Group9_Phase_3_HCDR_Final

April 16, 2024

1 Final Project Phase 3 - Home Credit Default Risk

Spring 2024

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1.1 Abstract

In phase three the goal was to improve the ability of our models to predict the TARGET feature by incorporating data outside the application train csv. To do this the team focused on feature engineering and hyperparameter tuning of the modeling pipelines. \

Recency, Frequency, and Monetary Value (RFM) features were added to the test and train data. These metrics are common in marketing analysis to compare segments of the customer base. Recency measures how recently an applicant was given a loan. Frequency gauges how often an applicant receives loans. Monetary value reflects the total sum of all loans let by Home Credit to the applicant. The RFM features were derived from features in the previous application csv. We discovered anomalies in several of the previous application features.

Preprocessing pipelines were implemented to automate this task.

[ ]:
```python
from pandas import concat, DataFrame,read_csv, set_option
import matplotlib.ticker as ticker
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
from __future__ import print_function

import numpy as np

from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, GridSearchCV,␣
 ↪RandomizedSearchCV
from sklearn.metrics import accuracy_score, f1_score, roc_auc_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.pipeline import Pipeline
```

```python
from sklearn.preprocessing import StandardScaler, OneHotEncoder,␣
↪FunctionTransformer
from sklearn.base import BaseEstimator, TransformerMixin

from scipy.stats import uniform, randint

from xgboost import XGBClassifier

np.random.seed(42)

# Suppress scientific notation and use 3 decimal places
set_option('display.float_format', '{:.3f}'.format)
```

All data downloaded from Kaggle:

https://www.kaggle.com/competitions/home-credit-default-risk/data

There are several other data files which contain information regarding a customer's financial profile, payment history etc obtained from Kaggle: - `bureau.csv` - `bureau_balance.csv` - `credit_card_balance.csv` - `installments_payments.csv` - `previous_application.csv` - `POS_CASH_balance.csv`

The baseline pipelines will only use data loaded from `application_train.csv`

[ ]:
```python
from google.colab import files
files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving kaggle.json to kaggle (1).json
```

[ ]:
```
{'kaggle (1).json':
 b'{"username":"alexbordanca","key":"d9c74782ba569bbacddf222b676a9d32"}'}
```

[ ]:
```
! mkdir ~/.kaggle
! cp kaggle.json ~/.kaggle/
! chmod 600 ~/.kaggle/kaggle.json
! kaggle datasets list
```

```
mkdir: cannot create directory '/root/.kaggle': File exists
Warning: Looks like you're using an outdated API Version, please consider
updating (server 1.6.12 / client 1.5.16)
ref                                                              title
size  lastUpdated          downloadCount  voteCount  usabilityRating
--------------------------------------------------------------
----------------------------------------------  -----  -------------------
-------------  ---------  ---------------
sudarshan24byte/online-food-dataset                              Online Food
Dataset                              3KB  2024-03-02 18:50:30          27375
533  0.9411765
nbroad/gemma-rewrite-nbroad                                      gemma-rewrite-
```

```
nbroad                            8MB  2024-03-03 04:52:39          1689
105  1.0
startalks/pii-models                                            pii-models
1GB  2024-03-21 21:23:40            148         22  1.0
sukhmandeepsinghbrar/most-subscribed-youtube-channel            Most Subscribed
YouTube Channel                   1KB  2024-04-10 20:33:05          1217
38  1.0
susanta21/student-attitude-and-behavior                         Student Attitude
and Behavior                     5KB  2024-04-13 12:16:32           721
28  1.0
sanyamgoyal401/customer-purchases-behaviour-dataset             Customer
Purchases Behaviour Dataset              1MB  2024-04-06 18:42:01           1812
42  1.0
joshuanaude/effects-of-alcohol-on-student-performance           Effects of
Alcohol on Student Performance.        9KB  2024-03-25 12:08:03           1793
35  1.0
fatemehmehrparvar/obesity-levels                                Obesity Levels
58KB  2024-04-07 16:28:30           2123         50  0.88235295
lovishbansal123/adult-census-income                             Adult Census
Income                            450KB  2024-04-12 08:18:30           674
25  1.0
willianoliveiragibin/worlds-wildlife                            world’s
wildlife?                               92KB  2024-04-12 19:44:08
442          21  1.0
sahirmaharajj/employee-salaries-analysis                        Employee
Salaries Analysis                      101KB  2024-03-31 16:32:47           1746
49  1.0
bhavikjikadara/student-study-performance                        Student Study
Performance                       9KB  2024-03-07 06:14:09         13170
168  1.0
efaniorimutembo/epl-player-shooting-stats-23-24-premier-league  EPL Player
Shooting Stats 23-24 Premier League   24KB  2024-04-11 13:10:10           476
25  1.0
rushikeshdane20/global-trends-in-atmospheric-carbon-dioxide     Global Trends in
Atmospheric CO2 Emission        20KB  2024-04-13 03:45:31           620
22  0.8235294
sukhmandeepsinghbrar/housing-price-dataset                      Housing Price
Dataset                          780KB  2024-04-04 19:45:43          1908
37  1.0
dansbecker/melbourne-housing-snapshot                           Melbourne
Housing Snapshot                     451KB  2018-06-05 12:52:24        144208
1458  0.7058824
sahirmaharajj/electric-vehicle-population-size-2024             Electric Vehicle
Population by Country (2024)   275KB  2024-03-30 19:16:06          2433
62  1.0
sahirmaharajj/air-pollution-dataset                             Air Pollution
Dataset                          213KB  2024-04-07 13:14:48          1299
41  1.0
```

```
jatinthakur706/most-watched-netflix-original-shows-tv-time      Most watched
Netflix original shows (TV Time)     2KB  2024-03-27 09:01:21          3012
50  1.0
sahirmaharajj/retail-sales-analysis                             Retail Sales
Analysis                             6MB  2024-03-31 15:37:11          2034
45  1.0
```

[ ]:
```
import os
DATA_DIR = "/HCDR/DATA_DIR/"   #same level as course repo in the data directory
#DATA_DIR = os.path.join('./ddddd/')
!mkdir DATA_DIR

! kaggle competitions download home-credit-default-risk -p $DATA_DIR
!ls -l $DATA_DIR
```

```
mkdir: cannot create directory ‘DATA_DIR’: File exists
home-credit-default-risk.zip: Skipping, found more recently modified local copy
(use --force to force download)
total 3326076
-rw-r--r-- 1 root root  26567651 Apr 16 21:30 application_test.csv
-rw-r--r-- 1 root root 166133370 Apr 16 21:30 application_train.csv
-rw-r--r-- 1 root root 375592889 Apr 16 21:30 bureau_balance.csv
-rw-r--r-- 1 root root 170016717 Apr 16 21:30 bureau.csv
-rw-r--r-- 1 root root 424582605 Apr 16 21:30 credit_card_balance.csv
-rw-r--r-- 1 root root     37383 Apr 16 21:30 HomeCredit_columns_description.csv
-rw-r--r-- 1 root root 721616255 Dec 11  2019 home-credit-default-risk.zip
-rw-r--r-- 1 root root 723118349 Apr 16 21:30 installments_payments.csv
-rw-r--r-- 1 root root 392703158 Apr 16 21:30 POS_CASH_balance.csv
-rw-r--r-- 1 root root 404973293 Apr 16 21:30 previous_application.csv
-rw-r--r-- 1 root root    536202 Apr 16 21:30 sample_submission.csv
```

[ ]:
```
import zipfile
unzippingReq = True #True# if unzippingReq: #please modify this code
zip_ref = zipfile.ZipFile(f'{DATA_DIR}/home-credit-default-risk.zip', 'r')
     # extractall():  Extract all members from the archive to the current␣
 ↪working directory. path specifies a different directory to extract to
zip_ref.extractall(f'{DATA_DIR}')
zip_ref.close()
```

[ ]:
```
!ls -l $DATA_DIR
```

```
total 3326076
-rw-r--r-- 1 root root  26567651 Apr 16 21:42 application_test.csv
-rw-r--r-- 1 root root 166133370 Apr 16 21:42 application_train.csv
-rw-r--r-- 1 root root 375592889 Apr 16 21:42 bureau_balance.csv
-rw-r--r-- 1 root root 170016717 Apr 16 21:42 bureau.csv
-rw-r--r-- 1 root root 424582605 Apr 16 21:42 credit_card_balance.csv
-rw-r--r-- 1 root root     37383 Apr 16 21:42 HomeCredit_columns_description.csv
-rw-r--r-- 1 root root 721616255 Dec 11  2019 home-credit-default-risk.zip
```

```
-rw-r--r-- 1 root root 723118349 Apr 16 21:43 installments_payments.csv
-rw-r--r-- 1 root root 392703158 Apr 16 21:42 POS_CASH_balance.csv
-rw-r--r-- 1 root root 404973293 Apr 16 21:43 previous_application.csv
-rw-r--r-- 1 root root    536202 Apr 16 21:43 sample_submission.csv
```

[ ]:
```
train_data = read_csv('/HCDR/DATA_DIR/application_train.csv')

print(f'Loaded {train_data.shape[0]:,} records.')
print()
train_data.head()
```

```
Loaded 307,511 records.
```

[ ]:

	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	202500.000	406597.500	24700.500	
1	N	0	270000.000	1293502.500	35698.500	
2	Y	0	67500.000	135000.000	6750.000	
3	Y	0	135000.000	312682.500	29686.500	
4	Y	0	121500.000	513000.000	21865.500	

	…	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	0.000	0.000	
1	0.000	0.000	
2	0.000	0.000	
3	NaN	NaN	
4	0.000	0.000	

	AMT_REQ_CREDIT_BUREAU_WEEK	AMT_REQ_CREDIT_BUREAU_MON	\
0	0.000	0.000	
1	0.000	0.000	
2	0.000	0.000	
3	NaN	NaN	
4	0.000	0.000	

```
   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                      0.000                       1.000
1                      0.000                       0.000
2                      0.000                       0.000
3                        NaN                         NaN
4                      0.000                       0.000

[5 rows x 122 columns]
```

Explore missing data in training dataset

[ ]:
```
#MISSING DATA FOR APPLICATION TRAIN

percent = (train_data.isnull().sum() / train_data.isnull().count()*100).
 ↪sort_values(ascending = False).round(2)
sum_missing = train_data.isna().sum().sort_values(ascending = False)
missing_application_train_data  = concat([percent, sum_missing], axis=1,␣
 ↪keys=['Percent', "Train Missing Count"])
missing_application_train_data.head(20)
```

[ ]:
```
                          Percent  Train Missing Count
COMMONAREA_MEDI            69.870               214865
COMMONAREA_AVG             69.870               214865
COMMONAREA_MODE            69.870               214865
NONLIVINGAPARTMENTS_MODE   69.430               213514
NONLIVINGAPARTMENTS_AVG    69.430               213514
NONLIVINGAPARTMENTS_MEDI   69.430               213514
FONDKAPREMONT_MODE         68.390               210295
LIVINGAPARTMENTS_MODE      68.350               210199
LIVINGAPARTMENTS_AVG       68.350               210199
LIVINGAPARTMENTS_MEDI      68.350               210199
FLOORSMIN_AVG              67.850               208642
FLOORSMIN_MODE             67.850               208642
FLOORSMIN_MEDI             67.850               208642
YEARS_BUILD_MEDI           66.500               204488
YEARS_BUILD_MODE           66.500               204488
YEARS_BUILD_AVG            66.500               204488
OWN_CAR_AGE                65.990               202929
LANDAREA_MEDI              59.380               182590
LANDAREA_MODE              59.380               182590
LANDAREA_AVG               59.380               182590
```

[ ]:

1.2 Features

1.2.1 Correlations

Find the features most correlated to the target. In Phase 2 we limited this to the 10 most positive and 10 most negative. In this phase we expanded that scope to the 20 most positive and 20 most negative.

After listing the most correlated features to the target, we created Seaborn heat maps to test for multicollinearity (if the features are correlated to each other.)

We discovered many features could be safely dropped since they are strongly correlated to a slightly different column.

For example FLOORSMAX_MODE is strongly correlated to FLOORSMAX_MEDI, so we used only FLOORSMAX_MEDI as a model feature.

1.2.2 Correlations to target

[ ]:
```
numeric_columns = train_data.select_dtypes(include=[np.number]).columns
correlations = train_data[numeric_columns].corr()['TARGET'].sort_values()
print('Most Positive Correlations:\n', correlations.tail(10))
print('\nMost Negative Correlations:\n', correlations.head(10))
```

```
Most Positive Correlations:
 FLAG_DOCUMENT_3                0.044
REG_CITY_NOT_LIVE_CITY         0.044
FLAG_EMP_PHONE                 0.046
REG_CITY_NOT_WORK_CITY         0.051
DAYS_ID_PUBLISH                0.051
DAYS_LAST_PHONE_CHANGE         0.055
REGION_RATING_CLIENT           0.059
REGION_RATING_CLIENT_W_CITY    0.061
DAYS_BIRTH                     0.078
TARGET                         1.000
Name: TARGET, dtype: float64

Most Negative Correlations:
 EXT_SOURCE_3                 -0.179
EXT_SOURCE_2                 -0.160
EXT_SOURCE_1                 -0.155
DAYS_EMPLOYED                -0.045
FLOORSMAX_AVG                -0.044
FLOORSMAX_MEDI               -0.044
FLOORSMAX_MODE               -0.043
AMT_GOODS_PRICE              -0.040
REGION_POPULATION_RELATIVE   -0.037
ELEVATORS_AVG                -0.034
Name: TARGET, dtype: float64
```

Print out most correlated features in list form to use when modeling.

```
[ ]: most_pos_corr = correlations.tail(21)
     most_neg_corr = correlations.head(20)

     neg_cols = most_neg_corr.index.to_list()
     pos_cols = most_pos_corr.index.to_list()
```

1.2.3 Check for multicollinearity in the top 20 features

We use only 10,000 randomly sampled rows as the original dataset was slow to work with.

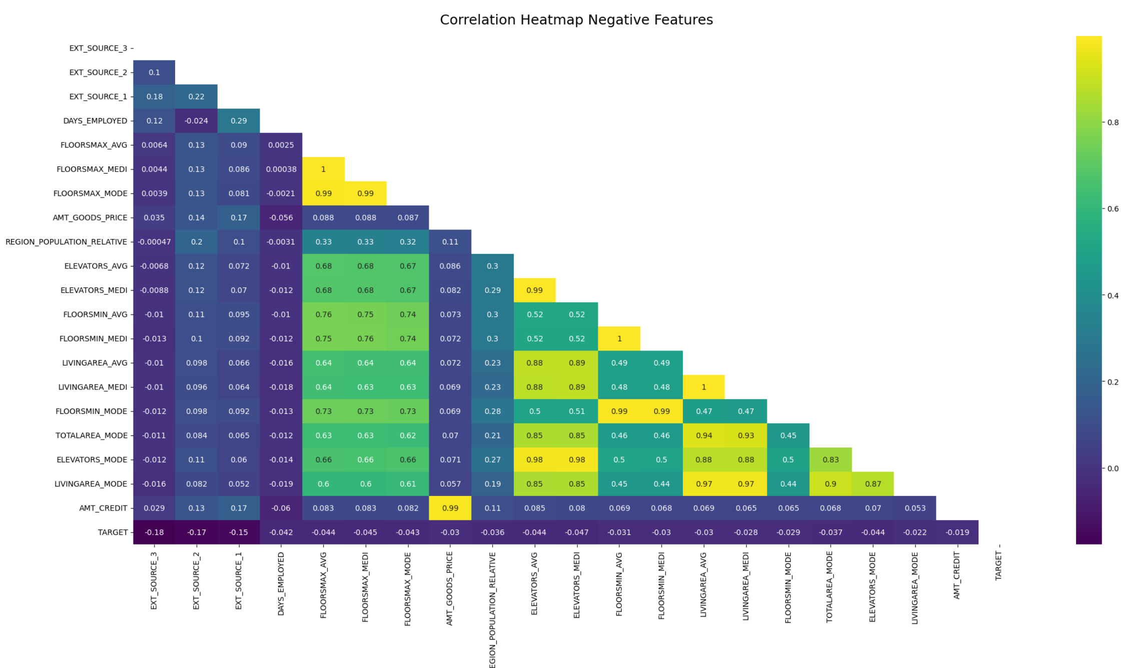
```
[ ]: train_data = train_data.sample(10_000)
```

```
[ ]: plt.figure(figsize=(26, 12))

     # define the mask to set the values in the upper triangle to True
     mask = np.triu(np.ones_like(train_data[neg_cols + ['TARGET']].corr(),␣
      ↪dtype=bool))

     top_20_heatmap = sns.heatmap(train_data[neg_cols + ['TARGET']].corr(),␣
      ↪mask=mask, annot=True, cmap='viridis')

     top_20_heatmap.set_title('Correlation Heatmap Negative Features',␣
      ↪fontdict={'fontsize':18}, pad=16);
```



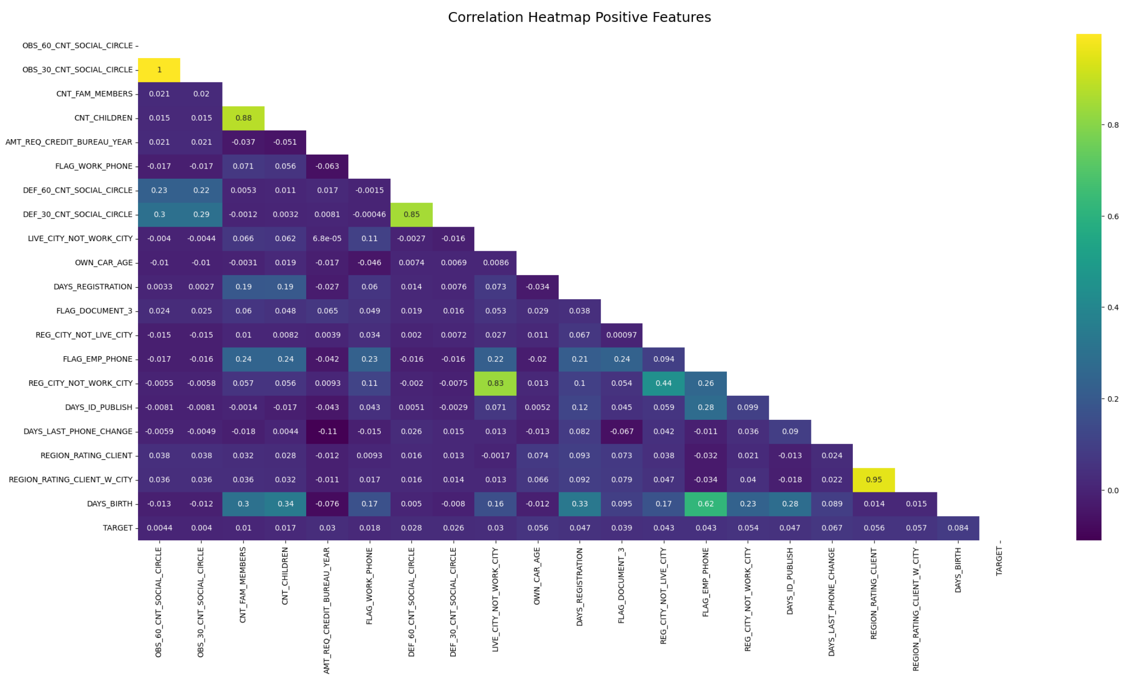
[ ]:

```python
plt.figure(figsize=(26, 12))

# define the mask to set the values in the upper triangle to True
mask = np.triu(np.ones_like(train_data[pos_cols].corr(), dtype=bool))

top_20_heatmap = sns.heatmap(train_data[pos_cols].corr(), mask=mask, annot=True, cmap='viridis')

top_20_heatmap.set_title('Correlation Heatmap Positive Features', fontdict={'fontsize':18}, pad=16);
```



1.2.4 Recency, Frequency and Monetary feature

Recency: How recently a customer has made a purchase. Time elapsed since customer's last purchase.

Frequency: How often a customer purchases. Number of transactions a customer has made.

Monetary: Represents how much money customer has spent on purchases. Sum of all transactions.

Typically each measure is scaled 1 to 5 with 5 being the best customer (recent purchase, frequent purchases, high spending)

How to translate to loans?

Monetary seems to translate well to loans. An applicant who borrows large amounts of money, all else being equal, would be a good customer. Then again if an appicant just borrowed a lot of money, it might not be logical to loan them even more money. Maybe the other features will account for how well the applicant is managing the previous high dollar loan.

Frequnecy might do ok with loans. An applicant who borrows frequnently, all else being equal, would be a good customer.

Recency might not do as well with loans. Is it good that a recent customer would be applying for another loan? This might depend quite a bit on what the loans are for. A business might take out loans frequently if it is part of their business model to loan money to start projects customers will pay for (home construction comes to mind).

[ ]:
```

```

1.2.5 Inspect loan amount the customer is applying for (`AMT_CREDIT` column)

This feature is not very important, but does have a -0.03 correlation to the target variable.

[ ]:
```
correlations["AMT_CREDIT"]
```

[ ]:
```
-0.03036928646142988
```

[ ]:
```
train_data["AMT_CREDIT"].describe()
```

[ ]:
```
count     10000.000
mean     601382.803
std      405995.920
min       45000.000
25%      270000.000
50%      512721.000
75%      810000.000
max     3600000.000
Name: AMT_CREDIT, dtype: float64
```

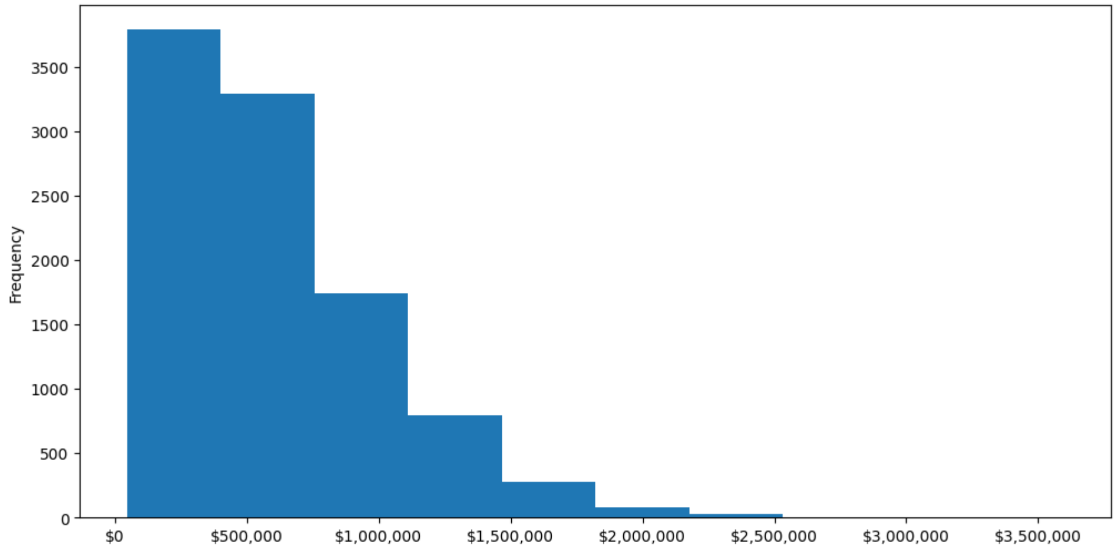
[ ]:
```
plt.figure(figsize=(12, 6))

ax = plt.gca()

def format_dollars(x, pos):
    """Format a number in dollars with commas."""
    return "${:,.0f}".format(x)

# Set the x-axis tick formatter to use the custom function
ax.xaxis.set_major_formatter(ticker.FuncFormatter(format_dollars))

ax.ticklabel_format(axis='y', style='plain')
train_data["AMT_CREDIT"].plot.hist();
```



There are some extremely high values that could be skewing the model's performance. One possible solution is to create a new feature which would create bins of the amounts.

For example, create bins of small, medium and large loan values.

We attempted to create a Transformer to perform this logic in a pipeline but ultimately could figure out the correct Python code to implement it.

[ ]:
```
# Define the bin edges for 'small', 'medium', and 'large' loans
bin_edges = (45000, 200000, 800000, 3000000)

# Define the corresponding category labels
bin_labels = ['small', 'medium', 'large']
```

1.2.6 DAYS_EMPLOYED feature analysis

In performing deeper analysis of the feature set, we found that the DAYS_EMPLOYED feature analysis column contained many rows of the number 365243. The Kaggle documentation describes this column as "How many days before the application the person started current employment" and expects a negative value.

[ ]:
```
train_data['DAYS_EMPLOYED'].describe()
```

[ ]:
```
count     10000.000
mean      62648.627
std      140304.398
min      -16607.000
25%       -2771.250
50%       -1188.500
75%        -292.000
```

```
max     365243.000
Name: DAYS_EMPLOYED, dtype: float64
```

[ ]:
```
# Convert the value counts to a DataFrame
days_employed_counts = train_data['DAYS_EMPLOYED'].value_counts().to_frame().
 ↪reset_index()

# Rename columns if necessary
days_employed_counts.columns = ['Value', 'Count']

# Sort by Count in descending order
days_employed_counts.sort_values(by='Count', ascending=False)[:10]
```

[ ]:

	Value	Count
0	365243	1769
2	-194	10
1	-118	10
8	-161	8
12	-237	8
11	-185	8
10	-609	8
9	-287	8
13	-232	8
7	-201	8

After keeping only negative values, the `DAYS_EMPLOYED` = "How many days before the application the person started current employment"

[ ]:
```
train_data[train_data['DAYS_EMPLOYED'] < 0]['DAYS_EMPLOYED'].describe()
```

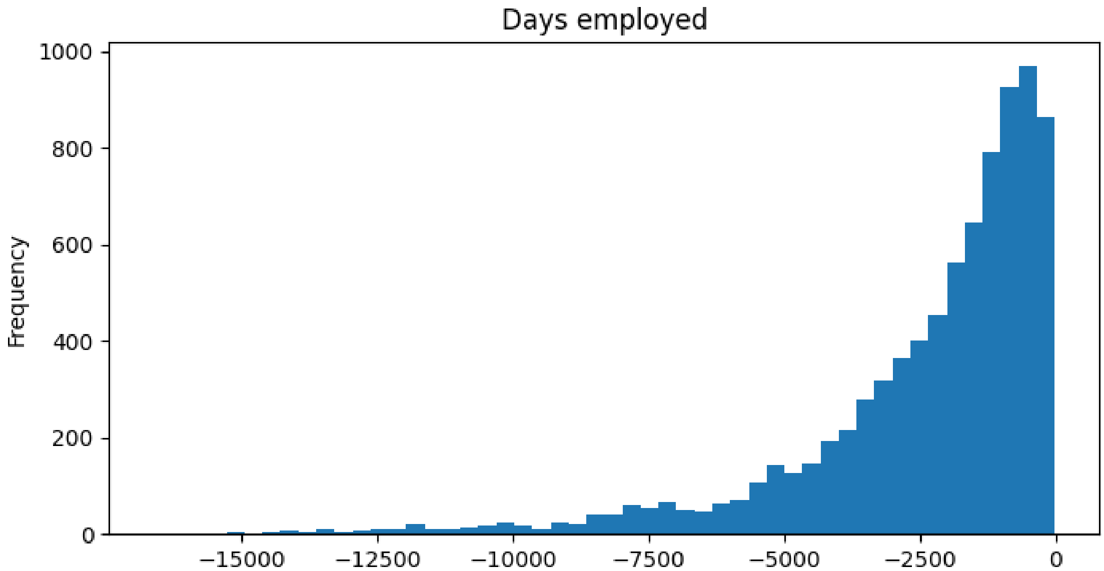
[ ]:
```
count     8231.000
mean     -2384.716
std       2372.393
min     -16607.000
25%      -3178.000
50%      -1625.000
75%       -752.500
max         -9.000
Name: DAYS_EMPLOYED, dtype: float64
```

[ ]:
```
plt.figure(figsize=(8, 4))

ax = plt.gca()

ax.ticklabel_format(axis='y', style='plain')

plt.title('Days employed')
train_data[train_data['DAYS_EMPLOYED'] < 0]['DAYS_EMPLOYED'].plot.hist(bins=50);
```



The histogram plot above shows the `DAYS_EMPLOYED` values after removing the erroneous rows containing 365243.

1.2.7 Model feature list

The final list of features to be used as inputs to the models. * FLOORSMAX_MEDI * ELEVATORS_MEDI * FLOORSMIN_MEDI * AMT_CREDIT * TOTALAREA_MODE * DAYS_EMPLOYED * OBS_30_CNT_SOCIAL_CIRCLE * CNT_FAM_MEMBERs * CNT_CHILDREN * OWN_CAR_AGE * DAYS_ID_PUBLISH * DAYS_LAST_PHONE_CHANGE * CODE_GENDER * OCCUPATION_TYPE * AMT_INCOME_TOTAL

Newly engineered features: * RECENCY_FEATURE * FREQUENCY_FEATURE * MONETARY_VALUE

2 Train, Test, Split data from `application_train.csv`

Initial attempts were crashing kernels because the dataset was too large (over 300,000 records)

We are taking a random sample of 10,000 rows to allow our models to function. Future models may expand the size of the model training set to improve model performance.

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

[ ]:
```
(10000, 122)
```

Create training, validation and testing data.

[ ]:
```python
X = train_data.drop('TARGET', axis=1)
y = train_data['TARGET']

# Split the provided training data into training and validationa and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15,␣
↪random_state=42)
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train,␣
↪test_size=0.2, random_state=42)
print(f"X train           shape: {X_train.shape}")
print(f"X validation      shape: {X_valid.shape}")
print(f"X test            shape: {X_test.shape}")


X_train.head()
```

```
X train           shape: (6800, 121)
X validation      shape: (1700, 121)
X test            shape: (1500, 121)
```

[ ]:
```
        SK_ID_CURR NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
297168      444286         Cash loans           M            Y
195175      326321         Cash loans           F            Y
105807      222774         Cash loans           F            N
40228       146602         Cash loans           F            N
15971       118637         Cash loans           F            N

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
297168               Y             1        112500.000  301464.000
195175               Y             1        180000.000  675000.000
105807               N             0        135000.000 1066320.000
40228                N             1         67500.000  339241.500
15971                N             0        135000.000  450000.000

        AMT_ANNUITY  AMT_GOODS_PRICE  … FLAG_DOCUMENT_18 FLAG_DOCUMENT_19  \
297168    23949.000       238500.000  …                0                0
195175    32602.500       675000.000  …                0                0
105807    38299.500       900000.000  …                0                0
40228     15943.500       238500.000  …                0                0
15971     16965.000       450000.000  …                0                0

       FLAG_DOCUMENT_20 FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR  \
297168                0                0                        NaN
195175                0                0                      0.000
105807                0                0                      0.000
40228                 0                0                      0.000
15971                 0                0                      0.000
```

```
        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
297168                        NaN                         NaN
195175                      0.000                       0.000
105807                      0.000                       1.000
40228                       0.000                       0.000
15971                       0.000                       0.000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
297168                        NaN                        NaN
195175                      0.000                      0.000
105807                      0.000                      0.000
40228                       0.000                      1.000
15971                       0.000                      0.000

        AMT_REQ_CREDIT_BUREAU_YEAR
297168                         NaN
195175                       1.000
105807                       2.000
40228                        0.000
15971                        3.000

[5 rows x 121 columns]
```

[ ]:

```

```

3 Pipelines

3.1 Pipeline Block Diagrams

3.2 Dataset issue

Data is organized by loan ID not customer ID

4 Load Dependencies and data

[ ]:

```
# from google.colab import files
# files.upload()
```

[ ]:

```
# ! mkdir ~/.kaggle
# ! cp kaggle.json ~/.kaggle/
# ! chmod 600 ~/.kaggle/kaggle.json
# ! kaggle datasets list
```

```
[ ]: # DATA_DIR = "/HCDR/DATA_DIR"   #same level as course repo in the data directory
     # #DATA_DIR = os.path.join('./ddddd/')
     # !mkdir DATA_DIR

     # ! kaggle competitions download home-credit-default-risk -p $DATA_DIR
     # !ls -l $DATA_DIR
```

```
[ ]: # import zipfile
     # unzippingReq = True #True
     # if unzippingReq: #please modify this code
     #     zip_ref = zipfile.ZipFile(f'{DATA_DIR}/home-credit-default-risk.zip', 'r')
     #     # extractall():  Extract all members from the archive to the current␣
      ↪working directory. path specifies a different directory to extract to
     #     zip_ref.extractall(f'{DATA_DIR}')
     #     zip_ref.close()
```

```
[ ]: # !ls -l $DATA_DIR
```

```
[ ]: import pandas as pd
     train_data = pd.read_csv('/HCDR/DATA_DIR/application_train.csv') #data we have␣
      ↪the target class for

     test_data = pd.read_csv('/HCDR/DATA_DIR/application_test.csv') #data we need to␣
      ↪predict target class for, for competition

     col_names = test_data.columns.values.tolist()
     col_names.sort()
     print(col_names)
```

```
['AMT_ANNUITY', 'AMT_CREDIT', 'AMT_GOODS_PRICE', 'AMT_INCOME_TOTAL',
'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_HOUR',
'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_YEAR', 'APARTMENTS_AVG',
'APARTMENTS_MEDI', 'APARTMENTS_MODE', 'BASEMENTAREA_AVG', 'BASEMENTAREA_MEDI',
'BASEMENTAREA_MODE', 'CNT_CHILDREN', 'CNT_FAM_MEMBERS', 'CODE_GENDER',
'COMMONAREA_AVG', 'COMMONAREA_MEDI', 'COMMONAREA_MODE', 'DAYS_BIRTH',
'DAYS_EMPLOYED', 'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE',
'DAYS_REGISTRATION', 'DEF_30_CNT_SOCIAL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE',
'ELEVATORS_AVG', 'ELEVATORS_MEDI', 'ELEVATORS_MODE', 'EMERGENCYSTATE_MODE',
'ENTRANCES_AVG', 'ENTRANCES_MEDI', 'ENTRANCES_MODE', 'EXT_SOURCE_1',
'EXT_SOURCE_2', 'EXT_SOURCE_3', 'FLAG_CONT_MOBILE', '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_2', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21',
'FLAG_DOCUMENT_3', 'FLAG_DOCUMENT_4', 'FLAG_DOCUMENT_5', 'FLAG_DOCUMENT_6',
'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9', 'FLAG_EMAIL',
'FLAG_EMP_PHONE', 'FLAG_MOBIL', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'FLAG_PHONE',
'FLAG_WORK_PHONE', 'FLOORSMAX_AVG', 'FLOORSMAX_MEDI', 'FLOORSMAX_MODE',
```

```
'FLOORSMIN_AVG', 'FLOORSMIN_MEDI', 'FLOORSMIN_MODE', 'FONDKAPREMONT_MODE',
'HOUR_APPR_PROCESS_START', 'HOUSETYPE_MODE', 'LANDAREA_AVG', 'LANDAREA_MEDI',
'LANDAREA_MODE', 'LIVE_CITY_NOT_WORK_CITY', 'LIVE_REGION_NOT_WORK_REGION',
'LIVINGAPARTMENTS_AVG', 'LIVINGAPARTMENTS_MEDI', 'LIVINGAPARTMENTS_MODE',
'LIVINGAREA_AVG', 'LIVINGAREA_MEDI', 'LIVINGAREA_MODE', 'NAME_CONTRACT_TYPE',
'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE',
'NAME_INCOME_TYPE', 'NAME_TYPE_SUITE', 'NONLIVINGAPARTMENTS_AVG',
'NONLIVINGAPARTMENTS_MEDI', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVINGAREA_AVG',
'NONLIVINGAREA_MEDI', 'NONLIVINGAREA_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE',
'OBS_60_CNT_SOCIAL_CIRCLE', 'OCCUPATION_TYPE', 'ORGANIZATION_TYPE',
'OWN_CAR_AGE', 'REGION_POPULATION_RELATIVE', 'REGION_RATING_CLIENT',
'REGION_RATING_CLIENT_W_CITY', 'REG_CITY_NOT_LIVE_CITY',
'REG_CITY_NOT_WORK_CITY', 'REG_REGION_NOT_LIVE_REGION',
'REG_REGION_NOT_WORK_REGION', 'SK_ID_CURR', 'TOTALAREA_MODE',
'WALLSMATERIAL_MODE', 'WEEKDAY_APPR_PROCESS_START',
'YEARS_BEGINEXPLUATATION_AVG', 'YEARS_BEGINEXPLUATATION_MEDI',
'YEARS_BEGINEXPLUATATION_MODE', 'YEARS_BUILD_AVG', 'YEARS_BUILD_MEDI',
'YEARS_BUILD_MODE']
```

4.1 Feature Engineering

[ ]:
```
import numpy as np
import pandas as pd
PrevApp_data = pd.read_csv('/HCDR/DATA_DIR/previous_application.csv') #data␣
↪from previous applications to Home Credit
print(np.shape(PrevApp_data))
col_names = PrevApp_data.columns.values.tolist()
col_names.sort()
print(col_names)
```

```
(1670214, 37)
['AMT_ANNUITY', 'AMT_APPLICATION', 'AMT_CREDIT', 'AMT_DOWN_PAYMENT',
'AMT_GOODS_PRICE', 'CHANNEL_TYPE', 'CNT_PAYMENT', 'CODE_REJECT_REASON',
'DAYS_DECISION', 'DAYS_FIRST_DRAWING', 'DAYS_FIRST_DUE', 'DAYS_LAST_DUE',
'DAYS_LAST_DUE_1ST_VERSION', 'DAYS_TERMINATION', 'FLAG_LAST_APPL_PER_CONTRACT',
'HOUR_APPR_PROCESS_START', 'NAME_CASH_LOAN_PURPOSE', 'NAME_CLIENT_TYPE',
'NAME_CONTRACT_STATUS', 'NAME_CONTRACT_TYPE', 'NAME_GOODS_CATEGORY',
'NAME_PAYMENT_TYPE', 'NAME_PORTFOLIO', 'NAME_PRODUCT_TYPE',
'NAME_SELLER_INDUSTRY', 'NAME_TYPE_SUITE', 'NAME_YIELD_GROUP',
'NFLAG_INSURED_ON_APPROVAL', 'NFLAG_LAST_APPL_IN_DAY', 'PRODUCT_COMBINATION',
'RATE_DOWN_PAYMENT', 'RATE_INTEREST_PRIMARY', 'RATE_INTEREST_PRIVILEGED',
'SELLERPLACE_AREA', 'SK_ID_CURR', 'SK_ID_PREV', 'WEEKDAY_APPR_PROCESS_START']
```

[ ]:
```
PrevApp_data.head(5)
```

[ ]:
```
   SK_ID_PREV  SK_ID_CURR NAME_CONTRACT_TYPE  AMT_ANNUITY  AMT_APPLICATION  \
0     2030495      271877     Consumer loans     1730.430        17145.000
1     2802425      108129         Cash loans    25188.615       607500.000
```

```
2     2523466      122040         Cash loans    15060.735       112500.000
3     2819243      176158         Cash loans    47041.335       450000.000
4     1784265      202054         Cash loans    31924.395       337500.000

   AMT_CREDIT  AMT_DOWN_PAYMENT  AMT_GOODS_PRICE WEEKDAY_APPR_PROCESS_START  \
0   17145.000             0.000        17145.000                   SATURDAY
1  679671.000               NaN       607500.000                   THURSDAY
2  136444.500               NaN       112500.000                    TUESDAY
3  470790.000               NaN       450000.000                     MONDAY
4  404055.000               NaN       337500.000                   THURSDAY

   HOUR_APPR_PROCESS_START  … NAME_SELLER_INDUSTRY  CNT_PAYMENT  \
0                       15  …         Connectivity       12.000
1                       11  …                  XNA       36.000
2                       11  …                  XNA       12.000
3                        7  …                  XNA       12.000
4                        9  …                  XNA       24.000

   NAME_YIELD_GROUP       PRODUCT_COMBINATION  DAYS_FIRST_DRAWING  \
0            middle  POS mobile with interest          365243.000
1        low_action          Cash X-Sell: low          365243.000
2              high         Cash X-Sell: high          365243.000
3            middle       Cash X-Sell: middle          365243.000
4              high         Cash Street: high                 NaN

  DAYS_FIRST_DUE DAYS_LAST_DUE_1ST_VERSION  DAYS_LAST_DUE DAYS_TERMINATION  \
0        -42.000                   300.000        -42.000          -37.000
1       -134.000                   916.000     365243.000       365243.000
2       -271.000                    59.000     365243.000       365243.000
3       -482.000                  -152.000       -182.000         -177.000
4            NaN                       NaN            NaN              NaN

  NFLAG_INSURED_ON_APPROVAL
0                     0.000
1                     1.000
2                     1.000
3                     1.000
4                       NaN

[5 rows x 37 columns]
```

[ ]:
```
!pip install --upgrade 'sqlalchemy<2.0'
!pip install -U pandasql
```

```
Requirement already satisfied: sqlalchemy<2.0 in /usr/local/lib/python3.10/dist-
packages (1.4.52)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.10/dist-packages (from sqlalchemy<2.0) (3.0.3)
```

```
Requirement already satisfied: pandasql in /usr/local/lib/python3.10/dist-
packages (0.7.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from pandasql) (1.25.2)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages
(from pandasql) (2.0.3)
Requirement already satisfied: sqlalchemy in /usr/local/lib/python3.10/dist-
packages (from pandasql) (1.4.52)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas->pandasql) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
packages (from pandas->pandasql) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas->pandasql) (2024.1)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.10/dist-packages (from sqlalchemy->pandasql) (3.0.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-
packages (from python-dateutil>=2.8.2->pandas->pandasql) (1.16.0)
```

[ ]:
```
from pandasql import sqldf

augmented_train_data = sqldf('''
with rfm as (select
SK_ID_CURR, sum(AMT_CREDIT) as MONETARY_VALUE,
max(DAYS_DECISION) as RECENCY_FEATURE,
(max(DAYS_DECISION) - min(DAYS_DECISION))/COUNT(DISTINCT SK_ID_PREV) as␣
↪FREQUENCY_FEATURE
from PrevApp_data
where AMT_CREDIT <> 0
group by 1
)
select train.*, rfm.RECENCY_FEATURE, rfm.FREQUENCY_FEATURE, rfm.MONETARY_VALUE
from train_data train
left join rfm
on train.SK_ID_CURR = rfm.SK_ID_CURR
''')
augmented_train_data
```

[ ]:
```
        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  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                    Y             0        202500.000  406597.500
1                    N             0        270000.000 1293502.500
2                    Y             0         67500.000  135000.000
3                    Y             0        135000.000  312682.500
4                    Y             0        121500.000  513000.000
…                  …             …                …          …
307506               N             0        157500.000  254700.000
307507               Y             0         72000.000  269550.000
307508               Y             0        153000.000  677664.000
307509               Y             0        171000.000  370107.000
307510               N             0        157500.000  675000.000

        AMT_ANNUITY  …  FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR  \
0         24700.500  …                 0                      0.000
1         35698.500  …                 0                      0.000
2          6750.000  …                 0                      0.000
3         29686.500  …                 0                        NaN
4         21865.500  …                 0                      0.000
…               …  …               …                         …
307506    27558.000  …                 0                        NaN
307507    12001.500  …                 0                        NaN
307508    29979.000  …                 0                      1.000
307509    20205.000  …                 0                      0.000
307510    49117.500  …                 0                      0.000

       AMT_REQ_CREDIT_BUREAU_DAY AMT_REQ_CREDIT_BUREAU_WEEK  \
0                          0.000                      0.000
1                          0.000                      0.000
2                          0.000                      0.000
3                            NaN                        NaN
4                          0.000                      0.000
…                          …                        …
307506                       NaN                        NaN
307507                       NaN                        NaN
307508                     0.000                      0.000
307509                     0.000                      0.000
307510                     0.000                      0.000

       AMT_REQ_CREDIT_BUREAU_MON AMT_REQ_CREDIT_BUREAU_QRT  \
0                          0.000                     0.000
1                          0.000                     0.000
2                          0.000                     0.000
```

```
3                             NaN                         NaN
4                           0.000                       0.000
…                             …                         …
307506                        NaN                         NaN
307507                        NaN                         NaN
307508                      1.000                       0.000
307509                      0.000                       0.000
307510                      2.000                       0.000

        AMT_REQ_CREDIT_BUREAU_YEAR  RECENCY_FEATURE  FREQUENCY_FEATURE  \
0                            1.000         -606.000              0.000
1                            0.000         -746.000            531.000
2                            0.000         -815.000              0.000
3                              NaN         -181.000             72.000
4                            0.000         -374.000            330.000
…                              …             …                 …
307506                         NaN         -273.000              0.000
307507                         NaN        -2497.000              0.000
307508                       1.000        -1909.000            471.000
307509                       0.000         -277.000             22.000
307510                       1.000         -171.000            102.000

        MONETARY_VALUE
0           179055.000
1          1452573.000
2            20106.000
3          2625259.500
4           999832.500
…                 …
307506       40455.000
307507       56821.500
307508       41251.500
307509      268879.500
307510     3395448.000

[307511 rows x 125 columns]
```

[ ]:
```
filtered_train_data = sqldf('''
SELECT
  TARGET,
  FLOORSMAX_MEDI,
  ELEVATORS_MEDI,
  FLOORSMIN_MEDI,
  AMT_CREDIT,
  TOTALAREA_MODE,
  DAYS_EMPLOYED,
  OBS_30_CNT_SOCIAL_CIRCLE,
```

```
  CNT_FAM_MEMBERs,
  CNT_CHILDREN,
  OWN_CAR_AGE,
  DAYS_ID_PUBLISH,
  DAYS_LAST_PHONE_CHANGE,
  CODE_GENDER,
  OCCUPATION_TYPE,
  AMT_INCOME_TOTAL,
  RECENCY_FEATURE,
  FREQUENCY_FEATURE,
  MONETARY_VALUE
FROM
  augmented_train_data
''')
```

[ ]:

```
filtered_train_data
```

[ ]:

```
        TARGET  FLOORSMAX_MEDI  ELEVATORS_MEDI  FLOORSMIN_MEDI  AMT_CREDIT  \
0            1           0.083           0.000           0.125  406597.500
1            0           0.292           0.080           0.333 1293502.500
2            0             NaN             NaN             NaN  135000.000
3            0             NaN             NaN             NaN  312682.500
4            0             NaN             NaN             NaN  513000.000
…          …             …             …             …          …
307506       0           0.604           0.220           0.271  254700.000
307507       0           0.083           0.000           0.125  269550.000
307508       0           0.167           0.000           0.208  677664.000
307509       1           0.042             NaN             NaN  370107.000
307510       0           0.375           0.080             NaN  675000.000

        TOTALAREA_MODE  DAYS_EMPLOYED  OBS_30_CNT_SOCIAL_CIRCLE  \
0                0.015           -637                     2.000
1                0.071          -1188                     1.000
2                  NaN           -225                     0.000
3                  NaN          -3039                     2.000
4                  NaN          -3038                     0.000
…                  …             …                       …
307506           0.290           -236                     0.000
307507           0.021         365243                     0.000
307508           0.797          -7921                     6.000
307509           0.009          -4786                     0.000
307510           0.072          -1262                     0.000

        CNT_FAM_MEMBERS  CNT_CHILDREN  OWN_CAR_AGE  DAYS_ID_PUBLISH  \
0                 1.000             0          NaN            -2120
1                 2.000             0          NaN             -291
2                 1.000             0       26.000            -2531
```

```
3                2.000          0        NaN          -2437
4                1.000          0        NaN          -3458
…                …          …       …            …
307506           1.000          0        NaN          -1982
307507           1.000          0        NaN          -4090
307508           1.000          0        NaN          -5150
307509           2.000          0        NaN           -931
307510           2.000          0        NaN           -410

        DAYS_LAST_PHONE_CHANGE CODE_GENDER OCCUPATION_TYPE  AMT_INCOME_TOTAL  \
0                    -1134.000           M        Laborers        202500.000
1                     -828.000           F      Core staff        270000.000
2                     -815.000           M        Laborers         67500.000
3                     -617.000           F        Laborers        135000.000
4                    -1106.000           M      Core staff        121500.000
…                          …        …              …              …
307506                -273.000           M     Sales staff        157500.000
307507                   0.000           F            None         72000.000
307508               -1909.000           F        Managers        153000.000
307509                -322.000           F        Laborers        171000.000
307510                -787.000           F        Laborers        157500.000

        RECENCY_FEATURE  FREQUENCY_FEATURE  MONETARY_VALUE
0              -606.000              0.000      179055.000
1              -746.000            531.000     1452573.000
2              -815.000              0.000       20106.000
3              -181.000             72.000     2625259.500
4              -374.000            330.000      999832.500
…                   …                …              …
307506         -273.000              0.000       40455.000
307507        -2497.000              0.000       56821.500
307508        -1909.000            471.000       41251.500
307509         -277.000             22.000      268879.500
307510         -171.000            102.000     3395448.000

[307511 rows x 19 columns]
```

[ ]:
```
from pandasql import sqldf

augmented_test_data = sqldf('''
with rfm as (select
   SK_ID_CURR, sum(AMT_CREDIT) as MONETARY_VALUE,
   max(DAYS_DECISION) as RECENCY_FEATURE,
   (max(DAYS_DECISION) - min(DAYS_DECISION))/COUNT(DISTINCT SK_ID_PREV) as␣
 ↪FREQUENCY_FEATURE
from PrevApp_data
where AMT_CREDIT <> 0
```

```
group by 1
)
select train.*, rfm.RECENCY_FEATURE, rfm.FREQUENCY_FEATURE, rfm.MONETARY_VALUE
from test_data train
left join rfm
on train.SK_ID_CURR = rfm.SK_ID_CURR
''')
filtered_test_data = sqldf('''
SELECT
   FLOORSMAX_MEDI,
   ELEVATORS_MEDI,
   FLOORSMIN_MEDI,
   AMT_CREDIT,
   TOTALAREA_MODE,
   DAYS_EMPLOYED,
   OBS_30_CNT_SOCIAL_CIRCLE,
   CNT_FAM_MEMBERs,
   CNT_CHILDREN,
   OWN_CAR_AGE,
   DAYS_ID_PUBLISH,
   DAYS_LAST_PHONE_CHANGE,
   CODE_GENDER,
   OCCUPATION_TYPE,
   AMT_INCOME_TOTAL,
   RECENCY_FEATURE,
   FREQUENCY_FEATURE,
   MONETARY_VALUE
 FROM
   augmented_test_data

''')
filtered_test_data
```

[ ]:

```
       FLOORSMAX_MEDI  ELEVATORS_MEDI  FLOORSMIN_MEDI  AMT_CREDIT  \
0               0.125             NaN             NaN   568800.000
1                 NaN             NaN             NaN   222768.000
2                 NaN             NaN             NaN   663264.000
3               0.375           0.320           0.042 1575000.000
4                 NaN             NaN             NaN   625500.000
…                 …             …             …           …
48739             NaN             NaN             NaN   412560.000
48740             NaN             NaN             NaN   622413.000
48741           0.333           0.160             NaN   315000.000
48742           0.625           0.160             NaN   450000.000
48743             NaN             NaN             NaN   312768.000

       TOTALAREA_MODE  DAYS_EMPLOYED  OBS_30_CNT_SOCIAL_CIRCLE  \
```

```
0               0.039          -2329                      0.000
1                 NaN          -4469                      0.000
2                 NaN          -4458                      0.000
3               0.370          -1866                      0.000
4                 NaN          -2191                      0.000
…                 …             …                        …
48739             NaN          -5169                      1.000
48740             NaN          -1149                      2.000
48741           0.166          -3037                      0.000
48742           0.197          -2731                      0.000
48743             NaN           -633                      0.000

       CNT_FAM_MEMBERS  CNT_CHILDREN  OWN_CAR_AGE  DAYS_ID_PUBLISH  \
0                2.000             0          NaN             -812
1                2.000             0          NaN            -1623
2                2.000             0        5.000            -3503
3                4.000             2          NaN            -4208
4                3.000             1       16.000            -4262
…                 …             …           …               …
48739            1.000             0          NaN            -3399
48740            4.000             2          NaN            -3003
48741            3.000             1        4.000            -1504
48742            2.000             0          NaN            -1364
48743            2.000             0       22.000            -4220

       DAYS_LAST_PHONE_CHANGE CODE_GENDER     OCCUPATION_TYPE  \
0                   -1740.000           F                None
1                       0.000           M  Low-skill Laborers
2                    -856.000           M             Drivers
3                   -1805.000           F         Sales staff
4                    -821.000           M                None
…                        …          …                  …
48739                -684.000           F                None
48740                   0.000           F         Sales staff
48741                -838.000           F                None
48742               -2308.000           M            Managers
48743                -327.000           F          Core staff

       AMT_INCOME_TOTAL  RECENCY_FEATURE  FREQUENCY_FEATURE  MONETARY_VALUE
0            135000.000        -1740.000              0.000       23787.000
1             99000.000         -757.000              0.000       40153.500
2            202500.000         -273.000            575.000      584536.500
3            315000.000         -797.000            252.000      464602.500
4            180000.000         -111.000            355.000      601101.000
…                  …               …                 …              …
48739        121500.000         -683.000              0.000      254700.000
48740        157500.000         -770.000            420.000      394816.500
```

```
48741        202500.000          -84.000             377.000       265033.665
48742        225000.000         -577.000             432.000       637893.000
48743        135000.000         -327.000             148.000      1166746.500

[48744 rows x 18 columns]
```

[ ]:
```
filtered_train_data.columns
```

[ ]:
```
Index(['TARGET', 'FLOORSMAX_MEDI', 'ELEVATORS_MEDI', 'FLOORSMIN_MEDI',
       'AMT_CREDIT', 'TOTALAREA_MODE', 'DAYS_EMPLOYED',
       'OBS_30_CNT_SOCIAL_CIRCLE', 'CNT_FAM_MEMBERS', 'CNT_CHILDREN',
       'OWN_CAR_AGE', 'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE',
       'CODE_GENDER', 'OCCUPATION_TYPE', 'AMT_INCOME_TOTAL', 'RECENCY_FEATURE',
       'FREQUENCY_FEATURE', 'MONETARY_VALUE'],
      dtype='object')
```

5 Subset the data to test pipelines

[ ]:
```
#train_data = train_data.sample(1000)

#print (f'Train data size:{train_data.shape[0]} rows')
```

6 Create models and pipelines

6.1 Hyperparameter tuning

Below we opted for a GridSearch with Cross Validation to determine the optimal hyperparameters for our models, seeking to directly maximize the ROC AUC.

There are noticeable differences in the size of the parameter grids for the repspective models. This is due to resource allocation of compute power as some models (XGBoost) train and fit much more rapidly than the other models for a similar parameter grid.

Create a custom transformer to use on the DAYS_EMPLOYED column. This replaces any positive number with 0.

[ ]:
```
class ReplaceValuesTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, column):
        self.column = column

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X_copy = X.copy()
        X_copy[self.column] = X_copy[self.column].apply(lambda x: 0 if x > 0␣
↪else x)
        return X_copy
```

6.2 XG Boost Pipeline

[ ]:
```
filtered_train_data_sample = filtered_train_data.sample(75000)
X = filtered_train_data_sample.drop(columns=['TARGET'])
y = filtered_train_data_sample['TARGET']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Sample data
#X = train_data.drop(columns=['TARGET'])
#y = train_data['TARGET']
#X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Define column transformer for numerical and categorical features
numeric_features = ['FLOORSMAX_MEDI', 'ELEVATORS_MEDI', 'FLOORSMIN_MEDI',
       'AMT_CREDIT', 'TOTALAREA_MODE', 'DAYS_EMPLOYED',
       'OBS_30_CNT_SOCIAL_CIRCLE', 'CNT_FAM_MEMBERS', 'CNT_CHILDREN',
       'OWN_CAR_AGE', 'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE']  # List of␣
↪numerical feature column indices
categorical_features = ['CODE_GENDER','OCCUPATION_TYPE']  # List of categorical␣
↪feature column indices

numeric_transformer = Pipeline(steps=[
    ('replace_values', ReplaceValuesTransformer(column='DAYS_EMPLOYED')),
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())

])

categorical_transformer = Pipeline(steps=[
     ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Create the pipeline with the preprocessor and XGBoost classifier
xgb_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', XGBClassifier())
])
```

```
# Fit the pipeline on the training data
xgb_pipeline.fit(X_train, y_train)

# Predict using the pipeline on the test data
y_pred = xgb_pipeline.predict(X_test)

# Calculate the accuracy of the classifier
xgb_score_pre_tuning = roc_auc_score(y_test, y_pred)
print()
print(f"ROC AUC score before tuning: {xgb_score_pre_tuning:.04f}")
```

```
ROC AUC score before tuning: 0.4997
```

6.2.1 Create log for model results.

[ ]:
```
try:
    del expLog
except:
    pass

exp_name = "XGBoost_baseline"
try:
    expLog
except NameError:
    expLog = DataFrame(columns=["exp_name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train F1",
                                   "Valid F1",
                                   "Test  F1"
                                  ])

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, xgb_pipeline.predict(X_train)),
                roc_auc_score(y_valid, xgb_pipeline.predict(X_valid)),
                roc_auc_score(y_test, xgb_pipeline.predict(X_test)),
                f1_score(y_train, xgb_pipeline.predict(X_train)),
                f1_score(y_valid, xgb_pipeline.predict(X_valid)),
                f1_score(y_test, xgb_pipeline.predict(X_test))],
    4))
expLog
```

[ ]:
```
           exp_name  Train Acc  Valid Acc  Test  Acc  Train F1  Valid F1  \
0  XGBoost_baseline      0.520      0.508       0.500     0.079     0.032
```

```
   Test  F1
0     0.000
```

6.3 Define hyperparameters and GridSearch

[ ]:
```
# Define parameter grid for XGBoost classifier
xgb_param_grid = {
    'classifier__n_estimators': [50, 100, 200],
    'classifier__learning_rate': [0.05, 0.1, 0.2],
    'classifier__max_depth': [3, 5, 7],
    'classifier__gamma': [0, 0.1, 0.2, 0.5]
}

# Create GridSearchCV with n_jobs=-1 and scoring='roc_auc'
xgb_grid_search = GridSearchCV(xgb_pipeline, xgb_param_grid, cv=3,␣
 ↪scoring='roc_auc', verbose=3, n_jobs=-1)

# Fit the grid search on the training data
xgb_grid_search.fit(X_train, y_train)

# Get the best estimator from the grid search
best_xgb_pipeline = xgb_grid_search.best_estimator_

# Predict using the best estimator
y_pred = best_xgb_pipeline.predict(X_test)

# Calculate the AUC-ROC of the best estimator
auc_roc = roc_auc_score(y_test, y_pred)
print(f"AUC-ROC: {auc_roc}")
```

```
Fitting 3 folds for each of 108 candidates, totalling 324 fits
AUC-ROC: 0.5
```

Add results to log

[ ]:
```
exp_name = "XGBoost_tuned"

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, best_xgb_pipeline.predict(X_train)),
                roc_auc_score(y_valid, best_xgb_pipeline.predict(X_valid)),
                roc_auc_score(y_test, best_xgb_pipeline.predict(X_test)),
                f1_score(y_train, best_xgb_pipeline.predict(X_train)),
                f1_score(y_valid, best_xgb_pipeline.predict(X_valid)),
                f1_score(y_test, best_xgb_pipeline.predict(X_test))],
    4))
expLog
```

```
[ ]:            exp_name  Train Acc  Valid Acc  Test  Acc  Train F1  Valid F1  \
    0  XGBoost_baseline      0.520      0.508      0.500     0.079     0.032
    1     XGBoost_tuned      0.500      0.500      0.500     0.000     0.000

       Test  F1
    0     0.000
    1     0.000
```

6.4 Define LogisticRegression model

```
[ ]: # List of numerical feature column indices
numeric_features = ['FLOORSMAX_MEDI', 'ELEVATORS_MEDI', 'FLOORSMIN_MEDI',
                    'AMT_CREDIT', 'TOTALAREA_MODE', 'DAYS_EMPLOYED',
                    'OBS_30_CNT_SOCIAL_CIRCLE', 'CNT_FAM_MEMBERS',␣
 ↪'CNT_CHILDREN',
                    'OWN_CAR_AGE', 'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE']

credit_amount_transformer = FunctionTransformer(lambda X: pd.
 ↪cut(X['AMT_CREDIT'], bins=bin_edges, labels=bin_labels,␣
 ↪include_lowest=True), validate=True)

numeric_log_reg_transformer = Pipeline(steps=[

    ('replace_values', ReplaceValuesTransformer(column='DAYS_EMPLOYED')),
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_features = ['CODE_GENDER', 'OCCUPATION_TYPE']

categorical_transformer = Pipeline(steps=[
    # ('credit_amount_binner', credit_amount_transformer),
    ('imputer', SimpleImputer(strategy='most_frequent', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

log_reg_preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_log_reg_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ]
)

log_reg_model = Pipeline(steps=[('preprocessor', log_reg_preprocessor),
                               ('classifier',␣
 ↪LogisticRegression(max_iter=10000))])
```

```
log_reg_model.fit(X_train, y_train)


# Predict using the pipeline on the test data
y_pred_log_reg = log_reg_model.predict(X_test)

# Calculate the accuracy of the classifier
log_reg_score_pre_tuning = roc_auc_score(y_test, y_pred_log_reg)
print()
print(f"ROC AUC score before tuning: {log_reg_score_pre_tuning:.04f}")
```

```
ROC AUC score before tuning: 0.5000
```

Add Logistic Regression baseline to log

[ ]:
```
exp_name = "LogReg_baseline"

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, log_reg_model.predict_proba(X_train)[:,␣
 ↪1]),
                roc_auc_score(y_valid, log_reg_model.predict_proba(X_valid)[:,␣
 ↪1]),
                roc_auc_score(y_test, log_reg_model.predict_proba(X_test)[:,␣
 ↪1]),
                f1_score(y_train, log_reg_model.predict(X_train)),
                f1_score(y_valid, log_reg_model.predict(X_valid)),
                f1_score(y_test, log_reg_model.predict(X_test))],
    4))
expLog
```

[ ]:
```
           exp_name  Train Acc  Valid Acc  Test  Acc  Train F1  Valid F1  \
0  XGBoost_baseline      0.520      0.508      0.500     0.079     0.032
1     XGBoost_tuned      0.500      0.500      0.500     0.000     0.000
2   LogReg_baseline      0.637      0.633      0.655     0.000     0.000

   Test  F1
0     0.000
1     0.000
2     0.000
```

[ ]:
```
# Create the pipeline with the preprocessor and logistic regression classifier
logreg_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(max_iter=10000))
])

logreg_param_grid = {
```

```
    'classifier__C': [0.1, 1],
    'classifier__penalty': ['l1', 'l2'],
    'classifier__solver': ['liblinear', 'saga']
}

# Create GridSearchCV with n_jobs=-1 and scoring='roc_auc'
logreg_grid_search = GridSearchCV(logreg_pipeline, logreg_param_grid, cv=3,␣
↪scoring='roc_auc', verbose=3, n_jobs=-1)

# Fit the grid search on the training data
logreg_grid_search.fit(X_train, y_train)

# Get the best estimator from the grid search
best_logreg_pipeline = logreg_grid_search.best_estimator_

# Predict using the best estimator
y_pred = best_logreg_pipeline.predict_proba(X_test)[:, 1]

# Calculate the AUC-ROC of the best estimator
auc_roc = roc_auc_score(y_test, y_pred)
print(f"AUC-ROC: {auc_roc}")
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
AUC-ROC: 0.6551630168140702
```

[ ]:
```
exp_name = "LogReg_tuned"

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, best_logreg_pipeline.
↪predict_proba(X_train)[:, 1]),
                roc_auc_score(y_valid, best_logreg_pipeline.
↪predict_proba(X_valid)[:, 1]),
                roc_auc_score(y_test, best_logreg_pipeline.
↪predict_proba(X_test)[:, 1]),
                f1_score(y_train, best_logreg_pipeline.predict(X_train)),
                f1_score(y_valid, best_logreg_pipeline.predict(X_valid)),
                f1_score(y_test, best_logreg_pipeline.predict(X_test))],
    4))
expLog
```

[ ]:
```
          exp_name  Train Acc  Valid Acc  Test  Acc  Train F1  Valid F1  \
0  XGBoost_baseline      0.520      0.508      0.500     0.079     0.032
1     XGBoost_tuned      0.500      0.500      0.500     0.000     0.000
2   LogReg_baseline      0.637      0.633      0.655     0.000     0.000
3      LogReg_tuned      0.637      0.633      0.655     0.000     0.000

   Test  F1
```

```
0      0.000
1      0.000
2      0.000
3      0.000
```

6.5 Define KNN model

```
[ ]: # List of numerical feature column indices
numeric_features = ['FLOORSMAX_MEDI', 'ELEVATORS_MEDI', 'FLOORSMIN_MEDI',
                    'AMT_CREDIT', 'TOTALAREA_MODE', 'DAYS_EMPLOYED',
                    'OBS_30_CNT_SOCIAL_CIRCLE', 'CNT_FAM_MEMBERS',␣
 ↪'CNT_CHILDREN',
                    'OWN_CAR_AGE', 'DAYS_ID_PUBLISH', 'DAYS_LAST_PHONE_CHANGE']

credit_amount_transformer = FunctionTransformer(lambda X: pd.
 ↪cut(X['AMT_CREDIT'], bins=bin_edges, labels=bin_labels,␣
 ↪include_lowest=True), validate=True)

numeric_log_reg_transformer = Pipeline(steps=[

    ('replace_values', ReplaceValuesTransformer(column='DAYS_EMPLOYED')),
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical_features = ['CODE_GENDER', 'OCCUPATION_TYPE']

categorical_transformer = Pipeline(steps=[
    # ('credit_amount_binner', credit_amount_transformer),
    ('imputer', SimpleImputer(strategy='most_frequent', fill_value='missing')),
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

knn_preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_log_reg_transformer, numeric_features),
        ('cat', categorical_transformer, categorical_features)
    ]
)

knn_model  = Pipeline(steps=[('preprocessor', knn_preprocessor),
                              ('classifier', KNeighborsClassifier())])

knn_model.fit(X_train, y_train)


# Predict using the pipeline on the test data
```

```
y_pred_knn = knn_model.predict(X_test)

# Calculate the accuracy of the classifier
knn_score_pre_tuning = roc_auc_score(y_test, y_pred_knn)
print()
print(f"ROC AUC score before tuning: {knn_score_pre_tuning:.04f}")
```

```
ROC AUC score before tuning: 0.5049
```

[ ]:
```
exp_name = "KNN_baseline"

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, knn_model.predict(X_train)),
                roc_auc_score(y_valid, knn_model.predict(X_valid)),
                roc_auc_score(y_test, knn_model.predict(X_test)),
                f1_score(y_train, knn_model.predict(X_train)),
                f1_score(y_valid, knn_model.predict(X_valid)),
                f1_score(y_test, knn_model.predict(X_test))],
    4))
expLog
```

[ ]:

	exp_name	Train Acc	Valid Acc	Test Acc	Train F1	Valid F1	\
0	XGBoost_baseline	0.520	0.508	0.500	0.079	0.032	
1	XGBoost_tuned	0.500	0.500	0.500	0.000	0.000	
2	LogReg_baseline	0.637	0.633	0.655	0.000	0.000	
3	LogReg_tuned	0.637	0.633	0.655	0.000	0.000	
4	KNN_baseline	0.534	0.500	0.505	0.129	0.015	

	Test F1
0	0.000
1	0.000
2	0.000
3	0.000
4	0.031

[ ]:
```
# Create the pipeline with the preprocessor and KNN classifier
knn_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', KNeighborsClassifier())
])

knn_param_grid = {
    'classifier__n_neighbors': [3, 5],  # Number of neighbors to use
    'classifier__weights': ['uniform', 'distance'],  # Weighting method for␣
 ↪predictions
}
# Create GridSearchCV with n_jobs=-1 and scoring='roc_auc'
```

```
knn_grid_search = GridSearchCV(knn_pipeline, knn_param_grid, cv=3,␣
↪scoring='roc_auc', verbose=3, n_jobs=-1)

# Fit the grid search on the training data
knn_grid_search.fit(X_train, y_train)

# Get the best estimator from the grid search
best_knn_pipeline = knn_grid_search.best_estimator_

# Predict using the best estimator
y_pred_knn_best = best_knn_pipeline.predict(X_test)

# Calculate the AUC-ROC of the best estimator
auc_roc_knn_best = roc_auc_score(y_test, y_pred_knn_best)
print(f"AUC-ROC: {auc_roc_knn_best}")
```

```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
AUC-ROC: 0.5049241192239554
```

[ ]:

```
exp_name = "KNN_tuned"
try:
    expLog
except NameError:
    expLog = DataFrame(columns=["exp_name",
                                   "Train Acc",
                                   "Valid Acc",
                                   "Test  Acc",
                                   "Train F1",
                                   "Valid F1",
                                   "Test  F1"
                                  ])

expLog.loc[len(expLog)] = [f"{exp_name}"] + list(np.round(
               [roc_auc_score(y_train, best_knn_pipeline.predict(X_train)),
                roc_auc_score(y_valid, best_knn_pipeline.predict(X_valid)),
                roc_auc_score(y_test, best_knn_pipeline.predict(X_test)),
                f1_score(y_train, best_knn_pipeline.predict(X_train)),
                f1_score(y_valid, best_knn_pipeline.predict(X_valid)),
                f1_score(y_test, best_knn_pipeline.predict(X_test))],
    4))
expLog
```

[ ]:

```
           exp_name  Train Acc  Valid Acc  Test  Acc  Train F1  Valid F1  \
0  XGBoost_baseline      0.520      0.508      0.500     0.079     0.032
1     XGBoost_tuned      0.500      0.500      0.500     0.000     0.000
2    LogReg_baseline      0.637      0.633      0.655     0.000     0.000
3       LogReg_tuned      0.637      0.633      0.655     0.000     0.000
```

```
4      KNN_baseline      0.534      0.500      0.505      0.129      0.015
5         KNN_tuned      0.534      0.500      0.505      0.129      0.015

   Test  F1
0     0.000
1     0.000
2     0.000
3     0.000
4     0.031
5     0.031
```

[ ]:
```
expLog.rename(columns={'Train Acc':'Train ROC AUC',
                       'Valid Acc':'Valid ROC AUC',
                       'Test  Acc':'Test ROC AUC'
                       },inplace=True)
expLog
```

[ ]:
```
           exp_name  Train ROC AUC  Valid ROC AUC  Test ROC AUC  Train F1  \
0  XGBoost_baseline          0.520          0.508         0.500     0.079
1     XGBoost_tuned          0.500          0.500         0.500     0.000
2   LogReg_baseline          0.637          0.633         0.655     0.000
3      LogReg_tuned          0.637          0.633         0.655     0.000
4      KNN_baseline          0.534          0.500         0.505     0.129
5         KNN_tuned          0.534          0.500         0.505     0.129

   Valid F1  Test  F1
0     0.032     0.000
1     0.000     0.000
2     0.000     0.000
3     0.000     0.000
4     0.015     0.031
5     0.015     0.031
```

[ ]:
```

```

7 Results

All models were trained on the 20 most correlated features of the 120 available in the `application_train.csv`. Future work will add additional features, as well as implemented feature engineering to create new features.

The baseline models all performed relatively well in predicting an outcome of a customer's default risk in both the validation and test sets in terms of accuracy. However the F1 scores are extremely low for all models. Since the F1 score is a combination of precision and recall, this implies one of those two metrics may be zero.

Precision is defined as

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall is defined as

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

The target is imbalanced, since 92.2% of the customers did not default. It is possible there are 0 True Positives in the validation and test set.

[ ]:
```
train_data['TARGET'].value_counts(normalize=True)
```

[ ]:
```
TARGET
0    0.919
1    0.081
Name: proportion, dtype: float64
```

[ ]:
```
print (f'The target class is 1 in the validation data: {round(y_valid.sum() /␣
↪len(y_valid), 4)}')

print (f'The target class is 1 in the test data: {round(y_test.sum() /␣
↪len(y_test), 4)}')
```

```
The target class is 1 in the validation data: 0.0735
The target class is 1 in the test data: 0.0781
```

Of the three trained and fitted models, performance was a mixed bag taken by KNN and Logistic Regression. Though Logistic Regression had a consistenly higher ROC AUC score across train, validation, and test data, it suffered from uniformly 0 F-1 scores. This could be due to the class imbalance in the dataset, where the minority class (positive class) is underrepresented, leading to a high accuracy but low F-1 score. Logistic Regression might struggle with capturing the complexities of the data or the relationships between features, especially if the data is non-linear.

In contrast KNN, had a slighlty lower ROC AUC score than Logistic Regression, though it still outperformed XGBoost. It shone across the train, validation, and test data delivering non zero F-1 scores, indicative of the model correctly identifying true positives in the test set. The performance can likely improve with further and more extensive hyperparameter tuning.

8 Conclusions

In phase three the goal was to improve the ability of our models to predict the TARGET feature by incorporating data outside the application train csv. The team implemented Recency, Frequency, and Monetary Value (RFM) features from the DAYS_DECISION and AMT_CREDIT features of the previous application csv.

Feature selection conducted by the team eliminated features with high correlation to each other, implying redundant predictive ability. Features with High correlation to TARGET were retained. Adding the RFM features and down selecting the existing features created an ideal dataset for model training. Hyperparameter tuning via grid search optimized the training of the KNN, XGBoost, and Logistic Regression models.

Our Logistic Regression model achieved the best predictive scores (as measured by ROC AUC) suggesting the data was largely linearly separable, and low dimensional. The KNN model was a close second, and even outperformed all other models with regard to F1 and may have been slightly overfit to the training data when compared to the Logistic Regression model.

9 Credit assignment plan

[ ]:

```

```