home_credit_default_oversample-draft

October 1, 2024

[218]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.metrics import accuracy_score, classification_report,␣
 ↪precision_score, recall_score, f1_score, confusion_matrix
from imblearn.pipeline import Pipeline as ImbPipeline  # Use imbalanced-learn's␣
 ↪pipeline to integrate SMOTE
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.exceptions import NotFittedError

# Display all columns
pd.set_option('display.max_columns', None)
```

[219]:
```
# Load application data
train_data = pd.read_csv('/home/ignatiusvmk/Downloads/home-credit-default-risk/
 ↪application_train.csv')
test_data = pd.read_csv('/home/ignatiusvmk/Downloads/home-credit-default-risk/
 ↪application_test.csv')

# Checking the target variable distribution
train_data['TARGET'].value_counts(normalize=True)
```

[219]:
```
TARGET
0    0.919271
1    0.080729
Name: proportion, dtype: float64
```

[220]:
```
# Display a sample of the data
train_data.head(5)
```

[220]:

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

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

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

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

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

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

	FLAG_CONT_MOBILE	FLAG_PHONE	FLAG_EMAIL	OCCUPATION_TYPE	CNT_FAM_MEMBERS
0	1	1	0	Laborers	1.0

```
1                1           1           0      Core staff              2.0
2                1           1           0        Laborers              1.0
3                1           0           0        Laborers              2.0
4                1           0           0      Core staff              1.0

   REGION_RATING_CLIENT  REGION_RATING_CLIENT_W_CITY  \
0                     2                            2
1                     1                            1
2                     2                            2
3                     2                            2
4                     2                            2

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

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

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

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

   EXT_SOURCE_1  EXT_SOURCE_2  EXT_SOURCE_3  APARTMENTS_AVG  BASEMENTAREA_AVG  \
0      0.083037      0.262949      0.139376          0.0247            0.0369
1      0.311267      0.622246           NaN          0.0959            0.0529
2           NaN      0.555912      0.729567             NaN               NaN
3           NaN      0.650442           NaN             NaN               NaN
4           NaN      0.322738           NaN             NaN               NaN
```

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

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

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

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

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

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

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

```
4           NaN                    NaN             NaN

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

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

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

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

   NONLIVINGAPARTMENTS_MEDI  NONLIVINGAREA_MEDI FONDKAPREMONT_MODE  \
0                    0.0000                0.00   reg oper account
1                    0.0039                0.01   reg oper account
2                       NaN                 NaN                NaN
3                       NaN                 NaN                NaN
4                       NaN                 NaN                NaN

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

   OBS_30_CNT_SOCIAL_CIRCLE  DEF_30_CNT_SOCIAL_CIRCLE  \
0                       2.0                       2.0
1                       1.0                       0.0
```

```
2                       0.0                       0.0
3                       2.0                       0.0
4                       0.0                       0.0

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

   FLAG_DOCUMENT_2  FLAG_DOCUMENT_3  FLAG_DOCUMENT_4  FLAG_DOCUMENT_5  \
0                0                1                0                0
1                0                1                0                0
2                0                0                0                0
3                0                1                0                0
4                0                0                0                0

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

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

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

   FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  \
0                 0                 0                 0                 0
1                 0                 0                 0                 0
2                 0                 0                 0                 0
3                 0                 0                 0                 0
4                 0                 0                 0                 0

   AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
```

```
0                           0.0                           0.0
1                           0.0                           0.0
2                           0.0                           0.0
3                           NaN                           NaN
4                           0.0                           0.0

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

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

[221]:
```
train_data.shape
```

[221]:
```
(307511, 122)
```

[222]:
```
test_data.shape
```

[222]:
```
(48744, 121)
```

[223]:
```
cols_to_drop = [
    'FLAG_MOBIL', # Low variance
    'FONDKAPREMONT_MODE', 'HOUSETYPE_MODE', 'WALLSMATERIAL_MODE',␣
 ↪'EMERGENCYSTATE_MODE',
    'APARTMENTS_MODE', 'APARTMENTS_MEDI', 'APARTMENTS_AVG',
    'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5',
    'FLAG_DOCUMENT_6', 'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9',
    'FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12',␣
 ↪'FLAG_DOCUMENT_13',
    'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15', 'FLAG_DOCUMENT_16',␣
 ↪'FLAG_DOCUMENT_17',
    'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',␣
 ↪'FLAG_DOCUMENT_21',
    'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY',␣
 ↪'AMT_REQ_CREDIT_BUREAU_WEEK',
    'AMT_REQ_CREDIT_BUREAU_MON', 'WALLSMATERIAL_MODE', 'FLAG_EMAIL',␣
 ↪'FLAG_PHONE', 'FLAG_WORK_PHONE',
    'OBS_60_CNT_SOCIAL_CIRCLE', 'OBS_30_CNT_SOCIAL_CIRCLE', 'OCCUPATION_TYPE',␣
 ↪'ORGANIZATION_TYPE',
```

```
    'NAME_HOUSING_TYPE', 'WEEKDAY_APPR_PROCESS_START', 'NAME_EDUCATION_TYPE',␣
 ↪'NAME_TYPE_SUITE'
]
train_data.drop(columns=cols_to_drop, inplace=True)
```

[224]:
```
# Calculate the percentage of missing values for each column
null_percentage = train_data.isnull().mean() * 100

# Display the DataFrame before cleaning
print(f"Original shape: {train_data.shape}")

# Specify the column to preserve
columns_to_preserve = ['SK_ID_CURR']

# Drop columns where more than 35% of the values are missing, except for␣
 ↪'SK_ID_CURR'
columns_to_drop = null_percentage[null_percentage > 35].index
columns_to_drop = [col for col in columns_to_drop if col not in␣
 ↪columns_to_preserve]  # Exclude 'SK_ID_CURR'

# Drop the columns
train_data = train_data.drop(columns=columns_to_drop)

# Display the cleaned DataFrame
print(f"New shape after dropping columns with >35% null values (except␣
 ↪'SK_ID_CURR'): {train_data.shape}")
```

```
Original shape: (307511, 79)
New shape after dropping columns with >35% null values (except 'SK_ID_CURR'):
(307511, 37)
```

[225]:
```
# Load bureau data
bureau = pd.read_csv('/home/ignatiusvmk/Downloads/home-credit-default-risk/
 ↪bureau.csv')

bureau.head()
```

[225]:

	SK_ID_CURR	SK_ID_BUREAU	CREDIT_ACTIVE	CREDIT_CURRENCY	DAYS_CREDIT	\
0	215354	5714462	Closed	currency 1	-497	
1	215354	5714463	Active	currency 1	-208	
2	215354	5714464	Active	currency 1	-203	
3	215354	5714465	Active	currency 1	-203	
4	215354	5714466	Active	currency 1	-629	

	CREDIT_DAY_OVERDUE	DAYS_CREDIT_ENDDATE	DAYS_ENDDATE_FACT	\
0	0	-153.0	-153.0	
1	0	1075.0	NaN	

```
2                   0                528.0                NaN
3                   0                  NaN                NaN
4                   0               1197.0                NaN

   AMT_CREDIT_MAX_OVERDUE  CNT_CREDIT_PROLONG  AMT_CREDIT_SUM  \
0                     NaN                   0         91323.0
1                     NaN                   0        225000.0
2                     NaN                   0        464323.5
3                     NaN                   0         90000.0
4                 77674.5                   0       2700000.0

   AMT_CREDIT_SUM_DEBT  AMT_CREDIT_SUM_LIMIT  AMT_CREDIT_SUM_OVERDUE  \
0                  0.0                   NaN                     0.0
1             171342.0                   NaN                     0.0
2                  NaN                   NaN                     0.0
3                  NaN                   NaN                     0.0
4                  NaN                   NaN                     0.0

       CREDIT_TYPE  DAYS_CREDIT_UPDATE  AMT_ANNUITY
0  Consumer credit                -131          NaN
1      Credit card                 -20          NaN
2  Consumer credit                 -16          NaN
3      Credit card                 -16          NaN
4  Consumer credit                 -21          NaN
```

[226]:
```
bureau.shape
```

[226]:
```
(1716428, 17)
```

[227]:
```
# Aggregation example: Sum and mean of credit amount
bureau_agg = bureau.groupby('SK_ID_CURR').agg({
    'AMT_CREDIT_SUM': ['sum', 'mean'],
    'CREDIT_DAY_OVERDUE': ['max'],
    'DAYS_CREDIT': ['mean'],
}).reset_index()

bureau_agg.head()
```

[227]:
```
   SK_ID_CURR AMT_CREDIT_SUM                CREDIT_DAY_OVERDUE  DAYS_CREDIT
                          sum           mean                max         mean
0      100001    1453365.000  207623.571429                  0  -735.000000
1      100002     865055.565  108131.945625                  0  -874.000000
2      100003    1017400.500  254350.125000                  0 -1400.750000
3      100004     189037.800   94518.900000                  0  -867.000000
4      100005     657126.000  219042.000000                  0  -190.666667
```

[228]:
```
# Rename the columns
bureau_agg.columns = ['SK_ID_CURR', 'CREDIT_SUM_TOTAL', 'CREDIT_SUM_MEAN',␣
↪'CREDIT_OVERDUE_MAX', 'CREDIT_DURATION_MEAN']
bureau_agg.head()
```

[228]:

	SK_ID_CURR	CREDIT_SUM_TOTAL	CREDIT_SUM_MEAN	CREDIT_OVERDUE_MAX	CREDIT_DURATION_MEAN
0	100001	1453365.000	207623.571429	0	-735.000000
1	100002	865055.565	108131.945625	0	-874.000000
2	100003	1017400.500	254350.125000	0	-1400.750000
3	100004	189037.800	94518.900000	0	-867.000000
4	100005	657126.000	219042.000000	0	-190.666667

[229]:
```
bureau_agg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 305811 entries, 0 to 305810
Data columns (total 5 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   SK_ID_CURR            305811 non-null  int64
 1   CREDIT_SUM_TOTAL      305811 non-null  float64
 2   CREDIT_SUM_MEAN       305809 non-null  float64
 3   CREDIT_OVERDUE_MAX    305811 non-null  int64
 4   CREDIT_DURATION_MEAN  305811 non-null  float64
dtypes: float64(3), int64(2)
memory usage: 11.7 MB
```

[230]:
```
# Merge with train data
train_data = train_data.merge(bureau_agg, on='SK_ID_CURR', how='left')
test_data = test_data.merge(bureau_agg, on='SK_ID_CURR', how='left')
```

[231]:
```
train_data.head()
```

[231]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	\
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						

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

   AMT_GOODS_PRICE NAME_INCOME_TYPE    NAME_FAMILY_STATUS  \
0         351000.0          Working  Single / not married
1        1129500.0    State servant               Married
2         135000.0          Working  Single / not married
3         297000.0          Working        Civil marriage
4         513000.0          Working  Single / not married

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

   DAYS_ID_PUBLISH  FLAG_EMP_PHONE  FLAG_CONT_MOBILE  CNT_FAM_MEMBERS  \
0            -2120               1                 1              1.0
1             -291               1                 1              2.0
2            -2531               1                 1              1.0
3            -2437               1                 1              2.0
4            -3458               1                 1              1.0

   REGION_RATING_CLIENT  REGION_RATING_CLIENT_W_CITY  HOUR_APPR_PROCESS_START  \
0                     2                            2                       10
1                     1                            1                       11
2                     2                            2                        9
3                     2                            2                       17
4                     2                            2                       11

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

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

```
   REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
0                       0                        0      0.262949
1                       0                        0      0.622246
2                       0                        0      0.555912
3                       0                        0      0.650442
4                       1                        1      0.322738

   EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE  \
0      0.139376                       2.0                       2.0
1           NaN                       0.0                       0.0
2      0.729567                       0.0                       0.0
3           NaN                       0.0                       0.0
4           NaN                       0.0                       0.0

   DAYS_LAST_PHONE_CHANGE  AMT_REQ_CREDIT_BUREAU_QRT  \
0                 -1134.0                        0.0
1                  -828.0                        0.0
2                  -815.0                        0.0
3                  -617.0                        NaN
4                 -1106.0                        0.0

   AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  \
0                         1.0        865055.565    108131.945625
1                         0.0       1017400.500    254350.125000
2                         0.0        189037.800     94518.900000
3                         NaN               NaN              NaN
4                         0.0        146250.000    146250.000000

   CREDIT_OVERDUE_MAX  CREDIT_DURATION_MEAN
0                 0.0               -874.00
1                 0.0              -1400.75
2                 0.0               -867.00
3                 NaN                   NaN
4                 0.0              -1149.00
```

[232]:
```
# Load bureau balance data
bureau_balance = pd.read_csv('/home/ignatiusvmk/Downloads/
 ↪home-credit-default-risk/bureau_balance.csv')

# Replace categorical values with numeric ones
bureau_balance['STATUS'] = bureau_balance['STATUS'].replace(['C', '0'], 0).
 ↪replace(['1', '2', '3', '4', '5'], 1)

# Convert the STATUS column to numeric to handle any unexpected non-numeric␣
 ↪values
```

```
bureau_balance['STATUS'] = pd.to_numeric(bureau_balance['STATUS'],␣
 ↪errors='coerce')

# Group by SK_ID_BUREAU and aggregate status as sum (missed payments) and count␣
 ↪(total months)
bureau_balance_agg = bureau_balance.groupby('SK_ID_BUREAU').agg({
    'STATUS': ['sum', 'count']
}).reset_index()

# Rename the columns
bureau_balance_agg.columns = ['SK_ID_BUREAU', 'MISSED_PAYMENTS', 'TOTAL_MONTHS']

bureau_balance_agg.head()
```

[232]:

	SK_ID_BUREAU	MISSED_PAYMENTS	TOTAL_MONTHS
0	5001709	0.0	86
1	5001710	0.0	53
2	5001711	0.0	3
3	5001712	0.0	19
4	5001713	0.0	0

[233]:
```
# Load POS_CASH_balance data
pos_cash_balance = pd.read_csv('/home/ignatiusvmk/Downloads/
 ↪home-credit-default-risk/POS_CASH_balance.csv')

# Aggregation example: Count of active loans
pos_cash_agg = pos_cash_balance.groupby('SK_ID_CURR').agg({
    'MONTHS_BALANCE': 'count',  # Count of months with POS loans
    'SK_DPD': ['mean', 'sum'],  # Delay in payment (mean and total)
}).reset_index()

# Rename columns
pos_cash_agg.columns = ['SK_ID_CURR', 'POS_LOANS_COUNT', 'POS_DPD_MEAN',␣
 ↪'POS_DPD_TOTAL']

# Merge with train and test data
train_data = train_data.merge(pos_cash_agg, on='SK_ID_CURR', how='left')
test_data = test_data.merge(pos_cash_agg, on='SK_ID_CURR', how='left')
```

[234]:
```
# Load credit card balance data
credit_card_balance = pd.read_csv('/home/ignatiusvmk/Downloads/
 ↪home-credit-default-risk/credit_card_balance.csv')

# Aggregation example: Average balance over time
credit_card_agg = credit_card_balance.groupby('SK_ID_CURR').agg({
    'AMT_BALANCE': ['mean', 'max'],
    'MONTHS_BALANCE': 'count'
```

```
}).reset_index()

# Rename columns
credit_card_agg.columns = ['SK_ID_CURR', 'CREDIT_BALANCE_MEAN',␣
 ↪'CREDIT_BALANCE_MAX', 'CREDIT_CARD_MONTHS']

# Merge with train and test data
train_data = train_data.merge(credit_card_agg, on='SK_ID_CURR', how='left')
test_data = test_data.merge(credit_card_agg, on='SK_ID_CURR', how='left')
```

[235]:
```
# Load installments payments data
installments_payments = pd.read_csv('/home/ignatiusvmk/Downloads/
 ↪home-credit-default-risk/installments_payments.csv')

# Aggregation example: Total and mean of payments
installments_agg = installments_payments.groupby('SK_ID_CURR').agg({
    'AMT_PAYMENT': ['sum', 'mean'],
    'DAYS_INSTALMENT': 'count'
}).reset_index()

# Rename columns
installments_agg.columns = ['SK_ID_CURR', 'PAYMENT_TOTAL', 'PAYMENT_MEAN',␣
 ↪'TOTAL_INSTALLMENTS']

# Merge with train and test data
train_data = train_data.merge(installments_agg, on='SK_ID_CURR', how='left')
test_data = test_data.merge(installments_agg, on='SK_ID_CURR', how='left')
```

[236]:
```
# Fill missing values in numeric columns with the mean
numeric_cols = train_data.select_dtypes(include=['number']).columns
train_data[numeric_cols] = train_data[numeric_cols].
 ↪fillna(train_data[numeric_cols].mean())
numeric_cols_test = test_data.select_dtypes(include=['number']).columns
test_data[numeric_cols_test] = test_data[numeric_cols_test].
 ↪fillna(test_data[numeric_cols_test].mean())

# Fill missing values in non-numeric columns (e.g., categorical) with the mode
non_numeric_cols = train_data.select_dtypes(exclude=['number']).columns
train_data[non_numeric_cols] = train_data[non_numeric_cols].
 ↪fillna(train_data[non_numeric_cols].mode().iloc[0])
non_numeric_cols_test = test_data.select_dtypes(exclude=['number']).columns
test_data[non_numeric_cols_test] = test_data[non_numeric_cols_test].
 ↪fillna(test_data[non_numeric_cols_test].mode().iloc[0])
```

[237]:
```
train_data.select_dtypes(exclude=['float'])

# train_data.info()
```

[237]:

	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
…	…	…	…	…	…
307506	456251	0	Cash loans	M	N
307507	456252	0	Cash loans	F	N
307508	456253	0	Cash loans	F	N
307509	456254	1	Cash loans	F	N
307510	456255	0	Cash loans	F	N

	FLAG_OWN_REALTY	CNT_CHILDREN	NAME_INCOME_TYPE
0	Y	0	Working
1	N	0	State servant
2	Y	0	Working
3	Y	0	Working
4	Y	0	Working
…	…	…	…
307506	N	0	Working
307507	Y	0	Pensioner
307508	Y	0	Working
307509	Y	0	Commercial associate
307510	N	0	Commercial associate

	NAME_FAMILY_STATUS	DAYS_BIRTH	DAYS_EMPLOYED	DAYS_ID_PUBLISH
0	Single / not married	-9461	-637	-2120
1	Married	-16765	-1188	-291
2	Single / not married	-19046	-225	-2531
3	Civil marriage	-19005	-3039	-2437
4	Single / not married	-19932	-3038	-3458
…	…	…	…	…
307506	Separated	-9327	-236	-1982
307507	Widow	-20775	365243	-4090
307508	Separated	-14966	-7921	-5150
307509	Married	-11961	-4786	-931
307510	Married	-16856	-1262	-410

	FLAG_EMP_PHONE	FLAG_CONT_MOBILE	REGION_RATING_CLIENT
0	1	1	2
1	1	1	1
2	1	1	2
3	1	1	2
4	1	1	2
…	…	…	…
307506	1	1	1

```
307507               0                 1                       2
307508               1                 1                       3
307509               1                 1                       2
307510               1                 1                       1

        REGION_RATING_CLIENT_W_CITY  HOUR_APPR_PROCESS_START  \
0                                 2                       10
1                                 1                       11
2                                 2                        9
3                                 2                       17
4                                 2                       11
…                               …                       …
307506                            1                       15
307507                            2                        8
307508                            3                        9
307509                            2                        9
307510                            1                       20

        REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION  \
0                                0                          0
1                                0                          0
2                                0                          0
3                                0                          0
4                                0                          0
…                              …                          …
307506                           0                          0
307507                           0                          0
307508                           0                          0
307509                           0                          0
307510                           0                          0

        LIVE_REGION_NOT_WORK_REGION  REG_CITY_NOT_LIVE_CITY  \
0                                 0                       0
1                                 0                       0
2                                 0                       0
3                                 0                       0
4                                 0                       0
…                               …                       …
307506                            0                       0
307507                            0                       0
307508                            0                       0
307509                            0                       1
307510                            0                       0

        REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY
0                            0                       0
1                            0                       0
```

```
2                              0                              0
3                              0                              0
4                              1                              1
…                              …                              …
307506                         0                              0
307507                         0                              0
307508                         1                              1
307509                         1                              0
307510                         1                              1

[307511 rows x 23 columns]
```

[238]:
```
# Calculate the percentage of missing values for each column
null_percentage = train_data.isnull().mean() * 100

# Display the DataFrame before cleaning
print(f"Original shape: {train_data.shape}")

# column to preserve
columns_to_preserve = ['TARGET']

# Drop columns where more than 35% of the values are missing, except for␣
 ↪'TARGET'
columns_to_drop = null_percentage[null_percentage > 35].index
columns_to_drop = [col for col in columns_to_drop if col not in␣
 ↪columns_to_preserve]  # Exclude 'TARGET'

# Drop the columns
train_data = train_data.drop(columns=columns_to_drop)

# Display the cleaned DataFrame
print(f"New shape after dropping columns with >35% null values (except␣
 ↪'TARGET'): {train_data.shape}")
```

```
Original shape: (307511, 50)
New shape after dropping columns with >35% null values (except 'TARGET'):
(307511, 50)
```

[239]:
```
# Save the TARGET column from train_data before encoding
target = train_data['TARGET']

# Identify categorical columns
categorical_cols = train_data.select_dtypes(include=['object']).columns

# Perform one-hot encoding on both train_data and test_data
train_data_encoded = pd.get_dummies(train_data.drop(columns=['TARGET']),␣
 ↪columns=categorical_cols)
```

```
test_data_encoded = pd.get_dummies(test_data, columns=categorical_cols)

# Align train_data and test_data (ensure they have the same columns)
train_data_aligned, test_data_aligned = train_data.align(test_data,␣
 ↪join='inner', axis=1)

# Add back the TARGET column to the aligned training data
train_data_aligned['TARGET'] = target

# proceed with your further processing (splitting, model building)
print(train_data_aligned.head())
print(test_data_aligned.head())
```

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

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  AMT_GOODS_PRICE  \
0             0          202500.0    406597.5      24700.5         351000.0
1             0          270000.0   1293502.5      35698.5        1129500.0
2             0           67500.0    135000.0       6750.0         135000.0
3             0          135000.0    312682.5      29686.5         297000.0
4             0          121500.0    513000.0      21865.5         513000.0

  NAME_INCOME_TYPE    NAME_FAMILY_STATUS  REGION_POPULATION_RELATIVE  \
0          Working  Single / not married                    0.018801
1    State servant               Married                    0.003541
2          Working  Single / not married                    0.010032
3          Working        Civil marriage                    0.008019
4          Working  Single / not married                    0.028663

   DAYS_BIRTH  DAYS_EMPLOYED  DAYS_REGISTRATION  DAYS_ID_PUBLISH  \
0       -9461           -637            -3648.0            -2120
1      -16765          -1188            -1186.0             -291
2      -19046           -225            -4260.0            -2531
3      -19005          -3039            -9833.0            -2437
4      -19932          -3038            -4311.0            -3458

   FLAG_EMP_PHONE  FLAG_CONT_MOBILE  CNT_FAM_MEMBERS  REGION_RATING_CLIENT  \
0               1                 1              1.0                     2
1               1                 1              2.0                     1
2               1                 1              1.0                     2
3               1                 1              2.0                     2
4               1                 1              1.0                     2
```

```
   REGION_RATING_CLIENT_W_CITY  HOUR_APPR_PROCESS_START  \
0                            2                       10
1                            1                       11
2                            2                        9
3                            2                       17
4                            2                       11

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

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

   REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
0                       0                       0      0.262949
1                       0                       0      0.622246
2                       0                       0      0.555912
3                       0                       0      0.650442
4                       1                       1      0.322738

   EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE  \
0      0.139376                       2.0                       2.0
1      0.510853                       0.0                       0.0
2      0.729567                       0.0                       0.0
3      0.510853                       0.0                       0.0
4      0.510853                       0.0                       0.0

   DAYS_LAST_PHONE_CHANGE  AMT_REQ_CREDIT_BUREAU_QRT  \
0                 -1134.0                   0.000000
1                  -828.0                   0.000000
2                  -815.0                   0.000000
3                  -617.0                   0.265474
4                 -1106.0                   0.000000

   AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  \
0                    1.000000      8.650556e+05    108131.945625
1                    0.000000      1.017400e+06    254350.125000
2                    0.000000      1.890378e+05     94518.900000
3                    1.899974      1.955807e+06    378080.200789
4                    0.000000      1.462500e+05    146250.000000
```

```
   CREDIT_OVERDUE_MAX  CREDIT_DURATION_MEAN  POS_LOANS_COUNT  POS_DPD_MEAN  \
0            0.000000            -874.00000             19.0           0.0
1            0.000000           -1400.75000             28.0           0.0
2            0.000000            -867.00000              4.0           0.0
3            4.772759           -1083.04711             21.0           0.0
4            0.000000           -1149.00000             66.0           0.0

   POS_DPD_TOTAL  CREDIT_BALANCE_MEAN  CREDIT_BALANCE_MAX  CREDIT_CARD_MONTHS  \
0            0.0         71459.926952       144501.306629           37.143605
1            0.0         71459.926952       144501.306629           37.143605
2            0.0         71459.926952       144501.306629           37.143605
3            0.0             0.000000            0.000000            6.000000
4            0.0         71459.926952       144501.306629           37.143605

   PAYMENT_TOTAL  PAYMENT_MEAN  TOTAL_INSTALLMENTS  TARGET
0     219625.695  11559.247105                19.0       1
1    1618864.650  64754.586000                25.0       0
2      21288.465   7096.155000                 3.0       0
3    1007153.415  62947.088438                16.0       0
4     806127.975  12214.060227                66.0       0
   SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR FLAG_OWN_REALTY  \
0      100001         Cash loans           F            N               Y
1      100005         Cash loans           M            N               Y
2      100013         Cash loans           M            Y               Y
3      100028         Cash loans           F            N               Y
4      100038         Cash loans           M            Y               N

   CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  AMT_GOODS_PRICE  \
0             0          135000.0    568800.0      20560.5         450000.0
1             0           99000.0    222768.0      17370.0         180000.0
2             0          202500.0    663264.0      69777.0         630000.0
3             2          315000.0   1575000.0      49018.5        1575000.0
4             1          180000.0    625500.0      32067.0         625500.0

  NAME_INCOME_TYPE NAME_FAMILY_STATUS  REGION_POPULATION_RELATIVE  DAYS_BIRTH  \
0          Working            Married                    0.018850      -19241
1          Working            Married                    0.035792      -18064
2          Working            Married                    0.019101      -20038
3          Working            Married                    0.026392      -13976
4          Working            Married                    0.010032      -13040

   DAYS_EMPLOYED  DAYS_REGISTRATION  DAYS_ID_PUBLISH  FLAG_EMP_PHONE  \
0          -2329            -5170.0             -812               1
1          -4469            -9118.0            -1623               1
2          -4458            -2175.0            -3503               1
3          -1866            -2000.0            -4208               1
4          -2191            -4000.0            -4262               1
```

```
   FLAG_CONT_MOBILE  CNT_FAM_MEMBERS  REGION_RATING_CLIENT  \
0                 1              2.0                     2
1                 1              2.0                     2
2                 1              2.0                     2
3                 1              4.0                     2
4                 1              3.0                     2

   REGION_RATING_CLIENT_W_CITY  HOUR_APPR_PROCESS_START  \
0                            2                       18
1                            2                        9
2                            2                       14
3                            2                       11
4                            2                        5

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

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

   REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
0                       0                        0      0.789654
1                       0                        0      0.291656
2                       0                        0      0.699787
3                       0                        0      0.509677
4                       1                        1      0.425687

   EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE  \
0      0.159520                       0.0                       0.0
1      0.432962                       0.0                       0.0
2      0.610991                       0.0                       0.0
3      0.612704                       0.0                       0.0
4      0.500106                       0.0                       0.0

   DAYS_LAST_PHONE_CHANGE  AMT_REQ_CREDIT_BUREAU_QRT  \
0                 -1740.0                   0.000000
1                     0.0                   0.000000
2                  -856.0                   1.000000
3                 -1805.0                   0.000000
```

```
4                  -821.0                   0.546902

   AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  \
0                    0.000000      1.453365e+06    207623.571429
1                    3.000000      6.571260e+05    219042.000000
2                    4.000000      2.072280e+06    518070.015000
3                    3.000000      1.520875e+06    126739.590000
4                    1.983769      2.220714e+06    397299.084758

   CREDIT_OVERDUE_MAX  CREDIT_DURATION_MEAN  POS_LOANS_COUNT  POS_DPD_MEAN  \
0            0.000000           -735.000000              9.0      0.777778
1            0.000000           -190.666667             11.0      0.000000
2            0.000000          -1737.500000             36.0      0.944444
3            0.000000          -1401.750000             31.0      0.000000
4            2.343833          -1088.502807             13.0      0.000000

   POS_DPD_TOTAL  CREDIT_BALANCE_MEAN  CREDIT_BALANCE_MAX  CREDIT_CARD_MONTHS  \
0            7.0         62214.550683       130799.447489           36.770972
1            0.0         62214.550683       130799.447489           36.770972
2           34.0         18159.919219       161420.220000           96.000000
3            0.0          8085.058163        37335.915000           49.000000
4            0.0         62214.550683       130799.447489           36.770972

   PAYMENT_TOTAL  PAYMENT_MEAN  TOTAL_INSTALLMENTS
0      41195.925   5885.132143                 7.0
1      56161.845   6240.205000                 9.0
2    1509736.545   9740.235774               155.0
3     492310.665   4356.731549               113.0
4     133204.050  11100.337500                12.0
```

[240]:
```
# Train-test split
X = train_data_aligned.drop('TARGET', axis=1)
y = train_data_aligned['TARGET']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

[241]:
```
X_train.shape
```

[241]:
```
(246008, 49)
```

[242]:
```
# Check for missing values in the training data
print(X_train.isnull().sum())
```

```
SK_ID_CURR                   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_INCOME_TYPE                0
NAME_FAMILY_STATUS              0
REGION_POPULATION_RELATIVE      0
DAYS_BIRTH                      0
DAYS_EMPLOYED                   0
DAYS_REGISTRATION               0
DAYS_ID_PUBLISH                 0
FLAG_EMP_PHONE                  0
FLAG_CONT_MOBILE                0
CNT_FAM_MEMBERS                 0
REGION_RATING_CLIENT            0
REGION_RATING_CLIENT_W_CITY     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
EXT_SOURCE_2                    0
EXT_SOURCE_3                    0
DEF_30_CNT_SOCIAL_CIRCLE        0
DEF_60_CNT_SOCIAL_CIRCLE        0
DAYS_LAST_PHONE_CHANGE          0
AMT_REQ_CREDIT_BUREAU_QRT       0
AMT_REQ_CREDIT_BUREAU_YEAR      0
CREDIT_SUM_TOTAL                0
CREDIT_SUM_MEAN                 0
CREDIT_OVERDUE_MAX              0
CREDIT_DURATION_MEAN            0
POS_LOANS_COUNT                 0
POS_DPD_MEAN                    0
POS_DPD_TOTAL                   0
CREDIT_BALANCE_MEAN             0
CREDIT_BALANCE_MAX              0
CREDIT_CARD_MONTHS              0
PAYMENT_TOTAL                   0
PAYMENT_MEAN                    0
TOTAL_INSTALLMENTS              0
dtype: int64
```

[243]:
```
# Check the data types of the columns in X_train
print(X_train.dtypes)

# Check for non-numeric data
non_numeric_cols = X_train.select_dtypes(exclude=['object']).columns
print("Non-numeric columns:", non_numeric_cols)
```

```
SK_ID_CURR                    int64
NAME_CONTRACT_TYPE           object
CODE_GENDER                  object
FLAG_OWN_CAR                 object
FLAG_OWN_REALTY              object
CNT_CHILDREN                  int64
AMT_INCOME_TOTAL            float64
AMT_CREDIT                  float64
AMT_ANNUITY                 float64
AMT_GOODS_PRICE             float64
NAME_INCOME_TYPE             object
NAME_FAMILY_STATUS           object
REGION_POPULATION_RELATIVE  float64
DAYS_BIRTH                    int64
DAYS_EMPLOYED                 int64
DAYS_REGISTRATION           float64
DAYS_ID_PUBLISH               int64
FLAG_EMP_PHONE                int64
FLAG_CONT_MOBILE              int64
CNT_FAM_MEMBERS             float64
REGION_RATING_CLIENT          int64
REGION_RATING_CLIENT_W_CITY   int64
HOUR_APPR_PROCESS_START       int64
REG_REGION_NOT_LIVE_REGION    int64
REG_REGION_NOT_WORK_REGION    int64
LIVE_REGION_NOT_WORK_REGION   int64
REG_CITY_NOT_LIVE_CITY        int64
REG_CITY_NOT_WORK_CITY        int64
LIVE_CITY_NOT_WORK_CITY       int64
EXT_SOURCE_2                float64
EXT_SOURCE_3                float64
DEF_30_CNT_SOCIAL_CIRCLE    float64
DEF_60_CNT_SOCIAL_CIRCLE    float64
DAYS_LAST_PHONE_CHANGE      float64
AMT_REQ_CREDIT_BUREAU_QRT   float64
AMT_REQ_CREDIT_BUREAU_YEAR  float64
CREDIT_SUM_TOTAL            float64
CREDIT_SUM_MEAN             float64
CREDIT_OVERDUE_MAX          float64
CREDIT_DURATION_MEAN        float64
POS_LOANS_COUNT             float64
```

```
POS_DPD_MEAN                    float64
POS_DPD_TOTAL                   float64
CREDIT_BALANCE_MEAN             float64
CREDIT_BALANCE_MAX              float64
CREDIT_CARD_MONTHS              float64
PAYMENT_TOTAL                   float64
PAYMENT_MEAN                    float64
TOTAL_INSTALLMENTS              float64
dtype: object
Non-numeric columns: Index(['SK_ID_CURR', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
'AMT_CREDIT',
       'AMT_ANNUITY', 'AMT_GOODS_PRICE', 'REGION_POPULATION_RELATIVE',
       'DAYS_BIRTH', 'DAYS_EMPLOYED', 'DAYS_REGISTRATION', 'DAYS_ID_PUBLISH',
       'FLAG_EMP_PHONE', 'FLAG_CONT_MOBILE', 'CNT_FAM_MEMBERS',
       'REGION_RATING_CLIENT', 'REGION_RATING_CLIENT_W_CITY',
       'HOUR_APPR_PROCESS_START', 'REG_REGION_NOT_LIVE_REGION',
       'REG_REGION_NOT_WORK_REGION', 'LIVE_REGION_NOT_WORK_REGION',
       'REG_CITY_NOT_LIVE_CITY', 'REG_CITY_NOT_WORK_CITY',
       'LIVE_CITY_NOT_WORK_CITY', 'EXT_SOURCE_2', 'EXT_SOURCE_3',
       'DEF_30_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
       'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR', 'CREDIT_SUM_TOTAL', 'CREDIT_SUM_MEAN',
       'CREDIT_OVERDUE_MAX', 'CREDIT_DURATION_MEAN', 'POS_LOANS_COUNT',
       'POS_DPD_MEAN', 'POS_DPD_TOTAL', 'CREDIT_BALANCE_MEAN',
       'CREDIT_BALANCE_MAX', 'CREDIT_CARD_MONTHS', 'PAYMENT_TOTAL',
       'PAYMENT_MEAN', 'TOTAL_INSTALLMENTS'],
      dtype='object')
```

[244]:
```
y_train.value_counts()
```

[244]:
```
TARGET
0    226148
1     19860
Name: count, dtype: int64
```

[245]:
```
def remove_highly_correlated_features(data, threshold=0.7):
    # Select only numerical columns for correlation
    numerical_data = data.select_dtypes(include=[np.number])

    corr_matrix = numerical_data.corr().abs()  # Compute absolute correlation␣
 ↪matrix
    upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).
 ↪astype(bool))  # Upper triangle

    to_drop = []

    while True:
```

```
        # Find the column with the highest correlation count
        max_corr_feature = None
        max_corr_count = 0

        for column in upper.columns:
            corr_count = (upper[column] > threshold).sum()
            if corr_count > max_corr_count:
                max_corr_count = corr_count
                max_corr_feature = column

        # If no column has correlations above the threshold, break the loop
        if max_corr_count == 0:
            break

        to_drop.append(max_corr_feature)  # Add the column to the drop list
        upper = upper.drop(columns=max_corr_feature).
↪drop(index=max_corr_feature)  # Drop it from the matrix

    return data.drop(columns=to_drop)

# Remove highly correlated features from the training data
X_filtered = remove_highly_correlated_features(X_train, threshold=0.7)
```

[246]:
```
X_filtered.shape
```

[246]:
```
(246008, 39)
```

[247]:
```
X_train.head()
```

[247]:
```
        SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
181648      310536         Cash loans           F            N
229245      365516         Cash loans           M            Y
122525      242055         Cash loans           M            N
306311      454894         Cash loans           M            N
300658      448321         Cash loans           F            N

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
181648               N             2           90000.0    227520.0
229245               Y             0           90000.0    161730.0
122525               Y             0          135000.0    728847.0
306311               N             0          135000.0    474183.0
300658               Y             0          180000.0    254700.0

        AMT_ANNUITY  AMT_GOODS_PRICE      NAME_INCOME_TYPE  \
181648      13189.5         180000.0  Commercial associate
229245      13095.0         135000.0  Commercial associate
122525      26307.0         553500.0               Working
```

```
306311      34636.5         391500.0  Commercial associate
300658      27558.0         225000.0  Commercial associate

          NAME_FAMILY_STATUS  REGION_POPULATION_RELATIVE  DAYS_BIRTH  \
181648               Married                    0.008230      -12298
229245               Married                    0.003069      -15375
122525  Single / not married                    0.020713      -19307
306311  Single / not married                    0.011703      -17791
300658  Single / not married                    0.006629       -8486

        DAYS_EMPLOYED  DAYS_REGISTRATION  DAYS_ID_PUBLISH  FLAG_EMP_PHONE  \
181648           -946            -6378.0            -4670               1
229245            -92            -1292.0            -1994               1
122525          -1646            -7951.0            -2842               1
306311          -1651            -1033.0            -1345               1
300658           -977            -2873.0             -852               1

        FLAG_CONT_MOBILE  CNT_FAM_MEMBERS  REGION_RATING_CLIENT  \
181648                 1              4.0                     2
229245                 1              2.0                     3
122525                 1              1.0                     3
306311                 1              1.0                     2
300658                 1              1.0                     2

        REGION_RATING_CLIENT_W_CITY  HOUR_APPR_PROCESS_START  \
181648                            2                       10
229245                            3                       13
122525                            2                        5
306311                            2                       10
300658                            2                        5

        REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION  \
181648                           0                           0
229245                           0                           0
122525                           0                           0
306311                           0                           0
300658                           0                           0

        LIVE_REGION_NOT_WORK_REGION  REG_CITY_NOT_LIVE_CITY  \
181648                            0                       0
229245                            0                       0
122525                            0                       0
306311                            0                       0
300658                            0                       0

        REG_CITY_NOT_WORK_CITY  LIVE_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
181648                       0                        0      0.289573
```

```
229245                     1                       1      0.514261
122525                     0                       0      0.486906
306311                     0                       0      0.675705
300658                     0                       0      0.154565

        EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DEF_60_CNT_SOCIAL_CIRCLE  \
181648      0.622922                       0.0                       0.0
229245      0.510853                       0.0                       0.0
122525      0.598926                       0.0                       0.0
306311      0.454321                       0.0                       0.0
300658      0.510853                       0.0                       0.0

        DAYS_LAST_PHONE_CHANGE  AMT_REQ_CREDIT_BUREAU_QRT  \
181648                     0.0                   1.000000
229245                  -509.0                   0.265474
122525                 -1474.0                   0.000000
306311                 -2016.0                   0.000000
300658                  -695.0                   0.265474

        AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  \
181648                    1.000000      5.679000e+05    113580.000000
229245                    1.899974      1.955807e+06    378080.200789
122525                    2.000000      1.099251e+06    274812.750000
306311                    4.000000      1.197855e+06    399285.000000
300658                    1.899974      1.955807e+06    378080.200789

        CREDIT_OVERDUE_MAX  CREDIT_DURATION_MEAN  POS_LOANS_COUNT  \
181648            0.000000          -1175.800000             34.0
229245            4.772759          -1083.047110             31.0
122525            0.000000          -1358.500000              5.0
306311            0.000000          -2005.333333             84.0
300658            4.772759          -1083.047110             12.0

        POS_DPD_MEAN  POS_DPD_TOTAL  CREDIT_BALANCE_MEAN  CREDIT_BALANCE_MAX  \
181648           0.0            0.0       213473.232857       385395.840000
229245           0.0            0.0        71459.926952       144501.306629
122525           0.0            0.0        71459.926952       144501.306629
306311           0.0            0.0        71459.926952       144501.306629
300658           0.0            0.0        71459.926952       144501.306629

        CREDIT_CARD_MONTHS  PAYMENT_TOTAL  PAYMENT_MEAN  TOTAL_INSTALLMENTS
181648           21.000000     550660.815   9660.716053                57.0
229245           37.143605     263064.645   9743.135000                27.0
122525           37.143605      51958.485  12989.621250                 4.0
306311           37.143605    1471327.965  17943.023963                82.0
300658           37.143605      37066.230   3369.657273                11.0
```

[248]:
```
X_filtered.head()
```

[248]:

	SK_ID_CURR	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR
181648	310536	Cash loans	F	N
229245	365516	Cash loans	M	Y
122525	242055	Cash loans	M	N
306311	454894	Cash loans	M	N
300658	448321	Cash loans	F	N

	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT
181648	N	2	90000.0	227520.0
229245	Y	0	90000.0	161730.0
122525	Y	0	135000.0	728847.0
306311	N	0	135000.0	474183.0
300658	Y	0	180000.0	254700.0

	NAME_INCOME_TYPE	NAME_FAMILY_STATUS
181648	Commercial associate	Married
229245	Commercial associate	Married
122525	Working	Single / not married
306311	Commercial associate	Single / not married
300658	Commercial associate	Single / not married

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED
181648	0.008230	-12298	-946
229245	0.003069	-15375	-92
122525	0.020713	-19307	-1646
306311	0.011703	-17791	-1651
300658	0.006629	-8486	-977

	DAYS_REGISTRATION	DAYS_ID_PUBLISH	FLAG_CONT_MOBILE
181648	-6378.0	-4670	1
229245	-1292.0	-1994	1
122525	-7951.0	-2842	1
306311	-1033.0	-1345	1
300658	-2873.0	-852	1

	REGION_RATING_CLIENT	HOUR_APPR_PROCESS_START
181648	2	10
229245	3	13
122525	3	5
306311	2	10
300658	2	5

	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION
181648	0	0
229245	0	0

```
122525                          0                          0
306311                          0                          0
300658                          0                          0

        REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
181648                       0                       0      0.289573
229245                       0                       1      0.514261
122525                       0                       0      0.486906
306311                       0                       0      0.675705
300658                       0                       0      0.154565

        EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DAYS_LAST_PHONE_CHANGE  \
181648      0.622922                       0.0                     0.0
229245      0.510853                       0.0                  -509.0
122525      0.598926                       0.0                 -1474.0
306311      0.454321                       0.0                 -2016.0
300658      0.510853                       0.0                  -695.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  \
181648                   1.000000                    1.000000
229245                   0.265474                    1.899974
122525                   0.000000                    2.000000
306311                   0.000000                    4.000000
300658                   0.265474                    1.899974

        CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  CREDIT_OVERDUE_MAX  \
181648      5.679000e+05    113580.000000            0.000000
229245      1.955807e+06    378080.200789            4.772759
122525      1.099251e+06    274812.750000            0.000000
306311      1.197855e+06    399285.000000            0.000000
300658      1.955807e+06    378080.200789            4.772759

        CREDIT_DURATION_MEAN  POS_LOANS_COUNT  POS_DPD_MEAN  \
181648          -1175.800000             34.0           0.0
229245          -1083.047110             31.0           0.0
122525          -1358.500000              5.0           0.0
306311          -2005.333333             84.0           0.0
300658          -1083.047110             12.0           0.0

        CREDIT_BALANCE_MEAN  CREDIT_CARD_MONTHS  PAYMENT_TOTAL  PAYMENT_MEAN  \
181648        213473.232857           21.000000     550660.815   9660.716053
229245         71459.926952           37.143605     263064.645   9743.135000
122525         71459.926952           37.143605      51958.485  12989.621250
306311         71459.926952           37.143605    1471327.965  17943.023963
300658         71459.926952           37.143605      37066.230   3369.657273

        TOTAL_INSTALLMENTS
```

```
181648                57.0
229245                27.0
122525                 4.0
306311                82.0
300658                11.0
```

[249]:
```
X_filtered
```

[249]:
```
        SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
181648      310536         Cash loans           F            N
229245      365516         Cash loans           M            Y
122525      242055         Cash loans           M            N
306311      454894         Cash loans           M            N
300658      448321         Cash loans           F            N
…            …                 …          …           …
31304       136325    Revolving loans           F            N
121193      240509         Cash loans           F            N
248504      387513         Cash loans           F            N
175469      303331         Cash loans           F            N
285162      430259         Cash loans           F            Y

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
181648               N             2           90000.0    227520.0
229245               Y             0           90000.0    161730.0
122525               Y             0          135000.0    728847.0
306311               N             0          135000.0    474183.0
300658               Y             0          180000.0    254700.0
…                …            …                 …          …
31304                Y             1          135000.0    405000.0
121193               N             0          157500.0    272520.0
248504               N             0           90000.0    246357.0
175469               Y             0          112500.0    810000.0
285162               Y             0          126000.0   1051245.0

           NAME_INCOME_TYPE    NAME_FAMILY_STATUS  \
181648  Commercial associate               Married
229245  Commercial associate               Married
122525               Working  Single / not married
306311  Commercial associate  Single / not married
300658  Commercial associate  Single / not married
…                        …                 …
31304   Commercial associate               Married
121193        State servant  Single / not married
248504            Pensioner        Civil marriage
175469            Pensioner               Married
285162            Pensioner               Married
```

```
        REGION_POPULATION_RELATIVE  DAYS_BIRTH  DAYS_EMPLOYED  \
181648                    0.008230      -12298           -946
229245                    0.003069      -15375            -92
122525                    0.020713      -19307          -1646
306311                    0.011703      -17791          -1651
300658                    0.006629       -8486           -977
…                              …           …              …
31304                     0.035792      -15374           -595
121193                    0.018801      -19035          -4334
248504                    0.025164      -23088         365243
175469                    0.018209      -22148         365243
285162                    0.018850      -22079         365243

        DAYS_REGISTRATION  DAYS_ID_PUBLISH  FLAG_CONT_MOBILE  \
181648            -6378.0            -4670                 1
229245            -1292.0            -1994                 1
122525            -7951.0            -2842                 1
306311            -1033.0            -1345                 1
300658            -2873.0             -852                 1
…                   …                …                    …
31304             -6831.0            -4420                 1
121193            -8490.0            -2561                 1
248504            -8975.0            -4636                 1
175469           -10162.0            -4636                 1
285162            -1487.0            -4266                 1

        REGION_RATING_CLIENT  HOUR_APPR_PROCESS_START  \
181648                     2                       10
229245                     3                       13
122525                     3                        5
306311                     2                       10
300658                     2                        5
…                        …                        …
31304                      2                       14
121193                     2                        8
248504                     2                       11
175469                     3                        9
285162                     2                       12

        REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION  \
181648                           0                           0
229245                           0                           0
122525                           0                           0
306311                           0                           0
300658                           0                           0
…                              …                           …
31304                            0                           0
```

```
121193                          0                          0
248504                          0                          0
175469                          0                          0
285162                          0                          0

        REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  EXT_SOURCE_2  \
181648                       0                       0      0.289573
229245                       0                       1      0.514261
122525                       0                       0      0.486906
306311                       0                       0      0.675705
300658                       0                       0      0.154565
…                            …                       …            …
31304                        0                       0      0.549668
121193                       0                       0      0.569702
248504                       0                       0      0.461966
175469                       0                       0      0.459173
285162                       0                       0      0.008171

        EXT_SOURCE_3  DEF_30_CNT_SOCIAL_CIRCLE  DAYS_LAST_PHONE_CHANGE  \
181648      0.622922                       0.0                     0.0
229245      0.510853                       0.0                  -509.0
122525      0.598926                       0.0                 -1474.0
306311      0.454321                       0.0                 -2016.0
300658      0.510853                       0.0                  -695.0
…              …                           …                       …
31304       0.510853                       0.0                  -379.0
121193      0.600658                       0.0                  -374.0
248504      0.683269                       0.0                 -1689.0
175469      0.812823                       0.0                 -1329.0
285162      0.676993                       0.0                  -720.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  \
181648                   1.000000                    1.000000
229245                   0.265474                    1.899974
122525                   0.000000                    2.000000
306311                   0.000000                    4.000000
300658                   0.265474                    1.899974
…                           …                           …
31304                    0.265474                    1.899974
121193                   1.000000                    4.000000
248504                   0.000000                    1.000000
175469                   0.000000                    5.000000
285162                   0.000000                    3.000000

        CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN  CREDIT_OVERDUE_MAX  \
181648      5.679000e+05    113580.000000            0.000000
229245      1.955807e+06    378080.200789            4.772759
```

```
122525      1.099251e+06    274812.750000            0.000000
306311      1.197855e+06    399285.000000            0.000000
300658      1.955807e+06    378080.200789            4.772759
…                  …             …                    …
31304       1.955807e+06    378080.200789            4.772759
121193      9.009000e+05    180180.000000           13.000000
248504      8.550000e+05    171000.000000            0.000000
175469      6.750000e+04     67500.000000            0.000000
285162      4.882500e+05     69750.000000            0.000000

        CREDIT_DURATION_MEAN  POS_LOANS_COUNT  POS_DPD_MEAN  \
181648          -1175.800000             34.0      0.000000
229245          -1083.047110             31.0      0.000000
122525          -1358.500000              5.0      0.000000
306311          -2005.333333             84.0      0.000000
300658          -1083.047110             12.0      0.000000
…                        …               …            …
31304           -1083.047110             12.0      0.000000
121193           -751.000000             37.0      0.432432
248504          -1519.200000             33.0      0.000000
175469          -1884.000000             64.0      0.265625
285162           -853.714286             50.0      0.000000

        CREDIT_BALANCE_MEAN  CREDIT_CARD_MONTHS  PAYMENT_TOTAL  PAYMENT_MEAN  \
181648        213473.232857           21.000000     550660.815   9660.716053
229245         71459.926952           37.143605     263064.645   9743.135000
122525         71459.926952           37.143605      51958.485  12989.621250
306311         71459.926952           37.143605    1471327.965  17943.023963
300658         71459.926952           37.143605      37066.230   3369.657273
…                       …                  …              …            …
31304          71459.926952           37.143605      91714.725   7642.893750
121193         24492.050000            9.000000     198316.125   3888.551471
248504         71459.926952           37.143605     278914.185   8716.068281
175469         71459.926952           37.143605    1814637.240  20620.877727
285162         20354.314091           22.000000    2388926.655  28439.603036

        TOTAL_INSTALLMENTS
181648                57.0
229245                27.0
122525                 4.0
306311                82.0
300658                11.0
…                      …
31304                 12.0
121193                51.0
248504                32.0
175469                88.0
```

```
285162                84.0

[246008 rows x 39 columns]
```

[250]:
```
X_filtered.value_counts()
```

[250]:
```
SK_ID_CURR  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  FLAG_OWN_REALTY
CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  NAME_INCOME_TYPE
NAME_FAMILY_STATUS    REGION_POPULATION_RELATIVE  DAYS_BIRTH  DAYS_EMPLOYED
DAYS_REGISTRATION  DAYS_ID_PUBLISH  FLAG_CONT_MOBILE  REGION_RATING_CLIENT
HOUR_APPR_PROCESS_START  REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION
REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  EXT_SOURCE_2  EXT_SOURCE_3
DEF_30_CNT_SOCIAL_CIRCLE  DAYS_LAST_PHONE_CHANGE  AMT_REQ_CREDIT_BUREAU_QRT
AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL  CREDIT_SUM_MEAN
CREDIT_OVERDUE_MAX  CREDIT_DURATION_MEAN  POS_LOANS_COUNT  POS_DPD_MEAN
CREDIT_BALANCE_MEAN  CREDIT_CARD_MONTHS  PAYMENT_TOTAL  PAYMENT_MEAN
TOTAL_INSTALLMENTS
456255      Cash loans          F            N             N                0
157500.0          675000.0    Commercial associate  Married
0.046220                    -16856      -1262          -5128.0            -410
1                 1                     20                      0
0                           0                       1
0.708569      0.113922      0.0                       -787.0
0.000000                   1.000000                    3.801920e+06
345629.045455    0.000000           -1089.454545          71.0
0.070423      71459.926952         37.143605           3525819.975
47646.215878  74.0                  1
100002      Cash loans          M            N             Y                0
202500.0          406597.5    Working               Single / not married
0.018801                    -9461       -637           -3648.0            -2120
1                 2                     10                      0
0                           0                       0
0.262949      0.139376      2.0                       -1134.0
0.000000                   1.000000                    8.650556e+05
108131.945625    0.000000           -874.000000           19.0
0.000000      71459.926952         37.143605           219625.695
11559.247105  19.0                  1
100003      Cash loans          F            N             N                0
270000.0          1293502.5   State servant         Married
0.003541                    -16765      -1188          -1186.0            -291
1                 1                     11                      0
0                           0                       0
0.622246      0.510853      0.0                       -828.0
0.000000                   0.000000                    1.017400e+06
254350.125000    0.000000           -1400.750000          28.0
0.000000      71459.926952         37.143605           1618864.650
64754.586000  25.0                  1
```

```
100004      Revolving loans     M            Y             Y                0
67500.0           135000.0    Working               Single / not married
0.010032                    -19046      -225          -4260.0            -2531
1                 2                     9                      0
0                           0                     0
0.555912      0.729567      0.0                     -815.0
0.000000                  0.000000                  1.890378e+05
94518.900000     0.000000           -867.000000          4.0
0.000000      71459.926952        37.143605          21288.465
7096.155000   3.0                  1
100006      Cash loans          F            N             Y                0
135000.0          312682.5    Working               Civil marriage
0.008019                    -19005      -3039         -9833.0            -2437
1                 2                     17                     0
0                           0                     0
0.650442      0.510853      0.0                     -617.0
0.265474                  1.899974                  1.955807e+06
378080.200789    4.772759           -1083.047110         21.0
0.000000      0.000000            6.000000          1007153.415
62947.088438  16.0                 1
                                   ..
100021      Revolving loans     F            N             Y                1
81000.0           270000.0    Working               Married
0.010966                    -9776       -191          -4143.0            -2427
1                 2                     10                     0
0                           1                     1
0.683513      0.510853      0.0                     -2811.0
0.265474                  1.899974                  1.955807e+06
378080.200789    4.772759           -1083.047110         27.0
0.000000      0.000000           17.000000          208357.515
9059.022391   23.0                 1
100019      Cash loans          M            Y             Y                0
157500.0          299772.0    Working               Single / not married
0.020713                    -8728       -1157         -3494.0            -1368
1                 3                     6                      0
0                           1                     1
0.346634      0.678568      0.0                     -925.0
0.000000                  1.000000                  7.200000e+05
360000.000000    0.000000           -495.000000          8.0
0.000000      71459.926952        37.143605          165093.030
20636.628750  8.0                  1
100017      Cash loans          M            Y             N                1
225000.0          918468.0    Working               Married
0.016612                    -14086      -3028         -643.0             -4911
1                 2                     13                     0
0                           0                     0
0.566907      0.770087      0.0                     -4.0
```

```
0.000000                    1.000000                    8.597700e+05
143295.000000    0.000000           -1944.333333          31.0
0.000000      71459.926952         37.143605           405267.615
13508.920500  30.0                  1
100016      Cash loans          F            N             Y                0
67500.0           80865.0     Working               Married
0.031329                    -13439      -2717          -311.0             -3227
1                 2                     10                       0
0                           0                     0
0.715042      0.176653      0.0                     -2370.0
0.000000                    0.000000                  4.749840e+05
67854.857143     0.000000           -618.428571          67.0
0.000000      71459.926952         37.143605           620981.820
8391.646216   74.0                  1
100012      Revolving loans     M            N             Y                0
135000.0          405000.0    Working               Single / not married
0.019689                    -14469      -2019          -14437.0           -3992
1                 2                     8                        0
0                           0                     0
0.746644      0.510853      0.0                     -1673.0
0.265474                    1.899974                  1.955807e+06
378080.200789    4.772759           -1083.047110          46.0
0.000000      71459.926952         37.143605           501661.710
10451.285625  48.0                  1
Name: count, Length: 246008, dtype: int64
```

[251]:
```
#working= 1, not working = 0, pension = 2
X_filtered['NAME_INCOME_TYPE']= X_filtered['NAME_INCOME_TYPE'].
 ↪replace({'Working':1,'Commercial associate':1,

 ↪'Pensioner':2, 'State servant':1, 'Unemployed':0, 'Student':0, 'Businessman':
 ↪1, 'Maternity leave':1})
```

```
/tmp/ipykernel_17311/3621634806.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_filtered['NAME_INCOME_TYPE']=
X_filtered['NAME_INCOME_TYPE'].replace({'Working':1,'Commercial associate':1,
```

[252]:
```
X_test1 = X_test
```

[253]:
```
#working= 1, not working = 0, pension = 2
X_test1['NAME_INCOME_TYPE']= X_test1['NAME_INCOME_TYPE'].replace({'Working':
 ↪1,'Commercial associate':1,
```

```
 ↪'Pensioner':2, 'State servant':1, 'Unemployed':0, 'Student':0, 'Businessman':␣
 ↪1, 'Maternity leave':1})
```

```
/tmp/ipykernel_17311/1173273511.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_test1['NAME_INCOME_TYPE']=
X_test1['NAME_INCOME_TYPE'].replace({'Working':1,'Commercial associate':1,
```

[254]:
```
X_filtered['NAME_CONTRACT_TYPE'] = X_filtered['NAME_CONTRACT_TYPE'].
 ↪replace({'Cash loans':0, 'Revolving loans':1})
X_test1['NAME_CONTRACT_TYPE'] = X_test1['NAME_CONTRACT_TYPE'].replace({'Cash␣
 ↪loans':0, 'Revolving loans':1})
```

```
/tmp/ipykernel_17311/3092756039.py:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_filtered['NAME_CONTRACT_TYPE'] =
X_filtered['NAME_CONTRACT_TYPE'].replace({'Cash loans':0, 'Revolving loans':1})
/tmp/ipykernel_17311/3092756039.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_test1['NAME_CONTRACT_TYPE'] = X_test1['NAME_CONTRACT_TYPE'].replace({'Cash
loans':0, 'Revolving loans':1})
/tmp/ipykernel_17311/3092756039.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_test1['NAME_CONTRACT_TYPE'] = X_test1['NAME_CONTRACT_TYPE'].replace({'Cash
loans':0, 'Revolving loans':1})
```

[255]:
```
X_filtered['CODE_GENDER']=X_filtered['CODE_GENDER'].replace({'M':1, 'F':0})
X_test1['CODE_GENDER']=X_test1['CODE_GENDER'].replace({'M':1, 'F':0})
```

[256]:
```
X_filtered['FLAG_OWN_CAR']=X_filtered['FLAG_OWN_CAR'].replace({'Y':1,'N':0})
X_test1['FLAG_OWN_CAR']=X_test1['FLAG_OWN_CAR'].replace({'Y':1,'N':0})
```

```
/tmp/ipykernel_17311/2337974619.py:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_filtered['FLAG_OWN_CAR']=X_filtered['FLAG_OWN_CAR'].replace({'Y':1,'N':0})
/tmp/ipykernel_17311/2337974619.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
```

```
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_test1['FLAG_OWN_CAR']=X_test1['FLAG_OWN_CAR'].replace({'Y':1,'N':0})
```

[257]:
```
X_filtered['FLAG_OWN_REALTY']=X_filtered['FLAG_OWN_REALTY'].replace({'Y':1,'N':
↪0})
X_test1['FLAG_OWN_REALTY']=X_test1['FLAG_OWN_REALTY'].replace({'Y':1,'N':0})
```

```
/tmp/ipykernel_17311/3118549609.py:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_filtered['FLAG_OWN_REALTY']=X_filtered['FLAG_OWN_REALTY'].replace({'Y':1,'N'
:0})
/tmp/ipykernel_17311/3118549609.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_test1['FLAG_OWN_REALTY']=X_test1['FLAG_OWN_REALTY'].replace({'Y':1,'N':0})
```

[258]:
```
# NAME_FAMILY_STATUS
X_filtered.NAME_FAMILY_STATUS.value_counts()
```

[258]:
```
NAME_FAMILY_STATUS
Married                 157153
Single / not married     36359
Civil marriage           23812
Separated                15840
Widow                    12842
Unknown                      2
Name: count, dtype: int64
```

[259]:
```
X_filtered['NAME_FAMILY_STATUS'] = X_filtered['NAME_FAMILY_STATUS'].
↪replace({'Married': 1, 'Single / not married': 0, 'Separated': 0, 'Widow':␣
↪0, 'Civil marriage': 1, 'Unknown': 0})
X_test1['NAME_FAMILY_STATUS'] = X_test1['NAME_FAMILY_STATUS'].
↪replace({'Married': 1, 'Single / not married': 0, 'Separated': 0, 'Widow':␣
↪0, 'Civil marriage': 1, 'Unknown': 0})
```

```
/tmp/ipykernel_17311/2246185276.py:1: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
  X_filtered['NAME_FAMILY_STATUS'] =
X_filtered['NAME_FAMILY_STATUS'].replace({'Married': 1, 'Single / not married':
0, 'Separated': 0, 'Widow': 0, 'Civil marriage': 1, 'Unknown': 0})
/tmp/ipykernel_17311/2246185276.py:2: FutureWarning: Downcasting behavior in
`replace` is deprecated and will be removed in a future version. To retain the
old behavior, explicitly call `result.infer_objects(copy=False)`. To opt-in to
the future behavior, set `pd.set_option('future.no_silent_downcasting', True)`
```

```
  X_test1['NAME_FAMILY_STATUS'] =
X_test1['NAME_FAMILY_STATUS'].replace({'Married': 1, 'Single / not married': 0,
'Separated': 0, 'Widow': 0, 'Civil marriage': 1, 'Unknown': 0})
```

[260]:
```
# Check for non-numeric columns
X_train_numeric = X_filtered.select_dtypes(include=[np.number])  # Select only␣
 ↪numeric columns

# Drop rows with NaN or Inf values
X_train_numeric_clean = X_train_numeric.replace([np.inf, -np.inf], np.nan).
 ↪dropna()

# Alternatively, fill NaN or Inf values with the mean
# X_train_numeric_clean = X_train_numeric.replace([np.inf, -np.inf], np.nan).
 ↪fillna(X_train_numeric.mean())

X_train1 = X_train_numeric_clean.drop (columns= {'FLAG_CONT_MOBILE',␣
 ↪'REGION_RATING_CLIENT', 'EXT_SOURCE_3',
                                'SK_ID_CURR', 'DAYS_BIRTH',␣
 ↪'HOUR_APPR_PROCESS_START', 'DEF_30_CNT_SOCIAL_CIRCLE',

},
axis=1)

# Calculate VIF for each feature
vif_data = pd.DataFrame()
vif_data['Feature'] = X_train1.columns
vif_data['VIF'] = [variance_inflation_factor(X_train1.values, i) for i in␣
 ↪range(X_train1.shape[1])]

# Drop features with VIF > 5
high_vif_features = vif_data[vif_data['VIF'] > 5]['Feature']
X_train1 = X_train1.drop(columns=high_vif_features, axis=1)

# Display the VIF for each feature
print(vif_data.sort_values(by='VIF', ascending=False))
```

```
                     Feature        VIF
6             NAME_INCOME_TYPE  53.491151
27          CREDIT_CARD_MONTHS   9.648713
16                EXT_SOURCE_2   9.205065
30          TOTAL_INSTALLMENTS   8.158715
9                DAYS_EMPLOYED   7.914757
24            POS_LOANS_COUNT   6.705858
23       CREDIT_DURATION_MEAN   5.753231
11             DAYS_ID_PUBLISH   5.641327
28               PAYMENT_TOTAL   4.652525
7           NAME_FAMILY_STATUS   4.061130
```

```
5                    AMT_CREDIT   3.822906
8    REGION_POPULATION_RELATIVE   3.492458
2                FLAG_OWN_REALTY   3.341929
10             DAYS_REGISTRATION   3.300402
19   AMT_REQ_CREDIT_BUREAU_YEAR   2.778601
26          CREDIT_BALANCE_MEAN   2.776052
17       DAYS_LAST_PHONE_CHANGE   2.697623
29                  PAYMENT_MEAN   2.589900
20              CREDIT_SUM_TOTAL   2.160202
21               CREDIT_SUM_MEAN   2.133942
15       REG_CITY_NOT_WORK_CITY   1.806853
1                   FLAG_OWN_CAR   1.630887
14       REG_CITY_NOT_LIVE_CITY   1.513535
3                   CNT_CHILDREN   1.510978
4               AMT_INCOME_TOTAL   1.488094
12   REG_REGION_NOT_LIVE_REGION   1.417843
13   REG_REGION_NOT_WORK_REGION   1.403150
18    AMT_REQ_CREDIT_BUREAU_QRT   1.231407
0             NAME_CONTRACT_TYPE   1.208849
25                  POS_DPD_MEAN   1.074710
22             CREDIT_OVERDUE_MAX   1.005297
```

[ ]:

[261]:
```
cols = X_train1.columns
X_test1 = X_test[cols]
```

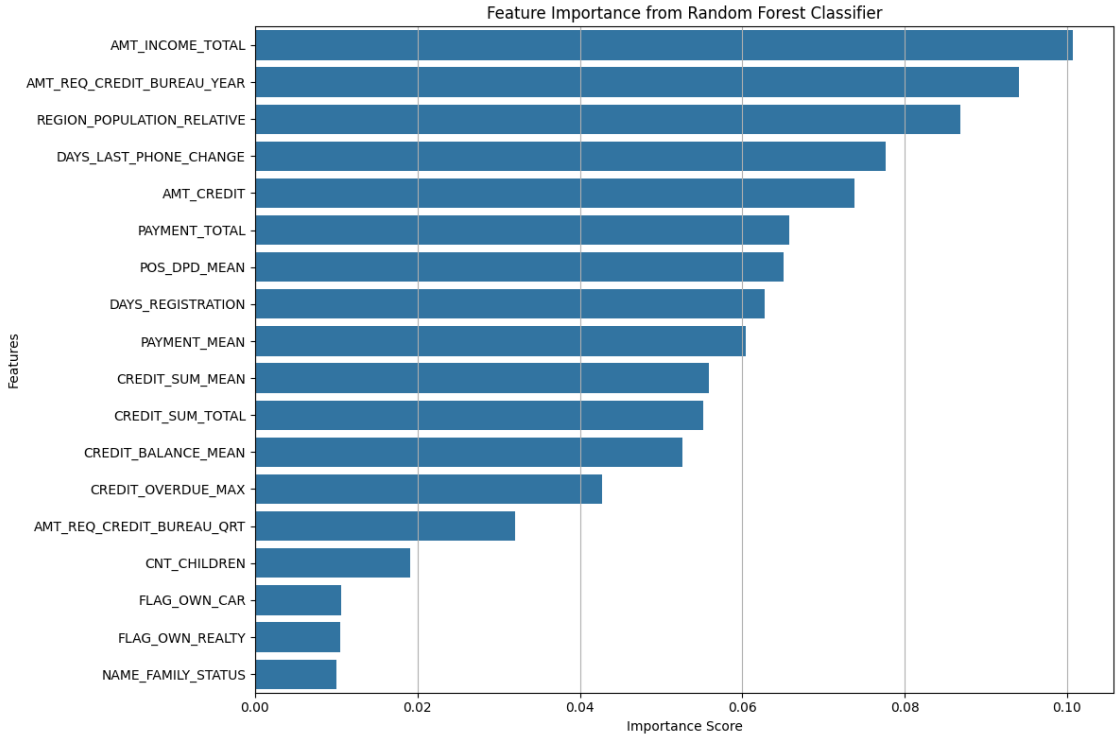
[262]:
```
#  Define numerical and categorical columns
numerical_cols = X_train1.select_dtypes(include=['number']).columns
categorical_cols = X_train1.select_dtypes(include=['object']).columns

# Imputers
numerical_imputer = SimpleImputer(strategy='mean')
categorical_imputer = SimpleImputer(strategy='most_frequent')
```

[263]:
```
# Build transformers list conditionally
transformers = []

# Numerical columns: apply numerical imputer and scaling
if len(numerical_cols) > 0:
    transformers.append(('num', Pipeline(steps=[
        ('imputer', SimpleImputer(strategy='mean')),  # Handle missing values␣
 ↪in numerical columns
        ('scaler', StandardScaler())  # Standardize numerical values
    ]), numerical_cols))

# Categorical columns: apply categorical imputer and one-hot encoding
```

```
if len(categorical_cols) > 0:
    transformers.append(('cat', Pipeline(steps=[
        ('imputer', SimpleImputer(strategy='most_frequent')),  # Handle missing␣
 ↪values in categorical columns
        ('onehot', OneHotEncoder(handle_unknown='ignore'))  # OneHotEncode␣
 ↪categorical variables
    ]), categorical_cols))

# Create the ColumnTransformer
preprocessor = ColumnTransformer(transformers=transformers)

# Create the pipeline
pipeline = ImbPipeline(steps=[
    ('preprocessor', preprocessor),  # Preprocess the data first
    ('smote', SMOTE(random_state=42)),  # Apply SMOTE after preprocessing
    ('classifier', RandomForestClassifier(n_estimators=100, random_state=42,␣
 ↪class_weight='balanced'))
])

# Fit the pipeline on the training data
pipeline.fit(X_train1, y_train)

# Make predictions on the test set
y_pred = pipeline.predict(X_test1)

# Evaluate performance
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.2f}")
print("Classification Report:\n", classification_report(y_test, y_pred))

# Feature Importance Extraction
try:
    if 'cat' in pipeline.named_steps['preprocessor'].named_transformers_:  #␣
 ↪Check if 'cat' step exists
        onehot_encoder = pipeline.named_steps['preprocessor'].
 ↪named_transformers_['cat'].named_steps['onehot']
        categorical_feature_names = onehot_encoder.
 ↪get_feature_names_out(categorical_cols)
    else:
        categorical_feature_names = []  # If there are no categorical features

    # Combine categorical and numerical feature names
    feature_names = list(categorical_feature_names) + list(numerical_cols)

    # Get feature importances from the classifier
    importance = pipeline.named_steps['classifier'].feature_importances_
```

```
    # Create a DataFrame for feature importances
    feature_importance_df = pd.DataFrame({
        'Feature': feature_names,
        'Importance': importance
    })

    # Set the threshold for feature importance
    importance_threshold = 0.01
    feature_importance_df = feature_importance_df[feature_importance_df['Importance'] >= importance_threshold]
    feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

    # Visualization
    plt.figure(figsize=(12, 8))
    sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
    plt.title('Feature Importance from Random Forest Classifier')
    plt.xlabel('Importance Score')
    plt.ylabel('Features')
    plt.grid(axis='x')
    plt.tight_layout()  # Adjust layout for better visibility
    plt.show()

except NotFittedError:
    print("The OneHotEncoder instance is not fitted. Ensure that the pipeline is fitted correctly.")
except Exception as e:
    print(f"An error occurred: {e}")
```

```
Accuracy: 0.89
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.96      0.94     56538
           1       0.17      0.08      0.11      4965

    accuracy                           0.89     61503
   macro avg       0.55      0.52      0.53     61503
weighted avg       0.86      0.89      0.88     61503
```



[264]:
```
X_train1.value_counts()
```

[264]:
```
NAME_CONTRACT_TYPE  FLAG_OWN_CAR  FLAG_OWN_REALTY  CNT_CHILDREN
AMT_INCOME_TOTAL  AMT_CREDIT  NAME_FAMILY_STATUS  REGION_POPULATION_RELATIVE
DAYS_REGISTRATION  REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION
REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  DAYS_LAST_PHONE_CHANGE
AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL
CREDIT_SUM_MEAN  CREDIT_OVERDUE_MAX  POS_DPD_MEAN  CREDIT_BALANCE_MEAN
PAYMENT_TOTAL  PAYMENT_MEAN
0                   1             0                0             202500.0
482530.5    0                   0.026392                   -9559.0           0
0                           0                          0
-516.0                  0.0                        0.0
2580646.59        645161.6475      0.0                 0.000000
71459.926952         2.779799e+04   9265.995000     2
                    0             1                0             76500.0
284400.0    0                   0.031329                   -15960.0          0
0                           0                          0                        0.0
0.0                         0.0                        180000.00
180000.0000      0.0                4.406493      71459.926952
6.785854e+05   18754.310245    2
                                                                    157500.0
284400.0    1                   0.018634                   -3803.0           0
```

```
0                          0                          0
-771.0                  0.0                        1.0
175189.50         87594.7500       0.0                0.000000
71459.926952         4.002592e+05   13341.975000    2
                                                              112500.0
508495.5    1                  0.003818                  -7321.0            0
0                          0                          0
-338.0                  1.0                        0.0
238500.00         238500.0000      0.0                0.000000
71459.926952         1.235886e+05   13732.070000    2
                      1             0                0             90000.0
254700.0    0                  0.007120                  -378.0             0
0                          0                          0
-2595.0                 0.0                        0.0
345390.75         115130.2500      0.0                0.000000
71459.926952         5.973917e+04   14934.791250    2
                                                                    ..
                      0             1                0             135000.0
454500.0    0                  0.035792                  -389.0             0
1                          0                          1
-173.0                  0.0                        1.0
156600.00         156600.0000      0.0                0.000000
71459.926952         1.249426e+06   78089.132812    1
               1                   0.002042                  -5804.0
0                          0                           0
0                      -790.0                  0.0                          3.0
717682.50         79742.5000       0.0                0.000000
71459.926952         3.740307e+05   41558.965000    1
                                                              -29.0
0                          0                           0
0                      -211.0                  0.0                          0.0
90000.00          15000.0000       0.0                0.000000
71459.926952         5.103036e+04   8505.060000     1
                                    0.003069                  -13043.0
0                          0                           0
0                      -1029.0                 0.0                          0.0
2398223.52        399703.9200      0.0                0.000000
71459.926952         1.817651e+05   18176.508000    1
               0                   0.025164                  -5078.0
0                          0                           0
0                      -65.0                   0.0                          0.0
1188000.00        297000.0000      0.0                0.000000
106546.874362        6.279727e+05   6156.594706     1
Name: count, Length: 245996, dtype: int64
```

[265]:
```
X_test1.value_counts()
```

[265]:
```
NAME_CONTRACT_TYPE  FLAG_OWN_CAR  FLAG_OWN_REALTY  CNT_CHILDREN
AMT_INCOME_TOTAL  AMT_CREDIT  NAME_FAMILY_STATUS  REGION_POPULATION_RELATIVE
DAYS_REGISTRATION  REG_REGION_NOT_LIVE_REGION  REG_REGION_NOT_WORK_REGION
REG_CITY_NOT_LIVE_CITY  REG_CITY_NOT_WORK_CITY  DAYS_LAST_PHONE_CHANGE
AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  CREDIT_SUM_TOTAL
CREDIT_SUM_MEAN  CREDIT_OVERDUE_MAX  POS_DPD_MEAN  CREDIT_BALANCE_MEAN
PAYMENT_TOTAL  PAYMENT_MEAN
1                   1             1                4             171000.0
585000.0    1                   0.018634                    -353.0             0
0                          0                       0
-2691.0                0.000000                    2.000000
3.077541e+06      769385.250000    0.000000           0.052632
71459.926952         1.606550e+06   44626.402500    1
0                   0             0                0             26100.0
90000.0     1                   0.022800                    -4469.0            0
0                          0                       0
-598.0                 0.000000                    1.000000
9.540000e+04      47700.000000     0.000000           0.000000
71459.926952         3.820703e+04   6367.837500     1
                                                                 27000.0
123637.5    1                   0.006207                    -4949.0            0
0                          0                       0
-1694.0                0.265474                    1.899974
1.955807e+06      378080.200789    4.772759           0.000000
42414.399818         9.559361e+05   7835.541639     1
   135000.0    1                   0.025164                   -6036.0
0                          0                         0
0                      -709.0                  0.000000
1.000000                   3.725518e+05      93137.951250     0.000000
0.153846      71459.926952         6.977111e+04   2790.844200     1
   225000.0    1                   0.007020                   -7309.0
0                          0                           1
1                      -1540.0                 0.000000
1.000000                   3.195000e+05      159750.000000    0.000000
0.000000      71459.926952         1.103888e+05   4088.473333     1
                                                                 ..
                                                                 31500.0
327024.0    1                   0.018801                    -3757.0            0
0                          0                       0
-380.0                 0.265474                    1.899974
1.955807e+06      378080.200789    4.772759           0.428571
71459.926952         2.106888e+05   5852.467500     1
   254700.0    1                   0.035792                   -8722.0
0                          0                         0
0                      -483.0                  0.000000
1.000000                   1.696918e+06      77132.626364     0.000000
0.000000      71459.926952         5.573146e+04   2533.248409     1
```

```
                                    0.010556                    -11611.0
0                           0                           0
0                       0.0                         0.000000
0.000000                    1.820817e+05       45520.425000     0.000000
0.000000       71459.926952         1.009894e+05    11221.040000     1
   187704.0    0                    0.031329                    -7726.0
0                           0                           0
0                      -2.0                         0.000000
0.000000                    2.620035e+05       52400.700000     0.000000
4.406493       71459.926952         6.785854e+05    18754.310245     1
   104256.0    1                    0.009630                    -3935.0
0                           0                           0
0                    -782.0                         0.000000
3.000000                    1.844100e+04       18441.000000     0.000000
0.035714       71459.926952         3.537956e+05    11793.187500     1
Name: count, Length: 61503, dtype: int64
```

[266]:
```
# # Build transformers list conditionally
# transformers = []
# if len(numerical_cols) > 0:
#     transformers.append(('num', Pipeline(steps=[
#         ('imputer', numerical_imputer),
#         ('scaler', StandardScaler())
#     ]), numerical_cols))
# if len(categorical_cols) > 0:
#     transformers.append(('cat', Pipeline(steps=[
#         ('imputer', categorical_imputer),
#         ('onehot', OneHotEncoder(handle_unknown='ignore'))
#     ]), categorical_cols))

# # Create the ColumnTransformer
# preprocessor = ColumnTransformer(transformers=transformers)

# # Create the pipeline
# pipeline = ImbPipeline(steps=[
#     ('preprocessor', preprocessor),  # Preprocess the data first
#     ('smote', SMOTE(random_state=42)),  # Apply SMOTE after preprocessing
#     ('classifier', RandomForestClassifier(n_estimators=100, random_state=42,␣
 ↪class_weight='balanced'))
# ])

# # Fit the pipeline on the training data
# pipeline.fit(X_train1, y_train)

# # Make predictions on the test set
# y_pred = pipeline.predict(X_test1)
```

```
# # Evaluate performance
# accuracy = accuracy_score(y_test, y_pred)
# print(f"Accuracy: {accuracy:.2f}")
# print("Classification Report:\n", classification_report(y_test, y_pred))

# # Feature Importance Extraction
# try:
#     if 'cat' in pipeline.named_steps['preprocessor'].named_transformers_:  # Check if 'cat' step exists
#         onehot_encoder = pipeline.named_steps['preprocessor'].named_transformers_['cat'].named_steps['onehot']
#         categorical_feature_names = onehot_encoder.get_feature_names_out(categorical_cols)
#     else:
#         categorical_feature_names = []  # If there are no categorical features

#     # Combine categorical and numerical feature names
#     feature_names = list(categorical_feature_names) + list(numerical_cols)

#     # Get feature importances from the classifier
#     importance = pipeline.named_steps['classifier'].feature_importances_

#     # Create a DataFrame for feature importances
#     feature_importance_df = pd.DataFrame({
#         'Feature': feature_names,
#         'Importance': importance
#     })

#     # Set the threshold for feature importance
#     importance_threshold = 0.01
#     feature_importance_df = feature_importance_df[feature_importance_df['Importance'] >= importance_threshold]
#     feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

#     # Step 8: Visualization
#     plt.figure(figsize=(12, 8))
#     sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
#     plt.title('Feature Importance from Random Forest Classifier')
#     plt.xlabel('Importance Score')
#     plt.ylabel('Features')
#     plt.grid(axis='x')
#     plt.tight_layout()  # Adjust layout for better visibility
#     plt.show()

# except NotFittedError:
```

```
#     print("The OneHotEncoder instance is not fitted. Ensure that the pipeline␣
 ↪is fitted correctly.")
# except Exception as e:
#     print(f"An error occurred: {e}")
```

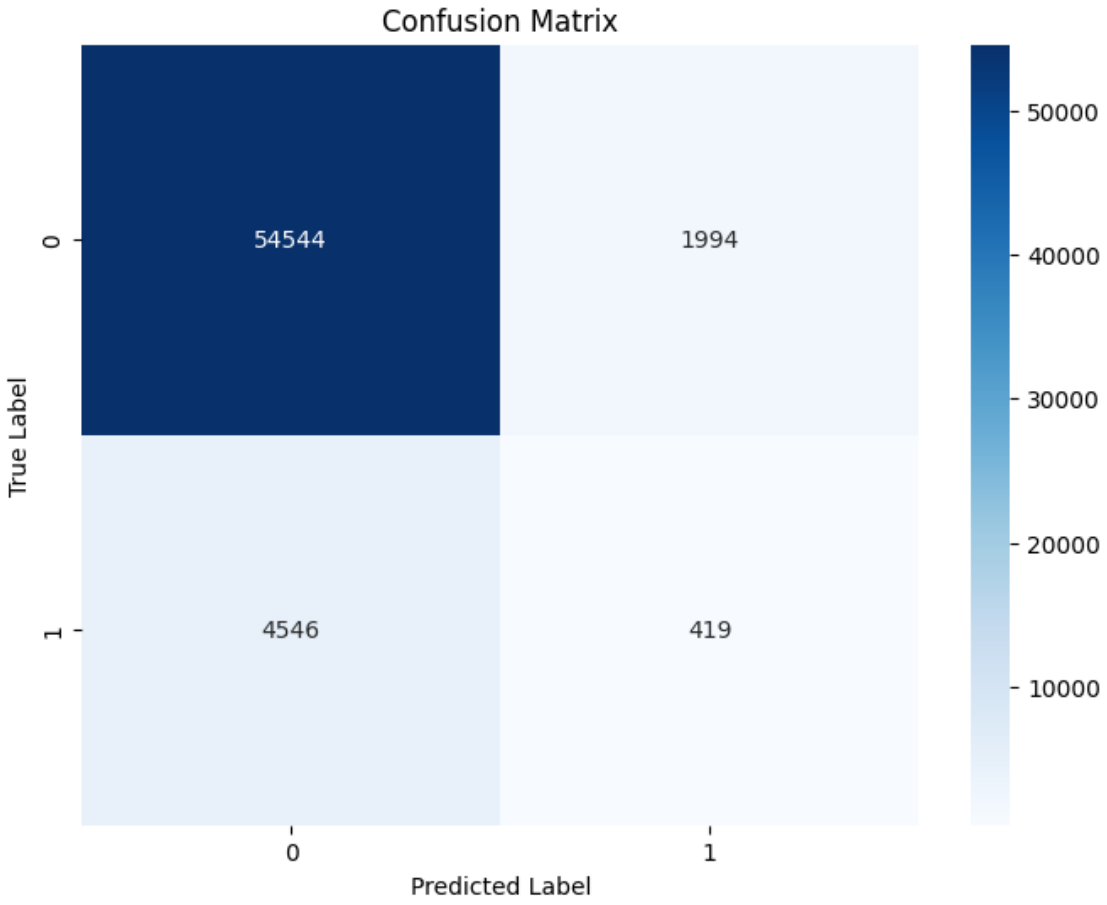
[267]:
```
# Make predictions on the test set
# y_pred = pipeline.predict(X_test)
y_pred_proba = pipeline.predict_proba(X_test)[:, 1]  # Probability of positive␣
 ↪class
y_pred_adjusted = (y_pred_proba >= 0.3).astype(int)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred_adjusted)
precision = precision_score(y_test, y_pred_adjusted)
recall = recall_score(y_test, y_pred_adjusted)
f1 = f1_score(y_test, y_pred_adjusted)

print(f"Accuracy: {accuracy:.2f}, Precision: {precision:.2f}, Recall: {recall:.
 ↪2f}, F1-Score: {f1:.2f}")
```

```
Accuracy: 0.76, Precision: 0.13, Recall: 0.35, F1-Score: 0.19
```

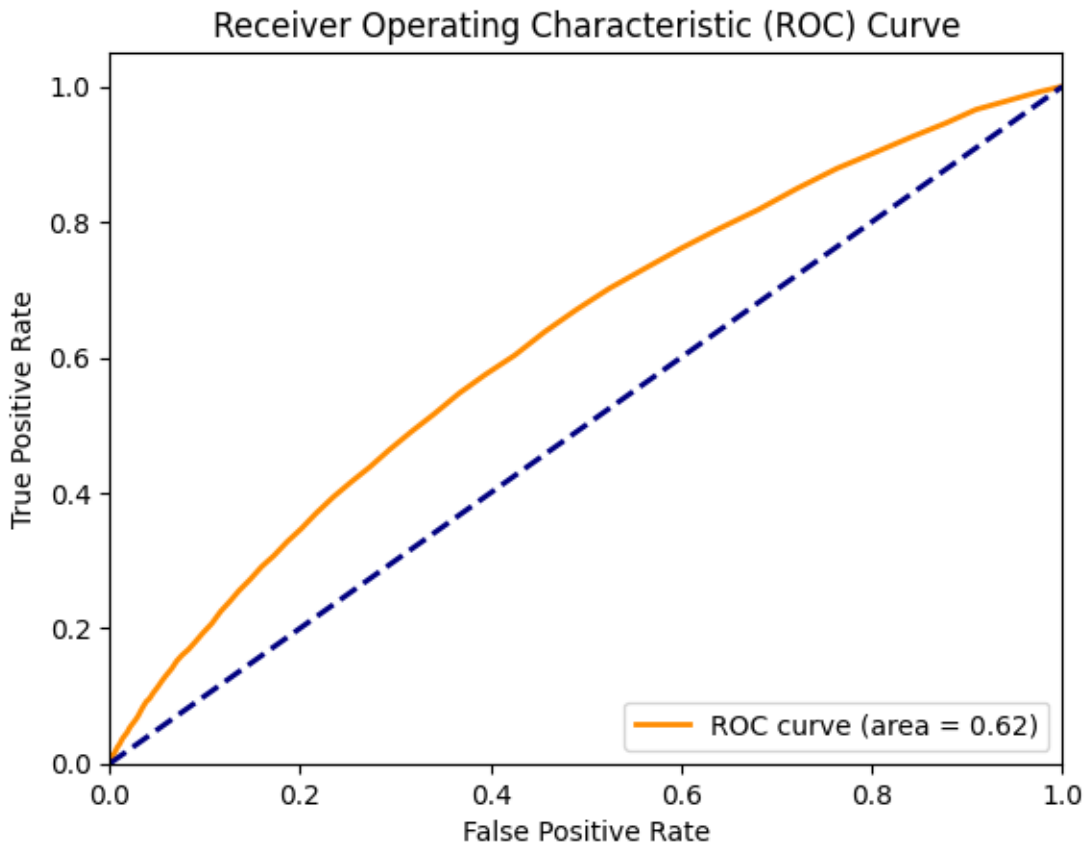
[268]:
```
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(cm)
```

```
Confusion Matrix:
[[54544  1994]
 [ 4546   419]]
```

[269]:
```
# Plot confusion matrix

# Confusion matrix visualization
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues')
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.title('Confusion Matrix')
plt.show()
```



[270]:
```
# ROC curve and AUC
from sklearn.metrics import roc_curve, auc
fpr, tpr, thresholds = roc_curve(y_test, pipeline.predict_proba(X_test)[:, 1])
roc_auc = auc(fpr, tpr)

# Plot ROC Curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
 ↪.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, 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 (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



[271]:
```
# #Hyperparameter Tuning

# from sklearn.model_selection import GridSearchCV

# # Define the parameter grid for Random Forest
# param_grid = {
#     'classifier__n_estimators': [50, 100, 200],
#     'classifier__max_depth': [None, 10, 20],
#     'classifier__min_samples_split': [2, 5, 10],
# }

# # Perform Grid Search
# grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy')
# grid_search.fit(X_train, y_train)

# # Print the best hyperparameters
# print("Best Hyperparameters:", grid_search.best_params_)
```

[274]:
```
## Model Comparison and Selection

from sklearn.linear_model import LogisticRegression

# Define other models
models = {
    'Random Forest': RandomForestClassifier(random_state=42),
    'Logistic Regression': LogisticRegression()
}

# Iterate through models and evaluate performance
for model_name, model in models.items():
    pipeline = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('classifier', model)
    ])

    pipeline.fit(X_train1, y_train)
    y_pred = pipeline.predict(X_test1)

    accuracy = accuracy_score(y_test, y_pred)
    print(f"{model_name} Accuracy: {accuracy:.2f}")
```

```
Random Forest Accuracy: 0.92
Logistic Regression Accuracy: 0.92
```