American Express - Default Prediction
MIDS - W207
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Agenda

1. Problem Motivation
2. Dataset Description
3. EDA
4. Models
   a. Clustering
   b. Random Forest
   c. Transformer
5. Results
6. Takeaways

Problem Motivation

- Goal of a credit issuer is to ensure credit is repaid back with interest to compensate risk
- Default events are unfavorable for a lender

Dataset Description

- Dataset dimensions
  - (5531451,191)
- Time Series Data
- Default is when a customer does not pay due amount in 120 days after their latest statement date.
- *Features are anonymized and normalized*

Feature Categories:

D_* = Delinquency variables

S_* = Spend variables

P_* = Payment variables

B_* = Balance variables

R_* = Risk variables

EDA

- Validated the data was standardized
- Categoricals Columns
  - Reindexed to 0
  - One-Hot Encoded
  - Dropped due to interpretability

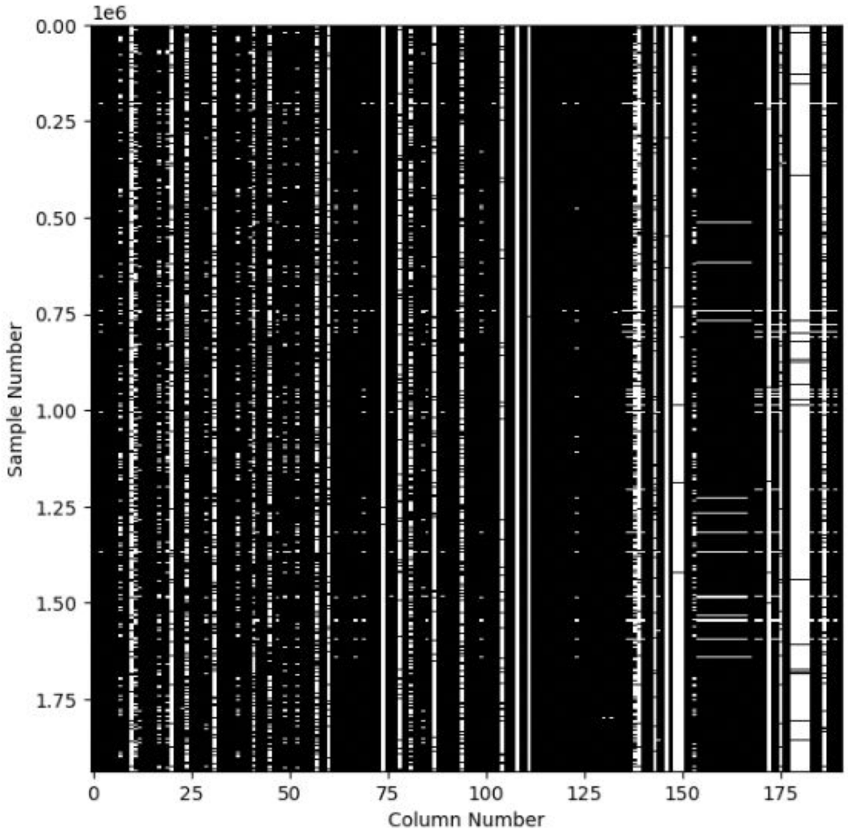
	count	mean	std	min	25%	50%	75%	max
D_42	283,952.000000	0.000000	0.000000	-0.000372	0.040314	0.123779	0.258057	4.187500
D_49	171,995.000000	0.000000	0.000000	0.000007	0.062439	0.131104	0.245972	19.953125
D_53	477,308.000000	0.000000	0.000000	0.000000	0.005875	0.011810	0.039185	7.902344
R_4	1,936,007.000000	0.000000	0.000000	0.000000	0.002539	0.005081	0.007626	1.009766
R_5	1,936,007.000000	0.000000	0.000000	0.000000	0.002550	0.005096	0.007645	17.515625

```
2.0      726993
3.0      442452
1.0      390498
5.0      147417
4.0       94695
7.0       81702
6.0       51298
Name: B_38, dtype: int64
```

```
CO      1428972
CR       336769
CL       154494
XZ         9405
XM         3672
XL         2695
Name: D_63, dtype: int64
```

```
O       1022626
U        514145
R        294146
          69495
-1        35595
Name: D_64, dtype: int64
```

EDA - NaNs



- Set max 40% threshold of NaNs per feature
  - Length before filtering out high NaN count cols: 191
  - Number of columns to drop: 62
- Imputed -1 for all NaNs

Train/Val/Test Split

```
Training Features dimensions:  (3318870, 190)
Training Labels dimensions:  (3318870,)
Validation Features dimensions:  (1106290, 190)
Validation Labels dimensions:  (1106290,)
Test Features dimensions:  (1106291, 190)
Test Labels dimensions:  (1106291,)

Training Percent of Positive Labels:  0.2440

Validation Percent of Positive Labels:  0.2553
```

- Implemented a 60/20/20 split
- To maintain integrity of the time series no shuffling was used
- Yet, similar target label distribution

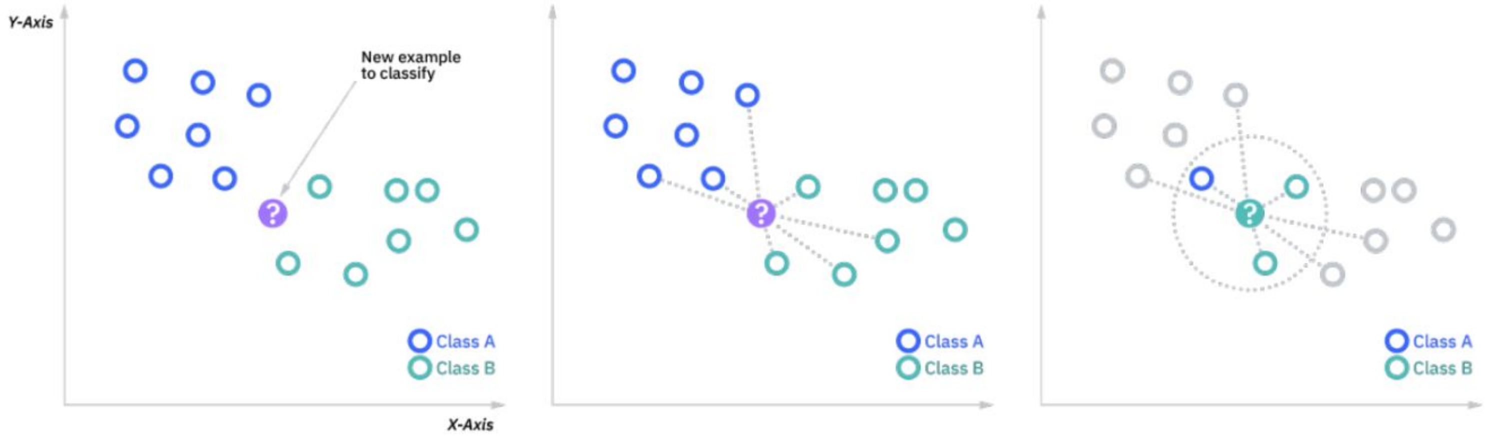
Models & Experiments

- Baseline Model - always predict no default event
    - Accuracy Score = 75.60%

Model - KNN

KNN models are relatively simple models great for both classification and regression problems

- Known as a lazy learner, and makes a great baseline model
- Calculates the distance between similar data points, and makes predictions based on the frequency of different classes



KNN Baseline Model

- Build a baseline KNN model with hyperparameters
  - n_neighbors = 5, p = 2, leaf_size = 30
- Resulted in an initial accuracy of 61% on the training data

	precision	recall	f1-score	support
0.0	0.74	0.74	0.74	82208
1.0	0.24	0.24	0.24	28421
accuracy			0.61	110629
macro avg	0.49	0.49	0.49	110629
weighted avg	0.61	0.61	0.61	110629

KNN Hyperparameter Tuning

- Use Grid Search CV to tune the hyperparameters
- Find the hyperparameters for the highest accuracy model

```
# Build a dictionary for the hyperparameters we are looking to tune
# ignore p value and leaf_size as gridsearchcv takes too long, so just tune n_neighbors
# p = [1, 2]
#leaf_size = list(range(1, 50))
n_neighbors = list(range(1, 50))
hyperparameters = dict(n_neighbors = n_neighbors)
```

```
# initiate another KNN model class
knn_2 = KNeighborsClassifier()

#run gridsearchcv on the hyperparameters for a KNN model with 10 folds
clf = GridSearchCV(knn_2, hyperparameters, cv = 10, n_jobs = -1)

# fit the model
best_model = clf.fit(X_train_pca, Y_train)
```

```
print('Best leafsize:' , best_model.best_estimator_.get_params()['leaf_size'])
print('Best n_neighbors:' , best_model.best_estimator_.get_params()['n_neighbors'])
#print('Best p:' , best_model.best_estimator_.get_params()['p'])
```

```
Best leafsize: 30
Best n_neighbors: 27
```

KNN Model Results

- Using the tuned hyperparameters, a KNN model fit on training data results in an accuracy on the test data of 67%
- Precision, recall, and F1-scores are 74%, 84%, and 79% respectively

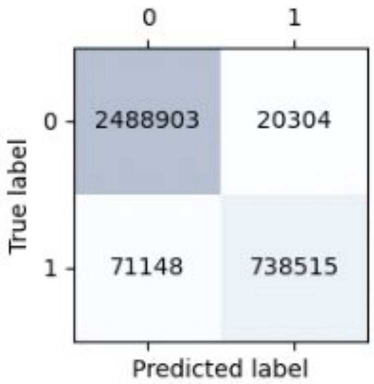
	precision	recall	f1-score	support
0.0	0.74	0.84	0.79	82208
1.0	0.27	0.17	0.21	28421
accuracy			0.67	110629
macro avg	0.51	0.50	0.50	110629
weighted avg	0.62	0.67	0.64	110629

Model - Random Forest

Building a random forest

```
%%time
random_forest = RandomForestClassifier(criterion='entropy', #function to measure the quality of a feature split
                                       n_estimators=10, #number of trees in the forest
                                       bootstrap = True, #different sample for each estimator
                                       max_samples = 0.6, #max number of samples is 50% of training data
                                       n_jobs=2) # The number of jobs to run in parallel.
clf = random_forest.fit(X_train, Y_train)
```

```
Accuracy on Training Data: 0.9724
Accuracy on Validation Data: 0.8727
Validation Precision score: 0.8360
Validation Recall score: 0.8239
Validation F1 score 0.8296
```



Random Forest - Hyperparameter Tuning

- Establish random forest parameter distribution
  - SKlearn’s RandomizedSearchCV will randomly sample from these

```python
criterion = ['entropy'] #what will be used to choose features at node splits
n_estimators = [i for i in range(10,18,2)] # number of trees in the random forest
bootstrap = [True] # drawing samples from our source data with replacement
max_samples = [i/10 for i in range(2,10,2)] #percentage of training samples to train each tree with
n_jobs=[-1]
max_features = ['sqrt']  #could add in 'log2' but took too long
max_depth = [i for i in range(110,160,10)] #max amount of layers in a tree
max_depth.append(None)  #if None, then nodes are expanded until all leaves are pure
min_samples_split = [2, 6, 10] # minimum sample number to split a node, need at least two to split
min_samples_leaf = [1,2, 3] # A split point at any depth will only be considered if it leaves at least
                             #min_samples_leaf training samples in each of the left and right branches.
                              #This may have the effect of smoothing the model, especially in regression

random_grid = { 'criterion' : criterion,
               'n_estimators' : n_estimators,
               'bootstrap' : bootstrap,
               'max_samples' : max_samples,
               'n_jobs' : n_jobs,
               'max_features' : max_features,
               'max_depth' : max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf' : min_samples_leaf
              }
```

Random Forest - Hyperparameter Tuning

- Initiate the tuning

```
%%time
#first we need to initiate a new base tree estimator
base_tree =  RandomForestClassifier()

#initialize the random search CV hyperparameter tuner
Random_Forest_HyperTuned = RandomizedSearchCV(estimator = base_tree,
                                              param_distributions = random_grid,#params defines above
                                              n_iter = 8, #Number of parameter settings that are sampled from distr
                                              cv = 3, #default is5-fold cross validation, so we will have 30 trees
                                              verbose = 1, #the higher, the more messages
                                              return_train_score = True # attribute will include training scores
                                             )
#now we need to train the model using our training data and labels
Random_Forest_HyperTuned.fit(X_train,Y_train)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
CPU times: user 21min 23s, sys: 2min 17s, total: 23min 40s
Wall time: 12h 50min 54s
```

```
▸ RandomizedSearchCV
▸ estimator: RandomForestClassifier
    ▸ RandomForestClassifier
```

Best parameters

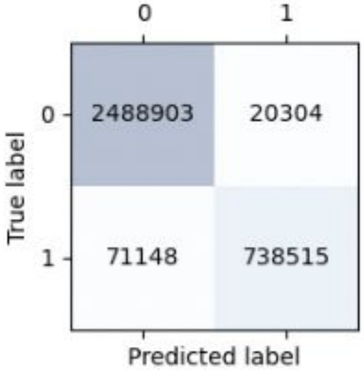
```
{'n_jobs': -1,
 'n_estimators': 16,
 'min_samples_split': 2,
 'min_samples_leaf': 3,
 'max_samples': 0.8,
 'max_features': 'sqrt',
 'max_depth': 150,
 'criterion': 'entropy',
 'bootstrap': True}
```

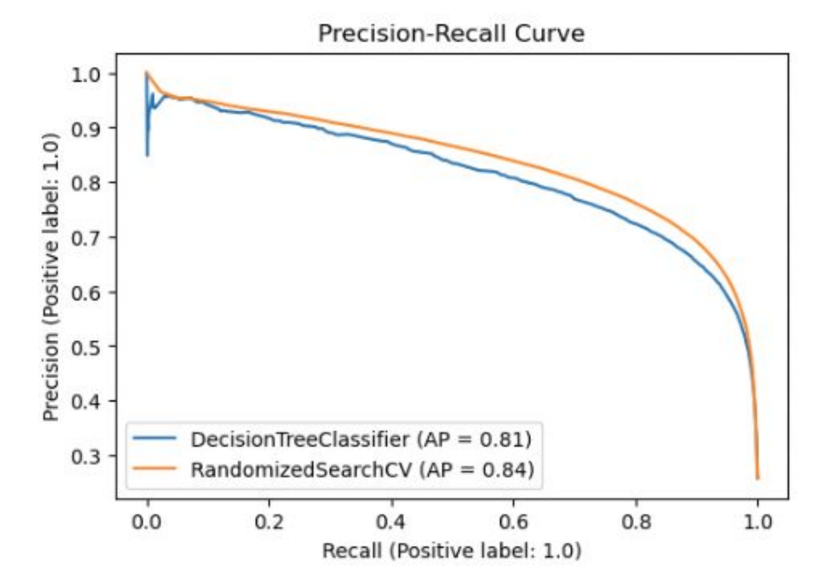
Feature Importances

	Feature	importance
0	P_2	0.076980
1	D_44	0.038740
2	D_48	0.032910
3	D_45	0.029680
4	D_61	0.027010
5	B_20	0.025950
6	B_3	0.021830
7	B_2	0.020580
8	B_10	0.019860
9	B_18	0.018480

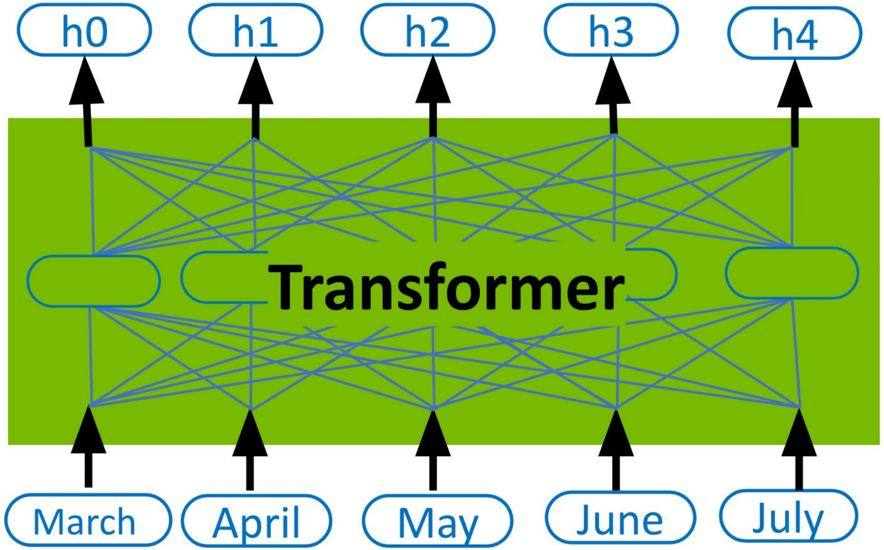
Random Forest - Test Set Evaluation

```
Accuracy on Test Data: 0.8829
Test Precision score: 0.8422
Test Recall score: 0.8641
Test F1 score 0.8520
```





Model Transformer

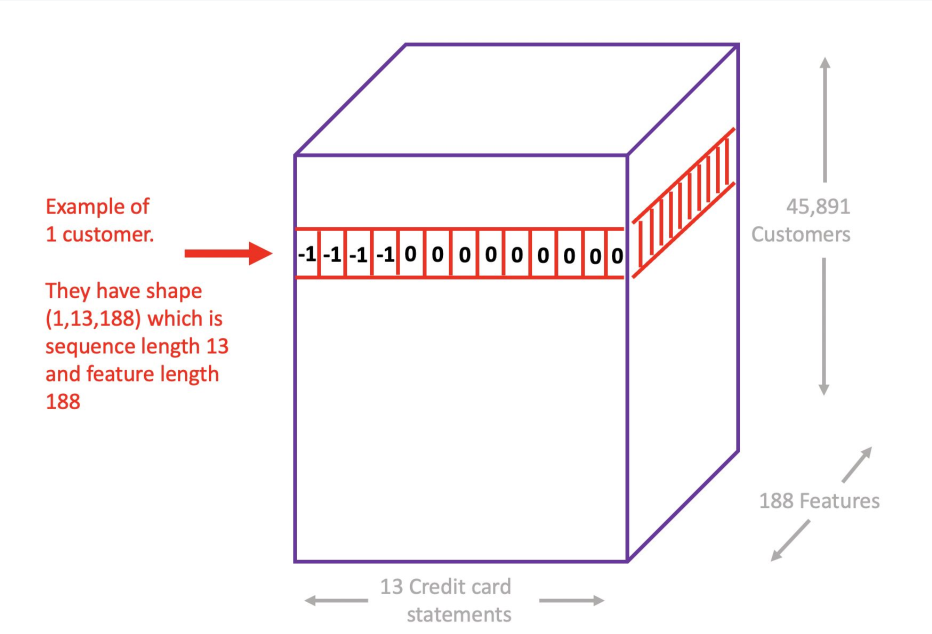


Time series data:

- Most of customers have 13 months credit history
- Transform data from 2d to 3d
- Implement transformer encoder and connect its output to a classification head using binary cross-entropy

Model Transformer - Pre-Processing and Feature Engineering

- Load and split training data:
  - 10 files
  - 45891 customers
  - 13 credit card statements
- Add padding
  - For customers has less than 13 credit card history, pad with -1
- Feature Engineer
  - Output shape (45891, 13, 188)



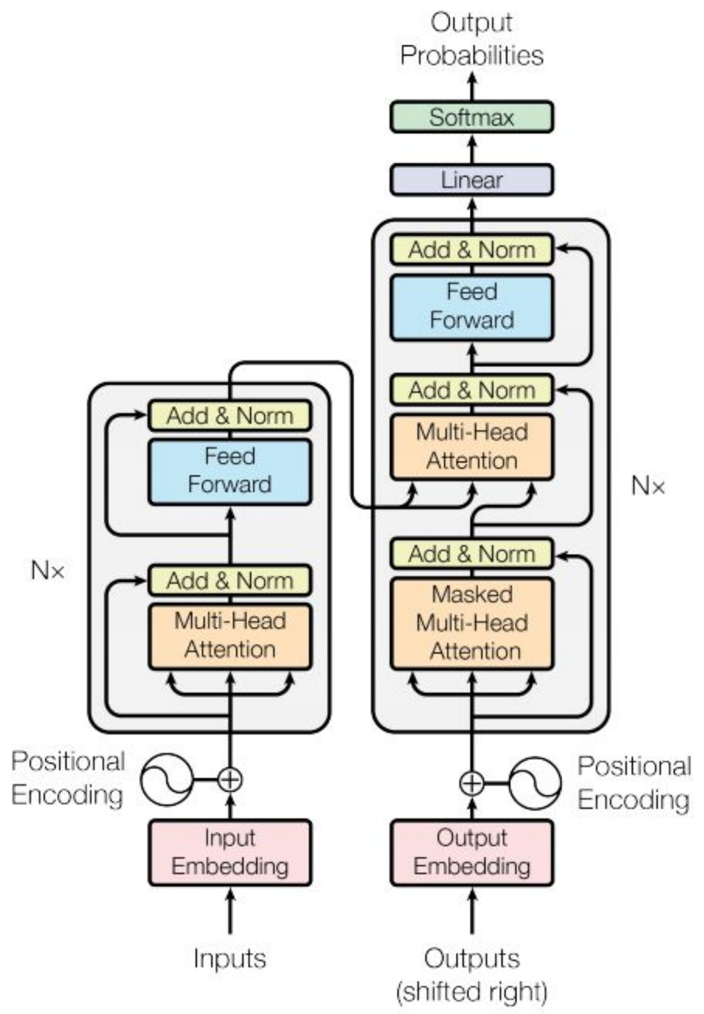
Transformer Block

▾ Hyper-parameters

```
feat_dim = 188
embed_dim = 64   # Embedding size for attention
num_heads = 4   # Number of attention heads
ff_dim = 128   # Hidden layer size in feed forward network inside transformer
dropout_rate = 0.3
num_blocks = 2
```

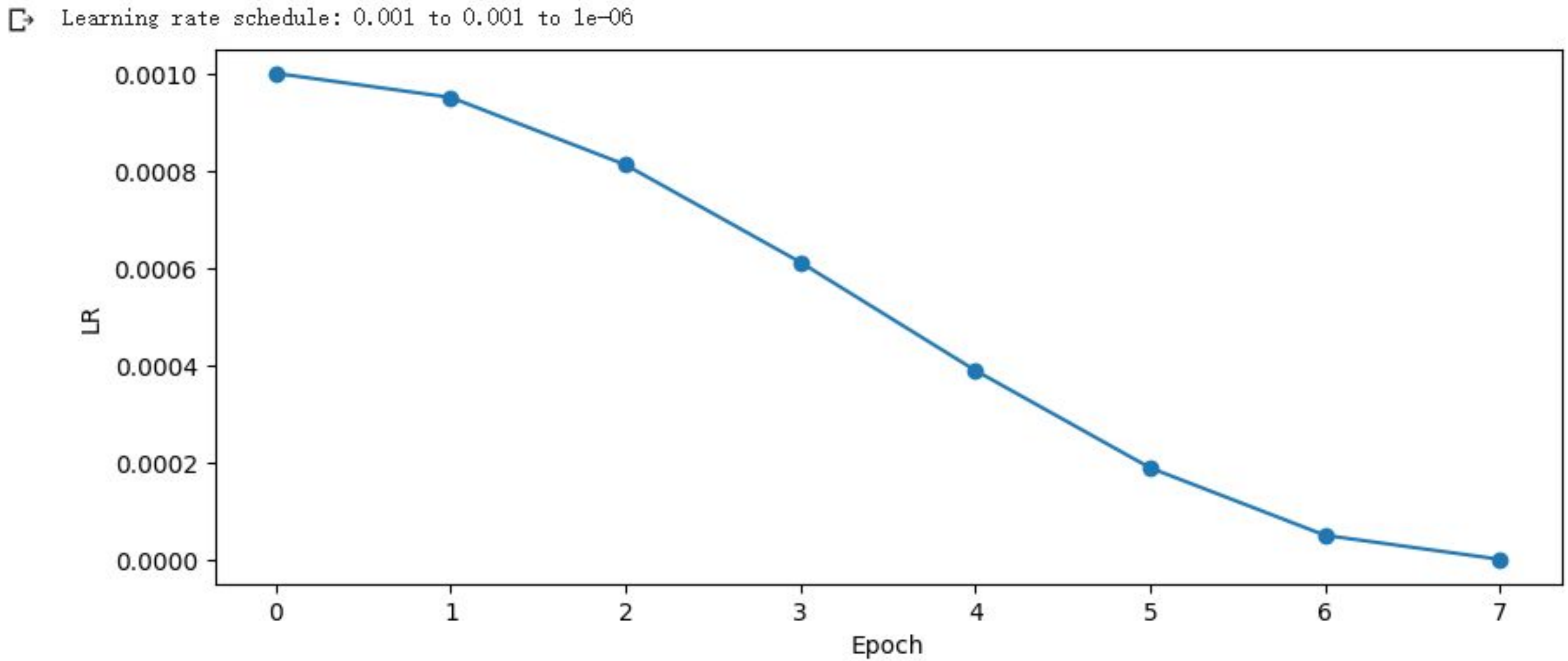
```
[ ]  class TransformerBlock(layers.Layer):
         def __init__(self, embed_dim, feat_dim, num_heads, ff_dim, rate=0.1):
             super(TransformerBlock, self).__init__()
             self.att = layers.MultiHeadAttention(num_heads=num_heads, key_dim=embed_dim)
             self.ffn = keras.Sequential(
                 [layers.Dense(ff_dim, activation="gelu"), layers.Dense(feat_dim),]
             )
             self.layernorm1 = layers.LayerNormalization(epsilon=1e-6)
             self.layernorm2 = layers.LayerNormalization(epsilon=1e-6)
             self.dropout1 = layers.Dropout(rate)
             self.dropout2 = layers.Dropout(rate)

         def call(self, inputs, training):
             attn_output = self.att(inputs, inputs)
             attn_output = self.dropout1(attn_output, training=training)
             out1 = self.layernorm1(inputs + attn_output)
             ffn_output = self.ffn(out1)
             ffn_output = self.dropout2(ffn_output, training=training)
             return self.layernorm2(out1 + ffn_output)
```



Transformer (cont.)

- Learning schedule



Transformer - Training

- We train 5 folds of model using cross validation
  - Use 8 files to trian, 2 files for validation
- 8 epochs for each fold
- Save 5 output transformer model into files

```
#########################
### Fold 5 with valid files [9, 10]
### Training data shapes (367128, 13, 188) (367128,)
### Validation data shapes (91785, 13, 188) (91785,)
#########################

Epoch 1: LearningRateScheduler setting learning rate to 0.001.
Epoch 1/8
718/718 - 24s - loss: 0.2424 - val_loss: 0.2307 - lr: 0.0010 - 24s/epoch - 34ms/step

Epoch 2: LearningRateScheduler setting learning rate to 0.0009505339495172585.
Epoch 2/8
718/718 - 19s - loss: 0.2312 - val_loss: 0.2370 - lr: 9.5053e-04 - 19s/epoch - 27ms/step

Epoch 3: LearningRateScheduler setting learning rate to 0.0008119331560284375.
Epoch 3/8
718/718 - 19s - loss: 0.2279 - val_loss: 0.2269 - lr: 8.1193e-04 - 19s/epoch - 27ms/step
```

Model Transformer - Performance

- Kaggle Evaluation Metrics
  - The metics M is defined as the the mean of two measures
  - G: Normalized Gini Coefficient
  - D: Default rate captured at 4%

$$M = 0.5 \cdot (G + D)$$

Cross Validation Score

```
Fold 1 CV= 0.7843216315379575
```

```
Fold 2 CV= 0.7821227060205045
```

```
Fold 3 CV= 0.7852668054694807
```

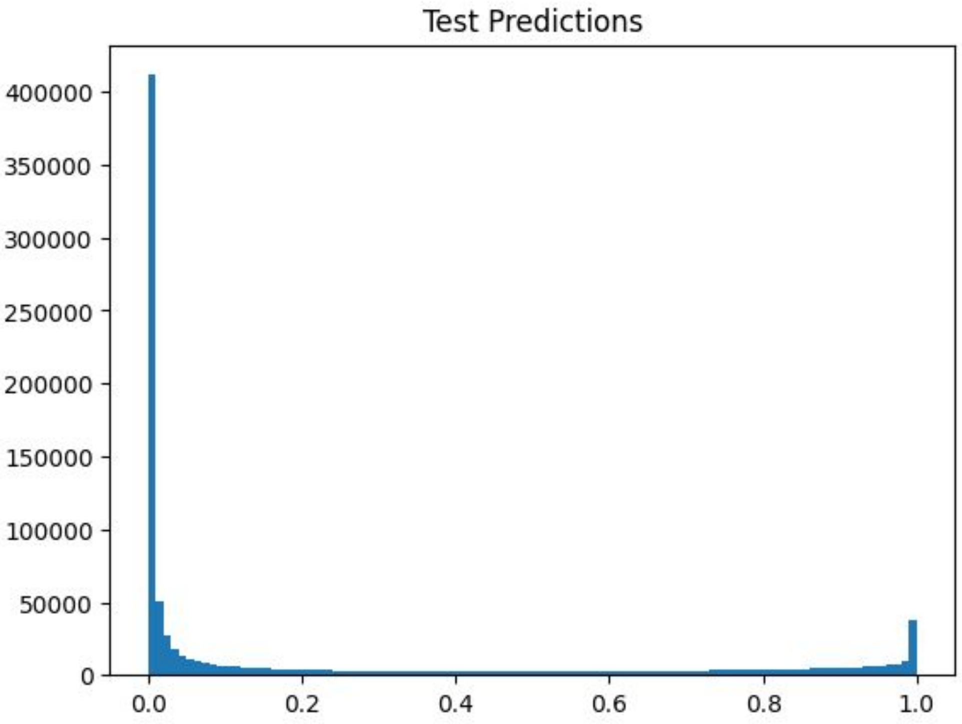
```
Fold 4 CV= 0.7878325830028957
```

```
Fold 5 CV= 0.7903108125684797

#########################
Overall CV = 0.7859054438364497
```

Model Transformer - Test Inference

- Process test data the same way as train data, the output will be 20 files with each file having shape (46231, 13, 188) as (customer x statement x feature)
- Ensemble 5 models from training and create predictions by averaging each model outputs
- Graph the predictions



Model Transformer - Kaggle submission

- Private score: 0.798, Public Score: 0.789

Submission and Description	Private Score	Public Score	Selected
submission.csv Complete (after deadline) · 3d ago · Transformer model	**0.79831**	**0.78911**	☐

Prize Winners

#	△	Team	Members	Score	Entries	Last	Solution
1	▲ 3	lucky shake		0.80977	91	8mo	
2	▲ 5	byDefault [JuneHomes]		0.80938	340	8mo	
3	▲ 2	AIBANK		0.80925	50	8mo	
4	▲ 6	GRE		0.80900	186	8mo	
5	▼ 3	VISA		0.80881	387	8mo	

Takeaways

- **No PII data in features**
  - No insight into categorical features
- **Models may be learning abstract biases about certain demographics**
- **Last 13 bank statements may introduce recency bias**

Contributions:

-EDA (**All**)

-Data Pre Processing (**All**)

-KNN (**Jim**)

-Random Forest (**Julian**)

-Transformer (**Rick**)