HCDR_Group9_Phase4

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1 Final Project Phase 4 - Home Credit Default Risk

Spring 2024

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2 Abstract

Our project aimed to predict loan repayment based on the data available at the time of application. To accomplish this the team down selected features in the application train data; implemented Recency, Frequency, and Monetary Value features; trained KNN, XGBoost, and Linear Regression models; as well as a deep learning model. We attempted to account for this by oversampling the minority class.

Along the way we discovered an imbalance in the TARGET data causing our models to overpredict the majority class. The team identified correlations among the training set features, motivating us to select only one of any set of correlated features, reducing our model complexity with minimal impact on predictions.

Other data anomalies included erroneous entries implying 1000-year credit history, and features with missing data. Mitigations for these anomalies included removal and imputing. By building our mitigations into data pipelines we were able to generalize our data preprocessing to our four model types with minimal rework.

The Neural Network model yielded the strongest prediction performance with 60.5% F1 score and 60.5% ROC_AUC.

3 Data Lineage

The data originated from the Kaggle source. Throughout out the course of building, training, and refining the models, the underlying datasets underwent several transformations detailed below: - Appending to the initial train dataset via left join a dataset consisting of RFM (Recency, Frequency, Monetary Value) metrics extracted from the previous_applications dataset. The recency feature was calculated as the max (of DAYS_DECISION) to capture the most recent decision date; the frequency as the range of decision dates divided by the number of previous applications (flagged by distinct number of SK_ID_PREV grouped by SK_ID_CURR); and the monetary value was the sum of total amounts credited. - Within the pipelines, the data was further transformed to control for scaling issues and missing values. Numerical features' missing values were imputed with the median, and then standard scaled. Categorical features' missing values were imputed with the most frequent value within the column.

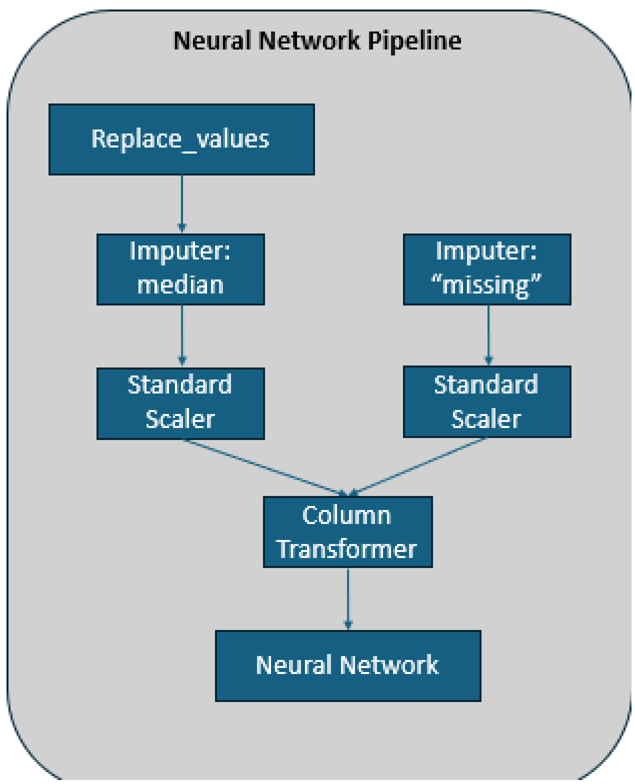
4 Neural Network

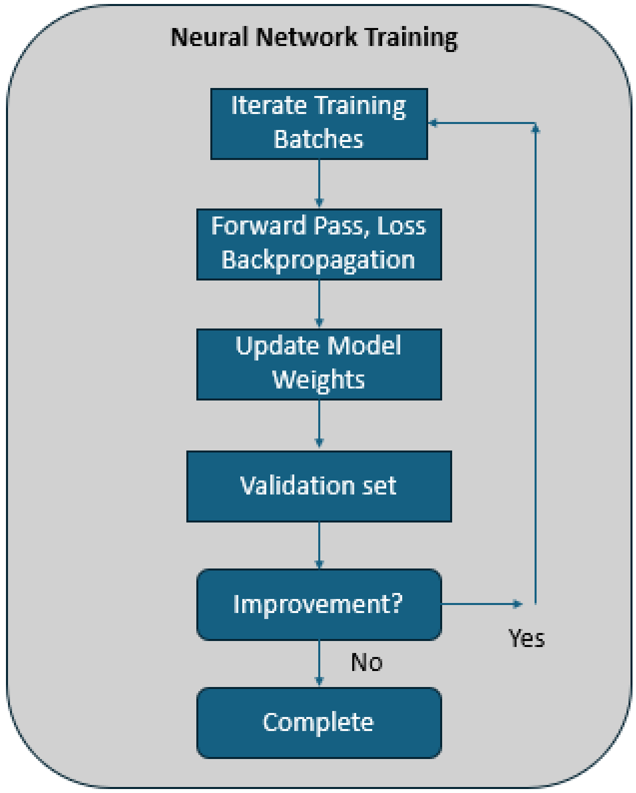
To implement the Neural Network (Deep Learning) models a pipeline was adapted from Homework 11. The pipeline allowed us to train and test Neural Networks with dynamically defined hidden layers, optimization functions, activation functions, and loss functions. We improved upon the intial code base by adding F1 scores and AUC_ROC scores. A feature was added for the code to exit the epoch training cycle if subsequent models were no longer improving, indicating the model had converged.

Intially we faced challenges with models hitting a performance ceiling around 92% accuracy. Upon further inspection we realized the models were learning to over predict the majoirty class becuase the TARGET data was 92% majority class. After added an oversampling step to the data processing to balance the majority and minority class the models hit a ceiling of ~60% performance.

The best performing model was: 34-200-100-2 using 'torch.optim.sgd.SGD' using 10 epochs.

4.1 Neural Network Pipeline





4.2 Architecture 1

We attempted many different configuration of neural networks, the first using Adadelta and a configuration in the form: 34-50-50-25-2

[15]:
```
import pandas as pd
from __future__ import print_function

import numpy as np

np.random.seed(0)

from pandasql import sqldf

import torch
import torch.utils.data
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader

import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error,␣
↪accuracy_score,roc_auc_score, f1_score
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.base import BaseEstimator, TransformerMixin

torch.manual_seed(0)
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

from imblearn.over_sampling import RandomOverSampler
```

4.3 Load data

[2]:
```
train_data = pd.read_csv('data/application_train.csv') #data we have the target␣
↪class for
test_data = pd.read_csv('data/application_test.csv') #data we need to predict␣
↪target class for

print (f'Loaded {train_data.shape[0]:,} rows in training set.')

print (f'Loaded {test_data.shape[0]:,} rows in testing set.')
```

```
Loaded 307,511 rows in training set.
Loaded 48,744 rows in testing set.
```

[3]:
```
PrevApp_data = pd.read_csv('data/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']
```

4.4 Join and filter previous application data with train data

[7]:
```
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
```

[7]:
```
        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          202500.0    406597.5
1                    N             0          270000.0   1293502.5
2                    Y             0           67500.0    135000.0
3                    Y             0          135000.0    312682.5
4                    Y             0          121500.0    513000.0
…                  …            …               …          …
307506               N             0          157500.0    254700.0
307507               Y             0           72000.0    269550.0
307508               Y             0          153000.0    677664.0
307509               Y             0          171000.0    370107.0
307510               N             0          157500.0    675000.0

        AMT_ANNUITY  …  FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR  \
0           24700.5  …                 0                        0.0
```

```
1             35698.5  …                  0                        0.0
2              6750.0  …                  0                        0.0
3             29686.5  …                  0                        NaN
4             21865.5  …                  0                        0.0
…                 …  …                 …                        …
307506        27558.0  …                  0                        NaN
307507        12001.5  …                  0                        NaN
307508        29979.0  …                  0                        1.0
307509        20205.0  …                  0                        0.0
307510        49117.5  …                  0                        0.0

       AMT_REQ_CREDIT_BUREAU_DAY AMT_REQ_CREDIT_BUREAU_WEEK  \
0                            0.0                        0.0
1                            0.0                        0.0
2                            0.0                        0.0
3                            NaN                        NaN
4                            0.0                        0.0
…                            …                          …
307506                       NaN                        NaN
307507                       NaN                        NaN
307508                       0.0                        0.0
307509                       0.0                        0.0
307510                       0.0                        0.0

       AMT_REQ_CREDIT_BUREAU_MON AMT_REQ_CREDIT_BUREAU_QRT  \
0                            0.0                       0.0
1                            0.0                       0.0
2                            0.0                       0.0
3                            NaN                       NaN
4                            0.0                       0.0
…                            …                         …
307506                       NaN                       NaN
307507                       NaN                       NaN
307508                       1.0                       0.0
307509                       0.0                       0.0
307510                       2.0                       0.0

        AMT_REQ_CREDIT_BUREAU_YEAR  RECENCY_FEATURE  FREQUENCY_FEATURE  \
0                              1.0           -606.0                0.0
1                              0.0           -746.0              531.0
2                              0.0           -815.0                0.0
3                              NaN           -181.0               72.0
4                              0.0           -374.0              330.0
…                              …             …                  …
307506                         NaN           -273.0                0.0
307507                         NaN          -2497.0                0.0
307508                         1.0          -1909.0              471.0
```

```
307509                          0.0           -277.0              22.0
307510                          1.0           -171.0             102.0

        MONETARY_VALUE
0             179055.0
1            1452573.0
2              20106.0
3            2625259.5
4             999832.5
…                  …
307506         40455.0
307507         56821.5
307508         41251.5
307509        268879.5
307510       3395448.0

[307511 rows x 125 columns]
```

[9]:
```
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

''')
```

[10]:
```
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
```

[10]:

```
       FLOORSMAX_MEDI  ELEVATORS_MEDI  FLOORSMIN_MEDI  AMT_CREDIT  \
0              0.1250             NaN             NaN    568800.0
1                 NaN             NaN             NaN    222768.0
2                 NaN             NaN             NaN    663264.0
3              0.3750            0.32          0.0417   1575000.0
4                 NaN             NaN             NaN    625500.0
…                 …              …               …           …
48739             NaN             NaN             NaN    412560.0
48740             NaN             NaN             NaN    622413.0
```

```
48741          0.3333            0.16            NaN    315000.0
48742          0.6250            0.16            NaN    450000.0
48743             NaN             NaN            NaN    312768.0

       TOTALAREA_MODE  DAYS_EMPLOYED  OBS_30_CNT_SOCIAL_CIRCLE  \
0              0.0392          -2329                       0.0
1                 NaN          -4469                       0.0
2                 NaN          -4458                       0.0
3              0.3700          -1866                       0.0
4                 NaN          -2191                       0.0
…                 …             …                        …
48739             NaN          -5169                       1.0
48740             NaN          -1149                       2.0
48741          0.1663          -3037                       0.0
48742          0.1974          -2731                       0.0
48743             NaN           -633                       0.0

       CNT_FAM_MEMBERS  CNT_CHILDREN  OWN_CAR_AGE  DAYS_ID_PUBLISH  \
0                  2.0             0          NaN             -812
1                  2.0             0          NaN            -1623
2                  2.0             0          5.0            -3503
3                  4.0             2          NaN            -4208
4                  3.0             1         16.0            -4262
…                  …             …          …              …
48739              1.0             0          NaN            -3399
48740              4.0             2          NaN            -3003
48741              3.0             1          4.0            -1504
48742              2.0             0          NaN            -1364
48743              2.0             0         22.0            -4220

       DAYS_LAST_PHONE_CHANGE CODE_GENDER     OCCUPATION_TYPE  \
0                     -1740.0           F                None
1                         0.0           M  Low-skill Laborers
2                      -856.0           M             Drivers
3                     -1805.0           F         Sales staff
4                      -821.0           M                None
…                         …          …                  …
48739                  -684.0           F                None
48740                     0.0           F         Sales staff
48741                  -838.0           F                None
48742                 -2308.0           M            Managers
48743                  -327.0           F          Core staff

       AMT_INCOME_TOTAL  RECENCY_FEATURE  FREQUENCY_FEATURE  MONETARY_VALUE
0              135000.0          -1740.0                0.0       23787.000
1               99000.0           -757.0                0.0       40153.500
2              202500.0           -273.0              575.0      584536.500
```

```
3            315000.0      -797.0         252.0     464602.500
4            180000.0      -111.0         355.0     601101.000
…               …           …          …          …
48739        121500.0      -683.0           0.0     254700.000
48740        157500.0      -770.0         420.0     394816.500
48741        202500.0       -84.0         377.0     265033.665
48742        225000.0      -577.0         432.0     637893.000
48743        135000.0      -327.0         148.0    1166746.500

[48744 rows x 18 columns]
```

4.5 Transformers and pipelines

[16]:
```
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
```

[17]:
```
# Sample data
X = filtered_train_data.drop(columns=['TARGET'])
y = filtered_train_data['TARGET']
```

Trying naive oversampling minority to match class proportions between zero class and one class

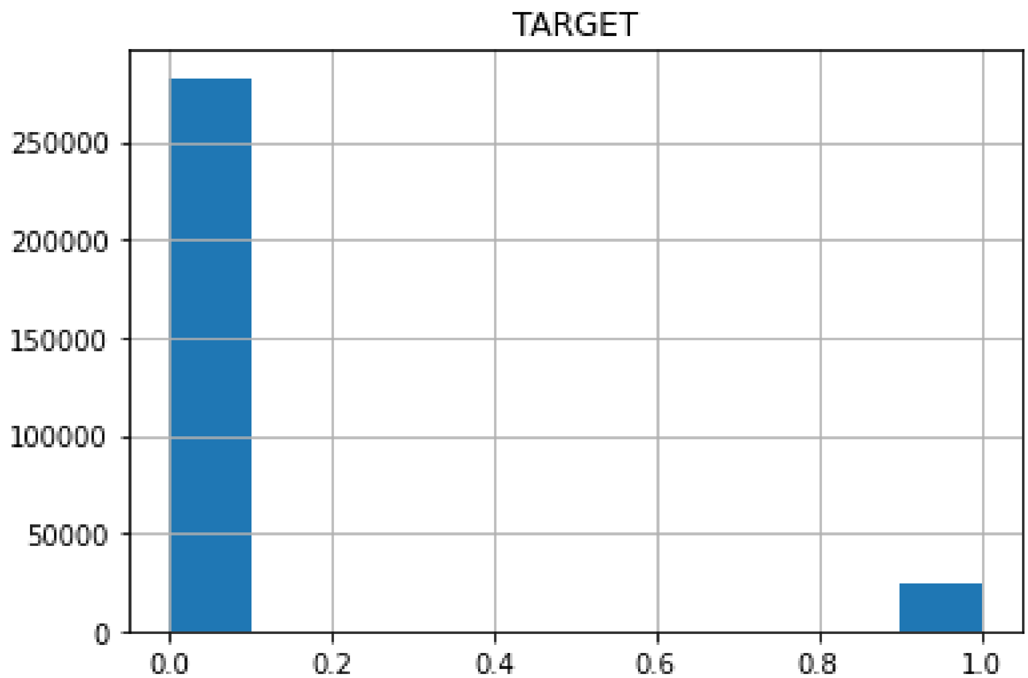
[18]:
```
ros = RandomOverSampler(random_state=42)
X_res, y_res = ros.fit_resample(X, y)
```

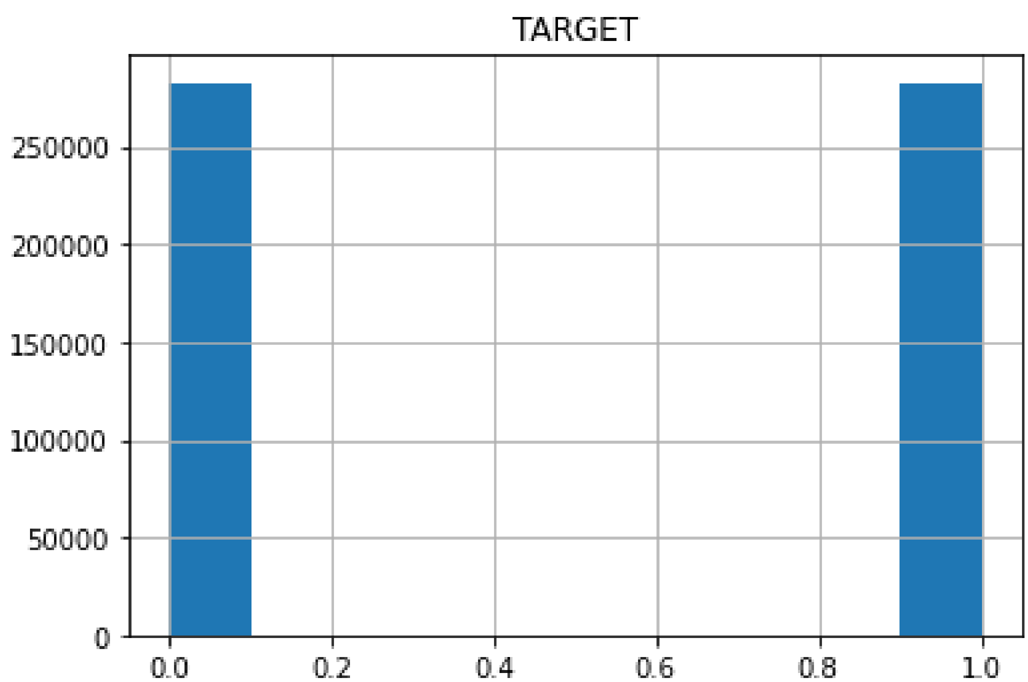
[19]:
```
test = pd.DataFrame(y)
test.hist()
print(test.describe())
print(np.sum(test == 1)/(len(test)))

test = pd.DataFrame(y_res)
test.hist()
print(test.describe())
print(np.sum(test == 1)/(len(test)))
```

```
              TARGET
count  307511.000000
mean        0.080729
```

```
std         0.272419
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000
TARGET    0.080729
dtype: float64
         TARGET
count  565372.0
mean        0.5
std         0.5
min         0.0
25%         0.0
50%         0.5
75%         1.0
max         1.0
TARGET    0.5
dtype: float64
```

```
/usr/local/lib/python3.9/site-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a
future version this will reduce over both axes and return a scalar. To retain
the old behavior, pass axis=0 (or do not pass axis)
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
/usr/local/lib/python3.9/site-packages/numpy/core/fromnumeric.py:86:
FutureWarning: The behavior of DataFrame.sum with axis=None is deprecated, in a
future version this will reduce over both axes and return a scalar. To retain
the old behavior, pass axis=0 (or do not pass axis)
  return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
```





[20]:
```
y = y_res
X = X_res
```

[22]:
```
# 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)
    ])
```

[24]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15,␣
 ↪random_state=42, shuffle = True)
X_train, X_validation, y_train, y_validation = train_test_split(X_train,␣
 ↪y_train, test_size=0.15, random_state=42, shuffle=True)
```

[25]:
```
X_train = preprocessor.fit_transform(X_train)
X_validation = preprocessor.transform(X_validation)
X_test = preprocessor.transform(X_test) #Transform test set with the same␣
 ↪constants



y_train = y_train.to_numpy()
y_validation = y_validation.to_numpy()
y_test = y_test.to_numpy()

# convert numpy arrays to tensors
X_train_tensor = torch.from_numpy(X_train)
X_valid_tensor = torch.from_numpy(X_validation)
X_test_tensor = torch.from_numpy(X_test)
y_train_tensor = torch.from_numpy(y_train)
```

```
y_valid_tensor = torch.from_numpy(y_validation)
y_test_tensor = torch.from_numpy(y_test)

# create TensorDataset in PyTorch
hcdr_train = torch.utils.data.TensorDataset(X_train_tensor, y_train_tensor)
hcdr_valid = torch.utils.data.TensorDataset(X_valid_tensor, y_valid_tensor)
hcdr_test = torch.utils.data.TensorDataset(X_test_tensor, y_test_tensor)

# print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
# create dataloader
# DataLoader is implemented in PyTorch, which will return an iterator to␣
↪iterate training data by batch.
train_batch_size = 96
valid_test_batch_size = 64
trainloader_hcdr = torch.utils.data.DataLoader(hcdr_train,␣
↪batch_size=train_batch_size, shuffle=True, num_workers=2)
validloader_hcdr = torch.utils.data.DataLoader(hcdr_valid,␣
↪batch_size=valid_test_batch_size, shuffle=True, num_workers=2)
testloader_hcdr = torch.utils.data.DataLoader(hcdr_test,␣
↪batch_size=valid_test_batch_size, shuffle=True, num_workers=2)
```

4.6 Define NN model (Rectified Linear Unit ver)

[26]:
```
def run_hcdr_model(
    hidden_layer_neurons=[32, 16, 8],
    opt=optim.SGD,
    epochs=5,
    learning_rate=1e-3
):

    D_in = X_test.shape[1]  # Input layer neurons depend on the input dataset␣
↪shape
    D_out = 2  # Output layer neurons - depend on what you're trying to␣
↪predict, here, 2 classes: 0 and 1

    str_neurons = [str(h) for h in hidden_layer_neurons]
    arch_string = f"{D_in}-{'-'.join(str_neurons)}-{D_out}"

    layers = [
        torch.nn.Linear(D_in, hidden_layer_neurons[0]),  # X.matmul(W1)
        nn.ReLU(),  # ReLU( X.matmul(W1))
    ]

    # Add hidden layers
    for i in range(1, len(hidden_layer_neurons)):
        prev, curr = hidden_layer_neurons[i - 1], hidden_layer_neurons[i]
```

```
        layers.append(torch.nn.Linear(prev, curr))
        layers.append(nn.ReLU())


    # Add final layer
    layers.append(nn.Linear(hidden_layer_neurons[-1], D_out)) # Relu( X.
↪matmul(W1)).matmul(W2))

    # Use the nn package to define our model and loss function.
    # use the sequential API makes things simple
    model = torch.nn.Sequential(*layers)

    model.to(device)

    # use Cross Entropy and SGD optimizer.
    loss_fn = nn.CrossEntropyLoss()  #for classfication
    optimizer = opt(model.parameters(), lr=learning_rate)

    #summary(model, (4, 20))
    print('-'*50)
    print('Model:')
    print(model)
    print('-'*50)

    '''
    Training Process:
        Load a batch of data.
        Zero the grad.
        Predict the batch of the data through net i.e forward pass.
        Calculate the loss value by predict value and true value.
        Backprop i.e get the gradient with respect to parameters
        Update optimizer i.e gradient update
    '''

    loss_history = []
    acc_history = []
    def train_epoch(epoch, model, loss_fn, opt, train_loader):
        running_loss = 0.0
        count = 0
        y_pred = []
        epoch_target = []
        # dataset API gives us pythonic batching
        for batch_id, data in enumerate(train_loader):
            inputs, target = data[0].to(device), data[1].to(device)
            # 1:zero the grad, 2:forward pass, 3:calculate loss,  and 4:
↪backprop!
            opt.zero_grad()
```

```
            preds = model(inputs.float()) #prediction over the input data

            # compute loss and gradients
            loss = loss_fn(preds, target)    #mean loss for this batch

            loss.backward() #calculate nabla_w
            loss_history.append(loss.item())
            opt.step()  #update W
            y_pred.extend(torch.argmax(preds, dim=1).tolist())
            epoch_target.extend(target.tolist())
            #from IPython.core.debugger import Pdb as pdb;    pdb().set_trace()␣
↪#breakpoint; dont forget to quit

            running_loss += loss.item()
            count += 1

        loss = np.round(running_loss/count, 3)

        #accuracy
        correct = (np.array(y_pred) == np.array(epoch_target))
        accuracy = correct.sum() / correct.size
        accuracy = np.round(accuracy, 3)
        #F1 score
        f1 = f1_score(np.array(epoch_target), np.array(y_pred),␣
↪average='weighted')
        f1 = np.round(f1, 3)
        #roc_auc score
        roc_auc = roc_auc_score(np.array(epoch_target), np.array(y_pred),␣
↪multi_class='ovo')
        roc_auc = np.round(roc_auc, 3)



        return loss, accuracy, f1, roc_auc



    #from IPython.core.debugger import Pdb as pdb;    pdb().set_trace()␣
↪#breakpoint; dont forget to quit
    def evaluate_model(epoch, model, loss_fn, opt, data_loader, tag = "Test"):
        overall_loss = 0.0
        count = 0
        y_pred = []
        epoch_target = []
        for i,data in enumerate(data_loader):
            inputs, target = data[0].to(device), data[1].to(device)
            preds = model(inputs.float())
```

```
            loss = loss_fn(preds, target)           # compute loss value

            overall_loss += (loss.item())  # compute total loss to save to logs
            y_pred.extend(torch.argmax(preds, dim=1).tolist())
            epoch_target.extend(target.tolist())
            count += 1

        # compute mean loss
        loss = np.round(overall_loss/count, 3)
        #accuracy
        correct = (np.array(y_pred) == np.array(epoch_target))
        accuracy = correct.sum() / correct.size
        accuracy = np.round(accuracy, 3)
        #F1 score
        f1 = f1_score(np.array(epoch_target), np.array(y_pred),␣
↪average='weighted')
        f1 = np.round(f1, 3)
        #roc_auc score
        roc_auc = roc_auc_score(np.array(epoch_target), np.array(y_pred),␣
↪multi_class='ovo')
        roc_auc = np.round(roc_auc, 3)

        return loss, accuracy, f1, roc_auc


    last_f1 = 0
    for epoch in range(epochs):
        # print(f"Epoch {epoch+1}")
        train_loss, train_accuracy, train_f1, train_roc_auc =␣
↪train_epoch(epoch, model, loss_fn, optimizer, trainloader_hcdr)
        valid_loss, valid_accuracy, valid_f1, valid_roc_auc =␣
↪evaluate_model(epoch, model, loss_fn, optimizer, validloader_hcdr, tag =␣
↪"Validation")
        print(f"Epoch {epoch+1}: Train Accuracy: {train_accuracy}\t Validation␣
↪Accuracy: {valid_accuracy} Validation F1 score: {valid_f1} Validation␣
↪roc_auc score: {valid_roc_auc}")
        if last_f1 == 0:
            last_f1 = valid_f1
        else:
            improvement = (valid_f1 - last_f1) / last_f1

            if improvement < 0.01:
                break


    print("-"*50)
```

```
    test_loss, test_accuracy, test_f1, test_roc_auc = evaluate_model(epoch,␣
↪model, loss_fn, opt, testloader_hcdr, tag="Test")

    return arch_string, train_accuracy, valid_accuracy, test_accuracy,␣
↪test_loss, test_f1, test_roc_auc
```

[28]:

```
#==================================================#
#    Modify START   #
#==================================================#
'''
(hidden_layers_neurons) - A list of the number of neurons in the hidden layers␣
↪in order. DEFAULT: [32, 16, 8] => 1st hidden layer: 32 neurons, 2nd: 16, 3rd:
↪ 8
(opt) - The optimizer function to use: SGD, Adam, etc.,  DEFAULT: optim.SGD
(epochs) - The total number of epochs to train your model for,  DEFAULT: 5
(learning_rate) - The learning rate to take the gradient descent step with
'''

hidden_layer_neurons = [100, 100]
opt = optim.Adadelta
epochs = 10
learning_rate = 1e-3

#==================================================#
#    Modify END #
#==================================================#

arch_string, train_accuracy, valid_accuracy, test_accuracy, test_loss, test_f1,␣
↪test_roc_auc = run_hcdr_model(
    hidden_layer_neurons,
    opt,
    epochs,
    learning_rate
)


try: hcdrLog
except : hcdrLog = pd.DataFrame(
    columns=[
        "Architecture string",
        "Optimizer",
        "Epochs",
        "Train accuracy",
        "Valid accuracy",
        "Test accuracy",
        "test F1 score",
        "test ROC_AUC score"
```

```
    ]
)

hcdrLog.loc[len(hcdrLog)] = [
    arch_string,
    f"{opt}",
    f"{epochs}",
    f"{np.round((train_accuracy * 100),3)}%",
    f"{np.round((valid_accuracy * 100),3)}%",
    f"{np.round((test_accuracy * 100),3)}%",
    f"{np.round((test_f1 * 100),3)}%",
    f"{np.round((test_roc_auc * 100),3)}%",
]

hcdrLog
```

```
--------------------------------------------------
Model:
Sequential(
  (0): Linear(in_features=34, out_features=100, bias=True)
  (1): ReLU()
  (2): Linear(in_features=100, out_features=100, bias=True)
  (3): ReLU()
  (4): Linear(in_features=100, out_features=2, bias=True)
)
--------------------------------------------------
Epoch 1: Train Accuracy: 0.52    Validation Accuracy: 0.553 Validation F1 score:
0.533 Validation roc_auc score: 0.553
Epoch 2: Train Accuracy: 0.571   Validation Accuracy: 0.582 Validation F1 score:
0.582 Validation roc_auc score: 0.582
Epoch 3: Train Accuracy: 0.584   Validation Accuracy: 0.588 Validation F1 score:
0.588 Validation roc_auc score: 0.588
Epoch 4: Train Accuracy: 0.588   Validation Accuracy: 0.59 Validation F1 score:
0.59 Validation roc_auc score: 0.59
Epoch 5: Train Accuracy: 0.59    Validation Accuracy: 0.592 Validation F1 score:
0.592 Validation roc_auc score: 0.592
Epoch 6: Train Accuracy: 0.591   Validation Accuracy: 0.593 Validation F1 score:
0.593 Validation roc_auc score: 0.593
Epoch 7: Train Accuracy: 0.592   Validation Accuracy: 0.595 Validation F1 score:
0.595 Validation roc_auc score: 0.595
Epoch 8: Train Accuracy: 0.594   Validation Accuracy: 0.596 Validation F1 score:
0.596 Validation roc_auc score: 0.596
Epoch 9: Train Accuracy: 0.595   Validation Accuracy: 0.597 Validation F1 score:
0.597 Validation roc_auc score: 0.597
Epoch 10: Train Accuracy: 0.595  Validation Accuracy: 0.597 Validation F1 score:
0.597 Validation roc_auc score: 0.597
--------------------------------------------------
```

[28]:
```
  Architecture string                                Optimizer Epochs  \
0       34-50-50-25-2  <class 'torch.optim.adadelta.Adadelta'>      5
1        34-100-100-2  <class 'torch.optim.adadelta.Adadelta'>     10

  Train accuracy Valid accuracy Test accuracy test F1 score test ROC_AUC score
0          56.6%          57.4%         57.4%         57.1%              57.4%
1          59.5%          59.7%         59.5%         59.5%              59.5%
```

4.7 Architecture 2

Our second neural network uses the SGD optimizer and various numbers of layers

[34]:
```
#==================================================#
#    Modify START   #
#==================================================#
'''
(hidden_layers_neurons) - A list of the number of neurons in the hidden layers␣
↪in order. DEFAULT: [32, 16, 8] => 1st hidden layer: 32 neurons, 2nd: 16, 3rd:
↪ 8
(opt) - The optimizer function to use: SGD, Adam, etc.,  DEFAULT: optim.SGD
(epochs) - The total number of epochs to train your model for,  DEFAULT: 5
(learning_rate) - The learning rate to take the gradient descent step with
'''

hidden_layer_neurons = [200, 100, 50]
opt = optim.SGD
epochs = 10
learning_rate = 1e-3

#==================================================#
#    Modify END #
#==================================================#

arch_string, train_accuracy, valid_accuracy, test_accuracy, test_loss, test_f1,␣
↪test_roc_auc = run_hcdr_model(
    hidden_layer_neurons,
    opt,
    epochs,
    learning_rate
)


try: hcdrLog
except : hcdrLog = pd.DataFrame(
    columns=[
        "Architecture string",
        "Optimizer",
```

```
        "Epochs",
        "Train accuracy",
        "Valid accuracy",
        "Test accuracy",
        "test F1 score",
        "test ROC_AUC score"
    ]
)

hcdrLog.loc[len(hcdrLog)] = [
    arch_string,
    f"{opt}",
    f"{epochs}",
    f"{np.round((train_accuracy * 100),3)}%",
    f"{np.round((valid_accuracy * 100),3)}%",
    f"{np.round((test_accuracy * 100),3)}%",
    f"{np.round((test_f1 * 100),3)}%",
    f"{np.round((test_roc_auc * 100),3)}%",
]

hcdrLog
```

```
--------------------------------------------------
Model:
Sequential(
  (0): Linear(in_features=34, out_features=200, bias=True)
  (1): ReLU()
  (2): Linear(in_features=200, out_features=100, bias=True)
  (3): ReLU()
  (4): Linear(in_features=100, out_features=50, bias=True)
  (5): ReLU()
  (6): Linear(in_features=50, out_features=2, bias=True)
)
--------------------------------------------------
Epoch 1: Train Accuracy: 0.523   Validation Accuracy: 0.562 Validation F1 score:
0.56 Validation roc_auc score: 0.562
Epoch 2: Train Accuracy: 0.572   Validation Accuracy: 0.577 Validation F1 score:
0.577 Validation roc_auc score: 0.577
Epoch 3: Train Accuracy: 0.58    Validation Accuracy: 0.583 Validation F1 score:
0.583 Validation roc_auc score: 0.583
Epoch 4: Train Accuracy: 0.584   Validation Accuracy: 0.588 Validation F1 score:
0.588 Validation roc_auc score: 0.588
Epoch 5: Train Accuracy: 0.588   Validation Accuracy: 0.592 Validation F1 score:
0.591 Validation roc_auc score: 0.592
Epoch 6: Train Accuracy: 0.591   Validation Accuracy: 0.595 Validation F1 score:
0.595 Validation roc_auc score: 0.595
Epoch 7: Train Accuracy: 0.594   Validation Accuracy: 0.598 Validation F1 score:
0.597 Validation roc_auc score: 0.598
```

```
Epoch 8: Train Accuracy: 0.596   Validation Accuracy: 0.599 Validation F1 score:
0.599 Validation roc_auc score: 0.599
Epoch 9: Train Accuracy: 0.597   Validation Accuracy: 0.601 Validation F1 score:
0.601 Validation roc_auc score: 0.601
Epoch 10: Train Accuracy: 0.599  Validation Accuracy: 0.602 Validation F1 score:
0.602 Validation roc_auc score: 0.602
--------------------------------------------------
```

[34]:

```
  Architecture string                                Optimizer Epochs  \
0       34-50-50-25-2  <class 'torch.optim.adadelta.Adadelta'>      5
1        34-100-100-2  <class 'torch.optim.adadelta.Adadelta'>     10
2        34-100-100-2            <class 'torch.optim.sgd.SGD'>     10
3       34-34-34-17-2            <class 'torch.optim.sgd.SGD'>     10
4        34-200-100-2            <class 'torch.optim.sgd.SGD'>     10
5     34-200-100-50-2            <class 'torch.optim.sgd.SGD'>     10

  Train accuracy Valid accuracy Test accuracy test F1 score test ROC_AUC score
0          56.6%          57.4%         57.4%         57.1%              57.4%
1          59.5%          59.7%         59.5%         59.5%              59.5%
2          60.0%          60.4%         60.2%         60.2%              60.2%
3          59.2%          59.4%         59.1%         59.0%              59.1%
4          60.2%          60.4%         60.3%         60.3%              60.3%
5          59.9%          60.2%         60.0%         60.0%              60.0%
```

5 Data Leakage

We suspected some degree of data leakage, due to the relatively high accuracies in comparison to middling ROC AUC scores. Part of this was, likely in large part, caused by a large class imbalance of repayments versus failures to repay in the training data. After we rebalanced using over/under-sampling techniques, these performance issues persisted thus we began to do root cause analysis to trace the data leakage.

We examined two potential sources: multicollinearity and autocorrelation among the features; and high correlation between any of the features and the target variable. We found no instances of very high correlation between the predictors and the target, all having correlation coefficients below 0.2.

In terms of the multicollinearity analysis, we examined the correlation matrix of the feature variables and found ELEVATORS_MEDI, FLOORSMIN_MEDI, AND TOTALAREA_MODE to be very highly correlation (> ~70%) to the FLOORSMAX_MEDI feature. However, dropping these variables and rerunning our models on the updated train set did not yield any substantial performance improvements.

[ ]:

```

```

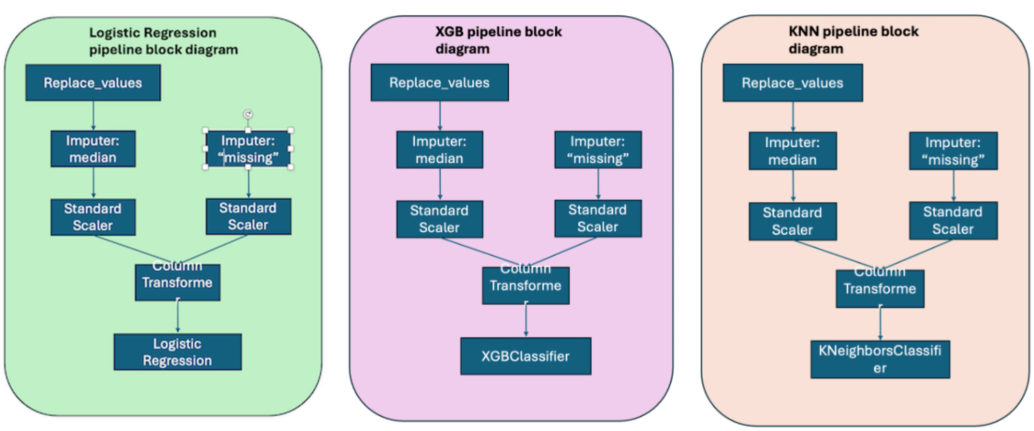
6 Modeling Pipelines

We defined 12 numerical features and two categorical to use in our neural networks.

Our pipelines implemented one custom transformer as well as the commonly used SimpleImputer to fill in missing values and a scaler to standardize model input values.

We also included a OneHotEncoder for the categorical features.

[ ]:
```python
# 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)
    ])
```



7 Results and Discussion

After training several different neural network model architectures, the test ROC AUC score did not see any improvement above the 60% level.

The best performing model was: 34-200-100-2 using 'torch.optim.sgd.SGD' using 10 epochs.

We can only speculate as to why the model did not improve. The model could be overfitting and using the same random seed could be preventing more variation in the training data.

8 Conclusion

Our project aimed to predict the probability of a loan being successfully repaid by a consumer. In building a model we used the training data provided as well as the previous applications data to help inform the model and improve performance.

We implemented Recency, Frequency, and Monetary Value features, created a feature engineering transformer, trained KNN, XGBoost, and Linear Regression models, as well as a deep learning model. In our exploratory data analysis we discovered the target variable was extremely imbalanced and would cause our models to overpredict the majority class. To overcome this we used a Python module called `imblearn` to oversample the minority class.

The team also identified correlations among the training set features, motivating us to select only one of any set of correlated features, reducing our model complexity with minimal impact on predictions.

After experimenting with various machine learning models, the best performing model was a neural network utilizing the SGD optimizer function. It produced a 60.5% F1 score and 60.5% ROC_AUC.

Future work could be exploring areas of the feature set and using different under and over-sampling techniques. They might be other ways to reduce feature multicollinearity and improve model performance.

9 Credit assignment plan

Home Credit Default Risk
Credit assignment
Applied Machine Learning

	Phase 4: Final Submission: Final Project. Team Lead: Glen Colletti	Team member
	Implement various Neural Network configurations	Glen Colletti, Alex Bordanca
	Code consolidation and notebook cleanup	Paul Miller
	Project final report	All team members
	Project final slides	All team members
	Record video	All team members

[ ]: