAST_DUE	0
DAYS_TERMINATION	0
NFLAG_INSURED_ON_APPROVAL	0
dtype:	int64

```
missing1_per = (prev.isnull().sum() / len(prev)) * 100
missing1_per
```

SK_ID_PREV	0.0
SK_ID_CURR	0.0
NAME_CONTRACT_TYPE	0.0
AMT_ANNUITY	0.0
AMT_APPLICATION	0.0
AMT_CREDIT	0.0
AMT_DOWN_PAYMENT	0.0
AMT_GOODS_PRICE	0.0
WEEKDAY_APPR_PROCESS_START	0.0
HOUR_APPR_PROCESS_START	0.0
FLAG_LAST_APPL_PER_CONTRACT	0.0
NFLAG_LAST_APPL_IN_DAY	0.0
RATE_DOWN_PAYMENT	0.0
RATE_INTEREST_PRIMARY	0.0
RATE_INTEREST_PRIVILEGED	0.0
NAME_CASH_LOAN_PURPOSE	0.0
NAME_CONTRACT_STATUS	0.0

DAYS_DECISION	0.0
NAME_PAYMENT_TYPE	0.0
CODE_REJECT_REASON	0.0
NAME_TYPE_SUITE	0.0
NAME_CLIENT_TYPE	0.0
NAME_GOODS_CATEGORY	0.0
NAME_PORTFOLIO	0.0
NAME_PRODUCT_TYPE	0.0
CHANNEL_TYPE	0.0
SELLERPLACE_AREA	0.0
NAME_SELLER_INDUSTRY	0.0
CNT_PAYMENT	0.0
NAME_YIELD_GROUP	0.0
PRODUCT_COMBINATION	0.0
DAYS_FIRST_DRAWING	0.0
DAYS_FIRST_DUE	0.0
DAYS_LAST_DUE_1ST_VERSION	0.0
DAYS_LAST_DUE	0.0
DAYS_TERMINATION	0.0
NFLAG_INSURED_ON_APPROVAL	0.0

dtype: float64

```
post = post.dropna()
post.head()
```

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

```
missing2_per = (post.isnull().sum() / len(post)) * 100
missing2_per
```

SK_ID_CURR	0.0
TARGET	0.0
NAME_CONTRACT_TYPE	0.0
CODE_GENDER	0.0
FLAG_OWN_CAR	0.0
...	
AMT_REQ_CREDIT_BUREAU_DAY	0.0
AMT_REQ_CREDIT_BUREAU_WEEK	0.0
AMT_REQ_CREDIT_BUREAU_MON	0.0
AMT_REQ_CREDIT_BUREAU_QRT	0.0
AMT_REQ_CREDIT_BUREAU_YEAR	0.0

Length: 122, dtype: float64

```
post.fillna(method='ffill', inplace=True)
post.head()
```

```
post['CODE_GENDER'].fillna('XNA', inplace=True)
post.head()
```

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


DIVISION OF DATA SET INTO TWO PARTS

```
default = post[post['TARGET'] == 1] # had difficulties
non_default = post[post["TARGET"] == 0]

default.head()

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

default.info()

<class 'pandas.core.frame.DataFrame'>
Index: 526 entries, 255 to 307407
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 505.5+ KB

default.describe()

{"type": "dataframe"}

non_default.head()

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

non_default.info()

<class 'pandas.core.frame.DataFrame'>
Index: 8076 entries, 71 to 307482
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 7.6+ MB

default.columns

Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
      'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',
      'AMT_INCOME_TOTAL',
      'AMT_CREDIT', 'AMT_ANNUITY',
      ...
      'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
      'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
      'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
      'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
      'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=122)
```

DATA ANALYSIS AND VISUALISATION OF "POST"

```
# calculating age // feature engineering
post['AGE'] = -post['DAYS_BIRTH'] // 365
print(post[['DAYS_BIRTH', 'AGE']])
```

	DAYS_BIRTH	AGE
71	-15406	42
124	-16282	44
152	-11375	31
161	-13972	38
255	-11356	31
...
307358	-15006	41
307359	-14007	38
307407	-11407	31
307456	-20246	55
307482	-14106	38

[8602 rows x 2 columns]

AGE

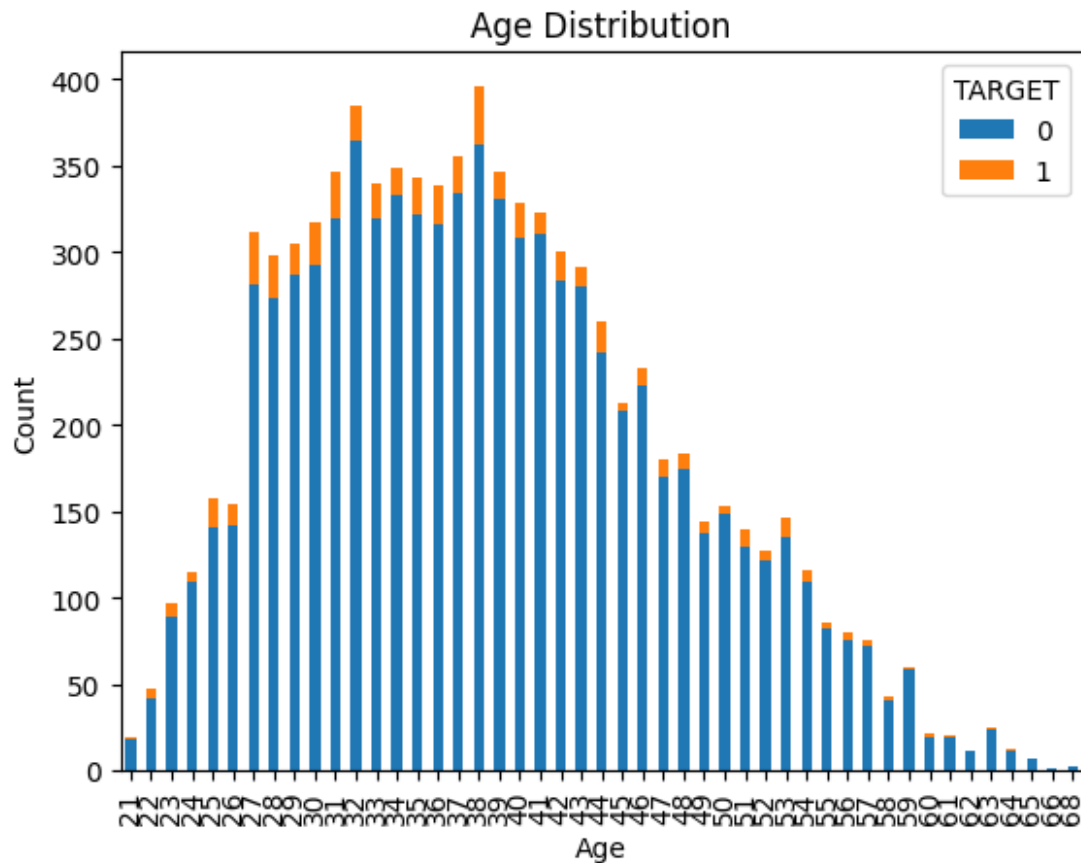
```
age = post.groupby('AGE')['TARGET'].value_counts().unstack()
print(age)
```

```
plt.figure(figsize=(20,15))
age.plot(kind='bar', stacked=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```

TARGET	0	1
AGE		
21	18.0	1.0
22	42.0	5.0
23	89.0	8.0
24	109.0	6.0
25	141.0	17.0
26	142.0	12.0
27	281.0	31.0
28	273.0	25.0
29	287.0	18.0
30	293.0	24.0
31	319.0	28.0
32	365.0	20.0
33	320.0	20.0
34	333.0	16.0
35	322.0	21.0
36	316.0	23.0
37	334.0	22.0
38	362.0	34.0
39	331.0	16.0
40	308.0	20.0
41	310.0	13.0

42	284.0	16.0
43	280.0	11.0
44	242.0	18.0
45	208.0	5.0
46	223.0	10.0
47	170.0	10.0
48	174.0	9.0
49	137.0	7.0
50	148.0	5.0
51	129.0	10.0
52	121.0	6.0
53	135.0	11.0
54	109.0	7.0
55	82.0	3.0
56	75.0	5.0
57	72.0	3.0
58	40.0	3.0
59	58.0	2.0
60	19.0	2.0
61	19.0	1.0
62	11.0	NaN
63	24.0	1.0
64	11.0	1.0
65	7.0	NaN
66	1.0	NaN
68	2.0	NaN

<Figure size 2000x1500 with 0 Axes>

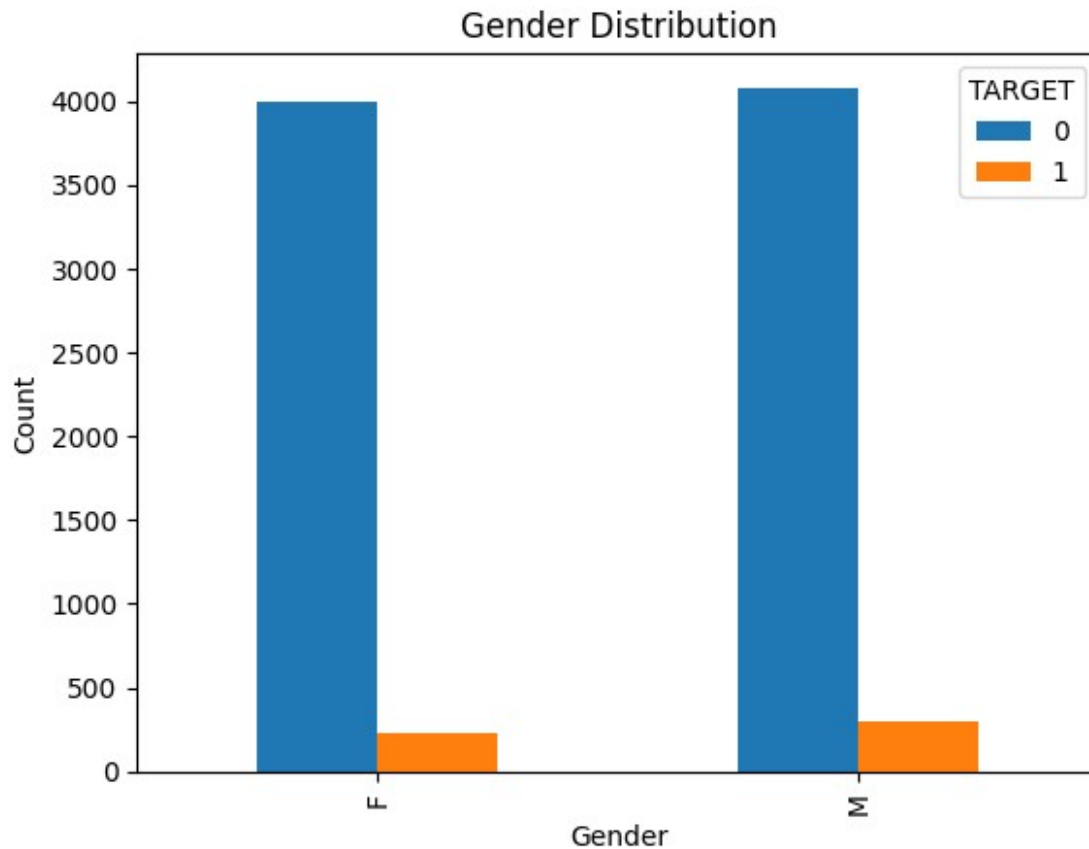


```
# GENDER
post = post[post['CODE_GENDER'] != 'XNA']
gender = post.groupby('CODE_GENDER')
['TARGET'].value_counts().unstack()
print(gender)
```

```
gender.plot(kind='bar', stacked=False)
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
```

TARGET	0	1
CODE_GENDER		
F	3997	224
M	4079	302

```
Text(0, 0.5, 'Count')
```



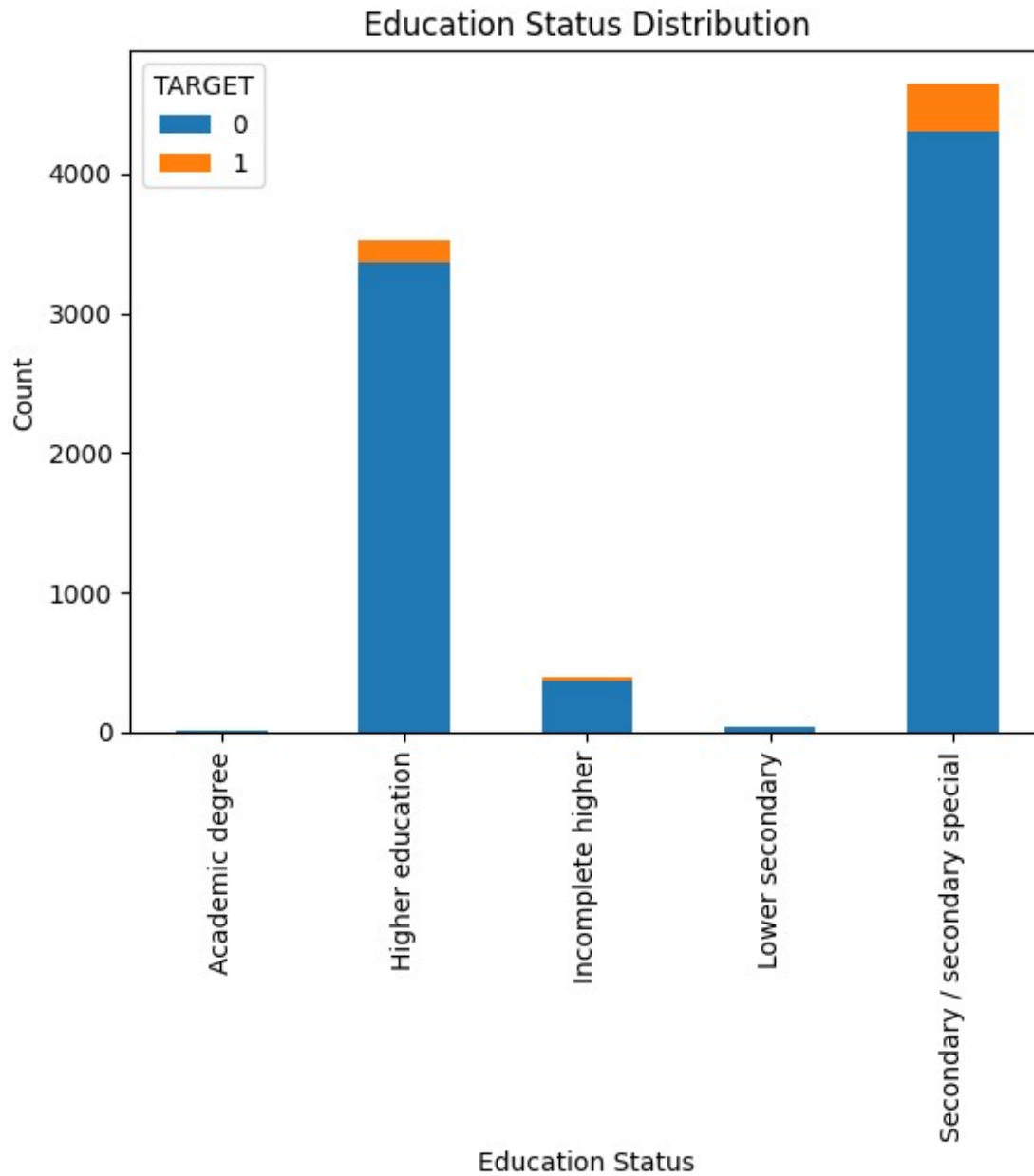
EDUCATION STATUS

```
edu = post.groupby('NAME_EDUCATION_TYPE')
['TARGET'].value_counts().unstack()
print(edu)
```

```
edu.plot(kind='bar', stacked=True)
plt.title('Education Status Distribution')
plt.xlabel('Education Status')
plt.ylabel('Count')
```

TARGET	0	1
NAME_EDUCATION_TYPE		
Academic degree	6.0	NaN
Higher education	3364.0	159.0
Incomplete higher	370.0	22.0
Lower secondary	32.0	3.0
Secondary / secondary special	4304.0	342.0

```
Text(0, 0.5, 'Count')
```



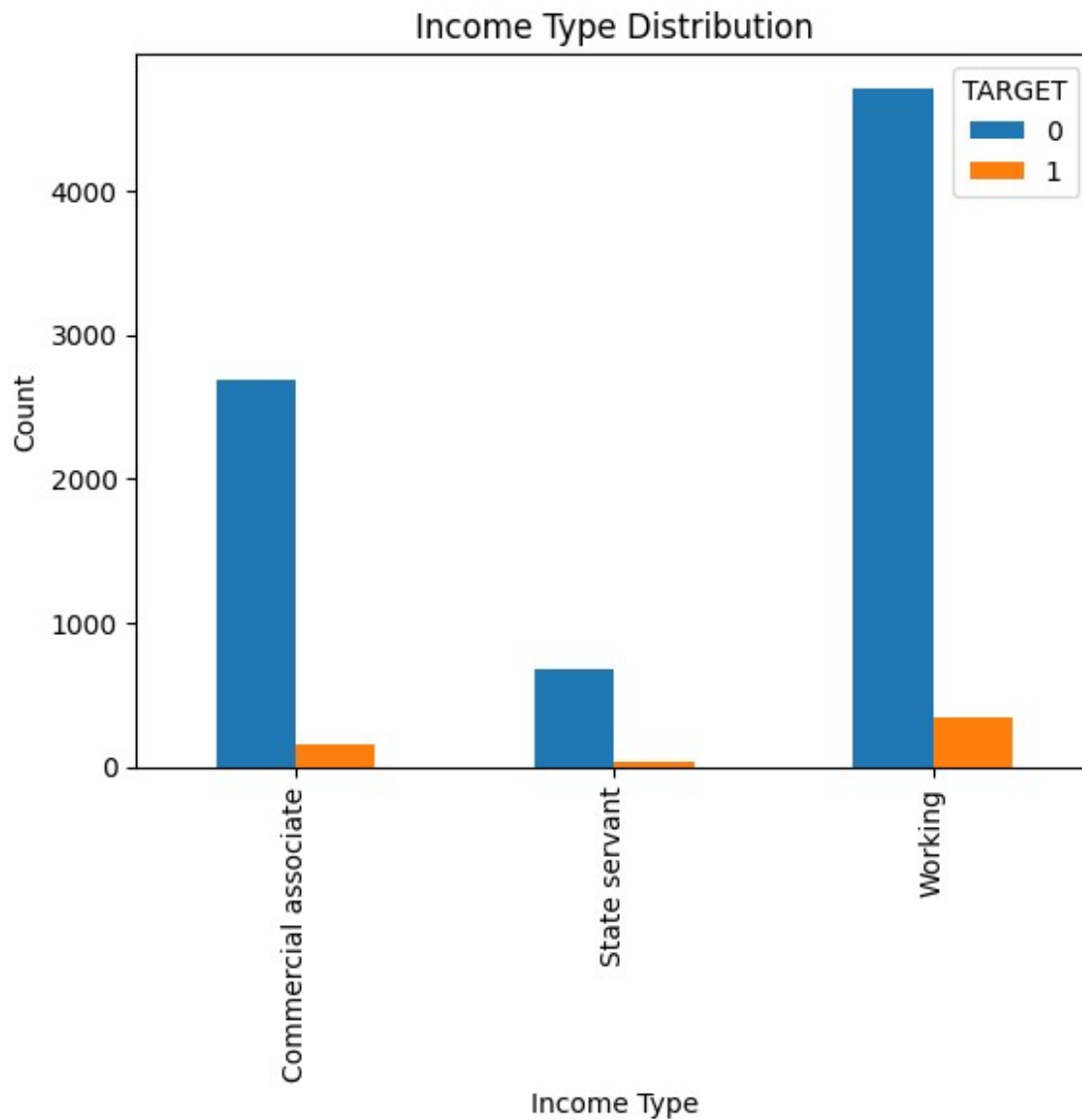
```
# INCOME TYPE // bu boyle gosterilmez
income_type = post.groupby('NAME_INCOME_TYPE')
['TARGET'].value_counts().unstack()
print(income_type)

income_type.plot(kind='bar', stacked=False)
plt.title('Income Type Distribution')
plt.xlabel('Income Type')
plt.ylabel('Count')

TARGET          0    1
NAME_INCOME_TYPE
```

Commercial associate	2683	153
State servant	680	36
Working	4713	337

```
Text(0, 0.5, 'Count')
```



```
# income group
income_group = post.groupby('AMT_INCOME_TOTAL')
['TARGET'].value_counts().unstack()
print(income_group)

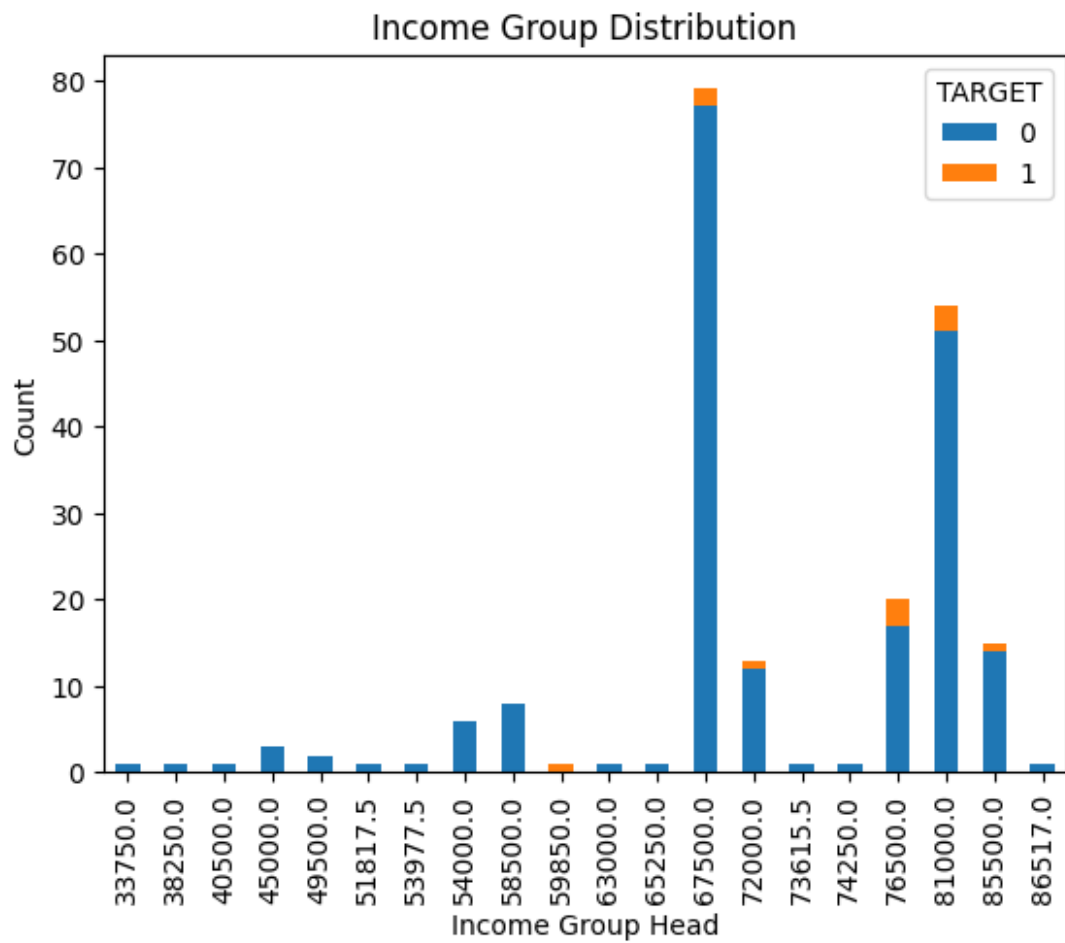
income_group.head(20).plot(kind='bar', stacked=True)
plt.title('Income Group Distribution')
plt.xlabel('Income Group Head')
```

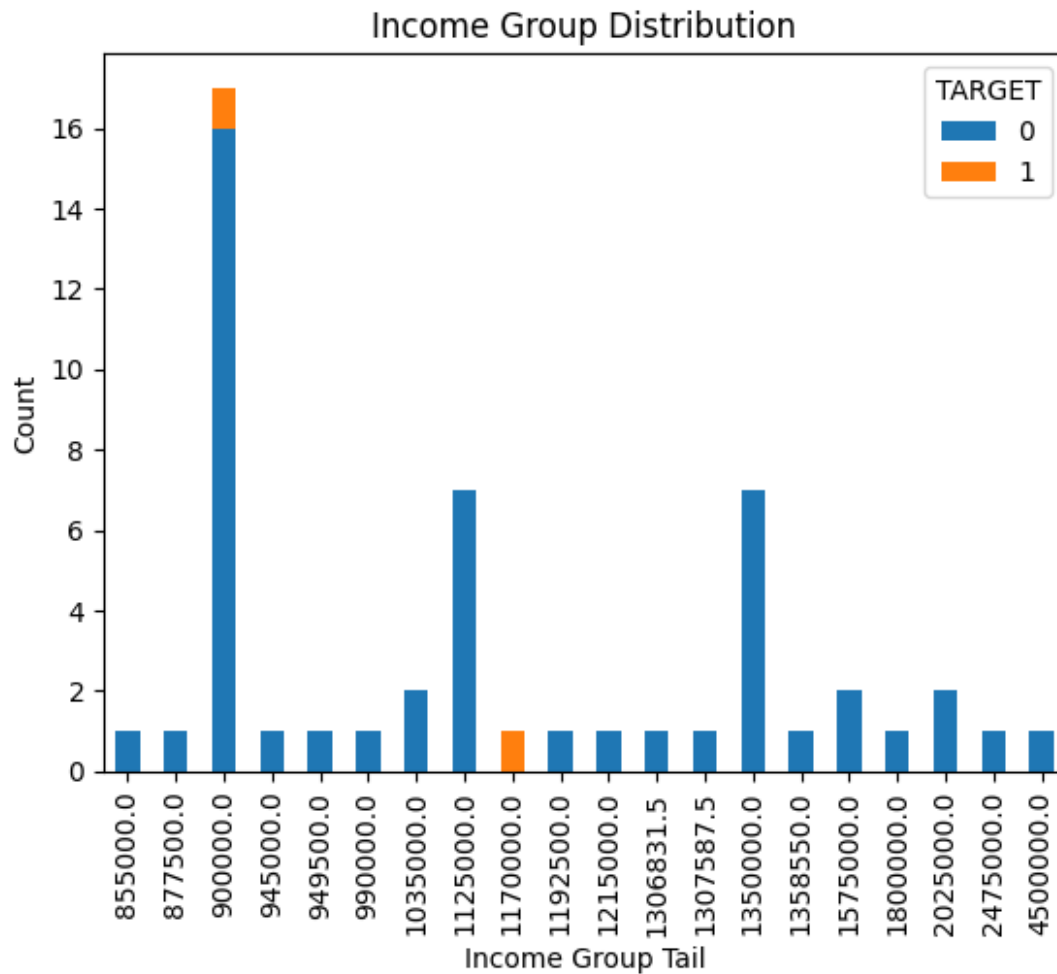
```
plt.ylabel('Count')

income_group.tail(20).plot(kind='bar', stacked=True)
plt.title('Income Group Distribution')
plt.xlabel('Income Group Tail')
plt.ylabel('Count')
plt.show()
```

TARGET	0	1
AMT_INCOME_TOTAL		
33750.0	1.0	NaN
38250.0	1.0	NaN
40500.0	1.0	NaN
45000.0	3.0	NaN
49500.0	2.0	NaN
...
1575000.0	2.0	NaN
1800000.0	1.0	NaN
2025000.0	2.0	NaN
2475000.0	1.0	NaN
4500000.0	1.0	NaN

```
[266 rows x 2 columns]
```

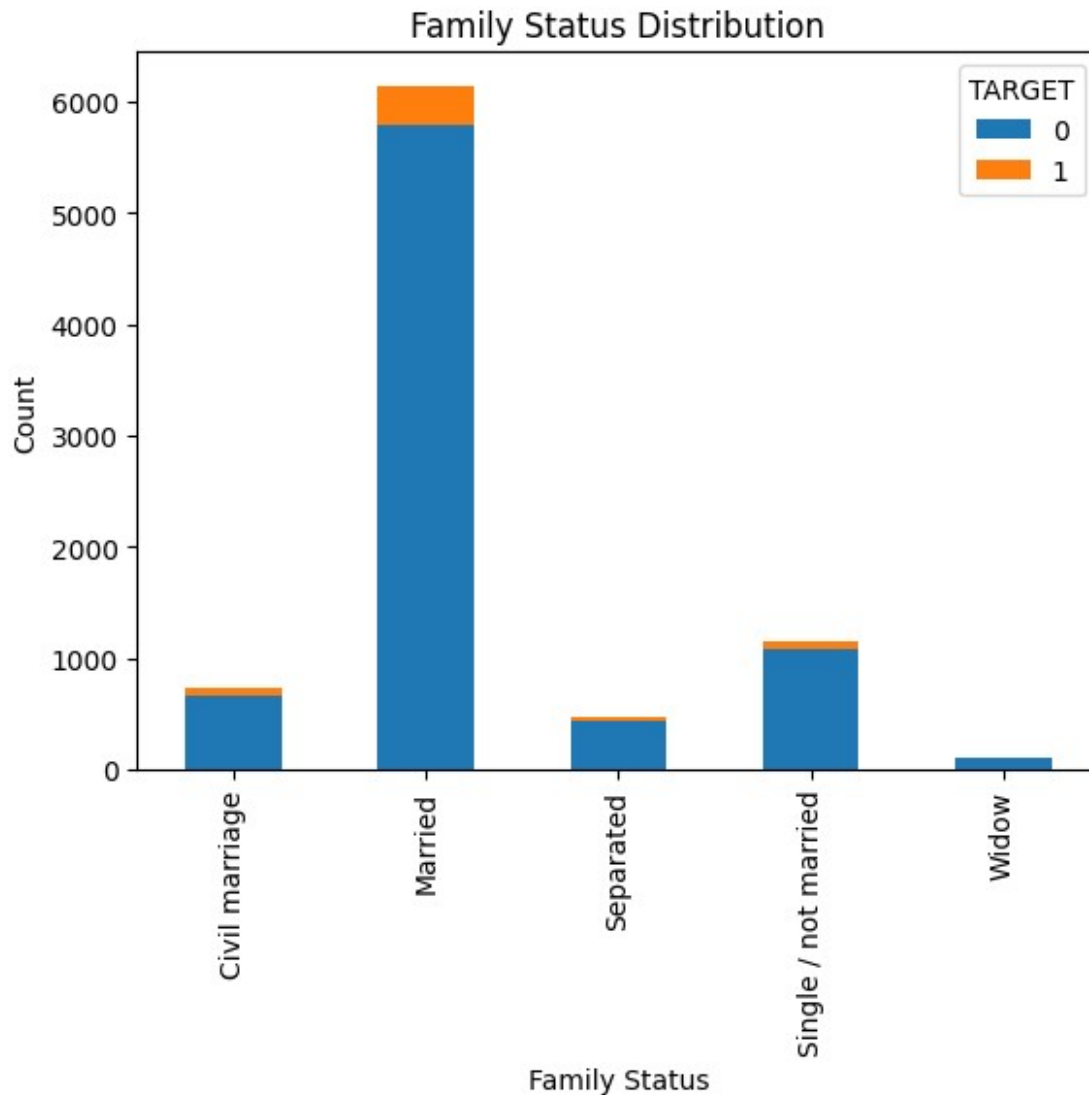


FAMILY STATUS

```
family_status = post.groupby('NAME_FAMILY_STATUS')
['TARGET'].value_counts().unstack()
print(family_status)
```

```
family_status.plot(kind='bar', stacked=True)
plt.title('Family Status Distribution')
plt.xlabel('Family Status')
plt.ylabel('Count')
plt.show()
```

TARGET	0	1
NAME_FAMILY_STATUS		
Civil marriage	669	64
Married	5796	343
Separated	437	33
Single / not married	1077	82
Widow	97	4



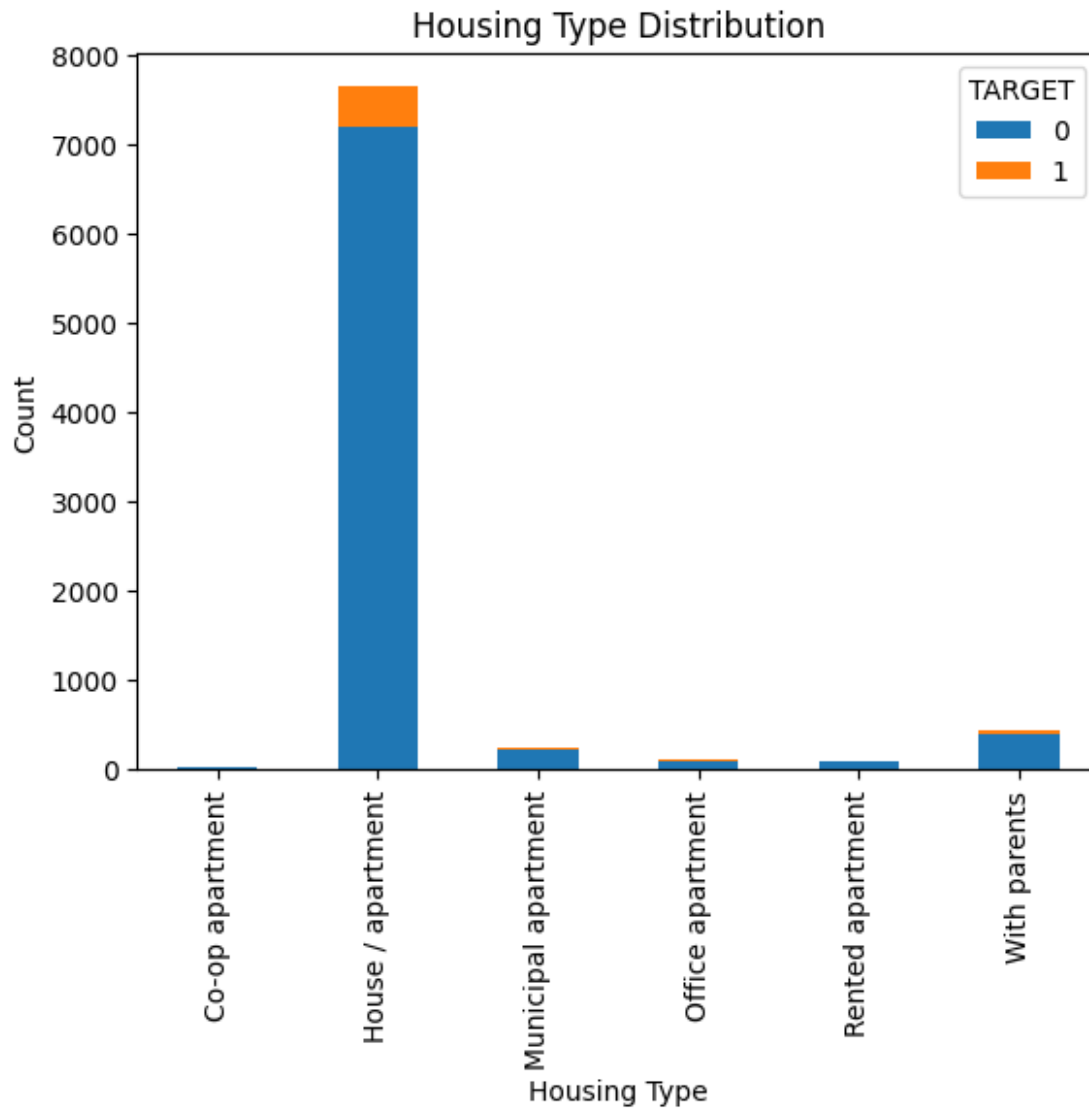
HOUSING TYPE

```
housing_type = post.groupby('NAME_HOUSING_TYPE')
['TARGET'].value_counts().unstack()
print(housing_type)
```

```
housing_type.plot(kind='bar', stacked=True)
plt.title('Housing Type Distribution')
plt.xlabel('Housing Type')
plt.ylabel('Count')
plt.show()
```

TARGET	0	1
NAME_HOUSING_TYPE		
Co-op apartment	31	4
House / apartment	7201	447

Municipal apartment	233	23
Office apartment	105	5
Rented apartment	95	3
With parents	411	44



```

post['HOUSING_TYPE'] = post['NAME_HOUSING_TYPE']
post['HOUSING_TYPE#'] =
post['NAME_HOUSING_TYPE'].astype('category').cat.codes
post.head()

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

# occupation
occupation = post.groupby('OCCUPATION_TYPE')

```

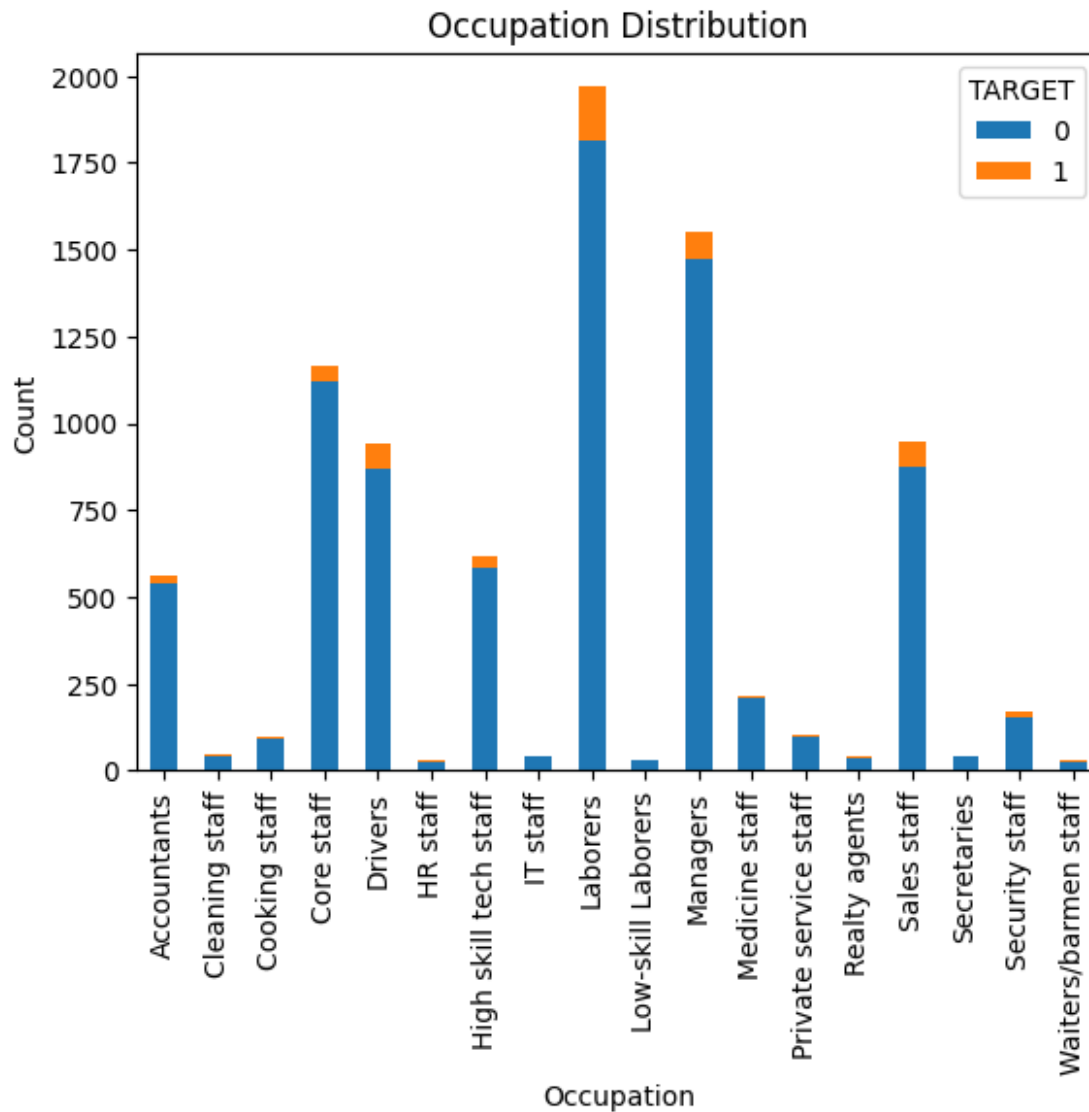
```

['TARGET'].value_counts().unstack()
print(occupation)

occupation.plot(kind='bar', stacked=True)
plt.title('Occupation Distribution')
plt.xlabel('Occupation')
plt.ylabel('Count')
plt.show()

```

TARGET	0	1
OCCUPATION_TYPE		
Accountants	541	20
Cleaning staff	43	3
Cooking staff	92	6
Core staff	1119	47
Drivers	868	72
HR staff	27	1
High skill tech staff	586	32
IT staff	41	3
Laborers	1812	155
Low-skill Laborers	30	3
Managers	1474	76
Medicine staff	207	10
Private service staff	98	4
Realty agents	38	3
Sales staff	875	72
Secretaries	43	1
Security staff	156	15
Waiters/barmen staff	26	3

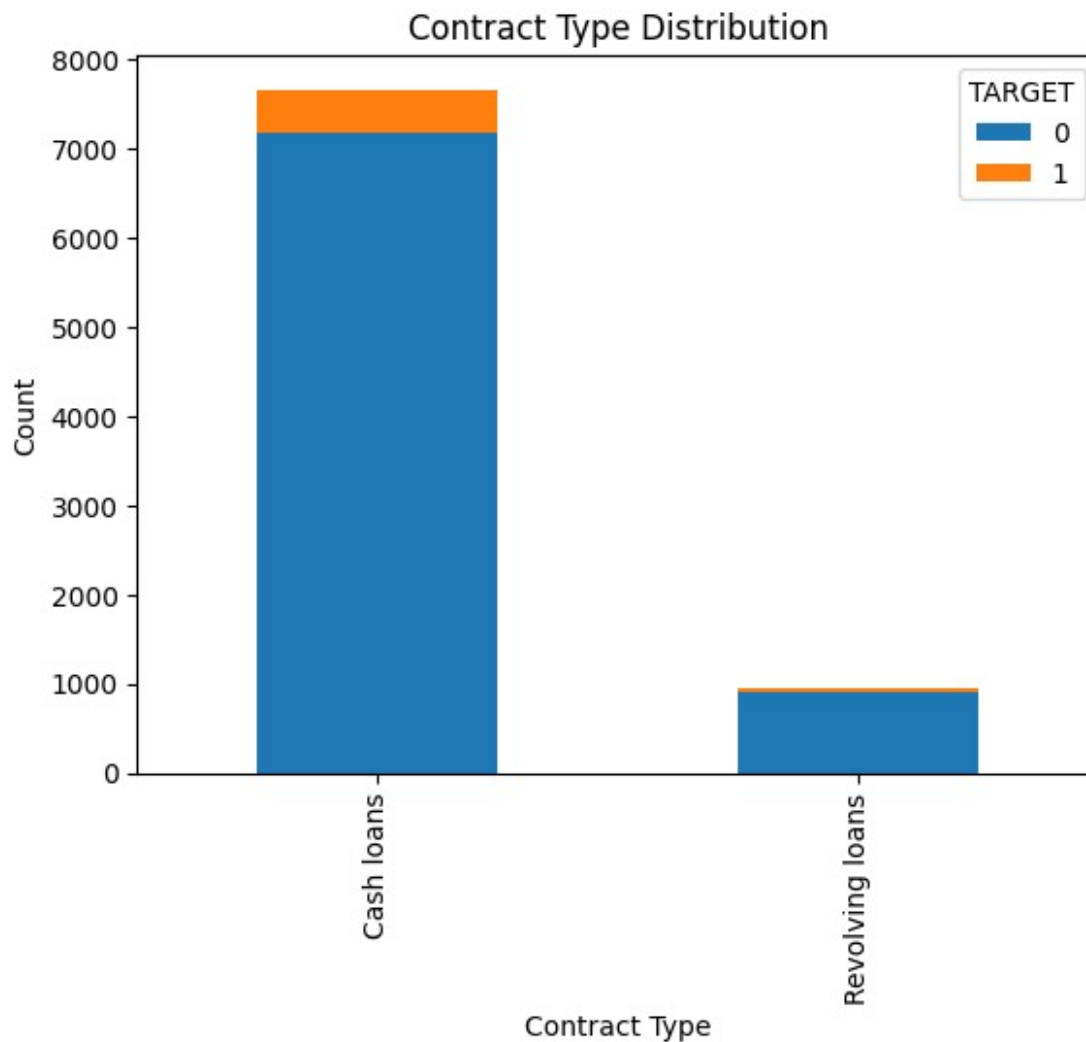


```
# contract type

contract_type = post.groupby('NAME_CONTRACT_TYPE')
['TARGET'].value_counts().unstack()
print(contract_type)

contract_type.plot(kind='bar', stacked=True)
plt.title('Contract Type Distribution')
plt.xlabel('Contract Type')
plt.ylabel('Count')
plt.show()
```

TARGET	0	1
Cash loans	7162	498
Revolving loans	914	28

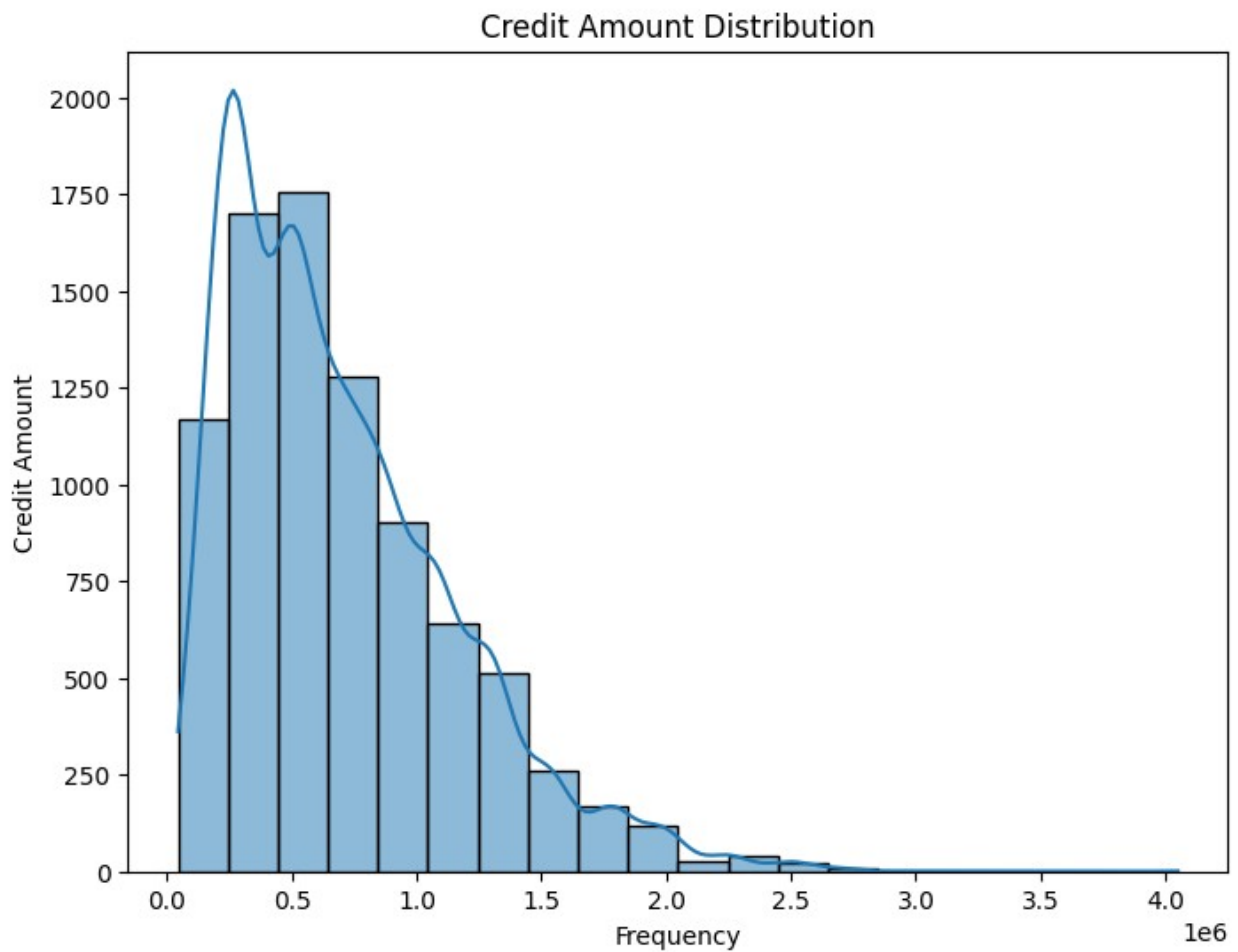


```
credit_amount = post.groupby('AMT_CREDIT')
['TARGET'].value_counts().unstack()
print(credit_amount)
plt.figure(figsize=(8, 6))
sns.histplot(post['AMT_CREDIT'], bins=20, kde=True)
plt.title('Credit Amount Distribution')
plt.ylabel('Credit Amount')
plt.xlabel('Frequency')
plt.show()
```

TARGET	0	1
AMT_CREDIT		
45000.0	5.0	NaN
47970.0	1.0	NaN
49752.0	1.0	NaN
50940.0	7.0	1.0
52128.0	3.0	NaN
...

2695500.0	6.0	1.0
2931660.0	1.0	NaN
3150000.0	1.0	NaN
3299688.0	1.0	NaN
4050000.0	1.0	NaN

[1806 rows x 2 columns]



```
# annuity amount
```

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

```
sns.boxplot(x='TARGET', y='AMT_ANNUITY', data=post)
```

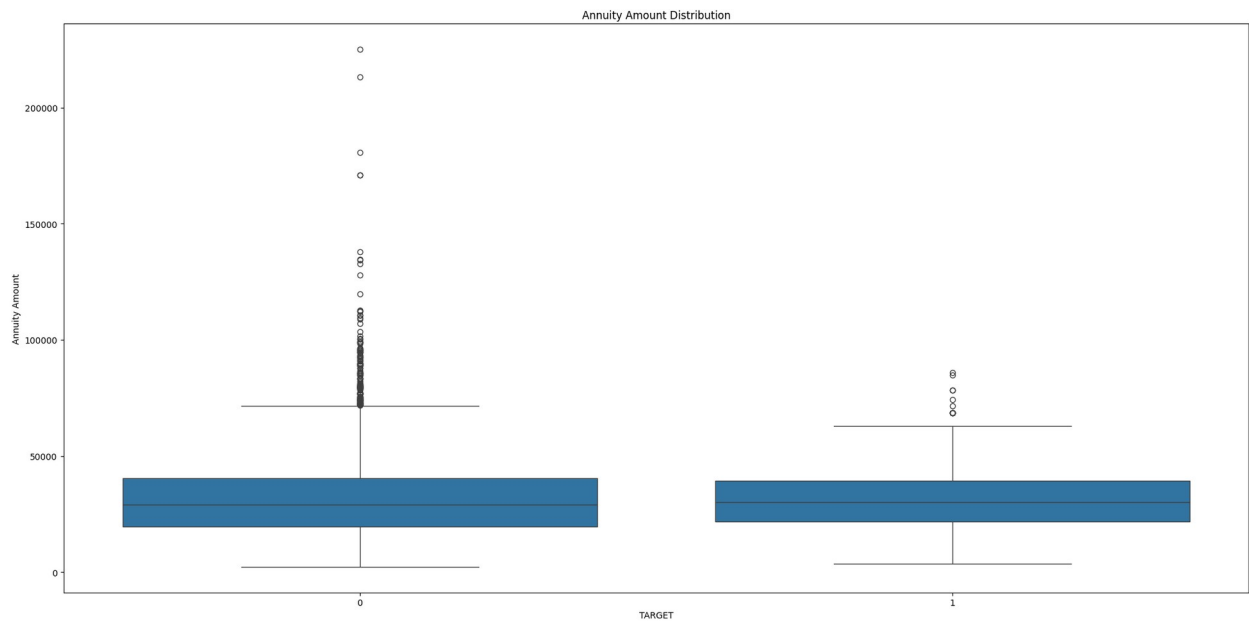
```
plt.title('Annuity Amount Distribution')
```

```
plt.xlabel('TARGET')
```

```
plt.ylabel('Annuity Amount')
```

```
plt.tight_layout()
```

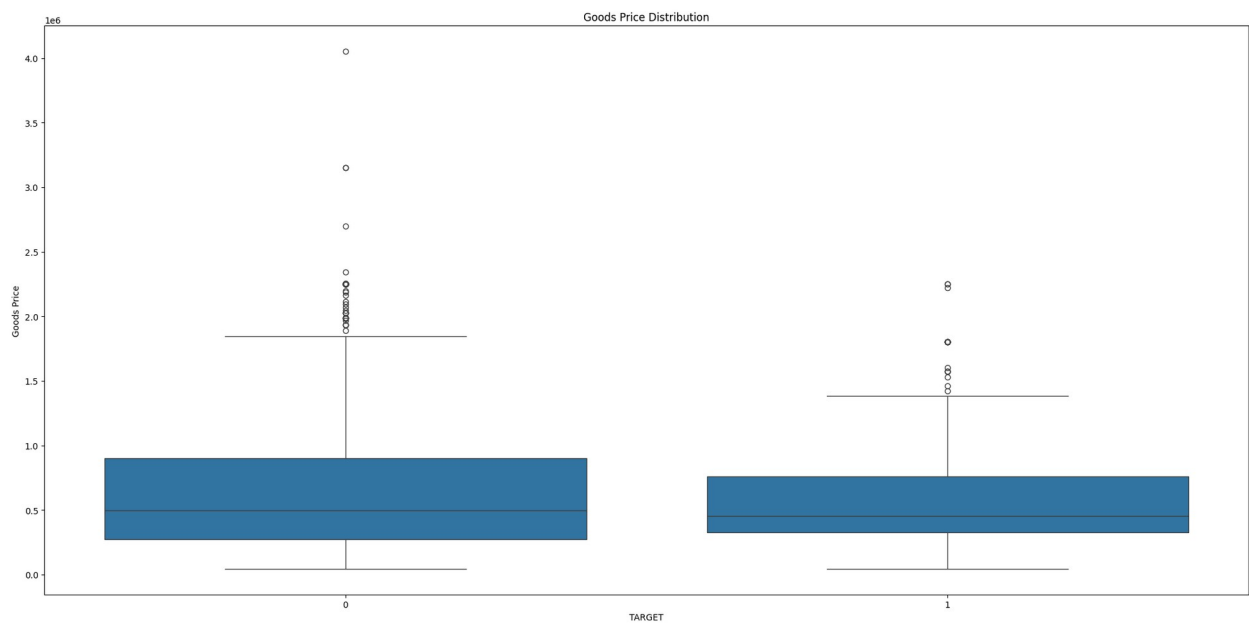
```
plt.show()
```

```
# goods price distribution
plt.figure(figsize=[20,10])

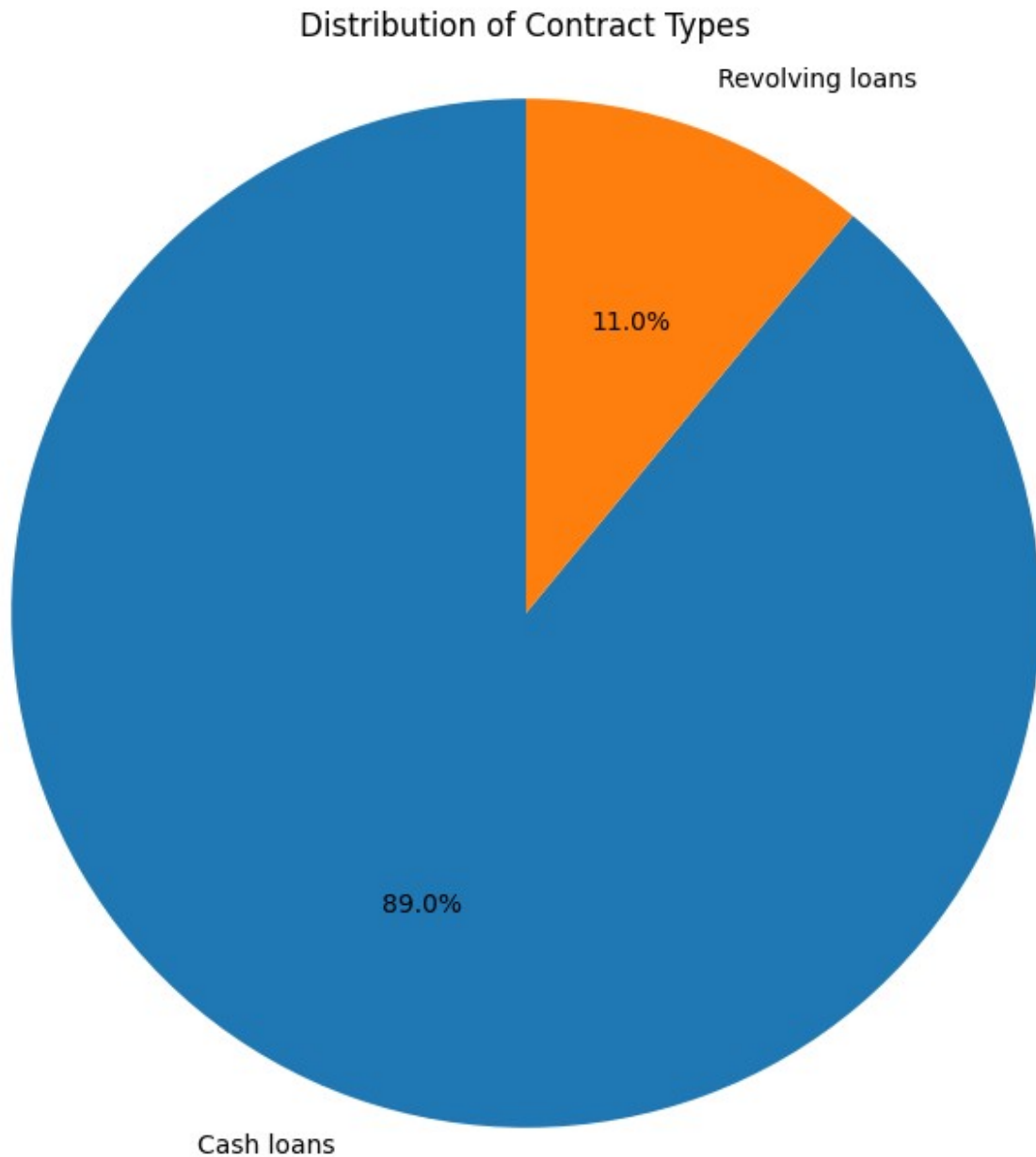
sns.boxplot(x='TARGET', y='AMT_GOODS_PRICE', data=post)
plt.title('Goods Price Distribution')
plt.xlabel('TARGET')
plt.ylabel('Goods Price')

plt.tight_layout()
plt.show()
```



```
contract_counts = post['NAME_CONTRACT_TYPE'].value_counts()

plt.figure(figsize=(8, 8))
plt.pie(contract_counts, labels=contract_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Distribution of Contract Types')
plt.axis('equal')
plt.show()
```



```

post.columns
if 'AMT_APPLICATTON' in post.columns:
    print("Column exists")
else:
    print("Does not exist")

Does not exist

annual_income = post.groupby("AMT_INCOME_TOTAL")
["TARGET"].value_counts().unstack()
print(annual_income)

TARGET          0    1
AMT_INCOME_TOTAL
33750.0          1.0 NaN
38250.0          1.0 NaN
40500.0          1.0 NaN
45000.0          3.0 NaN
49500.0          2.0 NaN
...
1575000.0        2.0 NaN
1800000.0        1.0 NaN
2025000.0        2.0 NaN
2475000.0        1.0 NaN
4500000.0        1.0 NaN

[266 rows x 2 columns]

numeric_data = post.select_dtypes(include=np.number)
numeric_data.head()

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

post.isnull().sum()
post

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

post_dropped = post.dropna()
post_dropped

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

```

A simple linear regression model

```

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import pandas as pd

features = ['AMT_INCOME_TOTAL', 'AMT_ANNUITY', 'CNT_CHILDREN']

```

```

x = post_dropped[features]
y = post_dropped["AMT_CREDIT"]

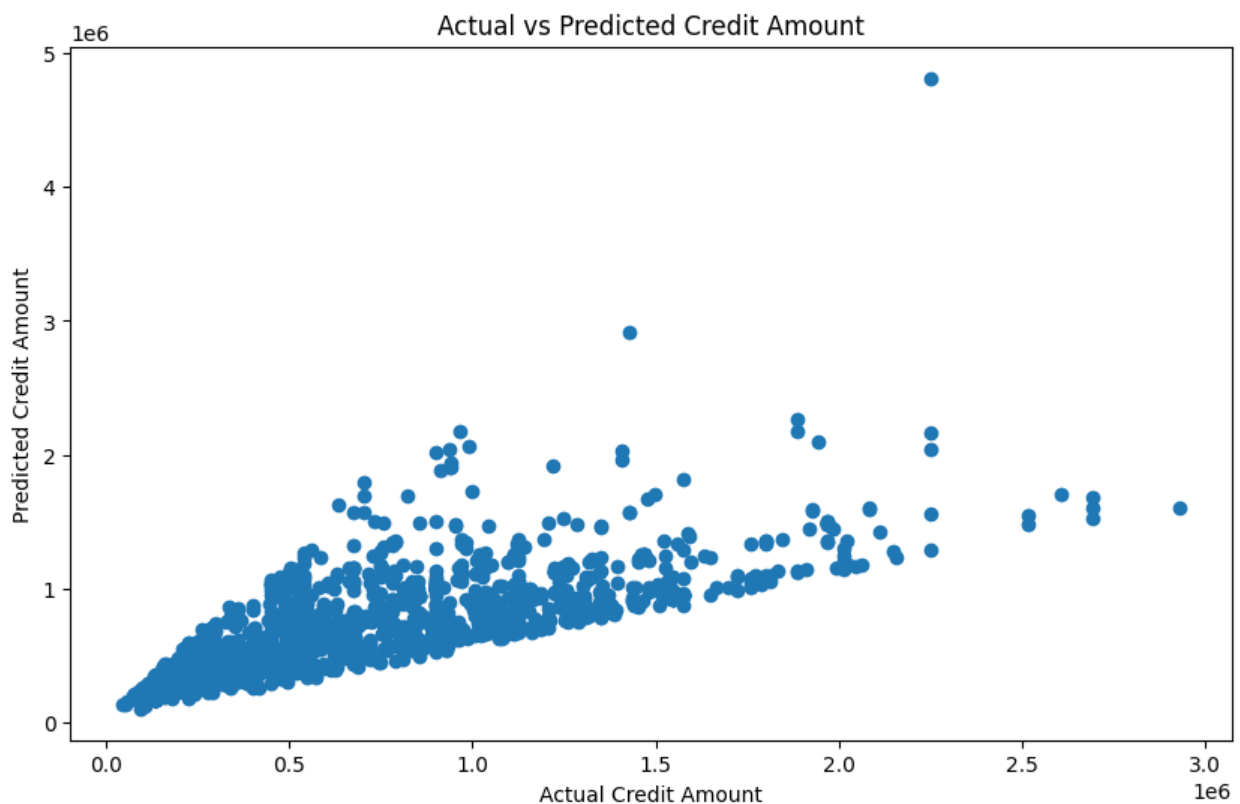
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2,
random_state = 42)
model = LinearRegression()
model.fit(x_train, y_train)
y_pred = model.predict(x_test)

mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean squared error: {mse}")
print(f"R-squared: {r2}")

plt.figure(figsize=(10,6))
plt.scatter(y_test, y_pred)
plt.xlabel("Actual Credit Amount")
plt.ylabel("Predicted Credit Amount")
plt.title("Actual vs Predicted Credit Amount")
plt.show()

Mean squared error: 94038873532.07123
R-squared: 0.5610474029402006

```



```

post.columns

Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
      'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN',
      'AMT_INCOME_TOTAL',
      'AMT_CREDIT', 'AMT_ANNUITY',
      ...,
      'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
      'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
      'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
      'AMT_REQ_CREDIT_BUREAU_YEAR', 'AGE', 'HOUSING_TYPE',
      'HOUSING_TYPE#'],
      dtype='object', length=125)

```

STATISTICAL ANALYSIS

```

from scipy import stats

# two sample t- test, credit amounts of default and non-default
loaners
group1 = post[post['TARGET'] == 0]['AMT_CREDIT']
group2 = post[post['TARGET'] == 1]['AMT_CREDIT']

t_stat, p_value = stats.ttest_ind(group1, group2)

print(f"T.statistic: {t_stat}, P-value: {p_value}")

T.statistic: 1.3572008503729496, P-value: 0.17475301721429964

prev.columns

Index(['SK_ID_PREV', 'SK_ID_CURR', 'NAME_CONTRACT_TYPE',
      'AMT_ANNUITY',
      'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
      'AMT_GOODS_PRICE',
      'WEEKDAY_APPR_PROCESS_START', 'HOUR_APPR_PROCESS_START',
      'FLAG_LAST_APPL_PER_CONTRACT', 'NFLAG_LAST_APPL_IN_DAY',
      'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY',
      'RATE_INTEREST_PRIVILEGED', 'NAME_CASH_LOAN_PURPOSE',
      'NAME_CONTRACT_STATUS', 'DAYS_DECISION', 'NAME_PAYMENT_TYPE',
      'CODE_REJECT_REASON', 'NAME_TYPE_SUITE', 'NAME_CLIENT_TYPE',
      'NAME_GOODS_CATEGORY', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
      'CHANNEL_TYPE', 'SELLERPLACE_AREA', 'NAME_SELLER_INDUSTRY',
      'CNT_PAYMENT', 'NAME_YIELD_GROUP', 'PRODUCT_COMBINATION',
      'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE',
      'DAYS_LAST_DUE_1ST_VERSION',
      'DAYS_LAST_DUE', 'DAYS_TERMINATION',
      'NFLAG_INSURED_ON_APPROVAL'],
      dtype='object')

```

```
prev.head()

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

prev.duplicated().sum()

0

post.duplicated().sum()

0

if 'AMT_APPLICATION' in post.columns:
    print("exists")
else:
    print("does not exist")

post = pd.read_csv("application_data.csv")
print(post.head())
```

```
does not exist
   SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR \
0      100002         1         Cash loans             M             N
1      100003         0         Cash loans             F             N
2      100004         0    Revolving loans             M             Y
3      100006         0         Cash loans             F             N
4      100007         0         Cash loans             M             N
```

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

```
   ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20
FLAG_DOCUMENT_21 \
0   ...              0              0              0
0
1   ...              0              0              0
0
2   ...              0              0              0
0
3   ...              0              0              0
0
```

4	...	0	0	0
0				

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

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

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

[5 rows x 122 columns]

ANOVA

```
group1 = post[post['TARGET'] == 0]['AMT_CREDIT']
group2 = post[post['TARGET'] == 1]['AMT_CREDIT']
```

```
F_statistic, p_value = stats.f_oneway(group1, group2)
```

```
print(f"F-statistic: {F_statistic}")
print(f"P-value: {p_value}")
```

```
F-statistic: 283.8753868374507
P-value: 1.1474602724260586e-63
```

```
post['AMT_CREDIT'].corr(post['AMT_GOODS_PRICE'])
```

```
0.9869683054221501
```

```
post['AMT_CREDIT'].corr(post['AMT_ANNUITY'])
```

```
0.7701380033118824
```

```
post2 = post.select_dtypes(include=np.number).corr()
post2
```

```
{"type": "dataframe", "variable_name": "post2"}
```

```

variables = post[['AMT_CREDIT', 'AMT_INCOME_TOTAL', 'CNT_CHILDREN'],]
matrix = variables.corr()
print(matrix)

```

	AMT_CREDIT	AMT_INCOME_TOTAL	CNT_CHILDREN
AMT_CREDIT	1.000000	0.156870	0.002145
AMT_INCOME_TOTAL	0.156870	1.000000	0.012882
CNT_CHILDREN	0.002145	0.012882	1.000000

```

variables2 = post[['AMT_CREDIT', 'AMT_INCOME_TOTAL', 'AMT_GOODS_PRICE',
'AMT_ANNUITY']]
matrix2 = variables2.corr()
print(matrix2)

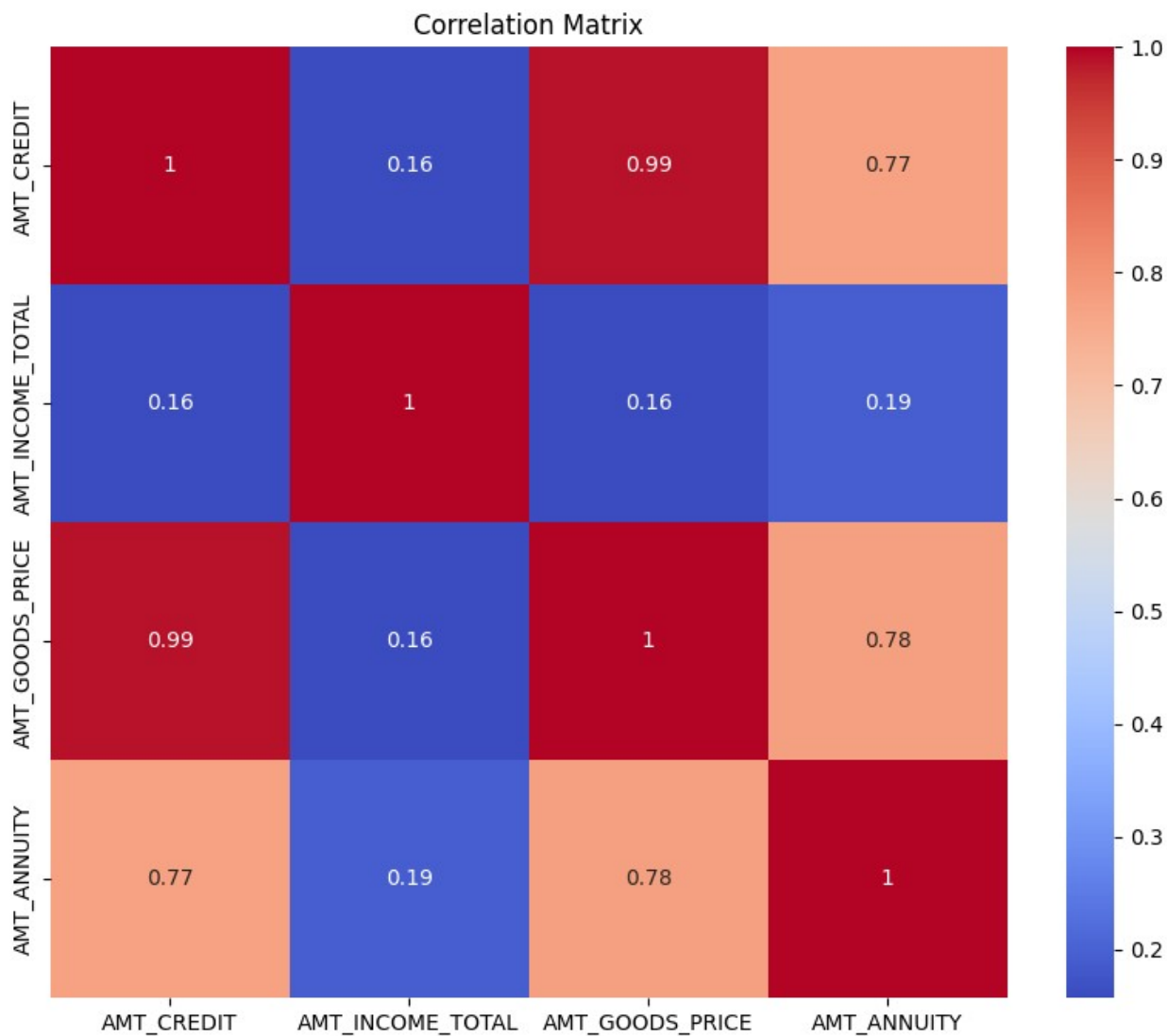
```

```

plt.figure(figsize=(10,8))
sns.heatmap(matrix2, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

```

	AMT_CREDIT	AMT_INCOME_TOTAL	AMT_GOODS_PRICE
AMT_ANNUITY			
AMT_CREDIT	1.000000	0.156870	0.986968
AMT_INCOME_TOTAL	0.156870	1.000000	0.159610
AMT_GOODS_PRICE	0.986968	0.159610	1.000000
AMT_ANNUITY	0.770138	0.191657	0.775109
AMT_CREDIT	0.770138		
AMT_INCOME_TOTAL		0.191657	
AMT_GOODS_PRICE			0.775109
AMT_ANNUITY	0.775109		
AMT_CREDIT	0.775109		
AMT_INCOME_TOTAL		0.775109	
AMT_GOODS_PRICE			0.775109
AMT_ANNUITY	0.775109		



```
prev_numerical = prev.select_dtypes(include=np.number)
corr_matrix1 = prev_numerical.corr()
print(corr_matrix1)
```

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY \
SK_ID_PREV	1.000000	-0.002514	-0.062103
SK_ID_CURR	-0.002514	1.000000	0.085439
AMT_ANNUITY	-0.062103	0.085439	1.000000
AMT_APPLICATION	-0.065285	0.113620	0.986229
AMT_CREDIT	-0.061630	0.086436	0.999939
AMT_DOWN_PAYMENT	-0.017276	0.175086	0.775581
AMT_GOODS_PRICE	-0.065285	0.113620	0.986229
HOUR_APPR_PROCESS_START	0.098916	-0.112946	-0.048648
NFLAG_LAST_APPL_IN_DAY	NaN	NaN	NaN
RATE_DOWN_PAYMENT	-0.022402	0.147016	0.072657
RATE_INTEREST_PRIMARY	0.096463	0.105772	-0.220981

RATE_INTEREST_PRIVILEGED	0.101816	0.154202	-0.146728
DAYS_DECISION	-0.057981	0.208837	-0.101702
SELLERPLACE_AREA	-0.183640	-0.052637	0.113311
CNT_PAYMENT	NaN	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN	NaN
DAYS_FIRST_DUE	-0.171873	-0.048295	-0.103207
DAYS_LAST_DUE_1ST_VERSION	-0.060763	0.206990	-0.100969
DAYS_LAST_DUE	-0.215247	-0.092463	-0.005796
DAYS_TERMINATION	-0.176348	-0.040080	0.051414
NFLAG_INSURED_ON_APPROVAL	0.115358	-0.047376	-0.060163

	AMT_APPLICATION	AMT_CREDIT	
AMT_DOWN_PAYMENT \			
SK_ID_PREV	-0.065285	-0.061630	-
0.017276			
SK_ID_CURR	0.113620	0.086436	
0.175086			
AMT_ANNUITY	0.986229	0.999939	
0.775581			
AMT_APPLICATION	1.000000	0.986439	
0.866017			
AMT_CREDIT	0.986439	1.000000	
0.776133			
AMT_DOWN_PAYMENT	0.866017	0.776133	
1.000000			
AMT_GOODS_PRICE	1.000000	0.986439	
0.866017			
HOUR_APPR_PROCESS_START	-0.037915	-0.047202	
0.003292			
NFLAG_LAST_APPL_IN_DAY	NaN	NaN	
NaN			
RATE_DOWN_PAYMENT	0.181470	0.074077	
0.496795			
RATE_INTEREST_PRIMARY	-0.199475	-0.221591	-
0.064177			
RATE_INTEREST_PRIVILEGED	-0.105586	-0.140401	
0.025169			
DAYS_DECISION	-0.065138	-0.099303	
0.044893			
SELLERPLACE_AREA	0.084914	0.111770	-
0.001798			
CNT_PAYMENT	NaN	NaN	
NaN			
DAYS_FIRST_DRAWING	NaN	NaN	
NaN			
DAYS_FIRST_DUE	-0.100672	-0.104360	-
0.076833			
DAYS_LAST_DUE_1ST_VERSION	-0.064507	-0.098585	
0.044578			

DAYS_LAST_DUE	-0.010928	-0.005403	-
0.052079			
DAYS_TERMINATION	0.025092	0.052355	-
0.075942			
NFLAG_INSURED_ON_APPROVAL	-0.091162	-0.058894	-
0.088352			

	AMT_GOODS_PRICE	HOUR_APPR_PROCESS_START	\
SK_ID_PREV	-0.065285	0.098916	
SK_ID_CURR	0.113620	-0.112946	
AMT_ANNUITY	0.986229	-0.048648	
AMT_APPLICATION	1.000000	-0.037915	
AMT_CREDIT	0.986439	-0.047202	
AMT_DOWN_PAYMENT	0.866017	0.003292	
AMT_GOODS_PRICE	1.000000	-0.037915	
HOUR_APPR_PROCESS_START	-0.037915	1.000000	
NFLAG_LAST_APPL_IN_DAY	NaN	NaN	
RATE_DOWN_PAYMENT	0.181470	0.168831	
RATE_INTEREST_PRIMARY	-0.199475	-0.011590	
RATE_INTEREST_PRIVILEGED	-0.105586	0.304157	
DAYS_DECISION	-0.065138	0.013474	
SELLERPLACE_AREA	0.084914	0.117393	
CNT_PAYMENT	NaN	NaN	
DAYS_FIRST_DRAWING	NaN	NaN	
DAYS_FIRST_DUE	-0.100672	-0.105091	
DAYS_LAST_DUE_1ST_VERSION	-0.064507	0.014113	
DAYS_LAST_DUE	-0.010928	0.114230	
DAYS_TERMINATION	0.025092	0.153627	
NFLAG_INSURED_ON_APPROVAL	-0.091162	-0.146447	

	NFLAG_LAST_APPL_IN_DAY
RATE_DOWN_PAYMENT ... \	
SK_ID_PREV	NaN
0.022402 ...	-
SK_ID_CURR	NaN
0.147016 ...	
AMT_ANNUITY	NaN
0.072657 ...	
AMT_APPLICATION	NaN
0.181470 ...	
AMT_CREDIT	NaN
0.074077 ...	
AMT_DOWN_PAYMENT	NaN
0.496795 ...	
AMT_GOODS_PRICE	NaN
0.181470 ...	
HOUR_APPR_PROCESS_START	NaN
0.168831 ...	
NFLAG_LAST_APPL_IN_DAY	NaN

NaN	...	
RATE_DOWN_PAYMENT		NaN
1.000000	...	
RATE_INTEREST_PRIMARY		NaN
0.058842	...	
RATE_INTEREST_PRIVILEGED		NaN
0.204840	...	
DAYS_DECISION		NaN
0.162642	...	
SELLERPLACE_AREA		NaN -
0.099124	...	
CNT_PAYMENT		NaN
NaN	...	
DAYS_FIRST_DRAWING		NaN
NaN	...	
DAYS_FIRST_DUE		NaN -
0.247103	...	
DAYS_LAST_DUE_1ST_VERSION		NaN
0.163324	...	
DAYS_LAST_DUE		NaN -
0.070213	...	
DAYS_TERMINATION		NaN -
0.151233	...	
NFLAG_INSURED_ON_APPROVAL		NaN -
0.039446	...	

	RATE_INTEREST_PRIVILEGED	DAYS_DECISION \
SK_ID_PREV	0.101816	-0.057981
SK_ID_CURR	0.154202	0.208837
AMT_ANNUITY	-0.146728	-0.101702
AMT_APPLICATION	-0.105586	-0.065138
AMT_CREDIT	-0.140401	-0.099303
AMT_DOWN_PAYMENT	0.025169	0.044893
AMT_GOODS_PRICE	-0.105586	-0.065138
HOURL_APPR_PROCESS_START	0.304157	0.013474
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
RATE_DOWN_PAYMENT	0.204840	0.162642
RATE_INTEREST_PRIMARY	-0.035909	0.086303
RATE_INTEREST_PRIVILEGED	1.000000	0.608370
DAYS_DECISION	0.608370	1.000000
SELLERPLACE_AREA	-0.159818	-0.000628
CNT_PAYMENT	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN
DAYS_FIRST_DUE	0.177689	0.192757
DAYS_LAST_DUE_1ST_VERSION	0.607948	0.999875
DAYS_LAST_DUE	0.215970	0.374097
DAYS_TERMINATION	0.265466	0.404214
NFLAG_INSURED_ON_APPROVAL	0.036203	0.250287

	SELLERPLACE_AREA	CNT_PAYMENT
DAYS_FIRST_DRAWING \		
SK_ID_PREV	-0.183640	NaN
NaN		
SK_ID_CURR	-0.052637	NaN
NaN		
AMT_ANNUITY	0.113311	NaN
NaN		
AMT_APPLICATION	0.084914	NaN
NaN		
AMT_CREDIT	0.111770	NaN
NaN		
AMT_DOWN_PAYMENT	-0.001798	NaN
NaN		
AMT_GOODS_PRICE	0.084914	NaN
NaN		
HOURL_APPR_PROCESS_START	0.117393	NaN
NaN		
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
NaN		
RATE_DOWN_PAYMENT	-0.099124	NaN
NaN		
RATE_INTEREST_PRIMARY	0.181596	NaN
NaN		
RATE_INTEREST_PRIVILEGED	-0.159818	NaN
NaN		
DAYS_DECISION	-0.000628	NaN
NaN		
SELLERPLACE_AREA	1.000000	NaN
NaN		
CNT_PAYMENT	NaN	NaN
NaN		
DAYS_FIRST_DRAWING	NaN	NaN
NaN		
DAYS_FIRST_DUE	-0.031593	NaN
NaN		
DAYS_LAST_DUE_1ST_VERSION	-0.002432	NaN
NaN		
DAYS_LAST_DUE	-0.011935	NaN
NaN		
DAYS_TERMINATION	-0.022329	NaN
NaN		
NFLAG_INSURED_ON_APPROVAL	0.241941	NaN
NaN		
	DAYS_FIRST_DUE	
DAYS_LAST_DUE_1ST_VERSION \		
SK_ID_PREV	-0.171873	-0.060763

SK_ID_CURR	-0.048295	0.206990
AMT_ANNUITY	-0.103207	-0.100969
AMT_APPLICATION	-0.100672	-0.064507
AMT_CREDIT	-0.104360	-0.098585
AMT_DOWN_PAYMENT	-0.076833	0.044578
AMT_GOODS_PRICE	-0.100672	-0.064507
HOURL_APPR_PROCESS_START	-0.105091	0.014113
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
RATE_DOWN_PAYMENT	-0.247103	0.163324
RATE_INTEREST_PRIMARY	0.006460	0.075696
RATE_INTEREST_PRIVILEGED	0.177689	0.607948
DAYS_DECISION	0.192757	0.999875
SELLERPLACE_AREA	-0.031593	-0.002432
CNT_PAYMENT	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN
DAYS_FIRST_DUE	1.000000	0.192068
DAYS_LAST_DUE_1ST_VERSION	0.192068	1.000000
DAYS_LAST_DUE	0.315712	0.375886
DAYS_TERMINATION	0.297415	0.405664
NFLAG_INSURED_ON_APPROVAL	-0.052273	0.246943
	DAYS_LAST_DUE	DAYS_TERMINATION \
SK_ID_PREV	-0.215247	-0.176348
SK_ID_CURR	-0.092463	-0.040080
AMT_ANNUITY	-0.005796	0.051414
AMT_APPLICATION	-0.010928	0.025092
AMT_CREDIT	-0.005403	0.052355
AMT_DOWN_PAYMENT	-0.052079	-0.075942
AMT_GOODS_PRICE	-0.010928	0.025092
HOURL_APPR_PROCESS_START	0.114230	0.153627
NFLAG_LAST_APPL_IN_DAY	NaN	NaN

RATE_DOWN_PAYMENT	-0.070213	-0.151233
RATE_INTEREST_PRIMARY	-0.063183	-0.039266
RATE_INTEREST_PRIVILEGED	0.215970	0.265466
DAYS_DECISION	0.374097	0.404214
SELLERPLACE_AREA	-0.011935	-0.022329
CNT_PAYMENT	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN
DAYS_FIRST_DUE	0.315712	0.297415
DAYS_LAST_DUE_1ST_VERSION	0.375886	0.405664
DAYS_LAST_DUE	1.000000	0.941107
DAYS_TERMINATION	0.941107	1.000000
NFLAG_INSURED_ON_APPROVAL	-0.058250	0.033985

	NFLAG_INSURED_ON_APPROVAL
SK_ID_PREV	0.115358
SK_ID_CURR	-0.047376
AMT_ANNUITY	-0.060163
AMT_APPLICATION	-0.091162
AMT_CREDIT	-0.058894
AMT_DOWN_PAYMENT	-0.088352
AMT_GOODS_PRICE	-0.091162
HOURL_APPR_PROCESS_START	-0.146447
NFLAG_LAST_APPL_IN_DAY	NaN
RATE_DOWN_PAYMENT	-0.039446
RATE_INTEREST_PRIMARY	0.307477
RATE_INTEREST_PRIVILEGED	0.036203
DAYS_DECISION	0.250287
SELLERPLACE_AREA	0.241941
CNT_PAYMENT	NaN
DAYS_FIRST_DRAWING	NaN
DAYS_FIRST_DUE	-0.052273
DAYS_LAST_DUE_1ST_VERSION	0.246943
DAYS_LAST_DUE	-0.058250
DAYS_TERMINATION	0.033985
NFLAG_INSURED_ON_APPROVAL	1.000000

[21 rows x 21 columns]

```
# t- test
```

```
group1 = post[post['TARGET'] == 0]['AMT_CREDIT']
group2 = post[post['TARGET'] == 1]['AMT_CREDIT']
```

```
t_stat, p_value = stats.ttest_ind(group1, group2)
```

```
print(f"T.statistic: {t_stat}, P-value: {p_value}")
```

```
T.statistic: 16.848601925306788, P-value: 1.1474602724788813e-63
```

```
prev_numerical = prev.select_dtypes(include=np.number)
corr_matrix1 = prev_numerical.corr()
```

```
print(corr_matrix1)
```

```
plt.figure(figsize=(10,8))
```

```
sns.heatmap(corr_matrix1, annot=True, cmap='coolwarm')
```

```
plt.title('Correlation Matrix')
```

```
plt.show()
```

	SK_ID_PREV	SK_ID_CURR	AMT_ANNUITY	\
SK_ID_PREV	1.000000	-0.002514	-0.062103	
SK_ID_CURR	-0.002514	1.000000	0.085439	
AMT_ANNUITY	-0.062103	0.085439	1.000000	
AMT_APPLICATION	-0.065285	0.113620	0.986229	
AMT_CREDIT	-0.061630	0.086436	0.999939	
AMT_DOWN_PAYMENT	-0.017276	0.175086	0.775581	
AMT_GOODS_PRICE	-0.065285	0.113620	0.986229	
hour_appr_process_start	0.098916	-0.112946	-0.048648	
nflag_last_appl_in_day	NaN	NaN	NaN	
rate_down_payment	-0.022402	0.147016	0.072657	
rate_interest_primary	0.096463	0.105772	-0.220981	
rate_interest_privileged	0.101816	0.154202	-0.146728	
days_decision	-0.057981	0.208837	-0.101702	
sellerplace_area	-0.183640	-0.052637	0.113311	
cnt_payment	NaN	NaN	NaN	
days_first_drawing	NaN	NaN	NaN	
days_first_due	-0.171873	-0.048295	-0.103207	
days_last_due_1st_version	-0.060763	0.206990	-0.100969	
days_last_due	-0.215247	-0.092463	-0.005796	
days_termination	-0.176348	-0.040080	0.051414	
nflag_insured_on_approval	0.115358	-0.047376	-0.060163	

	AMT_APPLICATION	AMT_CREDIT	
AMT_DOWN_PAYMENT \			
SK_ID_PREV	-0.065285	-0.061630	-
0.017276			
SK_ID_CURR	0.113620	0.086436	
0.175086			
AMT_ANNUITY	0.986229	0.999939	
0.775581			
AMT_APPLICATION	1.000000	0.986439	
0.866017			
AMT_CREDIT	0.986439	1.000000	
0.776133			
AMT_DOWN_PAYMENT	0.866017	0.776133	
1.000000			
AMT_GOODS_PRICE	1.000000	0.986439	
0.866017			
hour_appr_process_start	-0.037915	-0.047202	
0.003292			
nflag_last_appl_in_day	NaN	NaN	
NaN			

RATE_DOWN_PAYMENT	0.181470	0.074077	
0.496795			
RATE_INTEREST_PRIMARY	-0.199475	-0.221591	-
0.064177			
RATE_INTEREST_PRIVILEGED	-0.105586	-0.140401	
0.025169			
DAYS_DECISION	-0.065138	-0.099303	
0.044893			
SELLERPLACE_AREA	0.084914	0.111770	-
0.001798			
CNT_PAYMENT	NaN	NaN	
NaN			
DAYS_FIRST_DRAWING	NaN	NaN	
NaN			
DAYS_FIRST_DUE	-0.100672	-0.104360	-
0.076833			
DAYS_LAST_DUE_1ST_VERSION	-0.064507	-0.098585	
0.044578			
DAYS_LAST_DUE	-0.010928	-0.005403	-
0.052079			
DAYS_TERMINATION	0.025092	0.052355	-
0.075942			
NFLAG_INSURED_ON_APPROVAL	-0.091162	-0.058894	-
0.088352			

	AMT_GOODS_PRICE	hour_appr_process_start	\
SK_ID_PREV	-0.065285	0.098916	
SK_ID_CURR	0.113620	-0.112946	
AMT_ANNUITY	0.986229	-0.048648	
AMT_APPLICATION	1.000000	-0.037915	
AMT_CREDIT	0.986439	-0.047202	
AMT_DOWN_PAYMENT	0.866017	0.003292	
AMT_GOODS_PRICE	1.000000	-0.037915	
hour_appr_process_start	-0.037915	1.000000	
NFLAG_LAST_APPL_IN_DAY	NaN	NaN	
RATE_DOWN_PAYMENT	0.181470	0.168831	
RATE_INTEREST_PRIMARY	-0.199475	-0.011590	
RATE_INTEREST_PRIVILEGED	-0.105586	0.304157	
DAYS_DECISION	-0.065138	0.013474	
SELLERPLACE_AREA	0.084914	0.117393	
CNT_PAYMENT	NaN	NaN	
DAYS_FIRST_DRAWING	NaN	NaN	
DAYS_FIRST_DUE	-0.100672	-0.105091	
DAYS_LAST_DUE_1ST_VERSION	-0.064507	0.014113	
DAYS_LAST_DUE	-0.010928	0.114230	
DAYS_TERMINATION	0.025092	0.153627	
NFLAG_INSURED_ON_APPROVAL	-0.091162	-0.146447	

NFLAG_LAST_APPL_IN_DAY

RATE_DOWN_PAYMENT	...	\
SK_ID_PREV		NaN
0.022402	...	
SK_ID_CURR		NaN
0.147016	...	
AMT_ANNUITY		NaN
0.072657	...	
AMT_APPLICATION		NaN
0.181470	...	
AMT_CREDIT		NaN
0.074077	...	
AMT_DOWN_PAYMENT		NaN
0.496795	...	
AMT_GOODS_PRICE		NaN
0.181470	...	
HOUR_APPR_PROCESS_START		NaN
0.168831	...	
NFLAG_LAST_APPL_IN_DAY		NaN
NaN	...	
RATE_DOWN_PAYMENT		NaN
1.000000	...	
RATE_INTEREST_PRIMARY		NaN
0.058842	...	
RATE_INTEREST_PRIVILEGED		NaN
0.204840	...	
DAYS_DECISION		NaN
0.162642	...	
SELLERPLACE_AREA		NaN
0.099124	...	
CNT_PAYMENT		NaN
NaN	...	
DAYS_FIRST_DRAWING		NaN
NaN	...	
DAYS_FIRST_DUE		NaN
0.247103	...	
DAYS_LAST_DUE_1ST_VERSION		NaN
0.163324	...	
DAYS_LAST_DUE		NaN
0.070213	...	
DAYS_TERMINATION		NaN
0.151233	...	
NFLAG_INSURED_ON_APPROVAL		NaN
0.039446	...	

	RATE_INTEREST_PRIVILEGED	DAYS_DECISION	\
SK_ID_PREV	0.101816	-0.057981	
SK_ID_CURR	0.154202	0.208837	
AMT_ANNUITY	-0.146728	-0.101702	
AMT_APPLICATION	-0.105586	-0.065138	

AMT_CREDIT	-0.140401	-0.099303
AMT_DOWN_PAYMENT	0.025169	0.044893
AMT_GOODS_PRICE	-0.105586	-0.065138
HOURL_APPR_PROCESS_START	0.304157	0.013474
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
RATE_DOWN_PAYMENT	0.204840	0.162642
RATE_INTEREST_PRIMARY	-0.035909	0.086303
RATE_INTEREST_PRIVILEGED	1.000000	0.608370
DAYS_DECISION	0.608370	1.000000
SELLERPLACE_AREA	-0.159818	-0.000628
CNT_PAYMENT	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN
DAYS_FIRST_DUE	0.177689	0.192757
DAYS_LAST_DUE_1ST_VERSION	0.607948	0.999875
DAYS_LAST_DUE	0.215970	0.374097
DAYS_TERMINATION	0.265466	0.404214
NFLAG_INSURED_ON_APPROVAL	0.036203	0.250287

	SELLERPLACE_AREA	CNT_PAYMENT
DAYS_FIRST_DRAWING \		
SK_ID_PREV	-0.183640	NaN
NaN		
SK_ID_CURR	-0.052637	NaN
NaN		
AMT_ANNUITY	0.113311	NaN
NaN		
AMT_APPLICATION	0.084914	NaN
NaN		
AMT_CREDIT	0.111770	NaN
NaN		
AMT_DOWN_PAYMENT	-0.001798	NaN
NaN		
AMT_GOODS_PRICE	0.084914	NaN
NaN		
HOURL_APPR_PROCESS_START	0.117393	NaN
NaN		
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
NaN		
RATE_DOWN_PAYMENT	-0.099124	NaN
NaN		
RATE_INTEREST_PRIMARY	0.181596	NaN
NaN		
RATE_INTEREST_PRIVILEGED	-0.159818	NaN
NaN		
DAYS_DECISION	-0.000628	NaN
NaN		
SELLERPLACE_AREA	1.000000	NaN
NaN		
CNT_PAYMENT	NaN	NaN

NaN		
DAYS_FIRST_DRAWING	NaN	NaN
NaN		
DAYS_FIRST_DUE	-0.031593	NaN
NaN		
DAYS_LAST_DUE_1ST_VERSION	-0.002432	NaN
NaN		
DAYS_LAST_DUE	-0.011935	NaN
NaN		
DAYS_TERMINATION	-0.022329	NaN
NaN		
NFLAG_INSURED_ON_APPROVAL	0.241941	NaN
NaN		
	DAYS_FIRST_DUE	
DAYS_LAST_DUE_1ST_VERSION \		
SK_ID_PREV	-0.171873	-0.060763
SK_ID_CURR	-0.048295	0.206990
AMT_ANNUITY	-0.103207	-0.100969
AMT_APPLICATION	-0.100672	-0.064507
AMT_CREDIT	-0.104360	-0.098585
AMT_DOWN_PAYMENT	-0.076833	0.044578
AMT_GOODS_PRICE	-0.100672	-0.064507
HOURL_APPR_PROCESS_START	-0.105091	0.014113
NFLAG_LAST_APPL_IN_DAY	NaN	NaN
RATE_DOWN_PAYMENT	-0.247103	0.163324
RATE_INTEREST_PRIMARY	0.006460	0.075696
RATE_INTEREST_PRIVILEGED	0.177689	0.607948
DAYS_DECISION	0.192757	0.999875
SELLERPLACE_AREA	-0.031593	-0.002432
CNT_PAYMENT	NaN	NaN
DAYS_FIRST_DRAWING	NaN	NaN
DAYS_FIRST_DUE	1.000000	0.192068
DAYS_LAST_DUE_1ST_VERSION	0.192068	1.000000

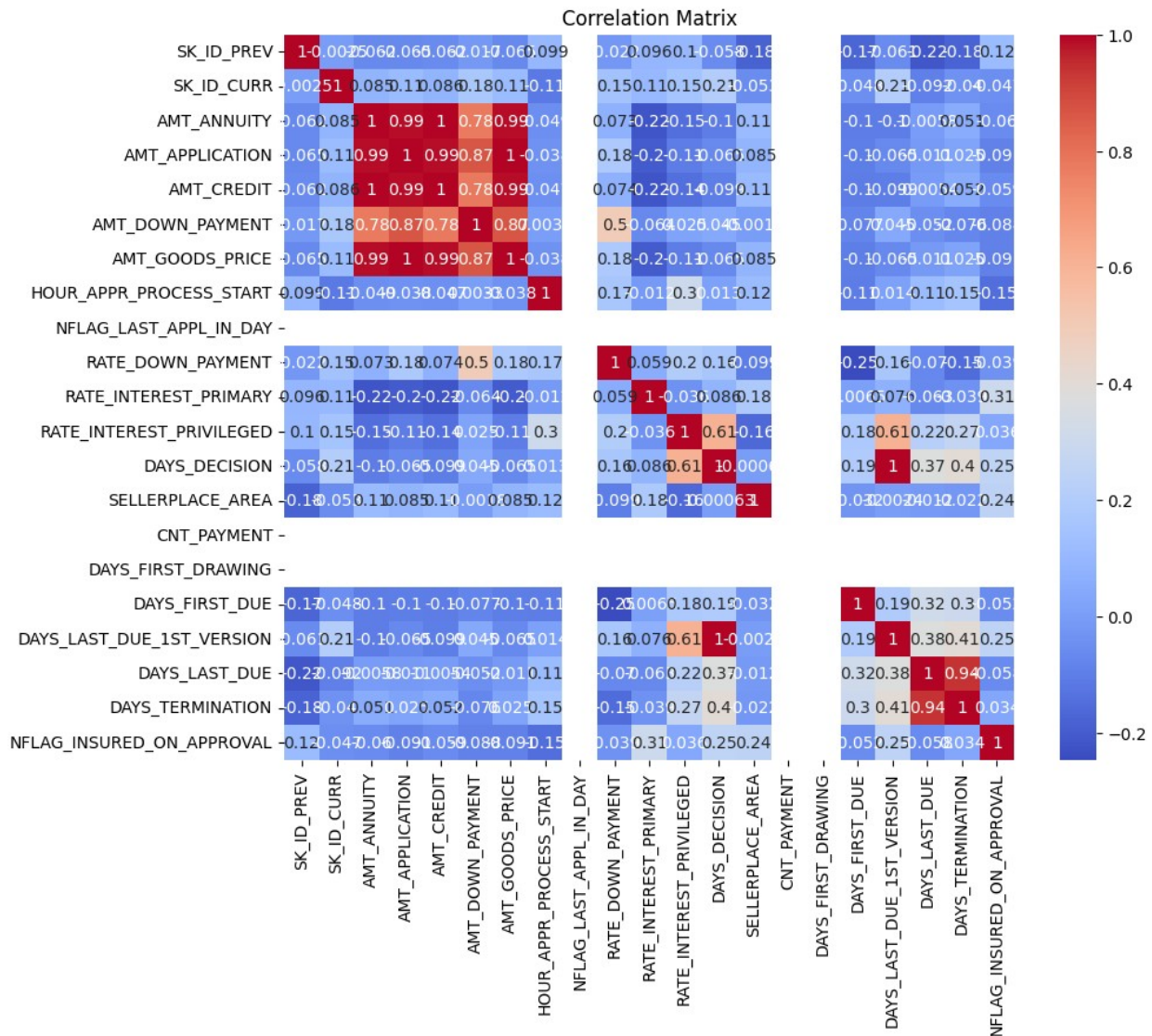
DAYS_LAST_DUE	0.315712	0.375886
DAYS_TERMINATION	0.297415	0.405664
NFLAG_INSURED_ON_APPROVAL	-0.052273	0.246943

	DAYS_LAST_DUE	DAYS_TERMINATION	\
SK_ID_PREV	-0.215247	-0.176348	
SK_ID_CURR	-0.092463	-0.040080	
AMT_ANNUITY	-0.005796	0.051414	
AMT_APPLICATION	-0.010928	0.025092	
AMT_CREDIT	-0.005403	0.052355	
AMT_DOWN_PAYMENT	-0.052079	-0.075942	
AMT_GOODS_PRICE	-0.010928	0.025092	
HOURL_APPR_PROCESS_START	0.114230	0.153627	
NFLAG_LAST_APPL_IN_DAY	NaN	NaN	
RATE_DOWN_PAYMENT	-0.070213	-0.151233	
RATE_INTEREST_PRIMARY	-0.063183	-0.039266	
RATE_INTEREST_PRIVILEGED	0.215970	0.265466	
DAYS_DECISION	0.374097	0.404214	
SELLERPLACE_AREA	-0.011935	-0.022329	
CNT_PAYMENT	NaN	NaN	
DAYS_FIRST_DRAWING	NaN	NaN	
DAYS_FIRST_DUE	0.315712	0.297415	
DAYS_LAST_DUE_1ST_VERSION	0.375886	0.405664	
DAYS_LAST_DUE	1.000000	0.941107	
DAYS_TERMINATION	0.941107	1.000000	
NFLAG_INSURED_ON_APPROVAL	-0.058250	0.033985	

	NFLAG_INSURED_ON_APPROVAL
SK_ID_PREV	0.115358
SK_ID_CURR	-0.047376
AMT_ANNUITY	-0.060163
AMT_APPLICATION	-0.091162
AMT_CREDIT	-0.058894
AMT_DOWN_PAYMENT	-0.088352
AMT_GOODS_PRICE	-0.091162
HOURL_APPR_PROCESS_START	-0.146447
NFLAG_LAST_APPL_IN_DAY	NaN
RATE_DOWN_PAYMENT	-0.039446
RATE_INTEREST_PRIMARY	0.307477
RATE_INTEREST_PRIVILEGED	0.036203
DAYS_DECISION	0.250287
SELLERPLACE_AREA	0.241941
CNT_PAYMENT	NaN
DAYS_FIRST_DRAWING	NaN
DAYS_FIRST_DUE	-0.052273
DAYS_LAST_DUE_1ST_VERSION	0.246943

DAYS_LAST_DUE	-0.058250
DAYS_TERMINATION	0.033985
NFLAG_INSURED_ON_APPROVAL	1.000000

[21 rows x 21 columns]



PLAYGROUND

```
amt_income = post.groupby('AMT_INCOME_TOTAL')
['TARGET'].value_counts().unstack()
print(amt_income)
```

TARGET	0	1
AMT_INCOME_TOTAL		
25650.0	1.0	1.0
26100.0	3.0	NaN

```

26460.0      1.0  NaN
26550.0      2.0  NaN
27000.0     63.0   3.0
...
6750000.0    1.0  NaN
9000000.0    1.0  NaN
13500000.0    1.0  NaN
18000090.0    1.0  NaN
117000000.0   NaN  1.0

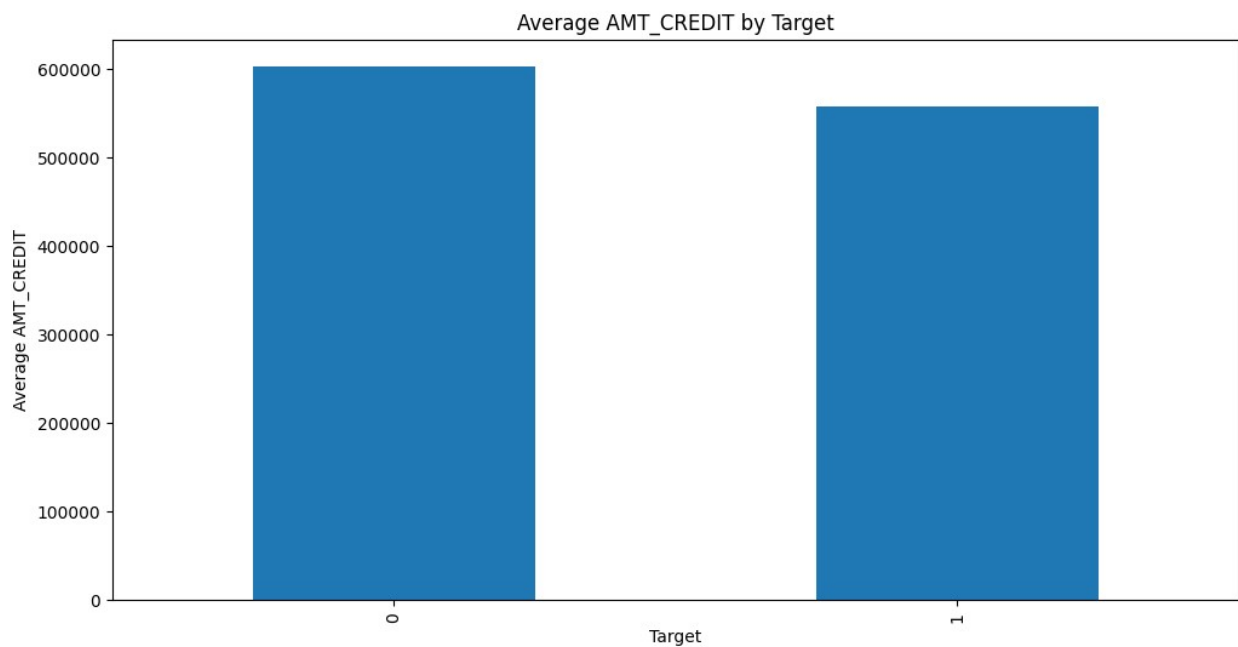
```

```
[2548 rows x 2 columns]
```

```

plt.figure(figsize=(12, 6))
post.groupby('TARGET')['AMT_CREDIT'].mean().plot(kind='bar')
plt.title('Average AMT_CREDIT by Target')
plt.xlabel('Target')
plt.ylabel('Average AMT_CREDIT')
plt.show()

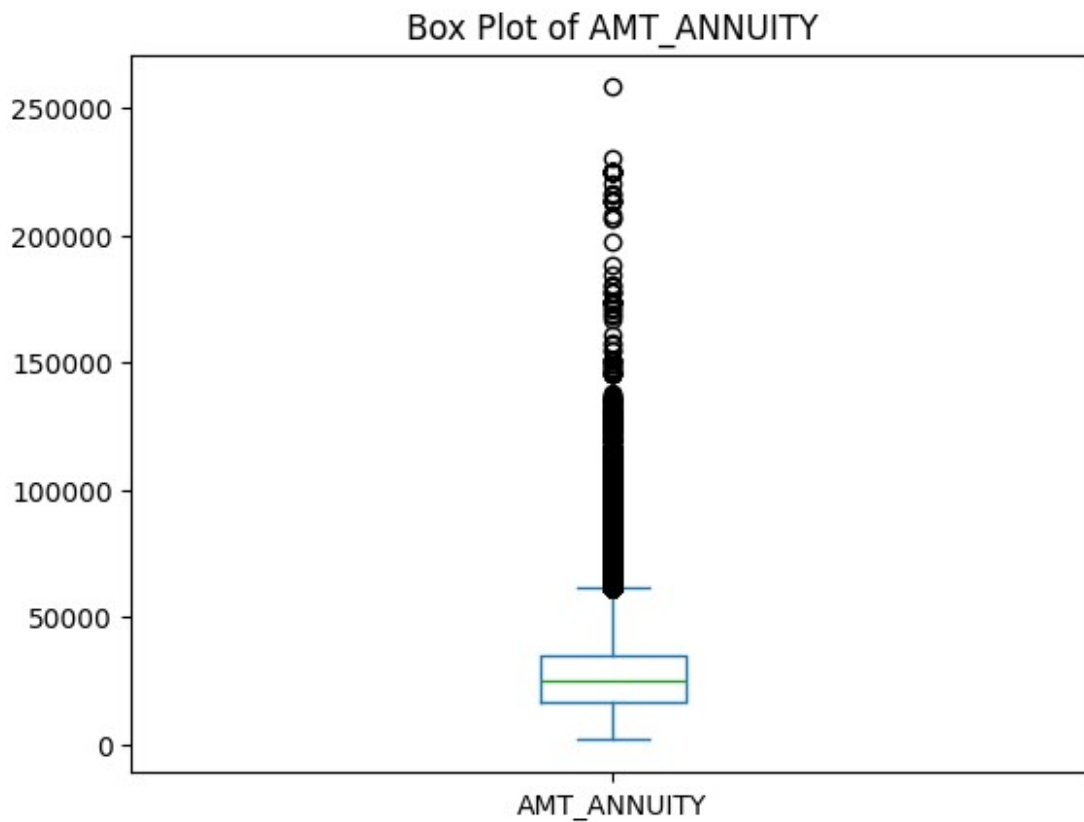
```



```

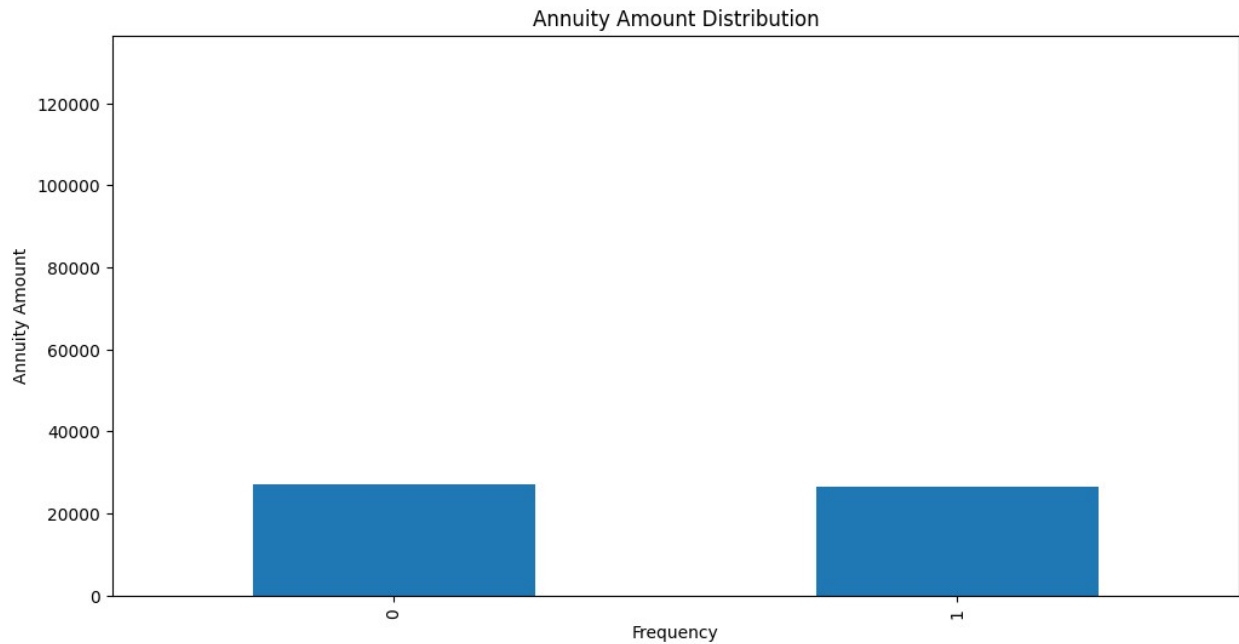
post['AMT_ANNUITY'].plot(kind='box')
plt.title('Box Plot of AMT_ANNUITY')
plt.show()

```

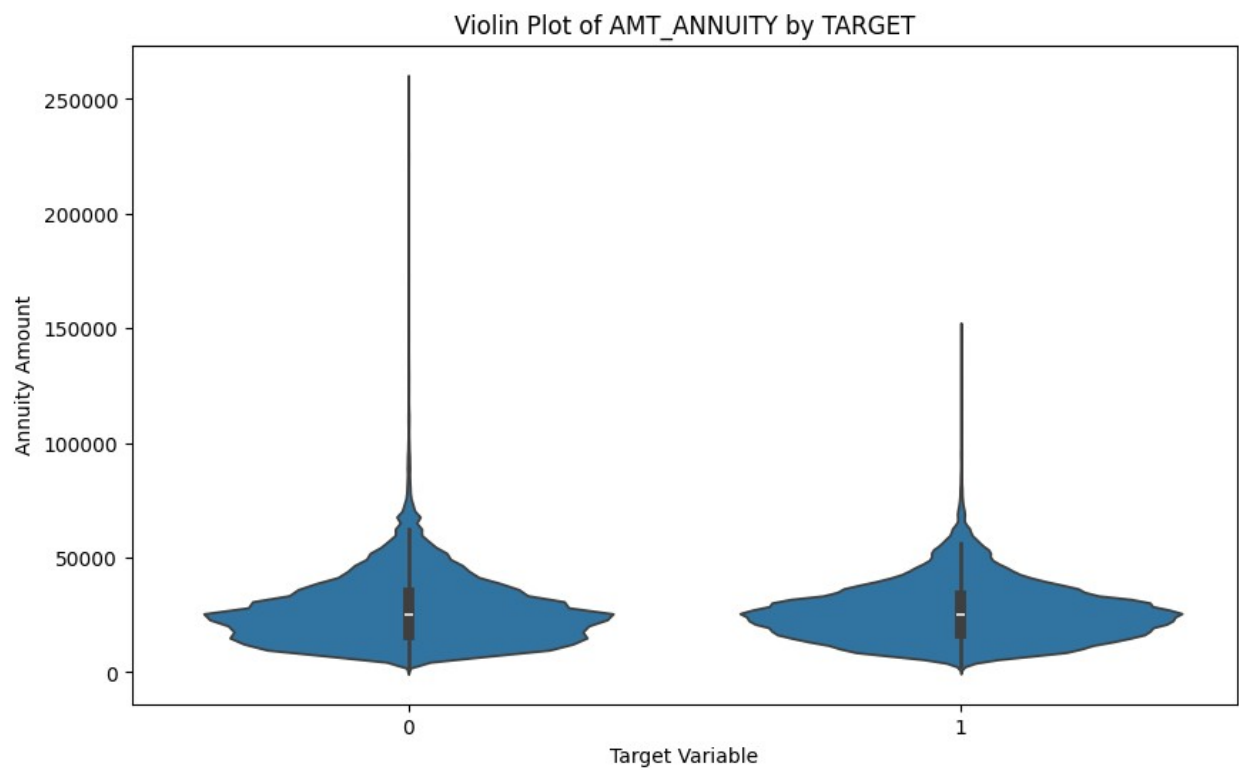


```
plt.figure(figsize=(12, 6))
post.groupby('TARGET')['AMT_ANNUIITY'].mean().plot(kind='bar')

sns.histplot(post['AMT_ANNUIITY'], bins=20, kde=True)
plt.title('Annuity Amount Distribution')
plt.ylabel('Annuity Amount')
plt.xlabel('Frequency')
plt.show()
```

```
plt.figure(figsize=(10, 6))
sns.violinplot(x='TARGET', y='AMT_ANNUIITY', data=post)
plt.title('Violin Plot of AMT_ANNUIITY by TARGET')
plt.xlabel('Target Variable')
plt.ylabel('Annuity Amount')
plt.show()
```



```
# t-tests for AMT_CREDIT against other relevant variables
variables_for_ttest = ['AMT_INCOME_TOTAL', 'AMT_ANNUITY',
                        'AMT_GOODS_PRICE', 'CNT_CHILDREN', 'DAYS_EMPLOYED']
```

```
for var in variables_for_ttest:
    group1 = post[post['TARGET'] == 0][var]
    group2 = post[post['TARGET'] == 1][var]
    t_stat, p_value = stats.ttest_ind(group1, group2)
    print(f"T-test for AMT_CREDIT vs {var}:")
    print(f"  T-statistic: {t_stat}")
    print(f"  P-value: {p_value}")
    print("-" * 20)
```

```
T-test for AMT_CREDIT vs AMT_INCOME_TOTAL:
T-statistic: 2.2081011084695983
P-value: 0.027237960879677118
-----
```

```
T-test for AMT_CREDIT vs AMT_ANNUITY:
T-statistic: nan
P-value: nan
-----
```

```
T-test for AMT_CREDIT vs AMT_GOODS_PRICE:
T-statistic: nan
P-value: nan
-----
```

```
T-test for AMT_CREDIT vs CNT_CHILDREN:
T-statistic: -10.64189504948037
P-value: 1.9224915502038074e-26
-----
```

```
T-test for AMT_CREDIT vs DAYS_EMPLOYED:
T-statistic: 24.94136608089604
P-value: 3.6311730828848897e-137
-----
```

```
# correlation coefficients between 'AMT_CREDIT' and other numerical
variables
```

```
numerical_cols = post.select_dtypes(include=np.number).columns
for col in numerical_cols:
    if col != 'AMT_CREDIT' and col != 'TARGET': # Exclude
        'AMT_CREDIT' and 'TARGET' itself
        correlation = post['AMT_CREDIT'].corr(post[col])
        print(f"Correlation between AMT_CREDIT and {col}:
{correlation}")
```

```
Correlation between AMT_CREDIT and SK_ID_CURR: -0.00034316120624785715
Correlation between AMT_CREDIT and CNT_CHILDREN: 0.0021454434616763416
Correlation between AMT_CREDIT and AMT_INCOME_TOTAL:
0.15687027185193095
Correlation between AMT_CREDIT and AMT_ANNUITY: 0.7701380033118824
```

Correlation between AMT_CREDIT and AMT_GOODS_PRICE: 0.9869683054221501
Correlation between AMT_CREDIT and REGION_POPULATION_RELATIVE:
0.09973787576226029
Correlation between AMT_CREDIT and DAYS_BIRTH: -0.055435947014526185
Correlation between AMT_CREDIT and DAYS_EMPLOYED: -0.06683834093092188
Correlation between AMT_CREDIT and DAYS_REGISTRATION:
0.009621325617372911
Correlation between AMT_CREDIT and DAYS_ID_PUBLISH: -
0.006574774427157878
Correlation between AMT_CREDIT and OWN_CAR_AGE: -0.09419071925702023
Correlation between AMT_CREDIT and FLAG_MOBIL: 0.001435572992417004
Correlation between AMT_CREDIT and FLAG_EMP_PHONE: 0.0655185936551337
Correlation between AMT_CREDIT and FLAG_WORK_PHONE: -
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Correlation between AMT_CREDIT and FLAG_CONT_MOBILE:
0.02365284569336862
Correlation between AMT_CREDIT and FLAG_PHONE: 0.026212789103157257
Correlation between AMT_CREDIT and FLAG_EMAIL: 0.016631912352195515
Correlation between AMT_CREDIT and CNT_FAM_MEMBERS:
0.06315981300414085
Correlation between AMT_CREDIT and REGION_RATING_CLIENT: -
0.10177638603517988
Correlation between AMT_CREDIT and REGION_RATING_CLIENT_W_CITY: -
0.11091525790094263
Correlation between AMT_CREDIT and HOUR_APPR_PROCESS_START:
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Correlation between AMT_CREDIT and REG_REGION_NOT_LIVE_REGION:
0.024009863420362577
Correlation between AMT_CREDIT and REG_REGION_NOT_WORK_REGION:
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Correlation between AMT_CREDIT and LIVE_REGION_NOT_WORK_REGION:
0.05260898463510743
Correlation between AMT_CREDIT and REG_CITY_NOT_LIVE_CITY: -
0.02688639203217113
Correlation between AMT_CREDIT and REG_CITY_NOT_WORK_CITY: -
0.018856162160153324
Correlation between AMT_CREDIT and LIVE_CITY_NOT_WORK_CITY:
8.081559967033301e-05
Correlation between AMT_CREDIT and EXT_SOURCE_1: 0.1684288997732408
Correlation between AMT_CREDIT and EXT_SOURCE_2: 0.13122793587324422
Correlation between AMT_CREDIT and EXT_SOURCE_3: 0.043516255467307655
Correlation between AMT_CREDIT and APARTMENTS_AVG:
0.060439225827111996
Correlation between AMT_CREDIT and BASEMENTAREA_AVG:
0.03922616454895798
Correlation between AMT_CREDIT and YEARS_BEGINEXPLUATATION_AVG:
0.006248757791297846
Correlation between AMT_CREDIT and YEARS_BUILD_AVG:
0.03587469910926304

Correlation between AMT_CREDIT and COMMONAREA_AVG: 0.04953654103383191
Correlation between AMT_CREDIT and ELEVATORS_AVG: 0.08063501985507392
Correlation between AMT_CREDIT and ENTRANCES_AVG: 0.014929275958488674
Correlation between AMT_CREDIT and FLOORSMAX_AVG: 0.10329576974789065
Correlation between AMT_CREDIT and FLOORSMIN_AVG: 0.07883228907176901
Correlation between AMT_CREDIT and LANDAREA_AVG: 0.006217970472558238
Correlation between AMT_CREDIT and LIVINGAPARTMENTS_AVG:
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Correlation between AMT_CREDIT and LIVINGAREA_AVG: 0.07214592307116335
Correlation between AMT_CREDIT and NONLIVINGAPARTMENTS_AVG:
0.014362257440574809
Correlation between AMT_CREDIT and NONLIVINGAREA_AVG:
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Correlation between AMT_CREDIT and APARTMENTS_MODE:
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Correlation between AMT_CREDIT and BASEMENTAREA_MODE:
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Correlation between AMT_CREDIT and YEARS_BEGINEXPLUATATION_MODE:
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Correlation between AMT_CREDIT and YEARS_BUILD_MODE:
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Correlation between AMT_CREDIT and COMMONAREA_MODE:
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Correlation between AMT_CREDIT and ELEVATORS_MODE: 0.07473989060992746
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Correlation between AMT_CREDIT and FLOORSMIN_MODE: 0.07548461793785806
Correlation between AMT_CREDIT and LANDAREA_MODE: 0.002532117987502865
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Correlation between AMT_CREDIT and NONLIVINGAPARTMENTS_MODE:
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Correlation between AMT_CREDIT and NONLIVINGAREA_MODE:
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Correlation between AMT_CREDIT and APARTMENTS_MEDI:
0.05868221353891732
Correlation between AMT_CREDIT and BASEMENTAREA_MEDI:
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Correlation between AMT_CREDIT and YEARS_BEGINEXPLUATATION_MEDI:
0.005765094016371986
Correlation between AMT_CREDIT and YEARS_BUILD_MEDI:
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Correlation between AMT_CREDIT and COMMONAREA_MEDI:
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Correlation between AMT_CREDIT and ELEVATORS_MEDI: 0.07909438259849577
Correlation between AMT_CREDIT and ENTRANCES_MEDI:
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Correlation between AMT_CREDIT and FLOORSMAX_MEDI: 0.10277029009650318
Correlation between AMT_CREDIT and FLOORSMIN_MEDI: 0.07837505102056644
Correlation between AMT_CREDIT and LANDAREA_MEDI: 0.005414971790057232
Correlation between AMT_CREDIT and LIVINGAPARTMENTS_MEDI:
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Correlation between AMT_CREDIT and LIVINGAREA_MEDI:
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Correlation between AMT_CREDIT and NONLIVINGAPARTMENTS_MEDI:
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Correlation between AMT_CREDIT and NONLIVINGAREA_MEDI:
0.035829431332536736
Correlation between AMT_CREDIT and TOTALAREA_MODE: 0.07281803102925878
Correlation between AMT_CREDIT and OBS_30_CNT_SOCIAL_CIRCLE:
0.00018955131512404333
Correlation between AMT_CREDIT and DEF_30_CNT_SOCIAL_CIRCLE: -
0.021229440364687283
Correlation between AMT_CREDIT and OBS_60_CNT_SOCIAL_CIRCLE:
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Correlation between AMT_CREDIT and DEF_60_CNT_SOCIAL_CIRCLE: -
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Correlation between AMT_CREDIT and DAYS_LAST_PHONE_CHANGE: -
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_5: -
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_6: -
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_7: -
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_12:
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_15:
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_18:
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_19:
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Correlation between AMT_CREDIT and FLAG_DOCUMENT_20:
0.031023062059498268
Correlation between AMT_CREDIT and FLAG_DOCUMENT_21: -
0.016148280699585547
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_HOUR: -
0.0039059183670565292
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_DAY:
0.004237703562044031
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_WEEK: -
0.0012748106379535452
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_MON:
0.054451451253393644
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_QRT:
0.015925231396336725
Correlation between AMT_CREDIT and AMT_REQ_CREDIT_BUREAU_YEAR: -
0.048447739061690975