In [164…
```
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

import warnings
import logging
from re import sub
from functools import reduce
import boto3
import io

import numpy as np
import pandas as pd
import cudf
import cupy as cp

from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import KFold
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import FunctionTransformer, OrdinalEncoder
from category_encoders import CatBoostEncoder
import preprocessor as pp

import xgboost as xgb
import catboost as cb
import lightgbm as lgb

import optuna
import joblib

import matplotlib.pyplot as plt
import plotly
import plotly.express as px
```

Global Settings

In [2]:
```
seed = 12
rs = np.random.RandomState(seed)

plt.rcParams['figure.figsize'] = (12, 10)

warnings.filterwarnings("ignore")

plotly.offline.init_notebook_mode()

logging.getLogger('matplotlib.font_manager').setLevel(logging.ERROR)

# Model path
model_path = '../output/models/'
eval_path = '../output/evals/'
prep_path = '../output/preprocessors/'
```

S3

In [162…
```
s3 = boto3.client('s3')

AWS_S3_BUCKET = 'yang-ml-sagemaker'
```

Data

In [86]:
```
train, test = pd.read_csv("../data/train_sanitized.csv"), pd.read_csv('../data/test_sanitized.csv')
train.shape, test.shape
```

Out[86]:
```
((338988, 32), (80000, 32))
```

In [87]:
```
X_train, y_train = train.drop(['interest_rate'], axis=1), train.interest_rate.to_numpy()
X_test = test.drop(['interest_rate'], axis=1)
X_train.shape, X_test.shape, y_train.shape
```

Out[87]:
```
((338988, 31), (80000, 31), (338988,))
```

Pipeline Ingredients

We will use three boosted tree frameworks that support GPU training--- XGBoost, CatBoost, and LightGBM. Catboost supports categorical features out of the box while XGBoost and LightGBM have support for pandas or integer-encoded categorical features, respectively. Therefore, our preprocessing pipelines will be slightly different between these three frameworks. Nevertheless, the preprocessing workloads share similar ingredients such as imputation. We define them below so that they can be reused.

In [5]:
```
# Numerical features
num_cols = ['loan_amt_requested', 'loan_amt_investor_funded_portion', 'borrower_annual_income', 'monthly_debt_to
            'num_of_past_dues', 'num_of_creditor_inquiries', 'num_of_months_since_delinquency', 'num_of_open_cre
            'num_of_derog_publib_rec', 'total_credit_rev_balance', 'rev_line_util_rate', 'total_credit_line']

# Categorical features
cat_cols = ['num_of_payment_months', 'loan_subgrade', 'num_of_years_employed', 'home_ownership_status', 'verify_
            'loan_issued_date', 'borrower_provided_loan_category', 'zip_first_three', 'borrower_state',
            'borrower_earliest_credit_open_date', 'init_loan_status']

# Categorical features to be encoded
encode_cols = ['num_of_payment_months', 'loan_subgrade', 'num_of_years_employed', 'home_ownership_status', 'ver
               'loan_issued_year', 'loan_issued_month', 'borrower_provided_loan_category', 'zip_first_three', 'l
               'borrower_earliest_credit_open_year', 'borrower_earliest_credit_open_month', 'init_loan_status']

# Extracted date features
date_cols = ['loan_issued_year', 'loan_issued_month', 'borrower_earliest_credit_open_year', 'borrower_earliest_
```

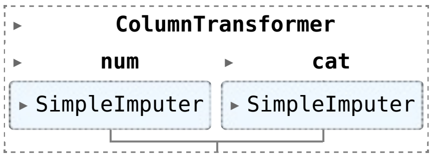
For imputation, the KNN imputation implementation from Sklearn is not really scalable to 338,988 rows. KNN using the kd-tree method generally has complexity $O(d N log N)$; according to this issue, the sklearn implementation also involves $O(n^2)$ computations, which can further slow down the training time. Unfortunately, the `cuml` implementation of KNN imputer has not been released yet. Due to all of this, we will use the simple imputer for all of the missing features. Also, we are using ensemble models, and, according to the sklearn documnetation:

> In a prediction context, simple imputation usually performs poorly when associated with a weak learner. However, with a powerful learner, it can lead to as good or better performance than complex imputation such as IterativeImputer or KNNImputer.

With more computing resources, I may opt to try the KNN imputation model and see if the results are better. But for now, we will proceed as best as we could.

In [6]:
```
imputers = ColumnTransformer([
    ('num', SimpleImputer(strategy='median').set_output(transform='pandas'), num_cols),
    ('cat', SimpleImputer(strategy='constant', fill_value='missing').set_output(transform='pandas'), cat_cols)
], remainder='drop').set_output(transform='pandas')
imputers
```

Out[6]:



The feature engineering pieces are encapsulated in the `preprocessor.py` module. The following steps are carried out:

1. Extract year and month from the the two date features, creating four categorical features

2. For each category in each of the categorical features, create primitive aggregate features--- max, sum, mean, std--- of the numerical features. This creates $11 \;(\text{numerical features}) \times 11 \; (\text{categorical features}) \times 4 \; ((\text{aggregation functions}))=484$ numerical features in total.

3. The categorical feature will be handled differently:

    - For XGBoost, the categorical features will be encoded using `CatBoostEncoder`, which is an implementation of target encoding

    - For CatBoost, the categorical features will be handled natively

    - For LightGBM, the categorical features will be encoded using `OrdinalEncoder`, which will then be handled by the LightGBM internals

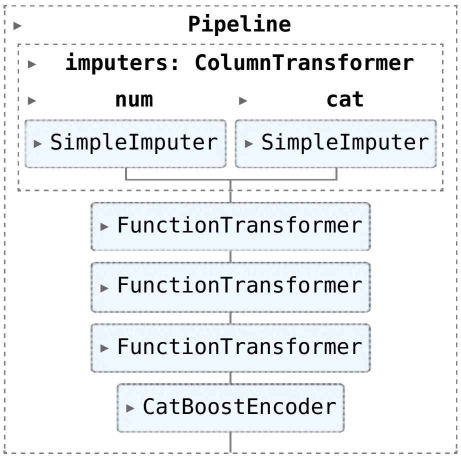
XGBoost

Pipeline

In [12]:
```
xgboost_preprocessor = Pipeline([
    ('imputers', imputers),
    ('restore_cols', FunctionTransformer(pp.restore_columns)),
    ('date_transformer', FunctionTransformer(pp.extract_date_features)),
    ('num_feat_eng', FunctionTransformer(pp.num_feat_eng)),
    ('cat_encoder', CatBoostEncoder(cols=encode_cols, handle_missing='value', handle_unknown='value')) # Catboos
])
joblib.dump(xgboost_preprocessor, prep_path + 'xgboost_preprocessor.joblib')
xgboost_preprocessor
```

Out[12]:
```
['../output/preprocessors/xgboost_preprocessor.joblib']
```

Out[12]:



Hyperparameter Search

The hyperparameter search will be carried out using Bayesian optimization, specifically, the Tree Parzen Estimator algorithm. Because we have limited compute budget where grid search can be hard to scale given the data size, we will use bayesian optimization, which generally requires fewer iterations to achieve acceptable results. In addition, we will use the implementation from `Optuna` rather than from `Hyperopt`. Optuna has more utilities and support for pruning. For all three frameworks, we will limit our budget to 20 trials.

In [43]:
```
def objective_xgboost(trial):

    # Fold and seed
    train = pd.read_csv("../data/train_sanitized.csv")
    X_train, y_train = train.drop(['interest_rate'], axis=1), train.interest_rate.to_numpy()
    folds = 5
    seed = 1227

    # Parameters
    search_space = {
        # Booster parameters
        'booster_params': {
                'booster': 'gbtree',
                'objective': 'reg:squarederror',
                'eval_metric': 'rmse', # Use RMSE for evaluation metric on train and validation sets
                'learning_rate': trial.suggest_float(name='learning_rate', low=0.001, high=0.5), # Range: [0, 1
                'gamma': trial.suggest_int('gamma', 0, 20), # Range: [0, inf], the larger the more conservative
                'max_delta_step': trial.suggest_int('max_delta_step', 1, 10), # Range: [0, inf], values from 1-
                'lambda': trial.suggest_categorical('lambda', [10, 100, 500]), # Range: [0, inf], L2 regulariza
                'alpha': trial.suggest_categorical('alpha', [10, 100, 500]), # Range: [0, inf], L1 regularizati
                'colsample_bylevel': trial.suggest_categorical('colsample_bylevel', np.linspace(0.3, 1, 6).tolis
                'colsample_bynode': trial.suggest_categorical('colsample_bynode', np.linspace(0.3, 1, 6).tolist
                'colsample_bytree': trial.suggest_categorical('colsample_bytree', np.linspace(0.3, 1, 6).tolist
                'subsample': trial.suggest_categorical('subsample', np.linspace(0.3, 1, 6).tolist()), # Range:
                'sampling_method': 'gradient_based', # Only supported for 'gpu_hist'
                'max_depth': trial.suggest_categorical('max_depth', np.arange(3, 12, dtype=np.int16).tolist()),
                'tree_method': 'gpu_hist',
                'predictor': 'gpu_predictor'
        },
        # Non-booster parameters
        'num_boost_round': trial.suggest_int('num_boost_round', low=500, high=2000, step=100), # Range: [0, inf
        }

    # K-fold cross validation
    kf = KFold(n_splits=folds, shuffle=True, random_state=rs)
    rmse_scores = np.empty(folds)

    for fold, (train_indx, val_indx) in enumerate(kf.split(X_train, y_train)):

        # Train and validation sets
        fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
        fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

        # Preprocessing using a fresh copy of the pipeline for every fold to prevent leakage
        preprocessor = joblib.load('../output/preprocessors/xgboost_preprocessor.joblib')
        print(f'Start processing fold {fold + 1}...')
        fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
        fold_X_val = preprocessor.transform(fold_X_val)

        # Data for modeling
        feature_names = fold_X_train.columns.tolist()
        dtrain = xgb.DMatrix(data=fold_X_train, label=fold_y_train, feature_names=feature_names)
        dvalid = xgb.DMatrix(data=fold_X_val, label=fold_y_val, feature_names=feature_names)

        # Model
        model = xgb.train(
            params=search_space['booster_params'],
            dtrain=dtrain,
            num_boost_round=search_space['num_boost_round'],
            early_stopping_rounds=200,
            evals=[(dtrain, 'train'), (dvalid, 'validate')],
            verbose_eval=200 # Print eval every 200 boosting rounds
          )

        # Out-of-fold prediction
        print(f'Predicting for fold {fold + 1}...')
        oof_pred = model.predict(data=dvalid)
        rmse_scores[fold] = mean_squared_error(fold_y_val, oof_pred, squared=False) # Use RMSE

    # Average across 5 folds
    mean_rmse = np.mean(rmse_scores)

    return mean_rmse
```

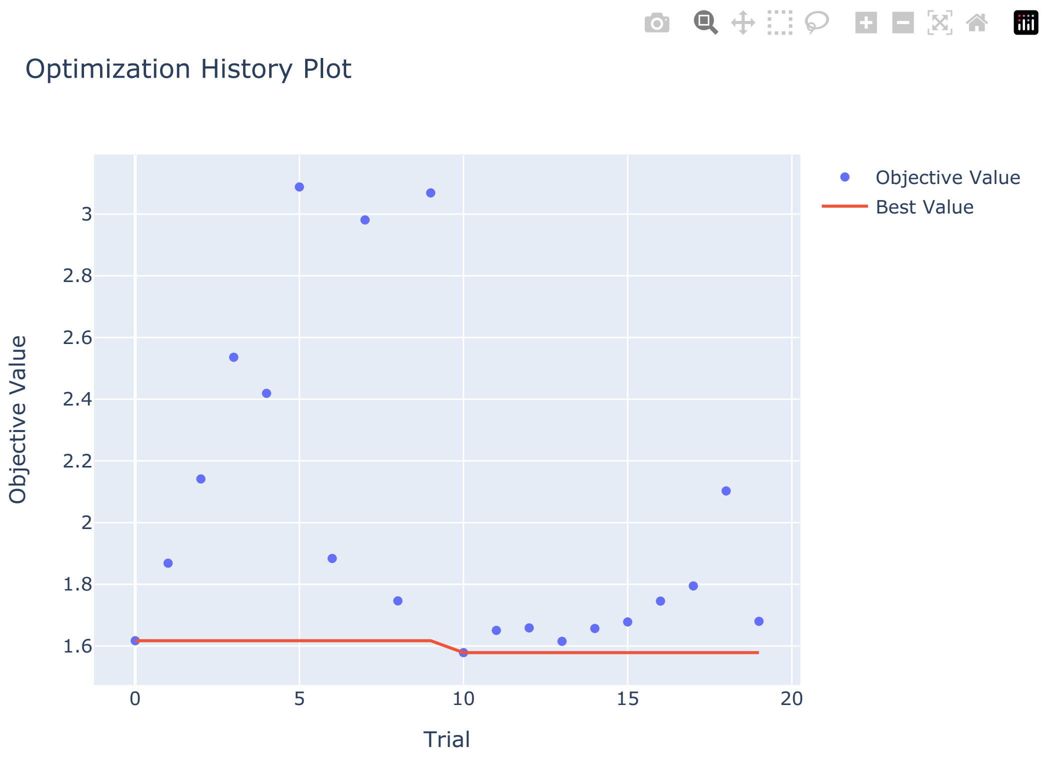
In [44]:
```
study_xgboost = optuna.create_study(sampler=optuna.samplers.TPESampler(), study_name='min_rmse_xgboost', direct
study_xgboost.optimize(objective_xgboost, n_trials=20)
```

```
[I 2023-02-12 08:57:23,065] A new study created in memory with name: min_rmse_xgboost
Start Processing fold 1...
[0]     train-rmse:13.61135     validate-rmse:13.61680
[200]   train-rmse:1.05672      validate-rmse:1.57748
[400]   train-rmse:1.05477      validate-rmse:1.57762
[412]   train-rmse:1.05477      validate-rmse:1.57762
Predicting for fold 1...
Start Processing fold 2...
[0]     train-rmse:13.61195     validate-rmse:13.61439
[200]   train-rmse:1.05722      validate-rmse:1.61548
[344]   train-rmse:1.05612      validate-rmse:1.61511
Predicting for fold 2...
Start Processing fold 3...
[0]     train-rmse:13.61381     validate-rmse:13.60694
[200]   train-rmse:1.05113      validate-rmse:1.61564
[400]   train-rmse:1.05002      validate-rmse:1.61536
[600]   train-rmse:1.04932      validate-rmse:1.61517
[800]   train-rmse:1.04828      validate-rmse:1.61422
[1000]  train-rmse:1.04817      validate-rmse:1.61421
[1136]  train-rmse:1.04817      validate-rmse:1.61421
Predicting for fold 3...
Start Processing fold 4...
[0]     train-rmse:13.60789     validate-rmse:13.63062
[200]   train-rmse:1.05917      validate-rmse:1.57633
[400]   train-rmse:1.05749      validate-rmse:1.57641
[476]   train-rmse:1.05641      validate-rmse:1.57640
Predicting for fold 4...
Start Processing fold 5...
[0]     train-rmse:13.61719     validate-rmse:13.59342
[200]   train-rmse:1.06073      validate-rmse:1.70401
[400]   train-rmse:1.05867      validate-rmse:1.70225
[600]   train-rmse:1.05851      validate-rmse:1.70222
[631]   train-rmse:1.05851      validate-rmse:1.70222
[I 2023-02-12 08:59:48,848] Trial 0 finished with value: 1.6171119920003556 and parameters: {'learning_rate': 0
.1856901734449837, 'gamma': 6, 'max_delta_step': 3, 'lambda': 100, 'alpha': 500, 'colsample_bylevel': 0.8599999
999999999, 'colsample_bynode': 0.8599999999999999, 'colsample_bytree': 0.8599999999999999, 'subsample': 0.3, 'm
ax_depth': 11, 'num_boost_round': 1800}. Best is trial 0 with value: 1.6171119920003556.
```

```
Predicting for fold 5...
Start Processing fold 1...
[0]     train-rmse:13.78072     validate-rmse:13.77241
[200]   train-rmse:1.09313      validate-rmse:1.72533
[350]   train-rmse:1.09291      validate-rmse:1.72502
Predicting for fold 1...
Start Processing fold 2...
[0]     train-rmse:13.77274     validate-rmse:13.80433
[200]   train-rmse:1.09583      validate-rmse:1.89320
[257]   train-rmse:1.09534      validate-rmse:1.89275
Predicting for fold 2...
Start Processing fold 3...
[0]     train-rmse:13.77995     validate-rmse:13.77550
[200]   train-rmse:1.09807      validate-rmse:1.89783
[257]   train-rmse:1.09787      validate-rmse:1.89750
Predicting for fold 3...
Start Processing fold 4...
[0]     train-rmse:13.77471     validate-rmse:13.79647
[200]   train-rmse:1.10069      validate-rmse:2.04729
[255]   train-rmse:1.10063      validate-rmse:2.04720
Predicting for fold 4...
Start Processing fold 5...
[0]     train-rmse:13.78718     validate-rmse:13.74652
[200]   train-rmse:1.10100      validate-rmse:1.78084
[255]   train-rmse:1.10010      validate-rmse:1.77956
[I 2023-02-12 09:01:32,849] Trial 1 finished with value: 1.8684071040199797 and parameters: {'learning_rate': 0
.38122271808122965, 'gamma': 8, 'max_delta_step': 1, 'lambda': 10, 'alpha': 500, 'colsample_bylevel': 0.58, 'co
lsample_bynode': 0.72, 'colsample_bytree': 1.0, 'subsample': 0.43999999999999995, 'max_depth': 5, 'num_boost_ro
und': 1100}. Best is trial 0 with value: 1.6171119920003556.
Predicting for fold 5...
Start Processing fold 1...
[0]     train-rmse:13.75529     validate-rmse:13.76219
[200]   train-rmse:1.00390      validate-rmse:2.05411
[251]   train-rmse:1.00328      validate-rmse:2.05398
Predicting for fold 1...
Start Processing fold 2...
[0]     train-rmse:13.75912     validate-rmse:13.74684
[200]   train-rmse:1.00619      validate-rmse:2.19115
[248]   train-rmse:1.00614      validate-rmse:2.19121
Predicting for fold 2...
Start Processing fold 3...
[0]     train-rmse:13.76288     validate-rmse:13.73180
[200]   train-rmse:0.99972      validate-rmse:2.22276
[249]   train-rmse:0.99972      validate-rmse:2.22278
Predicting for fold 3...
Start Processing fold 4...
[0]     train-rmse:13.74981     validate-rmse:13.78405
[200]   train-rmse:1.00156      validate-rmse:2.03566
[249]   train-rmse:1.00156      validate-rmse:2.03553
Predicting for fold 4...
Start Processing fold 5...
[0]     train-rmse:13.75623     validate-rmse:13.75840
[200]   train-rmse:1.00738      validate-rmse:2.20355
[247]   train-rmse:1.00738      validate-rmse:2.20352
[I 2023-02-12 09:03:16,472] Trial 2 finished with value: 2.141384130449744 and parameters: {'learning_rate': 0.
20242149604554308, 'gamma': 15, 'max_delta_step': 2, 'lambda': 10, 'alpha': 10, 'colsample_bylevel': 0.58, 'col
sample_bynode': 0.43999999999999995, 'colsample_bytree': 1.0, 'subsample': 0.3, 'max_depth': 7, 'num_boost_roun
d': 1000}. Best is trial 0 with value: 1.6171119920003556.
```

```
Predicting for fold 5...
Start Processing fold 1...
[0]	train-rmse:13.90105	validate-rmse:13.91708
[200]	train-rmse:1.06363	validate-rmse:2.27384
[279]	train-rmse:1.02663	validate-rmse:2.26951
Predicting for fold 1...
Start Processing fold 2...
[0]	train-rmse:13.90115	validate-rmse:13.91668
[200]	train-rmse:1.06231	validate-rmse:2.22709
[284]	train-rmse:1.01903	validate-rmse:2.21955
Predicting for fold 2...
Start Processing fold 3...
[0]	train-rmse:13.91049	validate-rmse:13.87930
[200]	train-rmse:1.06803	validate-rmse:2.29854
[280]	train-rmse:1.02817	validate-rmse:2.28679
Predicting for fold 3...
Start Processing fold 4...
[0]	train-rmse:13.90223	validate-rmse:13.91235
[200]	train-rmse:1.05879	validate-rmse:1.97315
[292]	train-rmse:1.01672	validate-rmse:1.96600
Predicting for fold 4...
Start Processing fold 5...
[0]	train-rmse:13.90636	validate-rmse:13.89582
[200]	train-rmse:1.05849	validate-rmse:1.77650
[307]	train-rmse:1.01203	validate-rmse:1.77131
[I 2023-02-12 09:51:56,795] Trial 18 finished with value: 2.102634994926789 and parameters: {'learning_rate': 0
.06231353236268271, 'gamma': 0, 'max_delta_step': 4, 'lambda': 100, 'alpha': 100, 'colsample_bylevel': 0.3, 'co
lsample_bynode': 1.0, 'colsample_bytree': 0.72, 'subsample': 1.0, 'max_depth': 8, 'num_boost_round': 1500}. Bes
t is trial 10 with value: 1.5785182273533465.
Predicting for fold 5...
Start Processing fold 1...
[0]	train-rmse:12.73862	validate-rmse:12.78280
[200]	train-rmse:0.98532	validate-rmse:1.63571
[400]	train-rmse:0.98198	validate-rmse:1.63494
[448]	train-rmse:0.98198	validate-rmse:1.63494
Predicting for fold 1...
Start Processing fold 2...
[0]	train-rmse:12.74389	validate-rmse:12.75112
[200]	train-rmse:0.98627	validate-rmse:1.75819
[279]	train-rmse:0.98495	validate-rmse:1.75818
Predicting for fold 2...
Start Processing fold 3...
[0]	train-rmse:12.74078	validate-rmse:12.76740
[200]	train-rmse:0.98417	validate-rmse:1.68106
[400]	train-rmse:0.98410	validate-rmse:1.68106
[444]	train-rmse:0.98410	validate-rmse:1.68106
Predicting for fold 3...
Start Processing fold 4...
[0]	train-rmse:12.74427	validate-rmse:12.75129
[200]	train-rmse:0.98263	validate-rmse:1.75061
[400]	train-rmse:0.98259	validate-rmse:1.75049
[600]	train-rmse:0.98254	validate-rmse:1.75050
[605]	train-rmse:0.98254	validate-rmse:1.75050
Predicting for fold 4...
Start Processing fold 5...
[0]	train-rmse:12.74733	validate-rmse:12.72373
[200]	train-rmse:0.98971	validate-rmse:1.57522
[400]	train-rmse:0.98894	validate-rmse:1.57522
[442]	train-rmse:0.98894	validate-rmse:1.57523
[I 2023-02-12 09:54:03,190] Trial 19 finished with value: 1.6799802107072614 and parameters: {'learning_rate':
0.15069330553741483, 'gamma': 7, 'max_delta_step': 10, 'lambda': 100, 'alpha': 100, 'colsample_bylevel': 0.72,
'colsample_bynode': 1.0, 'colsample_bytree': 0.72, 'subsample': 0.58, 'max_depth': 10, 'num_boost_round': 1700}
. Best is trial 10 with value: 1.5785182273533465.
Predicting for fold 5...
```

In [53]:
```python
fig_xgboost = optuna.visualization.plot_optimization_history(study_xgboost)
fig_xgboost.show();
```



Model Training

The set of parameters that resulted in the lowest RMSE is as follows:

```
In [54]: study_xgboost.best_params
```

```
Out[54]: {'learning_rate': 0.008732104299950916,
 'gamma': 0,
 'max_delta_step': 5,
 'lambda': 100,
 'alpha': 100,
 'colsample_bylevel': 1.0,
 'colsample_bynode': 0.8599999999999999,
 'colsample_bytree': 0.72,
 'subsample': 0.72,
 'max_depth': 8,
 'num_boost_round': 2000}
```

We now train the model:

```
In [118…
# Out-of-fold prediction dictionary
oof_xgboost = {}
# Feature importance container
feat_imp_xgboost = []
# K-fold cross validation
kf_xgboost = KFold(n_splits=5, shuffle=True, random_state=rs)

for fold, (train_indx, val_indx) in enumerate(kf_xgboost.split(X_train, y_train)):
    # Train and validation sets
    fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
    fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

    # Preprocessing using fresh copy of the pipeline for every fold
    preprocessor = joblib.load('../output/preprocessors/xgboost_preprocessor.joblib')
    print(f'Start processing fold {fold + 1}...')
    fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
    fold_X_val = preprocessor.transform(fold_X_val)
    # Write fitted preprocessor to disk
    joblib.dump(preprocessor, model_path + f'xgboost/preprocessor_fold_{fold + 1}.joblib')

    # Data for modeling
    feature_names = fold_X_train.columns.tolist()
    dtrain = xgb.DMatrix(data=fold_X_train, label=fold_y_train, feature_names=feature_names)
    dvalid = xgb.DMatrix(data=fold_X_val, label=fold_y_val, feature_names=feature_names)

    # Model
    evals_result = {}
    model = xgb.train(
        params={'learning_rate': 0.009,
                'gamma': 0,
                 'max_delta_step': 5,
                 'lambda': 100,
                 'alpha': 100,
                 'colsample_bylevel': 1,
                 'colsample_bynode': 0.8599999999999999,
                 'colsample_bytree': 0.72,
                 'subsample': 0.72,
                 'max_depth': 8,
                 'sampling_method': 'gradient_based',
                 'tree_method': 'gpu_hist',
                 'predictor': 'gpu_predictor'},
        dtrain=dtrain,
        num_boost_round=study_xgboost.best_params['num_boost_round'],
        early_stopping_rounds=200,
        evals=[(dtrain, 'train'), (dvalid, 'validate')],
        evals_result=evals_result,
        verbose_eval=200 # Print eval every 200 boosting rounds
      )
    model.save_model(model_path + f'xgboost/model_fold_{fold + 1}.xgb')
    joblib.dump(evals_result, model_path + f'xgboost/eval_fold_{fold + 1}.joblib')

    # Feature importance for top 20 features for the current fold
    # The booster object has a get_score method that returns a dictionary of feature names and their importance
    feat_imp = model.get_score(importance_type='weight')
    df = pd.DataFrame({'feature': feat_imp.keys(), f'importance_{fold + 1}': feat_imp.values()})
    feat_imp_xgboost.append(df)

    # Predictions
    print(f'predicting for fold {fold + 1}...')
    oof_pred = model.predict(data=dvalid)
    oof_xgboost[f'fold_{fold + 1}'] = {'target': fold_y_val, 'predictions': oof_pred}

    del dtrain, dvalid, preprocessor, model, evals_result, feat_imp, df, oof_pred
```

```
Start processing fold 1...
```

```
Out[118]: ['../output/models/xgboost/preprocessor_fold_1.joblib']
```

```
[0]     train-rmse:14.10195     validate-rmse:14.08351
[200]   train-rmse:6.24335      validate-rmse:6.29366
[400]   train-rmse:2.03898      validate-rmse:2.42746
[600]   train-rmse:1.25203      validate-rmse:1.72568
[800]   train-rmse:1.14223      validate-rmse:1.64578
[1000]  train-rmse:1.08700      validate-rmse:1.63519
[1200]  train-rmse:1.05480      validate-rmse:1.63334
[1400]  train-rmse:1.03457      validate-rmse:1.63284
[1600]  train-rmse:1.02108      validate-rmse:1.63264
[1800]  train-rmse:1.00929      validate-rmse:1.63254
[1999]  train-rmse:0.99884      validate-rmse:1.63293
```

```
Out[118]: ['../output/models/xgboost/eval_fold_1.joblib']
```

```
predicting for fold 1...
Start processing fold 2...
```

```
Out[118]: ['../output/models/xgboost/preprocessor_fold_2.joblib']
```

```
[0]     train-rmse:14.09135     validate-rmse:14.12589
[200]   train-rmse:6.23148      validate-rmse:6.31004
[400]   train-rmse:2.03349      validate-rmse:2.31435
[600]   train-rmse:1.25053      validate-rmse:1.64104
[800]   train-rmse:1.14159      validate-rmse:1.61230
[1000]  train-rmse:1.08716      validate-rmse:1.60911
[1098]  train-rmse:1.06923      validate-rmse:1.60915
```

```
Out[118]: ['../output/models/xgboost/eval_fold_2.joblib']
```

```
predicting for fold 2...
Start processing fold 3...
```

```
Out[118]: ['../output/models/xgboost/preprocessor_fold_3.joblib']
```

```
[0]     train-rmse:14.10141     validate-rmse:14.08567
[200]   train-rmse:6.24173      validate-rmse:6.25762
[400]   train-rmse:2.03730      validate-rmse:2.29337
[600]   train-rmse:1.25080      validate-rmse:1.66738
[800]   train-rmse:1.14343      validate-rmse:1.62506
[1000]  train-rmse:1.08942      validate-rmse:1.62046
[1200]  train-rmse:1.05792      validate-rmse:1.62104
[1212]  train-rmse:1.05646      validate-rmse:1.62110
```

```
Out[118]: ['../output/models/xgboost/eval_fold_3.joblib']
```

```
predicting for fold 3...
Start processing fold 4...
```

```
Out[118]: ['../output/models/xgboost/preprocessor_fold_4.joblib']
```

```
[0]     train-rmse:14.09775     validate-rmse:14.10034
[200]   train-rmse:6.23707      validate-rmse:6.27878
[400]   train-rmse:2.03466      validate-rmse:2.28574
[600]   train-rmse:1.24949      validate-rmse:1.60826
[800]   train-rmse:1.14053      validate-rmse:1.55816
[1000]  train-rmse:1.08597      validate-rmse:1.54573
[1200]  train-rmse:1.05402      validate-rmse:1.54003
[1400]  train-rmse:1.03457      validate-rmse:1.53832
[1600]  train-rmse:1.02071      validate-rmse:1.53708
[1800]  train-rmse:1.00923      validate-rmse:1.53580
[1999]  train-rmse:0.99950      validate-rmse:1.53528
```

```
Out[118]: ['../output/models/xgboost/eval_fold_4.joblib']
```

```
predicting for fold 4...
Start processing fold 5...
```

```
Out[118]: ['../output/models/xgboost/preprocessor_fold_5.joblib']
```

```
[0]     train-rmse:14.09886     validate-rmse:14.09588
[200]   train-rmse:6.23780      validate-rmse:6.32863
[400]   train-rmse:2.03405      validate-rmse:2.35200
[600]   train-rmse:1.24865      validate-rmse:1.57282
[800]   train-rmse:1.13978      validate-rmse:1.51728
[1000]  train-rmse:1.08546      validate-rmse:1.51096
[1200]  train-rmse:1.05330      validate-rmse:1.50851
[1400]  train-rmse:1.03444      validate-rmse:1.50786
[1600]  train-rmse:1.02027      validate-rmse:1.50699
[1800]  train-rmse:1.00859      validate-rmse:1.50684
[1999]  train-rmse:0.99859      validate-rmse:1.50644
```

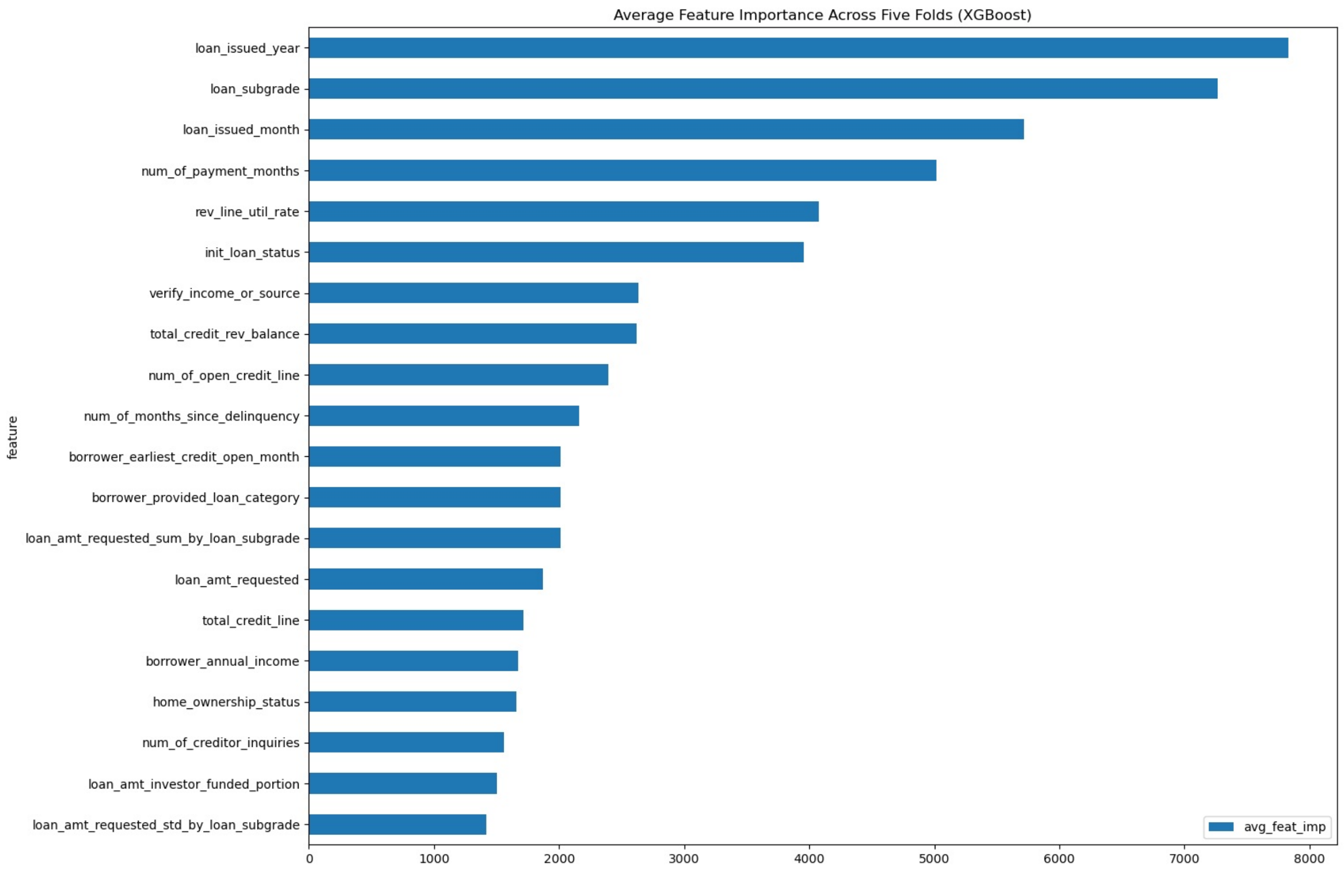
```
Out[118]: ['../output/models/xgboost/eval_fold_5.joblib']
```

```
predicting for fold 5...
```

Features Importance

Feature importance can be visualized as follows:

```
In [119…
# Join feature importance
feat_imp_xgboost = reduce(lambda x, y: pd.merge(x, y, on='feature', how='left'), feat_imp_xgboost)
feat_imp_xgboost['avg_feat_imp'] = feat_imp_xgboost.iloc[:, 1:].apply(lambda row: row.mean(), axis=1)

# Plot top feature importance
feat_imp_xgboost.sort_values(by='avg_feat_imp', ascending=True).iloc[-20:].plot(
    kind='barh', x='feature', y='avg_feat_imp',
    figsize=(15, 12),
    title='Average Feature Importance Across Five Folds (XGBoost)'
)
plt.show();
```

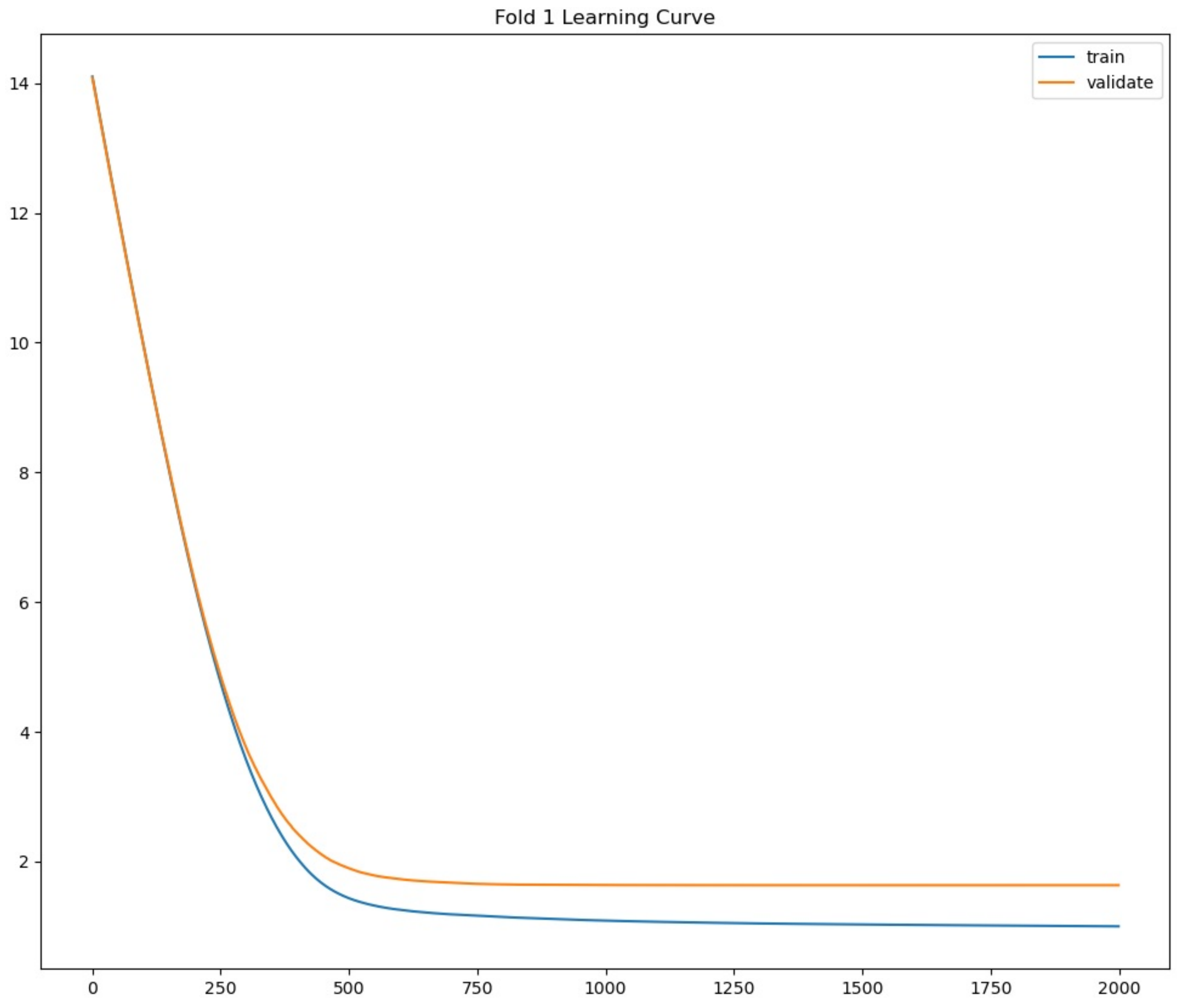


A few of these features are generated; it appears that subgrade is one of the most important categorical features. Interetingly, the year and month in which the loans were issued have strong predictive power.

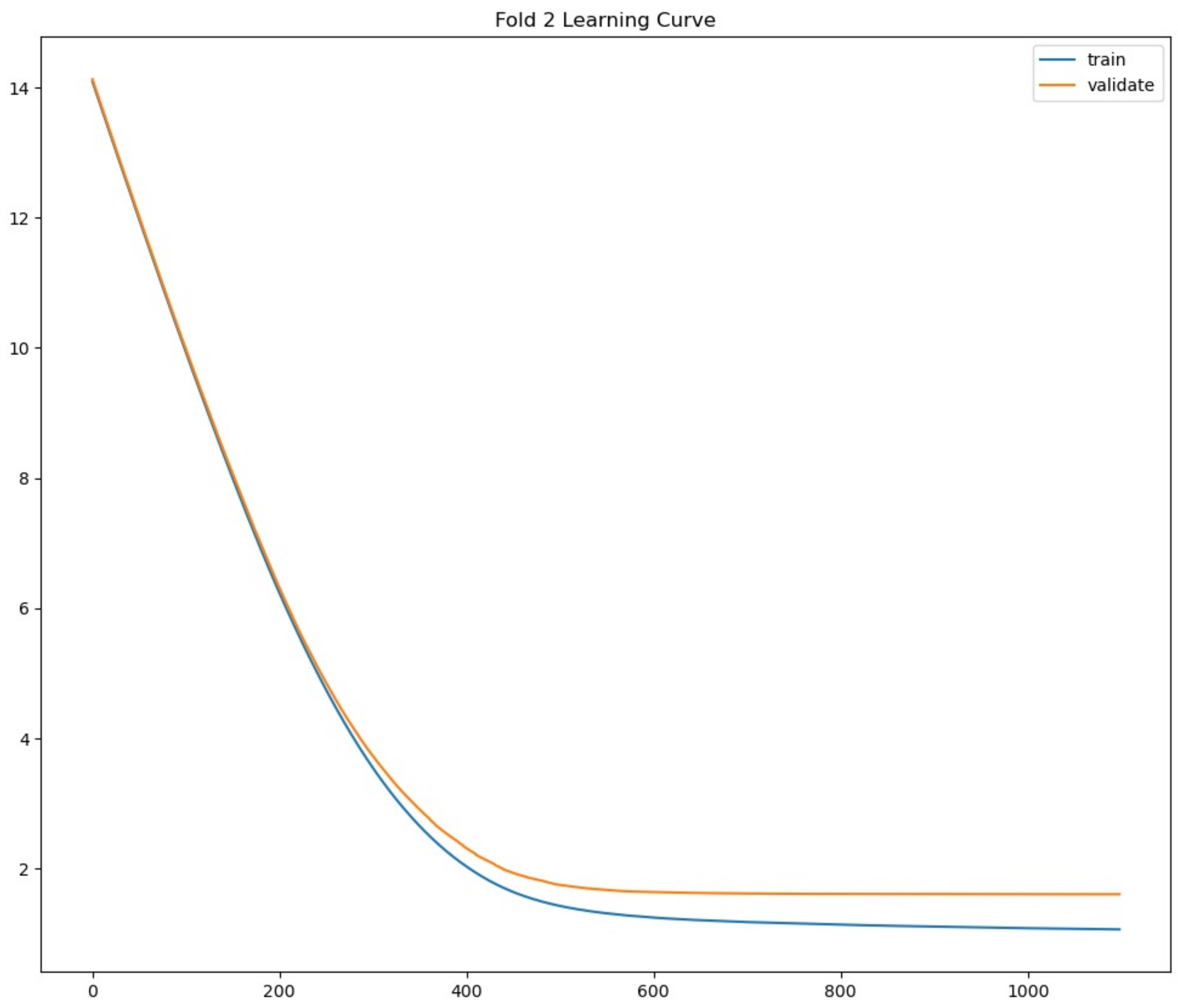
Learning Curves

```
In [120…  for fold in range(5):
              eval_result = joblib.load(model_path + f'xgboost/eval_fold_{fold + 1}.joblib')
              plt.plot(eval_result['train']['rmse'], label='train');
              plt.plot(eval_result['validate']['rmse'], label='validate');
              plt.legend();
              plt.title(f'Fold {fold + 1} Learning Curve');
              plt.show();
```

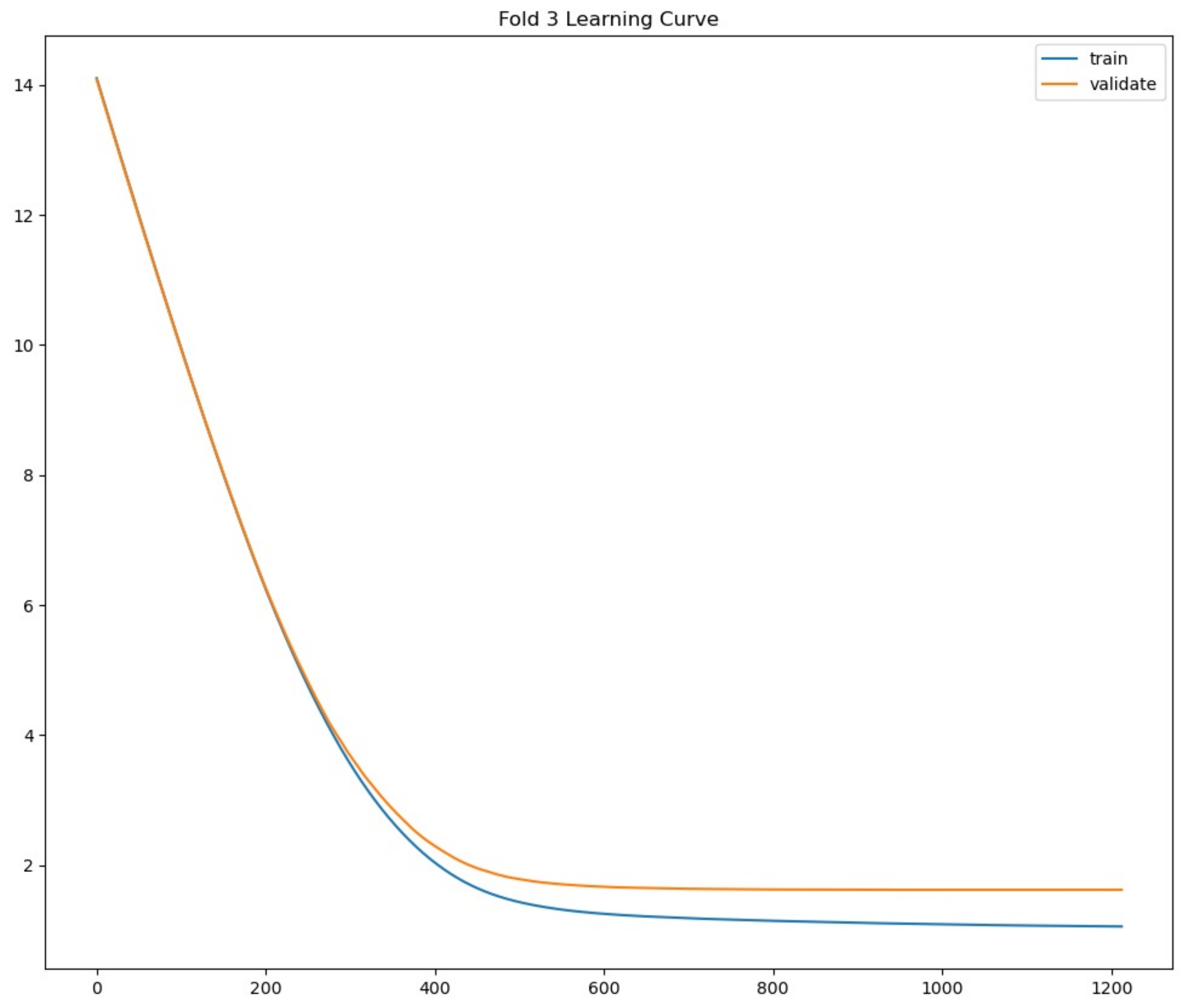
```
Out[120]: [<matplotlib.lines.Line2D at 0x7f23633d27c0>]

Out[120]: [<matplotlib.lines.Line2D at 0x7f23633b03a0>]

Out[120]: <matplotlib.legend.Legend at 0x7f23633d2340>

Out[120]: Text(0.5, 1.0, 'Fold 1 Learning Curve')
```



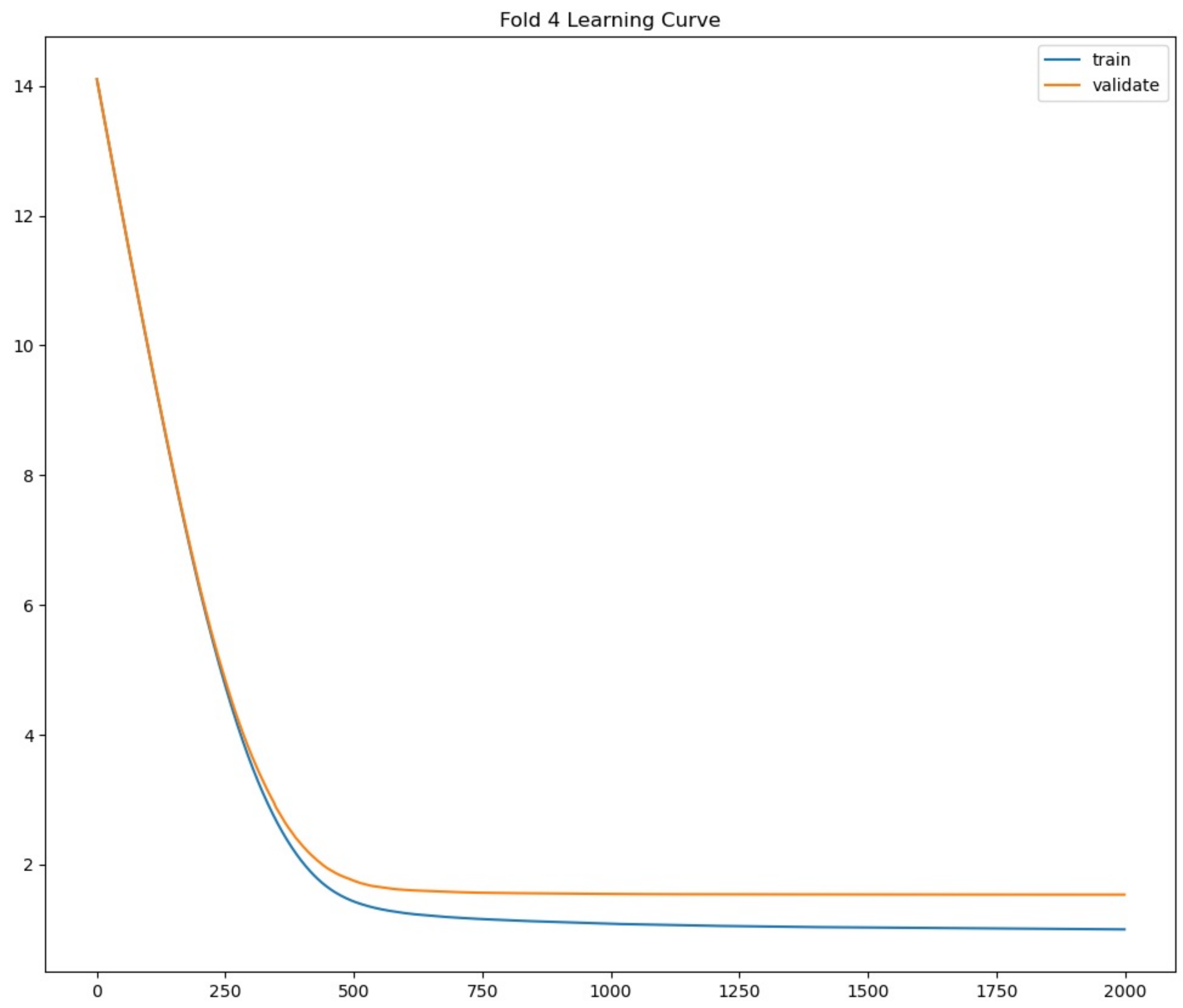
```
Out[120]: [<matplotlib.lines.Line2D at 0x7f230dd18ac0>]

Out[120]: [<matplotlib.lines.Line2D at 0x7f230d930b20>]

Out[120]: <matplotlib.legend.Legend at 0x7f231a0b87c0>

Out[120]: Text(0.5, 1.0, 'Fold 2 Learning Curve')
```



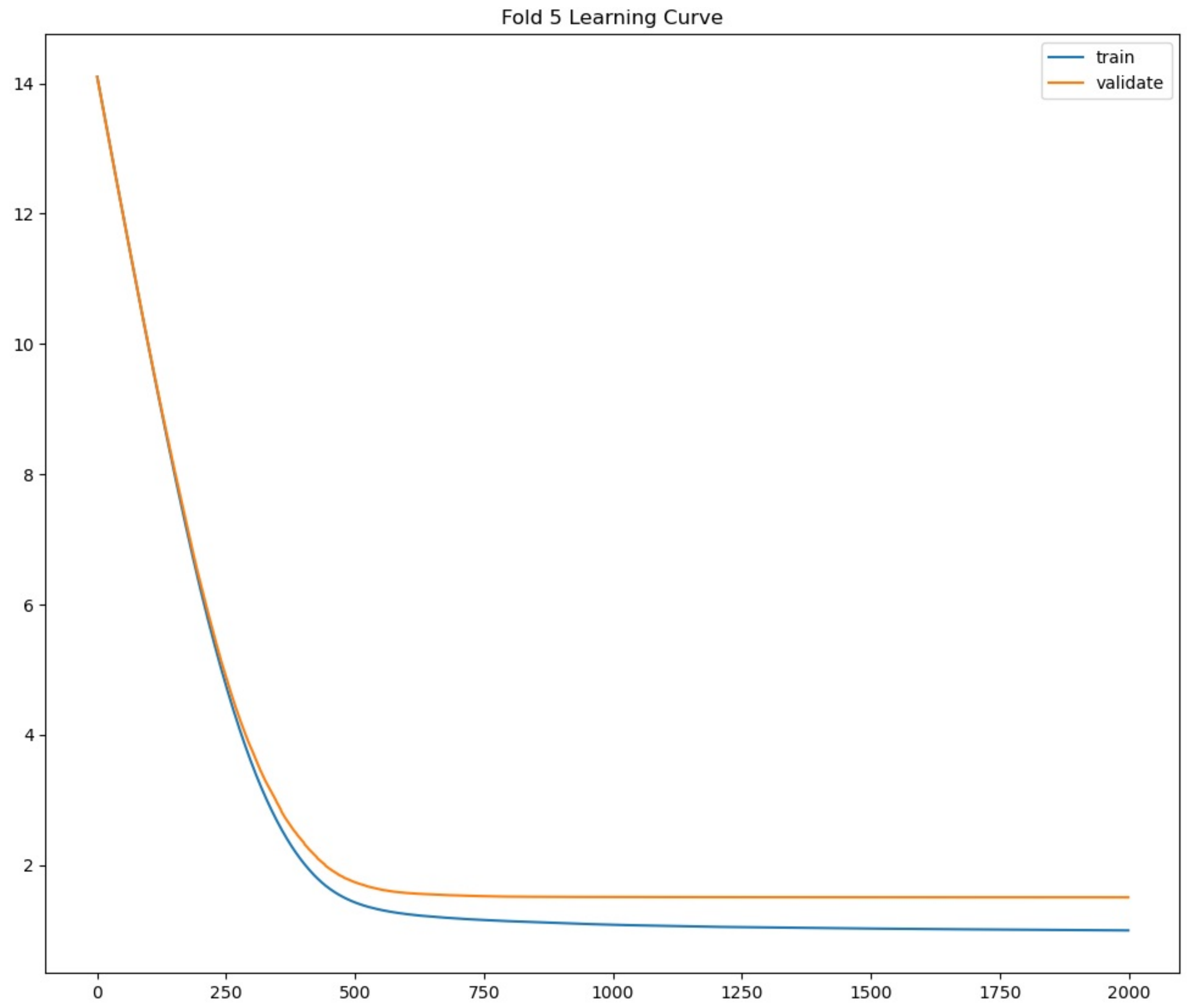
```
Out[120]:  [<matplotlib.lines.Line2D at 0x7f2362981190>]

Out[120]:  [<matplotlib.lines.Line2D at 0x7f23629813d0>]

Out[120]:  <matplotlib.legend.Legend at 0x7f2362981850>

Out[120]:  Text(0.5, 1.0, 'Fold 3 Learning Curve')
```



```
Out[120]: [<matplotlib.lines.Line2D at 0x7f23643a13d0>]
Out[120]: [<matplotlib.lines.Line2D at 0x7f23643a1070>]
Out[120]: <matplotlib.legend.Legend at 0x7f2362a65ac0>
Out[120]: Text(0.5, 1.0, 'Fold 4 Learning Curve')
```



```
Out[120]: [<matplotlib.lines.Line2D at 0x7f2363571e50>]

Out[120]: [<matplotlib.lines.Line2D at 0x7f2363e4f310>]

Out[120]: <matplotlib.legend.Legend at 0x7f236468ceb0>

Out[120]: Text(0.5, 1.0, 'Fold 5 Learning Curve')
```



Both the training and validation sets begin to converge at around 500 boosting rounds.

Performance on Validation Sets

In [121…

```
oof_xgboost_rmse = []
target_frame = cudf.DataFrame(index=['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max'])

for key in oof_xgboost:

    oof_xgboost_rmse.append(
        mean_squared_error(oof_xgboost[key]['target'], oof_xgboost[key]['predictions'], squared=False)
    )
    print(f'Finished computing rmse for {key}')

    target_frame[f'{key}_target_descriptive_stats'] = cudf.Series(oof_xgboost[key]['target']).describe()
    print(f'Finished computing descriptive stats for {key} target')
```

```
Finished computing rmse for fold_1
Finished computing descriptive stats for fold_1 target
Finished computing rmse for fold_2
Finished computing descriptive stats for fold_2 target
Finished computing rmse for fold_3
Finished computing descriptive stats for fold_3 target
Finished computing rmse for fold_4
Finished computing descriptive stats for fold_4 target
Finished computing rmse for fold_5
Finished computing descriptive stats for fold_5 target
```

In [122…
```
cudf.Series(oof_xgboost_rmse).describe()
```

Out[122]:
```
count    5.000000
mean     1.580978
std      0.056452
min      1.506437
25%      1.535277
50%      1.609146
75%      1.621096
max      1.632933
dtype: float64
```

On average, the predictions are off by 1.580978 percentage points with a standard deviation of about 0.056452 percentage points. This can be compared to the distributions of the true target interest rates.

In [118…
```
target_frame
```

Out[118]:

	fold_1_target_descriptive_stats	fold_2_target_descriptive_stats	fold_3_target_descriptive_stats	fold_4_target_descriptive_stats	fold_5_ta
count	67798.000000	67798.000000	67798.000000	67797.000000	
mean	13.943553	13.956328	13.940899	13.963181	
std	4.399556	4.354424	4.376767	4.384787	
min	5.420000	5.420000	5.420000	5.420000	
25%	10.990000	10.990000	10.990000	10.990000	
50%	13.680000	13.920000	13.680000	13.980000	
75%	16.780000	16.780000	16.780000	16.780000	
max	26.060000	26.060000	26.060000	26.060000	

The middle 50% of interest rates in the validation sets range between 10.99% and 16.78%; and so the RMSE of 1.580978 percentage points is acceptable. Although with more time, we would like to explore ways to perhaps reduce RMSE down to 1 percentage points or even lower.

CatBoost

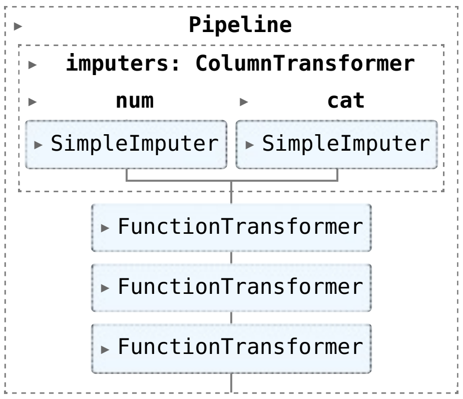
Pipeline

For catboost, as mentioned above, we do not include the catboost encode step and allow catboost to handle the text features as categorical variables natively.

In [8]:
```
catboost_preprocessor = Pipeline([
    ('imputers', imputers),
    ('restore_cols', FunctionTransformer(pp.restore_columns)),
    ('date_transformer', FunctionTransformer(pp.extract_date_features)),
    ('num_feat_eng', FunctionTransformer(pp.num_feat_eng))
])
joblib.dump(catboost_preprocessor, prep_path + 'catboost_preprocessor.joblib')
catboost_preprocessor
```

Out[8]:
```
['../output/preprocessors/catboost_preprocessor.joblib']
```

Out[8]:



Hyperparameter Search

In [260…

```
def objective_catboost(trial):

    # Fold and seed
    train = pd.read_csv("../data/train_sanitized.csv")
    X_train, y_train = train.drop(['interest_rate'], axis=1), train.interest_rate.to_numpy()
    folds = 5
    seed = 1227

    # Parameters
    search_space = {
        'objective': 'RMSE',
        'eval_metric': 'RMSE',
        'task_type': 'GPU', # GPU training
        'boosting_type': 'Plain', # Boosting scheme
        'border_count': 254, # Number of splits for numerical features (recommended 254 for best possible quali
        'use_best_model': True, # Use the validation dataset to identify the iteration with the optimal value o
        'iterations': trial.suggest_int('iterations', low=500, high=2000, step=100), # Range: [0, inf], number
        'learning_rate': trial.suggest_float(name='learning_rate', low=0.001, high=0.1), # Decrease the learning
        'depth': trial.suggest_int('depth', 6, 10), # Depth of trees, where values in the range from 6 to 10 are
        'l2_leaf_reg': trial.suggest_categorical('l2_leaf_reg', [10, 100, 500]), # Range: [0, inf], L2 regulari
        'random_strength': trial.suggest_float('random_strength', 100, 500), # Range: Positive floating point n
        'colsample_bylevel': None, # Range (0;1], also 'rsm', he percentage of features to use at each split se
        'bootstrap_type': trial.suggest_categorical(
            'bootstrap_type', ['Bayesian', 'Bernoulli']
        ), # The weight of each training example is varied over steps of choosing different splits (not over sc
        'score_function': trial.suggest_categorical(
            'score_function', ['L2', 'Cosine']
        ) # The score function measures the quality of the gradient approximation, which is used to select the
    }

    # These parameters are depended on the 'bootstrap_type' chosen
    if search_space['bootstrap_type'] == 'Bayesian':
        search_space['bagging_temperature'] = trial.suggest_float('bagging_temperature', 0, 50) # Range: [0;inf
    elif search_space['bootstrap_type'] == 'Bernoulli':
        search_space['subsample'] = trial.suggest_float("subsample", 0.1, 1, log=True) # Sample rate for bagging

    # K-fold cross validation
    kf = KFold(n_splits=folds, shuffle=True, random_state=rs)
    rmse_scores = np.empty(folds)

    for fold, (train_indx, val_indx) in enumerate(kf.split(X_train, y_train)):

        # Train and validation sets
        fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
        fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

        # Preprocessing using a fresh copy of the pipeline for every fold to prevent leakage
        preprocessor = joblib.load('../output/preprocessors/catboost_preprocessor.joblib')
        print(f'Start processing fold {fold + 1}...')
        fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
        fold_X_val = preprocessor.transform(fold_X_val)

        # Data for modeling
        feature_names = fold_X_train.columns.tolist()
        dtrain = cb.Pool(data=fold_X_train, label=fold_y_train, feature_names=feature_names, cat_features=encode
        dvalid = cb.Pool(data=fold_X_val, label=fold_y_val, feature_names=feature_names, cat_features=encode_co

        # Model
        model = cb.train(
            params=search_space,
            dtrain=dtrain,
            early_stopping_rounds=200,
            eval_set=dvalid,
            verbose=200 # Report every 200 rounds
          )

        # Out-of-fold prediction
        print(f'Predicting for fold {fold + 1}...')
        oof_pred = model.predict(data=dvalid)
        rmse_scores[fold] = mean_squared_error(fold_y_val, oof_pred, squared=False) # Use RMSE

    # Average across 5 folds
    mean_rmse = np.mean(rmse_scores)

    return mean_rmse
```

In [ ]:

```
study_catboost = optuna.create_study(sampler=optuna.samplers.TPESampler(), study_name='min_rmse_catboost', dire
study_catboost.optimize(objective_catboost, n_trials=20)
```

```
[I 2023-02-12 17:27:50,209] A new study created in memory with name: min_rmse_catboost
```

```
Start processing fold 1...
0:      learn: 4.0848596        test: 4.0723751 best: 4.0723751 (0)     total: 37ms     remaining: 1m 2s
200:    learn: 1.5473853        test: 2.7024220 best: 2.6968588 (45)    total: 6.71s    remaining: 50.1s
bestTest = 2.696858788
bestIteration = 45
Shrink model to first 46 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 4.1203519        test: 4.0742373 best: 4.0742373 (0)     total: 34.2ms   remaining: 58.1s
200:    learn: 1.5436217        test: 1.9945311 best: 1.9940960 (196)   total: 6.7s     remaining: 50s
400:    learn: 1.4338617        test: 1.9515568 best: 1.9514760 (389)   total: 13.4s    remaining: 43.3s
600:    learn: 1.3628402        test: 1.9294044 best: 1.9290701 (589)   total: 19.9s    remaining: 36.3s
800:    learn: 1.3122895        test: 1.9076298 best: 1.9076298 (800)   total: 26.4s    remaining: 29.6s
1000:   learn: 1.2774315        test: 1.9012140 best: 1.9000863 (991)   total: 32.9s    remaining: 23s
1200:   learn: 1.2526392        test: 1.8931661 best: 1.8927445 (1188)  total: 39.5s    remaining: 16.4s
1400:   learn: 1.2305494        test: 1.8850506 best: 1.8847245 (1389)  total: 46.1s    remaining: 9.83s
1600:   learn: 1.2120301        test: 1.8843298 best: 1.8842594 (1449)  total: 52.8s    remaining: 3.26s
1699:   learn: 1.2039046        test: 1.8846747 best: 1.8832456 (1685)  total: 56s      remaining: 0us
bestTest = 1.883245572
bestIteration = 1685
Shrink model to first 1686 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 4.1231846        test: 4.1023352 best: 4.1023352 (0)     total: 35.8ms   remaining: 1m
200:    learn: 1.5511281        test: 2.2707612 best: 2.2680511 (134)   total: 6.57s    remaining: 49s
400:    learn: 1.4269661        test: 2.2208782 best: 2.2208782 (400)   total: 13.1s    remaining: 42.5s
600:    learn: 1.3536703        test: 2.1869745 best: 2.1869745 (600)   total: 19.8s    remaining: 36.1s
800:    learn: 1.3056872        test: 2.1709075 best: 2.1707334 (796)   total: 26.3s    remaining: 29.5s
1000:   learn: 1.2752853        test: 2.1577518 best: 2.1572338 (976)   total: 32.9s    remaining: 23s
1200:   learn: 1.2449648        test: 2.1533405 best: 2.1531355 (1195)  total: 39.4s    remaining: 16.4s
1400:   learn: 1.2224910        test: 2.1435578 best: 2.1434680 (1396)  total: 46s      remaining: 9.82s
1600:   learn: 1.2033667        test: 2.1414529 best: 2.1413359 (1597)  total: 52.5s    remaining: 3.25s
1699:   learn: 1.1947402        test: 2.1395602 best: 2.1390459 (1668)  total: 55.7s    remaining: 0us
bestTest = 2.139045939
bestIteration = 1668
Shrink model to first 1669 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 4.2131120        test: 4.2899211 best: 4.2899211 (0)     total: 35.3ms   remaining: 59.9s
200:    learn: 1.5600864        test: 2.3840657 best: 2.3840657 (200)   total: 6.67s    remaining: 49.7s
400:    learn: 1.4283281        test: 2.3622502 best: 2.3609446 (392)   total: 13.2s    remaining: 42.9s
600:    learn: 1.3520794        test: 2.3468624 best: 2.3463829 (580)   total: 19.8s    remaining: 36.2s
800:    learn: 1.3029012        test: 2.3419366 best: 2.3419366 (800)   total: 26.3s    remaining: 29.6s
1000:   learn: 1.2741654        test: 2.3393090 best: 2.3391486 (997)   total: 32.9s    remaining: 22.9s
1200:   learn: 1.2519078        test: 2.3308172 best: 2.3290042 (1144)  total: 39.3s    remaining: 16.3s
1400:   learn: 1.2251457        test: 2.3272872 best: 2.3257725 (1308)  total: 45.8s    remaining: 9.77s
bestTest = 2.325772452
bestIteration = 1308
Shrink model to first 1309 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 4.2117981        test: 4.2022596 best: 4.2022596 (0)     total: 38.7ms   remaining: 1m 5s

200:    learn: 1.5642409        test: 2.0729604 best: 2.0729604 (200)   total: 6.71s    remaining: 50s
400:    learn: 1.4269476        test: 2.0189208 best: 2.0189208 (400)   total: 13.4s    remaining: 43.3s
600:    learn: 1.3668995        test: 2.0056792 best: 2.0054244 (584)   total: 20s      remaining: 36.6s
800:    learn: 1.3098762        test: 1.9842738 best: 1.9842455 (799)   total: 26.6s    remaining: 29.9s
1000:   learn: 1.2730691        test: 1.9749355 best: 1.9723649 (953)   total: 33.3s    remaining: 23.2s
1200:   learn: 1.2453016        test: 1.9607700 best: 1.9607700 (1200)  total: 40s      remaining: 16.6s
1400:   learn: 1.2267419        test: 1.9564191 best: 1.9556433 (1361)  total: 46.6s    remaining: 9.94s
1600:   learn: 1.2072765        test: 1.9446174 best: 1.9443208 (1582)  total: 53.1s    remaining: 3.28s
1699:   learn: 1.1997228        test: 1.9433751 best: 1.9432321 (1688)  total: 56.3s    remaining: 0us
bestTest = 1.943232137
bestIteration = 1688
Shrink model to first 1689 iterations.
Predicting for fold 5...
```

```
[I 2023-02-12 17:32:22,079] Trial 0 finished with value: 2.19763139748944 and parameters: {'iterations': 1700,
'learning_rate': 0.09243529468898837, 'depth': 7, 'l2_leaf_reg': 100, 'random_strength': 443.98205697337323, 'b
ootstrap_type': 'Bayesian', 'score_function': 'Cosine', 'bagging_temperature': 21.533709015144137}. Best is tri
al 0 with value: 2.19763139748944.
```

```
Start processing fold 1...
0:      learn: 3.4968570        test: 3.6328176 best: 3.6328176 (0)     total: 51ms     remaining: 25.4s
200:    learn: 1.2163275        test: 2.7258795 best: 2.7239090 (196)   total: 9.55s    remaining: 14.2s
400:    learn: 1.0750178        test: 2.7250388 best: 2.7161948 (219)   total: 19s      remaining: 4.7s
bestTest = 2.716194754
bestIteration = 219
Shrink model to first 220 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 3.4511862        test: 3.3999753 best: 3.3999753 (0)     total: 45.6ms   remaining: 22.8s
200:    learn: 1.1982550        test: 1.9702158 best: 1.9690059 (196)   total: 9.31s    remaining: 13.9s
400:    learn: 1.0596488        test: 1.9755263 best: 1.9605864 (245)   total: 18.6s    remaining: 4.58s
bestTest = 1.96058642

bestIteration = 245
Shrink model to first 246 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 3.4970091        test: 3.7061443 best: 3.7061443 (0)     total: 50.3ms   remaining: 25.1s
200:    learn: 1.2160255        test: 2.3135732 best: 2.2862840 (66)    total: 9.54s    remaining: 14.2s
bestTest = 2.286284025
bestIteration = 66
Shrink model to first 67 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 3.4334628        test: 3.4710775 best: 3.4710775 (0)     total: 47.1ms   remaining: 23.5s
200:    learn: 1.2024274        test: 2.5969827 best: 2.5755178 (145)   total: 9.47s    remaining: 14.1s
bestTest = 2.575517765
bestIteration = 145
Shrink model to first 146 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 3.4583370        test: 3.7710421 best: 3.7710421 (0)     total: 51.7ms   remaining: 25.8s
200:    learn: 1.2007035        test: 2.3290866 best: 2.3149984 (178)   total: 9.36s    remaining: 13.9s
400:    learn: 1.0505498        test: 2.2997804 best: 2.2938160 (383)   total: 18.7s    remaining: 4.62s
499:    learn: 0.9991515        test: 2.2972953 best: 2.2938160 (383)   total: 23.3s    remaining: 0us
bestTest = 2.293816045
bestIteration = 383
Shrink model to first 384 iterations.
Predicting for fold 5...
```

```
[I 2023-02-12 17:34:40,479] Trial 1 finished with value: 2.3664799006597526 and parameters: {'iterations': 500,
'learning_rate': 0.2876547994556458, 'depth': 9, 'l2_leaf_reg': 10, 'random_strength': 352.66894226927604, 'boo
tstrap_type': 'Bayesian', 'score_function': 'Cosine', 'bagging_temperature': 20.270770136272372}. Best is trial
0 with value: 2.19763139748944.
```

```
Start processing fold 1...
0:      learn: 4.0777904        test: 4.2151198 best: 4.2151198 (0)     total: 43.7ms   remaining: 39.2s
200:    learn: 1.1580801        test: 2.1777521 best: 2.1771445 (198)   total: 8s       remaining: 27.8s
400:    learn: 1.0787310        test: 2.1724619 best: 2.1684399 (361)   total: 16s      remaining: 19.9s
bestTest = 2.168439923
bestIteration = 361
Shrink model to first 362 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 4.0499645        test: 4.0376765 best: 4.0376765 (0)     total: 41.5ms   remaining: 37.3s
200:    learn: 1.1595877        test: 2.4730881 best: 2.4723799 (198)   total: 8.06s    remaining: 28s
400:    learn: 1.0628059        test: 2.4682939 best: 2.4665543 (393)   total: 16.1s    remaining: 20s
600:    learn: 1.0231657        test: 2.4657692 best: 2.4643577 (475)   total: 24.1s    remaining: 12s
bestTest = 2.464357713
bestIteration = 475
Shrink model to first 476 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 4.0400257        test: 3.9585732 best: 3.9585732 (0)     total: 46.4ms   remaining: 41.7s
200:    learn: 1.1522551        test: 2.4385676 best: 2.4385676 (200)   total: 8.01s    remaining: 27.9s
400:    learn: 1.0664529        test: 2.4093584 best: 2.4093584 (400)   total: 15.9s    remaining: 19.8s
600:    learn: 1.0258395        test: 2.4074760 best: 2.4058980 (534)   total: 23.8s    remaining: 11.9s
800:    learn: 0.9930525        test: 2.4058924 best: 2.4056433 (785)   total: 31.9s    remaining: 3.94s
899:    learn: 0.9775517        test: 2.4092458 best: 2.4056433 (785)   total: 35.9s    remaining: 0us
bestTest = 2.405643252
bestIteration = 785
Shrink model to first 786 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 4.0485282        test: 4.0965720 best: 4.0965720 (0)     total: 46.4ms   remaining: 41.7s
200:    learn: 1.1545757        test: 2.0374261 best: 2.0371794 (199)   total: 7.93s    remaining: 27.6s
400:    learn: 1.0734457        test: 2.0130988 best: 2.0128848 (399)   total: 15.7s    remaining: 19.5s
600:    learn: 1.0342822        test: 2.0112936 best: 2.0111861 (520)   total: 23.6s    remaining: 11.7s
800:    learn: 1.0006668        test: 2.0029292 best: 2.0027239 (775)   total: 31.6s    remaining: 3.91s
899:    learn: 0.9857980        test: 2.0030489 best: 2.0023056 (827)   total: 35.6s    remaining: 0us
bestTest = 2.00230565
bestIteration = 827
Shrink model to first 828 iterations.
Predicting for fold 4...

Start processing fold 5...
0:      learn: 4.0984718        test: 4.1526316 best: 4.1526316 (0)     total: 47.7ms   remaining: 42.9s
200:    learn: 1.1606541        test: 2.2896682 best: 2.2893970 (199)   total: 8.18s    remaining: 28.5s
400:    learn: 1.0736631        test: 2.2779428 best: 2.2777106 (385)   total: 16.2s    remaining: 20.1s
600:    learn: 1.0332423        test: 2.2753544 best: 2.2750193 (544)   total: 24.1s    remaining: 12s
800:    learn: 1.0008421        test: 2.2803834 best: 2.2747051 (655)   total: 32.1s    remaining: 3.96s
bestTest = 2.27470507
bestIteration = 655
Shrink model to first 656 iterations.
Predicting for fold 5...
[I 2023-02-12 17:38:05,358] Trial 2 finished with value: 2.263091107876284 and parameters: {'iterations': 900,
'learning_rate': 0.10545772184117341, 'depth': 8, 'l2_leaf_reg': 10, 'random_strength': 132.02105296824692, 'bo
otstrap_type': 'Bernoulli', 'score_function': 'Cosine', 'subsample': 0.13212373310354877}. Best is trial 0 with
value: 2.19763139748944.
```

```
Start processing fold 1...
0:      learn: 3.7618030        test: 3.7852330 best: 3.7852330 (0)     total: 51.8ms   remaining: 1m 22s
200:    learn: 1.2801650        test: 2.0991671 best: 2.0948465 (145)   total: 9.75s    remaining: 1m 7s
400:    learn: 1.2132436        test: 2.0993209 best: 2.0943914 (344)   total: 19.4s    remaining: 58s
bestTest = 2.094391383
bestIteration = 344
Shrink model to first 345 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 3.7750651        test: 3.8001021 best: 3.8001021 (0)     total: 47.6ms   remaining: 1m 16s
200:    learn: 1.2822394        test: 1.9222712 best: 1.9221592 (196)   total: 9.66s    remaining: 1m 7s
400:    learn: 1.2202816        test: 1.9020375 best: 1.9019627 (398)   total: 19.3s    remaining: 57.8s
600:    learn: 1.1776971        test: 1.8966319 best: 1.8961188 (570)   total: 28.8s    remaining: 48s
800:    learn: 1.1440243        test: 1.8931051 best: 1.8921635 (781)   total: 38.3s    remaining: 38.2s
1000:   learn: 1.1147822        test: 1.8927794 best: 1.8916243 (857)   total: 47.8s    remaining: 28.6s
1200:   learn: 1.0897026        test: 1.8917715 best: 1.8905452 (1086)  total: 57.3s    remaining: 19s
bestTest = 1.890545225
bestIteration = 1086
Shrink model to first 1087 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 3.7605555        test: 4.0347971 best: 4.0347971 (0)     total: 52.5ms   remaining: 1m 24s
200:    learn: 1.2668996        test: 2.0028822 best: 2.0028011 (199)   total: 9.45s    remaining: 1m 5s
400:    learn: 1.2096007        test: 1.9844220 best: 1.9844016 (399)   total: 18.8s    remaining: 56.3s
600:    learn: 1.1650471        test: 1.9791947 best: 1.9791947 (600)   total: 28.2s    remaining: 47s
800:    learn: 1.1336122        test: 1.9728185 best: 1.9728004 (799)   total: 37.6s    remaining: 37.5s
1000:   learn: 1.1060521        test: 1.9684674 best: 1.9683143 (997)   total: 47.1s    remaining: 28.2s
1200:   learn: 1.0814493        test: 1.9692201 best: 1.9682965 (1008)  total: 56.6s    remaining: 18.8s
bestTest = 1.96829649

bestIteration = 1008
Shrink model to first 1009 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 3.7808159        test: 3.9535966 best: 3.9535966 (0)     total: 51.7ms   remaining: 1m 22s
200:    learn: 1.2877353        test: 2.0804752 best: 2.0793087 (195)   total: 9.51s    remaining: 1m 6s
400:    learn: 1.2165688        test: 2.0564227 best: 2.0563241 (394)   total: 19.1s    remaining: 57s
600:    learn: 1.1743506        test: 2.0568480 best: 2.0557177 (416)   total: 28.5s    remaining: 47.4s
bestTest = 2.055717674
bestIteration = 416
Shrink model to first 417 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 3.7848651        test: 3.8846603 best: 3.8846603 (0)     total: 48ms     remaining: 1m 16s
200:    learn: 1.2682368        test: 1.9256688 best: 1.9252221 (198)   total: 9.47s    remaining: 1m 5s
400:    learn: 1.2120032        test: 1.9001580 best: 1.9001580 (400)   total: 18.9s    remaining: 56.4s
600:    learn: 1.1686133        test: 1.8792366 best: 1.8792148 (597)   total: 28.2s    remaining: 46.9s
800:    learn: 1.1336706        test: 1.8695701 best: 1.8687617 (764)   total: 37.8s    remaining: 37.7s
1000:   learn: 1.1068532        test: 1.8698741 best: 1.8675164 (964)   total: 47.3s    remaining: 28.3s
1200:   learn: 1.0836473        test: 1.8631398 best: 1.8629739 (1197)  total: 56.7s    remaining: 18.8s
1400:   learn: 1.0609423        test: 1.8604759 best: 1.8598902 (1388)  total: 1m 6s    remaining: 9.39s
1599:   learn: 1.0407010        test: 1.8540146 best: 1.8539517 (1596)  total: 1m 15s   remaining: 0us
bestTest = 1.853951729
bestIteration = 1596
Shrink model to first 1597 iterations.
Predicting for fold 5...
```

```
[I 2023-02-12 17:43:02,821] Trial 3 finished with value: 1.9725806096138503 and parameters: {'iterations': 1600
, 'learning_rate': 0.21065008859344805, 'depth': 9, 'l2_leaf_reg': 500, 'random_strength': 122.57161445434504,
'bootstrap_type': 'Bayesian', 'score_function': 'L2', 'bagging_temperature': 7.960423129118915}. Best is trial
3 with value: 1.9725806096138503.
```

```
Start processing fold 1...
0:      learn: 3.6509066        test: 3.8018097 best: 3.8018097 (0)     total: 52.7ms   remaining: 36.8s
200:    learn: 1.0792543        test: 3.5708527 best: 3.5708527 (200)   total: 9.5s     remaining: 23.6s
400:    learn: 1.0292823        test: 3.5773411 best: 3.5660097 (249)   total: 19.1s    remaining: 14.2s
bestTest = 3.566009686
bestIteration = 249
Shrink model to first 250 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 3.6678501        test: 3.8660457 best: 3.8660457 (0)     total: 48.7ms   remaining: 34s
200:    learn: 1.0840214        test: 3.0704321 best: 3.0628918 (171)   total: 9.65s    remaining: 24s
bestTest = 3.062891839
bestIteration = 171
Shrink model to first 172 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 3.5893861        test: 3.9051212 best: 3.9051212 (0)     total: 57.7ms   remaining: 40.3s
200:    learn: 1.0727138        test: 3.2999636 best: 3.2996514 (199)   total: 9.48s    remaining: 23.5s
400:    learn: 1.0308172        test: 3.2883986 best: 3.2823433 (347)   total: 18.8s    remaining: 14s
bestTest = 3.282343284
bestIteration = 347
Shrink model to first 348 iterations.
Predicting for fold 3...

Start processing fold 4...
0:      learn: 3.5586934        test: 3.6621947 best: 3.6621947 (0)     total: 53.3ms   remaining: 37.3s
200:    learn: 1.0727155        test: 2.7152242 best: 2.7150923 (199)   total: 9.62s    remaining: 23.9s
400:    learn: 1.0263183        test: 2.7109000 best: 2.7074339 (364)   total: 19.1s    remaining: 14.2s
bestTest = 2.707433936
bestIteration = 364
Shrink model to first 365 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 3.7240634        test: 3.8098981 best: 3.8098981 (0)     total: 60.1ms   remaining: 42s
200:    learn: 1.0791372        test: 3.1748232 best: 3.1684538 (178)   total: 9.65s    remaining: 24s
bestTest = 3.168453765
bestIteration = 178
Shrink model to first 179 iterations.
Predicting for fold 5...
```

```
[I 2023-02-12 17:45:41,321] Trial 4 finished with value: 3.1574260620229095 and parameters: {'iterations': 700,
'learning_rate': 0.27296590435850876, 'depth': 9, 'l2_leaf_reg': 500, 'random_strength': 482.8209104403226, 'bo
otstrap_type': 'Bernoulli', 'score_function': 'Cosine', 'subsample': 0.562988418591445}. Best is trial 3 with v
alue: 1.9725806096138503.
```

```
Start processing fold 1...
0:      learn: 3.7032788        test: 3.7047728 best: 3.7047728 (0)     total: 39.2ms   remaining: 1m 18s
200:    learn: 1.4036859        test: 2.4250500 best: 2.4105033 (178)   total: 7.8s     remaining: 1m 9s
400:    learn: 1.2959469        test: 2.4218086 best: 2.3980371 (281)   total: 15.5s    remaining: 1m 1s
bestTest = 2.398037146
bestIteration = 281
Shrink model to first 282 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 3.6641951        test: 3.7780716 best: 3.7780716 (0)     total: 42.7ms   remaining: 1m 25s
200:    learn: 1.4133520        test: 2.1027656 best: 2.1027656 (200)   total: 7.74s    remaining: 1m 9s
400:    learn: 1.2861666        test: 2.0066951 best: 2.0061327 (399)   total: 15.4s    remaining: 1m 1s
600:    learn: 1.2162303        test: 1.9912529 best: 1.9865342 (441)   total: 23s      remaining: 53.6s
800:    learn: 1.1656672        test: 1.9810809 best: 1.9743689 (762)   total: 30.7s    remaining: 46s
1000:   learn: 1.1258115        test: 1.9750002 best: 1.9721495 (930)   total: 38.5s    remaining: 38.5s
bestTest = 1.972149482
bestIteration = 930
Shrink model to first 931 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 3.6875692        test: 3.8285542 best: 3.8285542 (0)     total: 43.4ms   remaining: 1m 26s
200:    learn: 1.4422921        test: 2.3547477 best: 2.3547477 (200)   total: 7.73s    remaining: 1m 9s
400:    learn: 1.3016802        test: 2.2937991 best: 2.2931333 (372)   total: 15.6s    remaining: 1m 2s
600:    learn: 1.2371372        test: 2.2895046 best: 2.2874688 (554)   total: 23.3s    remaining: 54.3s
800:    learn: 1.1717906        test: 2.3076659 best: 2.2858239 (641)   total: 31.2s    remaining: 46.7s
bestTest = 2.285823914
bestIteration = 641
Shrink model to first 642 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 3.7724871        test: 3.8512094 best: 3.8512094 (0)     total: 40.6ms   remaining: 1m 21s
200:    learn: 1.4440473        test: 2.3258132 best: 2.3249970 (175)   total: 7.83s    remaining: 1m 10s
400:    learn: 1.3030968        test: 2.3285040 best: 2.3235688 (370)   total: 15.7s    remaining: 1m 2s
600:    learn: 1.2331889        test: 2.3263343 best: 2.3197331 (576)   total: 23.5s    remaining: 54.6s
800:    learn: 1.1819443        test: 2.3178971 best: 2.3126289 (695)   total: 31.3s    remaining: 46.8s
bestTest = 2.312628896
bestIteration = 695
Shrink model to first 696 iterations.
Predicting for fold 4...
Start processing fold 5...

0:      learn: 3.6938607        test: 3.4972496 best: 3.4972496 (0)     total: 42.5ms   remaining: 1m 25s
200:    learn: 1.4498925        test: 2.1687930 best: 2.1683824 (154)   total: 7.81s    remaining: 1m 9s
400:    learn: 1.3078301        test: 2.1482541 best: 2.1421694 (273)   total: 15.5s    remaining: 1m 1s
bestTest = 2.142169438
bestIteration = 273
Shrink model to first 274 iterations.
Predicting for fold 5...
[I 2023-02-12 17:48:55,771] Trial 5 finished with value: 2.222161643786955 and parameters: {'iterations': 2000,
'learning_rate': 0.2457514208222952, 'depth': 8, 'l2_leaf_reg': 100, 'random_strength': 225.5153077107271, 'boo
tstrap_type': 'Bayesian', 'score_function': 'L2', 'bagging_temperature': 28.983593683335464}. Best is trial 3 w
ith value: 1.9725806096138503.
```

```
Start processing fold 1...
0:      learn: 4.3003305        test: 4.3342562 best: 4.3342562 (0)     total: 28.5ms   remaining: 57s
200:    learn: 1.3643183        test: 2.4698198 best: 2.4545976 (87)    total: 5.59s    remaining: 50s
400:    learn: 1.2021255        test: 2.4368202 best: 2.4365513 (399)   total: 11.1s    remaining: 44.4s
600:    learn: 1.1405471        test: 2.4328034 best: 2.4325062 (587)   total: 16.7s    remaining: 38.8s
800:    learn: 1.1079051        test: 2.4329232 best: 2.4319892 (738)   total: 22.1s    remaining: 33.1s
bestTest = 2.431989226
bestIteration = 738
Shrink model to first 739 iterations.
Predicting for fold 1...
Start processing fold 2...
0:      learn: 4.3041845        test: 4.3015893 best: 4.3015893 (0)     total: 29.8ms   remaining: 59.5s
200:    learn: 1.3743687        test: 2.4198597 best: 2.3034945 (78)    total: 5.56s    remaining: 49.7s
bestTest = 2.303494543
bestIteration = 78
Shrink model to first 79 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 4.3021296        test: 4.3149652 best: 4.3149652 (0)     total: 27.8ms   remaining: 55.7s
200:    learn: 1.3757776        test: 2.3153795 best: 2.2162449 (78)    total: 5.6s     remaining: 50.1s
bestTest = 2.216244909
bestIteration = 78
Shrink model to first 79 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 4.3025354        test: 4.3061905 best: 4.3061905 (0)     total: 27.8ms   remaining: 55.5s
200:    learn: 1.3737359        test: 2.6186714 best: 2.3887200 (55)    total: 5.46s    remaining: 48.9s
bestTest = 2.388719956
bestIteration = 55
Shrink model to first 56 iterations.
Predicting for fold 4...

Start processing fold 5...
0:      learn: 4.3057406        test: 4.3039510 best: 4.3039510 (0)     total: 30.5ms   remaining: 1m
200:    learn: 1.3745383        test: 2.4326439 best: 2.3428188 (83)    total: 5.55s    remaining: 49.7s
[I 2023-02-12 17:50:38,022] Trial 6 finished with value: 2.336653728565746 and parameters: {'iterations': 2000,
'learning_rate': 0.02056948406702553, 'depth': 6, 'l2_leaf_reg': 10, 'random_strength': 247.61142570207707, 'bo
otstrap_type': 'Bernoulli', 'score_function': 'L2', 'subsample': 0.3699579076859651}. Best is trial 3 with valu
e: 1.9725806096138503.
bestTest = 2.34281876
bestIteration = 83
Shrink model to first 84 iterations.
Predicting for fold 5...
Start processing fold 1...
0:      learn: 3.9260586        test: 3.9941262 best: 3.9941262 (0)     total: 47.2ms   remaining: 33s
200:    learn: 1.4521354        test: 2.3555567 best: 2.3551621 (198)   total: 9.28s    remaining: 23s
bestTest = 2.266953027
bestIteration = 975
Shrink model to first 976 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 4.3696102        test: 4.3773716 best: 4.3773716 (0)     total: 34.9ms   remaining: 1m 2s
200:    learn: 1.0365771        test: 1.9675331 best: 1.9675331 (200)   total: 11.8s    remaining: 1m 33s
400:    learn: 0.9856710        test: 1.9644075 best: 1.9638971 (368)   total: 23.8s    remaining: 1m 23s
600:    learn: 0.9439555        test: 1.9616074 best: 1.9615820 (599)   total: 35.9s    remaining: 1m 11s
800:    learn: 0.9075639        test: 1.9614794 best: 1.9614794 (800)   total: 48.1s    remaining: 60s
1000:   learn: 0.8745723        test: 1.9606410 best: 1.9606063 (996)   total: 1m       remaining: 48.2s
1200:   learn: 0.8423074        test: 1.9592372 best: 1.9592372 (1200)  total: 1m 12s   remaining: 36.1s
1400:   learn: 0.8115288        test: 1.9613687 best: 1.9592022 (1202)  total: 1m 24s   remaining: 24.1s
bestTest = 1.959202248
bestIteration = 1202
Shrink model to first 1203 iterations.
Predicting for fold 4...
Start processing fold 5...
0:      learn: 3.7388224        test: 3.7827831 best: 3.7827831 (0)     total: 59.5ms   remaining: 1m 46s
200:    learn: 1.0363323        test: 2.4924087 best: 2.3888544 (4)     total: 11.7s    remaining: 1m 33s
[I 2023-02-12 18:29:17,464] Trial 18 finished with value: 2.203492765210925 and parameters: {'iterations': 1800
, 'learning_rate': 0.18553819894546034, 'depth': 10, 'l2_leaf_reg': 500, 'random_strength': 277.893968218993, '
bootstrap_type': 'Bernoulli', 'score_function': 'L2', 'subsample': 0.8296535954749351}. Best is trial 3 with va
lue: 1.9725806096138503.
```

```
bestTest = 2.388854351
bestIteration = 4
Shrink model to first 5 iterations.
Predicting for fold 5...
Start processing fold 1...
0:      learn: 4.1543841        test: 4.1270020 best: 4.1270020 (0)     total: 40.3ms   remaining: 44.3s
200:    learn: 1.4679340        test: 2.2525211 best: 2.2501099 (185)   total: 7.88s    remaining: 35.3s
400:    learn: 1.3294188        test: 2.2363308 best: 2.2363308 (400)   total: 15.8s    remaining: 27.5s
600:    learn: 1.2690285        test: 2.2393402 best: 2.2294294 (517)   total: 23.6s    remaining: 19.6s
bestTest = 2.229429392
bestIteration = 517
Shrink model to first 518 iterations.
Predicting for fold 1...

Start processing fold 2...
0:      learn: 4.1795961        test: 4.2100459 best: 4.2100459 (0)     total: 43ms     remaining: 47.3s
200:    learn: 1.4269875        test: 2.2032511 best: 2.2026144 (196)   total: 8.03s    remaining: 35.9s
400:    learn: 1.3229699        test: 2.1739985 best: 2.1714599 (394)   total: 16s      remaining: 27.8s
bestTest = 2.171459921
bestIteration = 394
Shrink model to first 395 iterations.
Predicting for fold 2...
Start processing fold 3...
0:      learn: 4.1724948        test: 4.3693814 best: 4.3693814 (0)     total: 39.4ms   remaining: 43.3s
200:    learn: 1.4480570        test: 2.0793979 best: 2.0751591 (152)   total: 8s       remaining: 35.8s
400:    learn: 1.3281120        test: 2.0443287 best: 2.0439836 (387)   total: 16s      remaining: 27.8s
600:    learn: 1.2616592        test: 2.0245049 best: 2.0245049 (600)   total: 23.9s    remaining: 19.9s
800:    learn: 1.2189871        test: 2.0210007 best: 2.0183766 (793)   total: 31.9s    remaining: 11.9s
1000:   learn: 1.1870541        test: 2.0164697 best: 2.0163148 (989)   total: 39.9s    remaining: 3.94s
1099:   learn: 1.1730093        test: 2.0163640 best: 2.0157656 (1079)  total: 43.8s    remaining: 0us
bestTest = 2.015765555
bestIteration = 1079
Shrink model to first 1080 iterations.
Predicting for fold 3...
Start processing fold 4...
0:      learn: 4.1499020        test: 4.2005455 best: 4.2005455 (0)     total: 43.4ms   remaining: 47.7s
200:    learn: 1.4370082        test: 2.2490725 best: 2.2444321 (82)    total: 8.07s    remaining: 36.1s
400:    learn: 1.3224691        test: 2.2102485 best: 2.2097509 (394)   total: 16s      remaining: 28s
600:    learn: 1.2619467        test: 2.1992855 best: 2.1990257 (586)   total: 24s      remaining: 20s
800:    learn: 1.2156625        test: 2.1931757 best: 2.1931757 (800)   total: 32s      remaining: 12s
1000:   learn: 1.1813572        test: 2.1836485 best: 2.1836204 (992)   total: 40.1s    remaining: 3.96s
1099:   learn: 1.1663943        test: 2.1828387 best: 2.1828387 (1099)  total: 44s      remaining: 0us
bestTest = 2.182838736
bestIteration = 1099
Predicting for fold 4...
Start processing fold 5...
0:      learn: 4.1562173        test: 4.1976456 best: 4.1976456 (0)     total: 43.6ms   remaining: 48s
200:    learn: 1.4419683        test: 2.1979926 best: 2.1857741 (163)   total: 8.09s    remaining: 36.2s
400:    learn: 1.3176110        test: 2.1812219 best: 2.1774058 (392)   total: 16s      remaining: 28s
600:    learn: 1.2513098        test: 2.1681635 best: 2.1669276 (572)   total: 24s      remaining: 19.9s
800:    learn: 1.2075787        test: 2.1578364 best: 2.1578364 (800)   total: 32s      remaining: 11.9s
1000:   learn: 1.1761045        test: 2.1487069 best: 2.1487069 (1000)  total: 39.9s    remaining: 3.94s
1099:   learn: 1.1620604        test: 2.1487532 best: 2.1481219 (1096)  total: 43.8s    remaining: 0us
bestTest = 2.148121863
bestIteration = 1096
Shrink model to first 1097 iterations.
Predicting for fold 5...
```

```
[I 2023-02-12 18:33:07,031] Trial 19 finished with value: 2.149522811224378 and parameters: {'iterations': 1100
, 'learning_rate': 0.06594318493279969, 'depth': 8, 'l2_leaf_reg': 10, 'random_strength': 196.4654452403077, 'b
ootstrap_type': 'Bayesian', 'score_function': 'Cosine', 'bagging_temperature': 15.182113058121327}. Best is tri
al 3 with value: 1.9725806096138503.
```

In [264…

```
fig_catboost = optuna.visualization.plot_optimization_history(study_catboost)
fig_catboost.show();
```

The objective values do appear to be trending downwards. Perhaps with more trials allocated, we would be able to achiever finer-tuned models.

Model Training

The best parameters returned can be further fine-tuned manually. Below, we will tweak one of the hyperparameters--- lowering the learning rate.

In [266…
```
study_catboost.best_params
```

Out[266]:
```
{'iterations': 1600,
 'learning_rate': 0.21065008859344805,
 'depth': 9,
 'l2_leaf_reg': 500,
 'random_strength': 122.57161445434504,
 'bootstrap_type': 'Bayesian',
 'score_function': 'L2',
 'bagging_temperature': 7.960423129118915}
```

In [105…
```
# Out-of-fold prediction dictionary
oof_catboost = {}
# Feature importance container
feat_imp_catboost = []
# K-fold cross validation
kf_catboost = KFold(n_splits=5, shuffle=True, random_state=rs)

for fold, (train_indx, val_indx) in enumerate(kf_catboost.split(X_train, y_train)):

    # Train and validation sets
    fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
    fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

    # Preprocessing using a fresh copy of the pipeline for every fold to prevent leakage
    preprocessor = joblib.load('../output/preprocessors/catboost_preprocessor.joblib')
    print(f'Start processing fold {fold + 1}...')
    fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
    fold_X_val = preprocessor.transform(fold_X_val)
    # Write fitted preprocessor to disk
    joblib.dump(preprocessor, model_path + f'catboost/preprocessor_fold_{fold + 1}.joblib')

    # Data for modeling
    feature_names = fold_X_train.columns.tolist()
    dtrain = cb.Pool(data=fold_X_train, label=fold_y_train, feature_names=feature_names, cat_features=encode_co
    dvalid = cb.Pool(data=fold_X_val, label=fold_y_val, feature_names=feature_names, cat_features=encode_cols)

    # Model
    model = cb.train(
        params={'iterations': 1600,
                'learning_rate': 0.03,
                 'depth': 9,
                 'l2_leaf_reg': 500,
                 'random_strength': 122.57161445434504,
                 'bootstrap_type': 'Bayesian',
                 'score_function': 'L2',
                 'bagging_temperature': 7.960423129118915,
                 'objective': 'RMSE',
                 'eval_metric': 'RMSE',
                 'task_type': 'GPU', # GPU training
                 'border_count': 254,
                 'use_best_model': True,
                 'boosting_type': 'Plain'},
        dtrain=dtrain,
        early_stopping_rounds=200,
        eval_set=dvalid,
        verbose=200 # Report every 200 rounds
      )
    model.save_model(model_path + f'catboost/model_fold_{fold + 1}.cbm')
    joblib.dump(model.get_evals_result(), model_path + f'catboost/eval_fold_{fold + 1}.joblib')

    # Return feature importance as a list of (feature_id, feature importance)
    feat_imp_catboost.append(model.get_feature_importance(type='FeatureImportance', prettified=True))

    # Predictions
    print(f'Predicting for fold {fold + 1}...')
    oof_pred = model.predict(data=dvalid)
    oof_catboost[f'fold_{fold + 1}'] = {'target': fold_y_val, 'predictions': oof_pred}

    del dtrain, dvalid, preprocessor, model, oof_pred
```

```
Start processing fold 1...
```

Out[105]:
```
['../output/models/catboost/preprocessor_fold_1.joblib']
```

```
0:      learn: 4.2942860        test: 4.3481472 best: 4.3481472 (0)     total: 52.3ms   remaining: 1m 23s
200:    learn: 1.4846321        test: 2.0264708 best: 2.0264708 (200)   total: 9.6s     remaining: 1m 6s
400:    learn: 1.3742982        test: 1.9483631 best: 1.9483551 (397)   total: 19.2s    remaining: 57.4s
600:    learn: 1.3332005        test: 1.9358437 best: 1.9357838 (599)   total: 28.9s    remaining: 48.1s
800:    learn: 1.3054368        test: 1.9269489 best: 1.9263232 (799)   total: 38.4s    remaining: 38.3s
1000:   learn: 1.2833531        test: 1.9170145 best: 1.9169861 (997)   total: 48s      remaining: 28.7s
1200:   learn: 1.2680810        test: 1.9136113 best: 1.9131233 (1123)  total: 57.6s    remaining: 19.1s
1400:   learn: 1.2534695        test: 1.9083046 best: 1.9080637 (1399)  total: 1m 7s    remaining: 9.53s
1599:   learn: 1.2414106        test: 1.9044369 best: 1.9041122 (1553)  total: 1m 16s   remaining: 0us
bestTest = 1.904112249
bestIteration = 1553
Shrink model to first 1554 iterations.
```

Out[105]:
```
['../output/models/catboost/eval_fold_1.joblib']
```

```
Predicting for fold 1...
Start processing fold 2...
```

Out[105]:
```
['../output/models/catboost/preprocessor_fold_2.joblib']
```

```
0:      learn: 4.2972292        test: 4.3050925 best: 4.3050925 (0)     total: 53ms     remaining: 1m 24s
200:    learn: 1.4682031        test: 2.0364287 best: 2.0364287 (200)   total: 9.63s    remaining: 1m 6s
400:    learn: 1.3678735        test: 1.9756398 best: 1.9750068 (395)   total: 19.2s    remaining: 57.5s
600:    learn: 1.3260084        test: 1.9540601 best: 1.9532478 (596)   total: 29s      remaining: 48.1s
800:    learn: 1.2979784        test: 1.9415586 best: 1.9415586 (800)   total: 38.7s    remaining: 38.6s
1000:   learn: 1.2782562        test: 1.9310207 best: 1.9309814 (995)   total: 48.4s    remaining: 29s
1200:   learn: 1.2642259        test: 1.9257172 best: 1.9255771 (1194)  total: 58.2s    remaining: 19.3s
1400:   learn: 1.2513337        test: 1.9208633 best: 1.9208505 (1399)  total: 1m 7s    remaining: 9.65s
1599:   learn: 1.2388092        test: 1.9146963 best: 1.9146254 (1597)  total: 1m 17s   remaining: 0us
bestTest = 1.914625425
bestIteration = 1597
Shrink model to first 1598 iterations.
```

Out[105]:
```
['../output/models/catboost/eval_fold_2.joblib']
```

```
Predicting for fold 2...
Start processing fold 3...
```

Out[105]:
```
['../output/models/catboost/preprocessor_fold_3.joblib']
```

```
0:      learn: 4.2973890        test: 4.2776678 best: 4.2776678 (0)     total: 53.5ms   remaining: 1m 25s
200:    learn: 1.4602346        test: 2.0156389 best: 2.0156389 (200)   total: 9.72s    remaining: 1m 7s
400:    learn: 1.3690786        test: 1.9731652 best: 1.9728916 (393)   total: 19.4s    remaining: 58.1s
600:    learn: 1.3264653        test: 1.9573255 best: 1.9573244 (599)   total: 29.1s    remaining: 48.4s
800:    learn: 1.2982251        test: 1.9470217 best: 1.9470099 (794)   total: 38.6s    remaining: 38.5s
1000:   learn: 1.2770995        test: 1.9388541 best: 1.9387614 (992)   total: 48.4s    remaining: 28.9s
1200:   learn: 1.2603996        test: 1.9342572 best: 1.9342572 (1200)  total: 58s      remaining: 19.3s
1400:   learn: 1.2468703        test: 1.9308011 best: 1.9308011 (1400)  total: 1m 7s    remaining: 9.62s
1599:   learn: 1.2345420        test: 1.9267397 best: 1.9267269 (1598)  total: 1m 17s   remaining: 0us
bestTest = 1.926726947
bestIteration = 1598
Shrink model to first 1599 iterations.
```

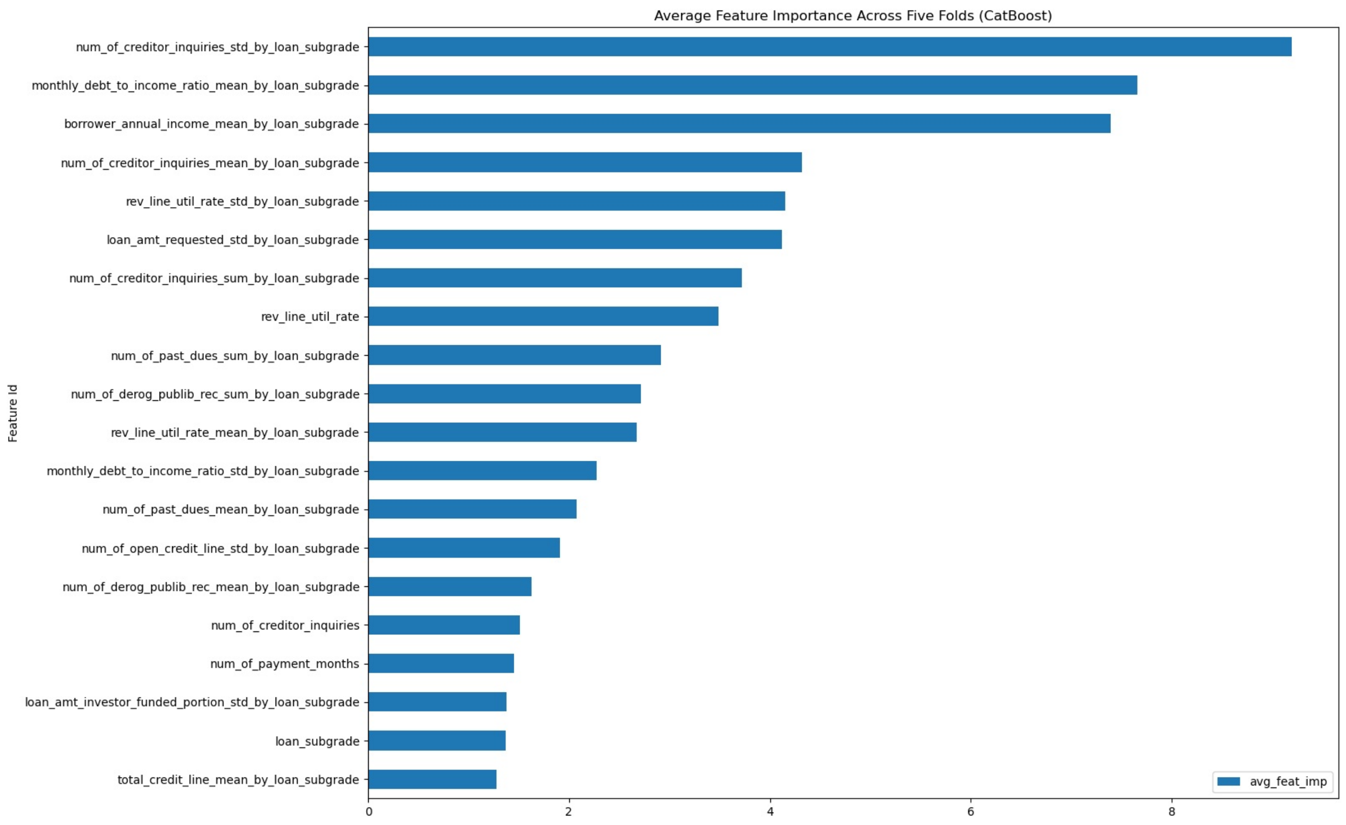
Out[105]:
```
['../output/models/catboost/eval_fold_3.joblib']
```

```
Predicting for fold 3...
Start processing fold 4...
```

```
Out[105]: ['../output/models/catboost/preprocessor_fold_4.joblib']
          0:      learn: 4.2942688        test: 4.3187485 best: 4.3187485 (0)     total: 51.9ms   remaining: 1m 22s
          200:    learn: 1.4656432        test: 1.9762537 best: 1.9762537 (200)   total: 9.56s    remaining: 1m 6s
          400:    learn: 1.3677487        test: 1.9062980 best: 1.9062980 (400)   total: 19.1s    remaining: 57.1s
          600:    learn: 1.3255955        test: 1.8836513 best: 1.8836513 (600)   total: 28.7s    remaining: 47.7s
          800:    learn: 1.2981092        test: 1.8679248 best: 1.8679206 (799)   total: 38.2s    remaining: 38.1s
          1000:   learn: 1.2764594        test: 1.8567059 best: 1.8567059 (1000)  total: 47.9s    remaining: 28.6s
          1200:   learn: 1.2590459        test: 1.8482693 best: 1.8482693 (1200)  total: 57.5s    remaining: 19.1s
          1400:   learn: 1.2470191        test: 1.8418291 best: 1.8418291 (1400)  total: 1m 7s    remaining: 9.53s
          1599:   learn: 1.2350771        test: 1.8354936 best: 1.8353143 (1578)  total: 1m 16s   remaining: 0us
          bestTest = 1.835314325
          bestIteration = 1578
          Shrink model to first 1579 iterations.
Out[105]: ['../output/models/catboost/eval_fold_4.joblib']
          Predicting for fold 4...
          Start processing fold 5...
Out[105]: ['../output/models/catboost/preprocessor_fold_5.joblib']
          0:      learn: 4.3050323        test: 4.3343444 best: 4.3343444 (0)     total: 50.8ms   remaining: 1m 21s
          200:    learn: 1.4696808        test: 2.1308574 best: 2.1308574 (200)   total: 9.72s    remaining: 1m 7s
          400:    learn: 1.3702882        test: 2.0761662 best: 2.0761662 (400)   total: 19.3s    remaining: 57.7s
          600:    learn: 1.3224202        test: 2.0474226 best: 2.0473729 (599)   total: 28.9s    remaining: 48.1s
          800:    learn: 1.2930671        test: 2.0327357 best: 2.0327357 (800)   total: 38.5s    remaining: 38.4s
          1000:   learn: 1.2723030        test: 2.0214952 best: 2.0214952 (1000)  total: 48s      remaining: 28.8s
          1200:   learn: 1.2560228        test: 2.0134869 best: 2.0134794 (1199)  total: 57.8s    remaining: 19.2s
          1400:   learn: 1.2421490        test: 2.0087456 best: 2.0086940 (1396)  total: 1m 7s    remaining: 9.58s
          1599:   learn: 1.2323502        test: 2.0049508 best: 2.0049508 (1599)  total: 1m 16s   remaining: 0us
          bestTest = 2.004950766
          bestIteration = 1599
Out[105]: ['../output/models/catboost/eval_fold_5.joblib']
          Predicting for fold 5...
```

Feature Importance

```
In [106…
# Join feature importance
feat_imp_catboost = reduce(lambda x, y: pd.merge(x, y, on='Feature Id', how='left'), feat_imp_catboost)
feat_imp_catboost['avg_feat_imp'] = feat_imp_catboost.iloc[:, 1:].apply(lambda row: row.mean(), axis=1)

# Plot top feature importance
feat_imp_catboost.sort_values(by='avg_feat_imp', ascending=True).iloc[-20:].plot(
    kind='barh', x='Feature Id', y='avg_feat_imp',
    figsize=(15, 12),
    title='Average Feature Importance Across Five Folds (CatBoost)'
)
plt.show();
```

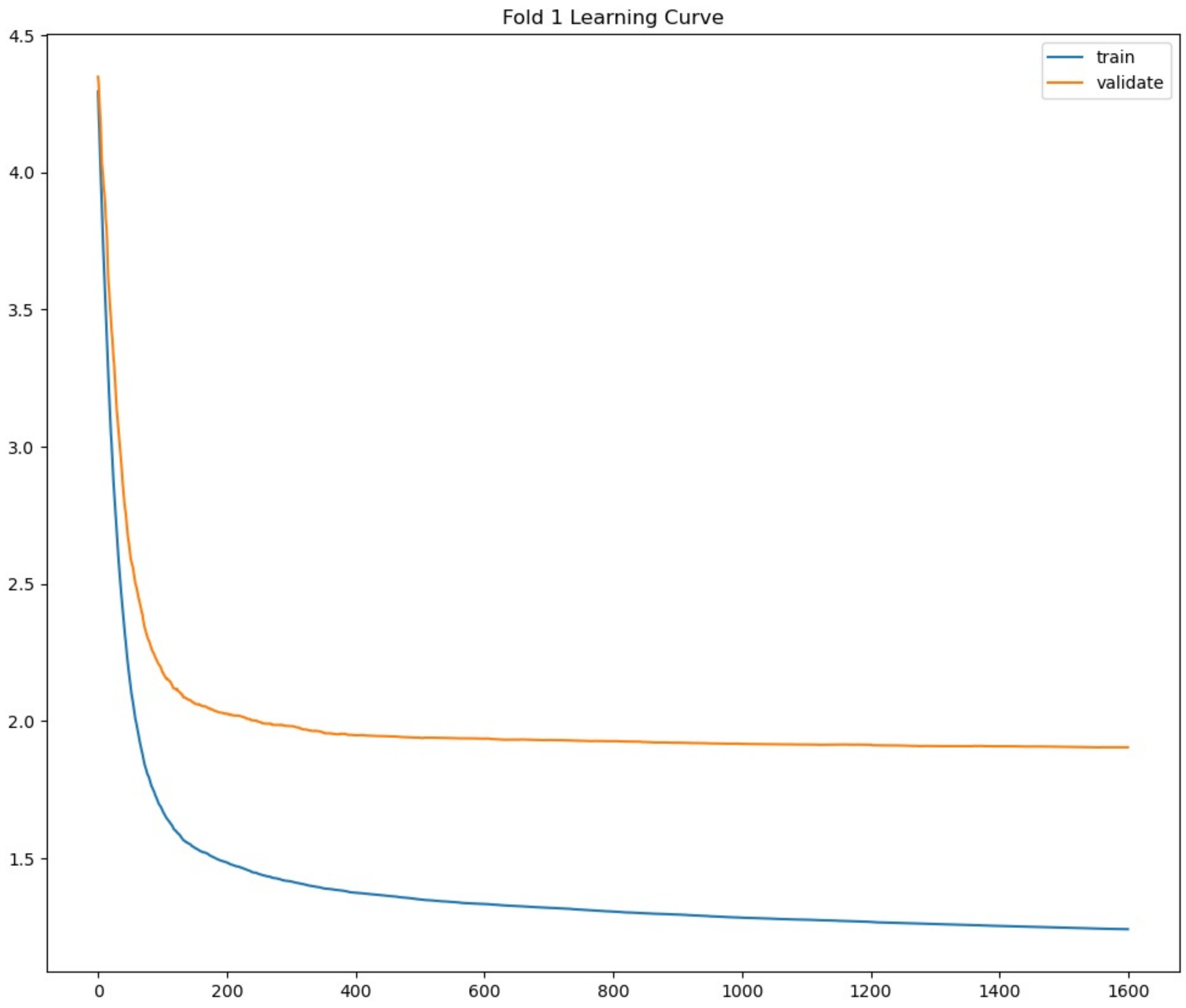


Again, similar to the output of XGBoost, the loan subgrade feature is of crucial importance. Many of the generated features based on this grade feature are also ranked highly in terms of importance.

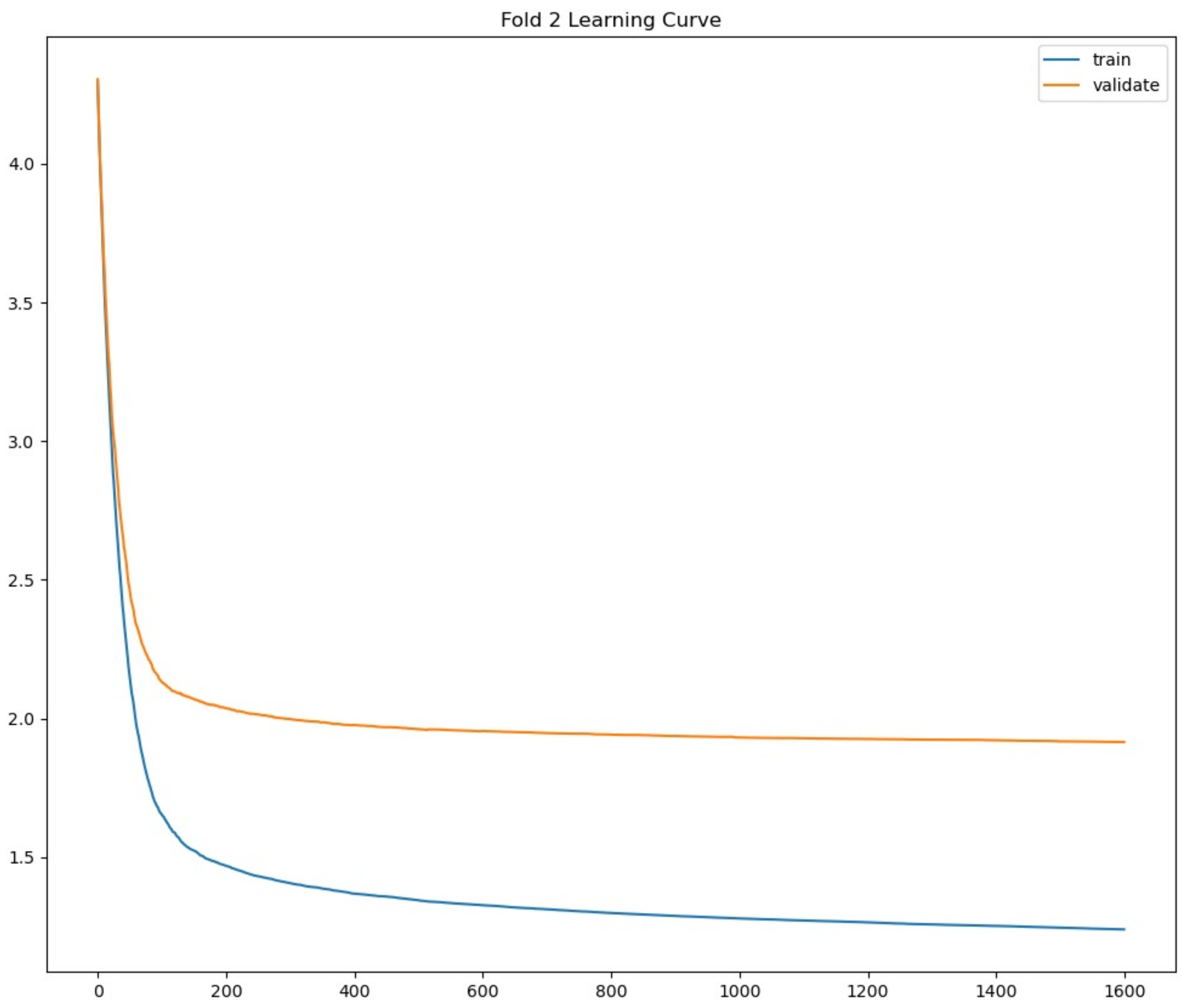
Learning Curves

```
In [107…
for fold in range(5):
    eval_result = joblib.load(model_path + f'catboost/eval_fold_{fold + 1}.joblib')
    plt.plot(eval_result['learn']['RMSE'], label='train');
    plt.plot(eval_result['validation']['RMSE'], label='validate');
    plt.legend();
    plt.title(f'Fold {fold + 1} Learning Curve');
    plt.show();
```

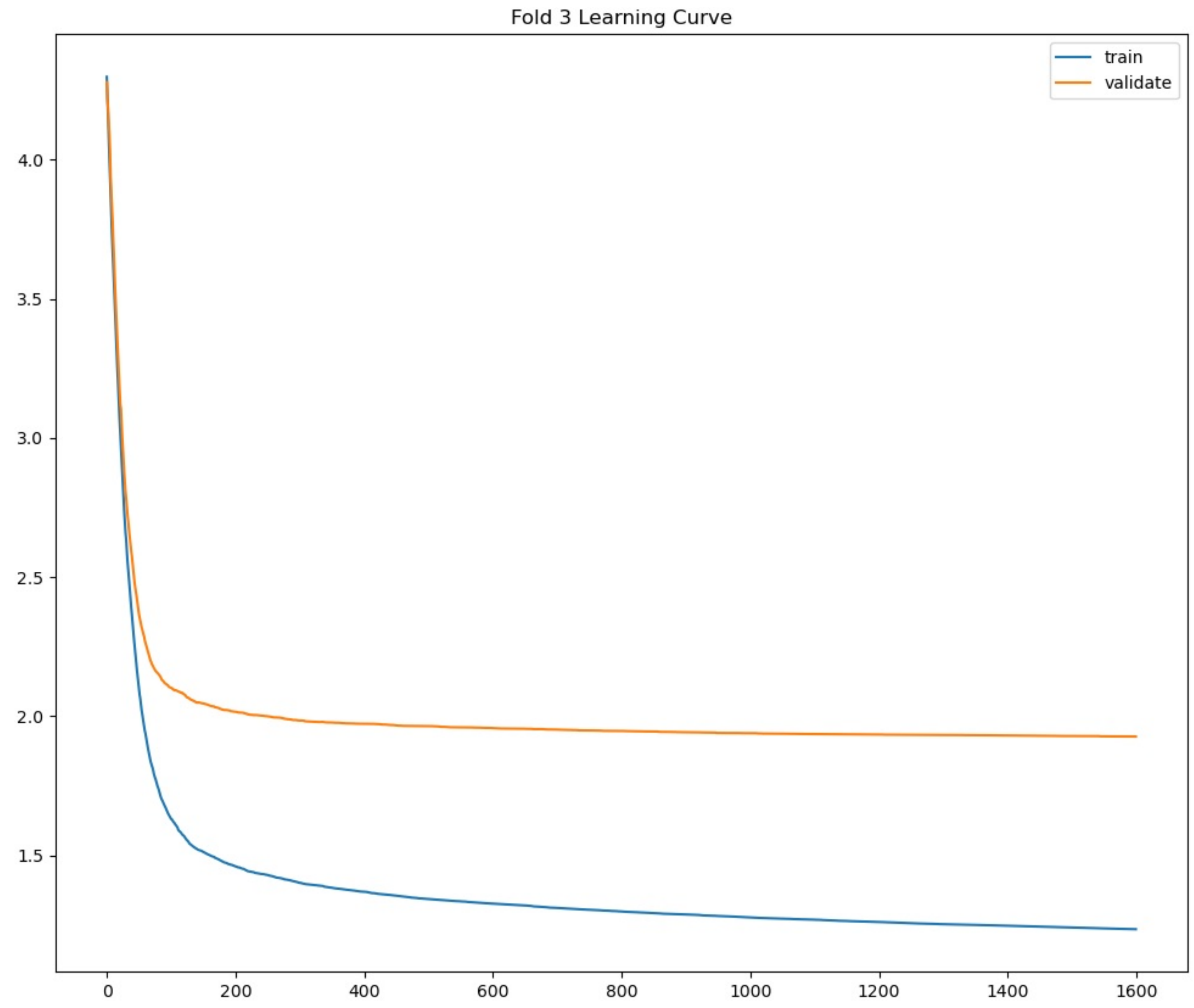
```
Out[107]: [<matplotlib.lines.Line2D at 0x7f2364608a30>]
Out[107]: [<matplotlib.lines.Line2D at 0x7f2364608df0>]
Out[107]: <matplotlib.legend.Legend at 0x7f2364608cd0>
Out[107]: Text(0.5, 1.0, 'Fold 1 Learning Curve')
```



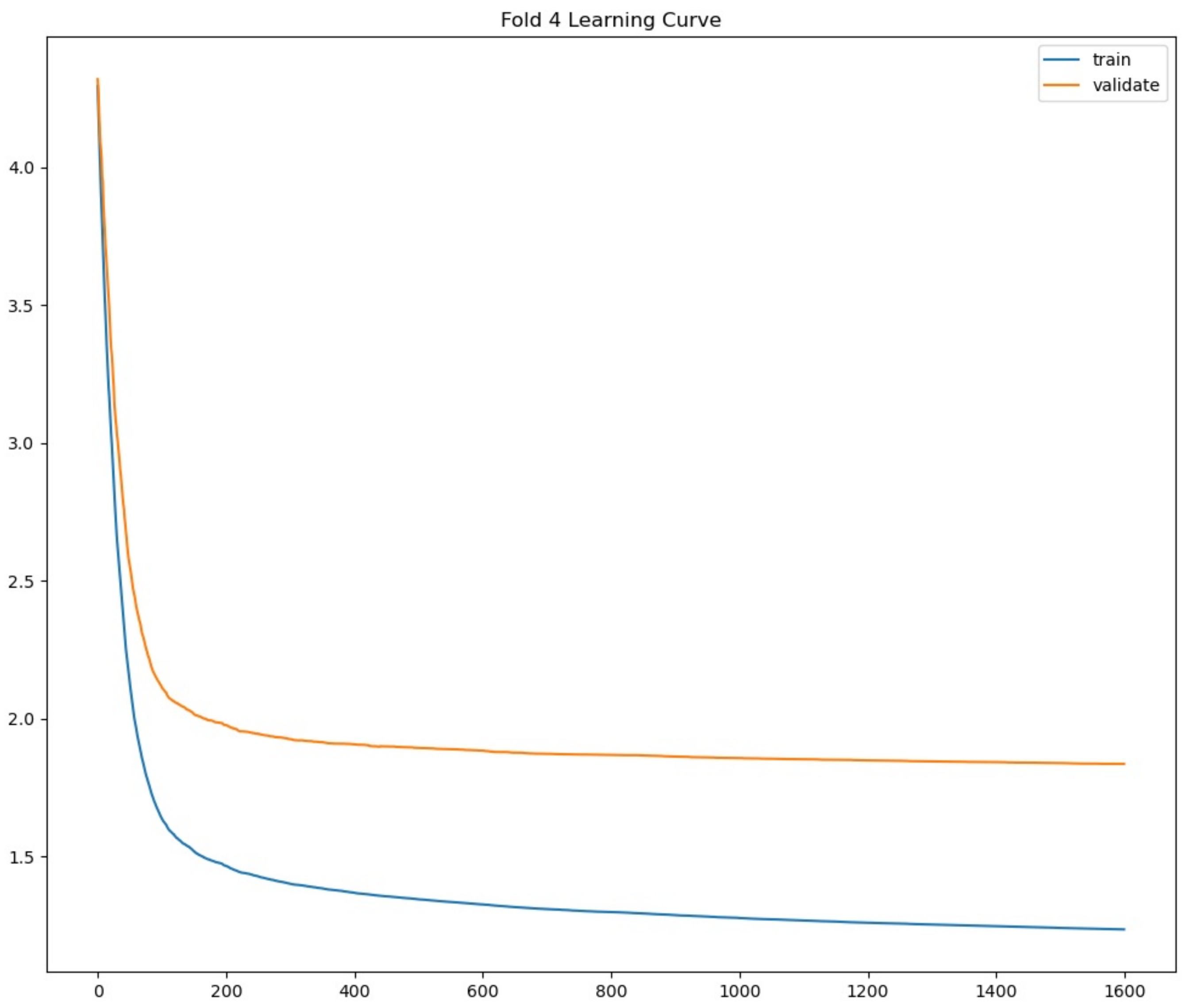
```
Out[107]: [<matplotlib.lines.Line2D at 0x7f2362a125e0>]
Out[107]: [<matplotlib.lines.Line2D at 0x7f2362a12970>]
Out[107]: <matplotlib.legend.Legend at 0x7f2362a12850>
Out[107]: Text(0.5, 1.0, 'Fold 2 Learning Curve')
```



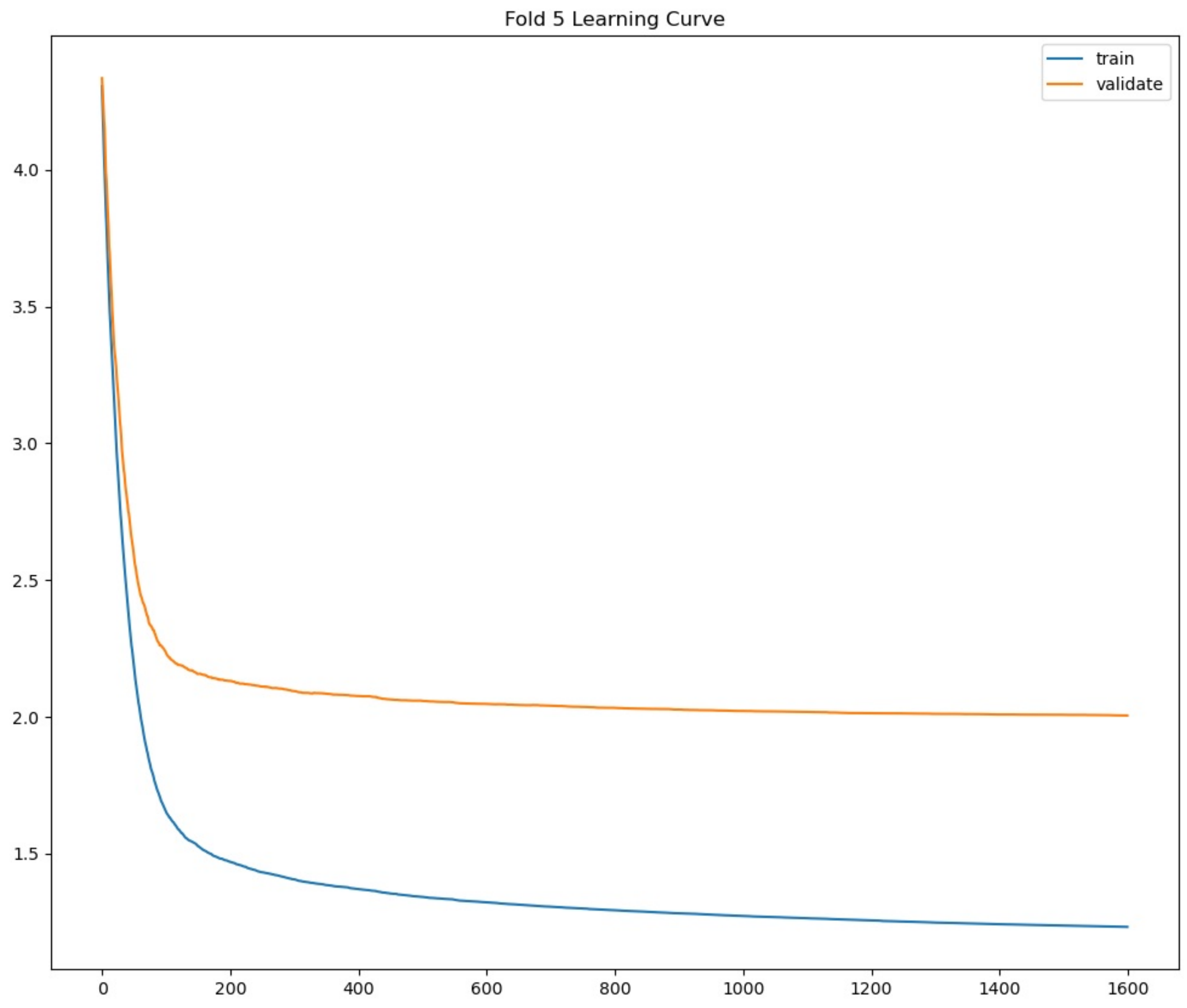
```
Out[107]: [<matplotlib.lines.Line2D at 0x7f23633d3f10>]

Out[107]: [<matplotlib.lines.Line2D at 0x7f23633ec1f0>]

Out[107]: <matplotlib.legend.Legend at 0x7f236420b7c0>

Out[107]: Text(0.5, 1.0, 'Fold 3 Learning Curve')
```



```
Out[107]: [<matplotlib.lines.Line2D at 0x7f2363725190>]

Out[107]: [<matplotlib.lines.Line2D at 0x7f2363725400>]

Out[107]: <matplotlib.legend.Legend at 0x7f2364879580>

Out[107]: Text(0.5, 1.0, 'Fold 4 Learning Curve')
```



```
Out[107]: [<matplotlib.lines.Line2D at 0x7f2364c5ff10>]

Out[107]: [<matplotlib.lines.Line2D at 0x7f2364c4e1c0>]

Out[107]: <matplotlib.legend.Legend at 0x7f2364c5ff70>

Out[107]: Text(0.5, 1.0, 'Fold 5 Learning Curve')
```



Contrary to XGBoost, the learning curves for CatBoost show that the models begin to overfit as soon as we reach about 200 rounds. We also set the parameter `use_best_model` to true in the train method to identify the iteration with the optimal value of the metric.

Performance on Validation Sets

In [108…
```
oof_catboost_rmse = []
target_frame = cudf.DataFrame(index=['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max'])

for key in oof_catboost:

    oof_catboost_rmse.append(
        mean_squared_error(oof_catboost[key]['target'], oof_catboost[key]['predictions'], squared=False)
    )
    print(f'Finished computing rmse for {key}')

    target_frame[f'{key}_target_descriptive_stats'] = cudf.Series(oof_catboost[key]['target']).describe()
    print(f'Finished computing descriptive stats for {key} target')
```

```
Finished computing rmse for fold_1
Finished computing descriptive stats for fold_1 target
Finished computing rmse for fold_2
Finished computing descriptive stats for fold_2 target
Finished computing rmse for fold_3
Finished computing descriptive stats for fold_3 target
Finished computing rmse for fold_4
Finished computing descriptive stats for fold_4 target
Finished computing rmse for fold_5
Finished computing descriptive stats for fold_5 target
```

In [109…
```
cudf.Series(oof_catboost_rmse).describe()
```

Out[109]:
```
count    5.000000
mean     1.917146
std      0.060569
min      1.835314
25%      1.904114
50%      1.914625
75%      1.926727
max      2.004952
dtype: float64
```

In [301…
```
target_frame
```

Out[301]:

	fold_1_target_descriptive_stats	fold_2_target_descriptive_stats	fold_3_target_descriptive_stats	fold_4_target_descriptive_stats	fold_5_ta
count	67798.000000	67798.000000	67798.000000	67797.000000	
mean	13.946219	13.940915	13.924338	13.952788	
std	4.354851	4.380408	4.363100	4.404952	
min	5.420000	5.420000	5.420000	5.420000	
25%	10.990000	10.990000	10.990000	10.990000	
50%	13.980000	13.680000	13.670000	13.680000	
75%	16.780000	16.780000	16.770000	16.780000	
max	26.060000	26.060000	26.060000	26.060000	

On average, we are off by 1.913222 percentage points. This value is higher than that of XGBoost. However, cross-validation scores are usually better than the real test scores anyways, since it is likely that our system is fine-tuned to perform well on the validation data but will likely not perform as well on unknown datasets. Therefore, these models may perform better on certain training examples than the XGBoost models even when their performances on the validation sets are relatively worse.

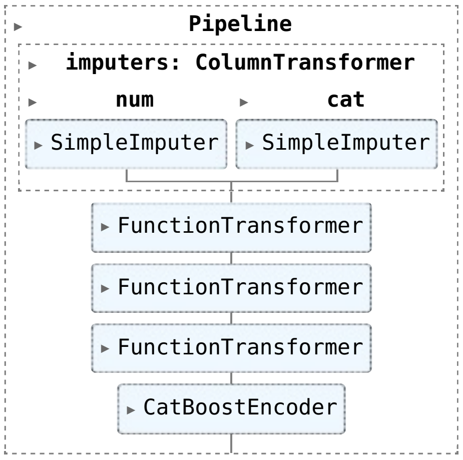
LightGBM

Pipeline

In [22]:
```
lightgbm_preprocessor = Pipeline([
    ('imputers', imputers),
    ('restore_cols', FunctionTransformer(pp.restore_columns)),
    ('date_transformer', FunctionTransformer(pp.extract_date_features)),
    ('num_feat_eng', FunctionTransformer(pp.num_feat_eng)),
    ('cat_encoder', CatBoostEncoder(cols=encode_cols, handle_missing='value', handle_unknown='value'))
])
joblib.dump(lightgbm_preprocessor, prep_path + 'lightgbm_preprocessor.joblib')
lightgbm_preprocessor
```

Out[22]:
```
['../output/preprocessors/lightgbm_preprocessor.joblib']
```

Out[22]:



Hyperparameter Search

```
In [44]: def objective_lightgbm(trial):

             # Fold and seed
             train = pd.read_csv("../data/train_sanitized.csv")
             X_train, y_train = train.drop(['interest_rate'], axis=1), train.interest_rate.to_numpy()
             folds = 5
             seed = 1227

             # Parameters
             search_space = {
                 'objective': 'rmse',
                 'metric': 'rmse',
                 'device_type': 'gpu',
                 'verbosity': -1,
                 'early_stopping_round': 200,
                 'boosting': 'gbdt',
                 # For better accuracy
                 'num_iterations': trial.suggest_int('num_iterations', low=500, high=2000, step=100), # Range: [0, inf],
                 'learning_rate': trial.suggest_float(name='learning_rate', low=0.001, high=0.1), # Shrinkage rate
                 'num_leaves': trial.suggest_int('num_leaves', 31, 100), # Constrained: 1 < num_leaves <= 131072, max nu
                 # Regularizers
                 'max_depth': trial.suggest_int('max_depth', low=4, high=12), # Reguralizer that controls max depth for
                 'max_bin': trial.suggest_int('max_bin', low=150, high=255), # Constrained: max_bin > 1, small values ma
                 'bagging_fraction': trial.suggest_float('bagging_fraction', 0.1, 0.6), # Constrained: 0.0 < bagging_fra
                 'bagging_freq': trial.suggest_int('bagging_freq', 20, 100), # Every k-th iteration, LightGBM will rando
                 'feature_fraction': trial.suggest_float('feature_fraction', 0.1, 0.6), # Constrained: 0.0 < feature_fra
                 'feature_fraction_bynode': trial.suggest_float('feature_fraction_bynode', 0.1, 0.6), # Constrained: 0.0
                 'lambda_l1': trial.suggest_int('lambda_l1', low=100, high=1000), # Constrained: lambda_l1 >= 0.0 (regul
                 'lambda_l2': trial.suggest_int('lambda_l2', low=100, high=1000), # Constrained: lambda_l2 >= 0.0 (regul
                 'extra_trees': trial.suggest_categorical('extra_trees', [True, False]), # If set to true, when evaluati
                 'path_smooth': trial.suggest_int('path_smooth', low=100, high=1000) # Controls smoothing applied to tre
             }

             # K-fold cross validation
             kf = KFold(n_splits=folds, shuffle=True, random_state=rs)
             rmse_scores = np.empty(folds)

             for fold, (train_indx, val_indx) in enumerate(kf.split(X_train, y_train)):

                 # Train and validation sets
                 fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
                 fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

                 # Preprocessing using a fresh copy of the pipeline for every fold to prevent leakage
                 preprocessor = joblib.load('../output/preprocessors/lightgbm_preprocessor.joblib')
                 print(f'Start processing fold {fold + 1}...')
                 fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
                 fold_X_val = preprocessor.transform(fold_X_val)

                 # Data for modeling
                 feature_names = fold_X_train.columns.tolist()
                 dtrain = lgb.Dataset(data=fold_X_train, label=fold_y_train, feature_name=feature_names)
                 dvalid = lgb.Dataset(data=fold_X_val, label=fold_y_val, feature_name=feature_names, reference=dtrain)

                 # Model
                 model = lgb.train(
                     params=search_space,
                     train_set=dtrain,
                     valid_sets=[dtrain, dvalid],
                     valid_names=['train', 'valid'],
                     callbacks=[lgb.log_evaluation(period=200), lgb.early_stopping(stopping_rounds=200)] # Log evaluatio
                   )

                 # Out-of-fold prediction
                 print(f'Predicting for fold {fold + 1}...')
                 oof_pred = model.predict(data=fold_X_val)
                 rmse_scores[fold] = mean_squared_error(fold_y_val, oof_pred, squared=False) # Use RMSE

             # Average across 5 folds
             mean_rmse = np.mean(rmse_scores)

             return mean_rmse
```

```
In [ ]: study_lightgbm = optuna.create_study(sampler=optuna.samplers.TPESampler(), study_name='min_rmse_lightgbm', dire
        study_lightgbm.optimize(objective_lightgbm, n_trials=20)
```

```
[I 2023-02-13 05:49:58,496] A new study created in memory with name: min_rmse_lightgbm
```

```
Start processing fold 1...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.64927   valid's rmse: 2.41888
Predicting for fold 1...
Start processing fold 2...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.67731   valid's rmse: 2.05804
[400]   train's rmse: 1.61628   valid's rmse: 2.03081
Predicting for fold 2...
Start processing fold 3...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.67464   valid's rmse: 2.09431
Early stopping, best iteration is:
[120]   train's rmse: 1.73483   valid's rmse: 2.07136
Predicting for fold 3...
Start processing fold 4...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.69319   valid's rmse: 2.41033
Predicting for fold 4...
Start processing fold 5...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.68245   valid's rmse: 2.7383
[400]   train's rmse: 1.62956   valid's rmse: 2.70514
[600]   train's rmse: 1.59952   valid's rmse: 2.69378
[800]   train's rmse: 1.57291   valid's rmse: 2.67713
[1000]  train's rmse: 1.56285   valid's rmse: 2.67525
Predicting for fold 5...
[I 2023-02-13 05:52:13,914] Trial 0 finished with value: 2.310950566601096 and parameters: {'num_iterations': 1
900, 'learning_rate': 0.054172139977479834, 'num_leaves': 66, 'max_depth': 10, 'max_bin': 204, 'bagging_fractio
n': 0.48543255102322513, 'bagging_freq': 68, 'feature_fraction': 0.3114237062389975, 'feature_fraction_bynode':
0.1277763428763173, 'lambda_l1': 780, 'lambda_l2': 730, 'extra_trees': True, 'path_smooth': 455}. Best is trial
0 with value: 2.310950566601096.
Start processing fold 1...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.56156   valid's rmse: 2.16705
Early stopping, best iteration is:
[60]    train's rmse: 1.75489   valid's rmse: 2.13457
Predicting for fold 1...
Start processing fold 2...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.55126   valid's rmse: 2.23048
[400]   train's rmse: 1.46439   valid's rmse: 2.21595
[600]   train's rmse: 1.42421   valid's rmse: 2.19913
[800]   train's rmse: 1.40755   valid's rmse: 2.19024
[1000]  train's rmse: 1.39621   valid's rmse: 2.18313
[1200]  train's rmse: 1.39142   valid's rmse: 2.17547
[1400]  train's rmse: 1.3874    valid's rmse: 2.17116
[1600]  train's rmse: 1.38455   valid's rmse: 2.1707
Predicting for fold 2...
Start processing fold 3...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.55056   valid's rmse: 2.2756
Early stopping, best iteration is:
[46]    train's rmse: 1.84841   valid's rmse: 2.14609
Predicting for fold 3...
Start processing fold 4...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.55253   valid's rmse: 2.19018
[400]   train's rmse: 1.45906   valid's rmse: 2.14005
[600]   train's rmse: 1.42694   valid's rmse: 2.12182
[800]   train's rmse: 1.40526   valid's rmse: 2.10873
[1000]  train's rmse: 1.39055   valid's rmse: 2.10049
[1200]  train's rmse: 1.38353   valid's rmse: 2.09632
[1400]  train's rmse: 1.37932   valid's rmse: 2.09187
[1600]  train's rmse: 1.37403   valid's rmse: 2.08828
Predicting for fold 4...
Start processing fold 5...
Training until validation scores don't improve for 200 rounds
[200]   train's rmse: 1.55719   valid's rmse: 2.46119
Predicting for fold 5...
[I 2023-02-13 05:54:43,899] Trial 1 finished with value: 2.168692672835806 and parameters: {'num_iterations': 1
700, 'learning_rate': 0.050868051185383324, 'num_leaves': 32, 'max_depth': 9, 'max_bin': 227, 'bagging_fraction
': 0.5913533561366116, 'bagging_freq': 87, 'feature_fraction': 0.28333655555498927, 'feature_fraction_bynode':
0.4234284426180617, 'lambda_l1': 770, 'lambda_l2': 530, 'extra_trees': True, 'path_smooth': 782}. Best is trial
1 with value: 2.168692672835806.
```

```
Start processing fold 1...
Training until validation scores don't improve for 200 rounds
[200]	train's rmse: 3.00748	valid's rmse: 3.0146
[400]	train's rmse: 2.28672	valid's rmse: 2.41993
Predicting for fold 1...
Start processing fold 2...
Training until validation scores don't improve for 200 rounds
[200]	train's rmse: 3.00229	valid's rmse: 3.05832
[400]	train's rmse: 2.28295	valid's rmse: 2.41542
Predicting for fold 2...
Start processing fold 3...
Training until validation scores don't improve for 200 rounds
[200]	train's rmse: 3.00726	valid's rmse: 3.04171
[400]	train's rmse: 2.28413	valid's rmse: 2.41983
Did not meet early stopping. Best iteration is:
[500]	train's rmse: 2.06901	valid's rmse: 2.2868
Predicting for fold 3...
Start processing fold 4...
Training until validation scores don't improve for 200 rounds
[200]	train's rmse: 3.00542	valid's rmse: 3.04034
[400]	train's rmse: 2.28593	valid's rmse: 2.42163
Predicting for fold 4...
Start processing fold 5...
Training until validation scores don't improve for 200 rounds
[200]	train's rmse: 3.00545	valid's rmse: 3.00927
[400]	train's rmse: 2.28872	valid's rmse: 2.40772
Did not meet early stopping. Best iteration is:
[500]	train's rmse: 2.07431	valid's rmse: 2.27024
Predicting for fold 5...
```

```
[I 2023-02-13 06:35:36,154] Trial 19 finished with value: 2.2739637834415745 and parameters: {'num_iterations':
500, 'learning_rate': 0.003105282285168102, 'num_leaves': 60, 'max_depth': 7, 'max_bin': 243, 'bagging_fraction
': 0.16632944108350842, 'bagging_freq': 47, 'feature_fraction': 0.5989188643494747, 'feature_fraction_bynode':
0.3932645009593174, 'lambda_l1': 558, 'lambda_l2': 880, 'extra_trees': False, 'path_smooth': 328}. Best is tria
l 14 with value: 2.02999775969229.
```

In [46]:
```python
fig_lightgbm = optuna.visualization.plot_optimization_history(study_lightgbm)
fig_lightgbm.show();
```

There appears to be a downward trend with only a few number of trials. What is important is the fact that we can use Bayesian optimization to give us a good starting point to carry out some manual tuning.

Model Training

In [ ]:
```python
study_lightgbm.best_params
```

Out[ ]:
```
{'num_iterations': 1500,
 'learning_rate': 0.019908450044620562,
 'num_leaves': 90,
 'max_depth': 5,
 'max_bin': 239,
 'bagging_fraction': 0.18078231391179356,
 'bagging_freq': 43,
 'feature_fraction': 0.5980226845999467,
 'feature_fraction_bynode': 0.5458756726159959,
 'lambda_l1': 310,
 'lambda_l2': 827,
 'extra_trees': False,
 'path_smooth': 239}
```

In [66]:
```
# Out-of-fold prediction dictionary
oof_lightgbm = {}
# Feature importance container
feat_imp_lightgbm = []
# K-fold cross validation
kf_lightgbm = KFold(n_splits=5, shuffle=True, random_state=rs)

for fold, (train_indx, val_indx) in enumerate(kf_lightgbm.split(X_train, y_train)):

    # Train and validation sets
    fold_X_train, fold_y_train = X_train.iloc[train_indx], y_train[train_indx]
    fold_X_val, fold_y_val = X_train.iloc[val_indx], y_train[val_indx]

    # Preprocessing using a fresh copy of the pipeline for every fold to prevent leakage
    preprocessor = joblib.load('../output/preprocessors/lightgbm_preprocessor.joblib')
    print(f'Start processing fold {fold + 1}...')
    fold_X_train = preprocessor.fit_transform(fold_X_train, fold_y_train)
    fold_X_val = preprocessor.transform(fold_X_val)
    # Write fitted preprocessor to disk
    joblib.dump(preprocessor, model_path + f'lightgbm/preprocessor_fold_{fold + 1}.joblib')

    # Data for modeling
    feature_names = fold_X_train.columns.tolist()
    dtrain = lgb.Dataset(data=fold_X_train, label=fold_y_train, feature_name=feature_names)
    dvalid = lgb.Dataset(data=fold_X_val, label=fold_y_val, feature_name=feature_names, reference=dtrain)

    # Model
    eval_results = {}
    model = lgb.train(
        params={'objective': 'rmse',
                'metric': 'rmse',
                'device_type': 'gpu',
                'verbosity': -1,
                'early_stopping_round': 200,
                'boosting': 'gbdt',
                'num_iterations': 1500,
                 'learning_rate': 0.01,
                 'num_leaves': 100,
                 'max_depth': 5,
                 'max_bin': 239,
                 'bagging_fraction': 0.2,
                 'bagging_freq': 43,
                 'feature_fraction': 0.6,
                 'feature_fraction_bynode': 0.6,
                 'lambda_l1': 310,
                 'lambda_l2': 827,
                 'extra_trees': False,
                 'path_smooth': 239},
        train_set=dtrain,
        valid_sets=[dtrain, dvalid],
        valid_names=['train', 'valid'],
        callbacks=[lgb.log_evaluation(period=50), lgb.early_stopping(stopping_rounds=200), lgb.record_evaluatio
      )
    model.save_model(model_path + f'lightgbm/model_fold_{fold + 1}.txt', importance_type='gain') # Save gain-ba
    joblib.dump(eval_results, model_path + f'lightgbm/eval_fold_{fold + 1}.joblib')

    # Feature importance
    df = pd.DataFrame({'features': fold_X_val.columns.tolist(), 'feat_imp': model.feature_importance(importance_
    feat_imp_lightgbm.append(df)

    # Predictions
    print(f'Predicting for fold {fold + 1}...')
    oof_pred = model.predict(data=fold_X_val)
    oof_lightgbm[f'fold_{fold + 1}'] = {'target': fold_y_val, 'predictions': oof_pred}

    del dtrain, dvalid, preprocessor, model, eval_results, df, oof_pred
```

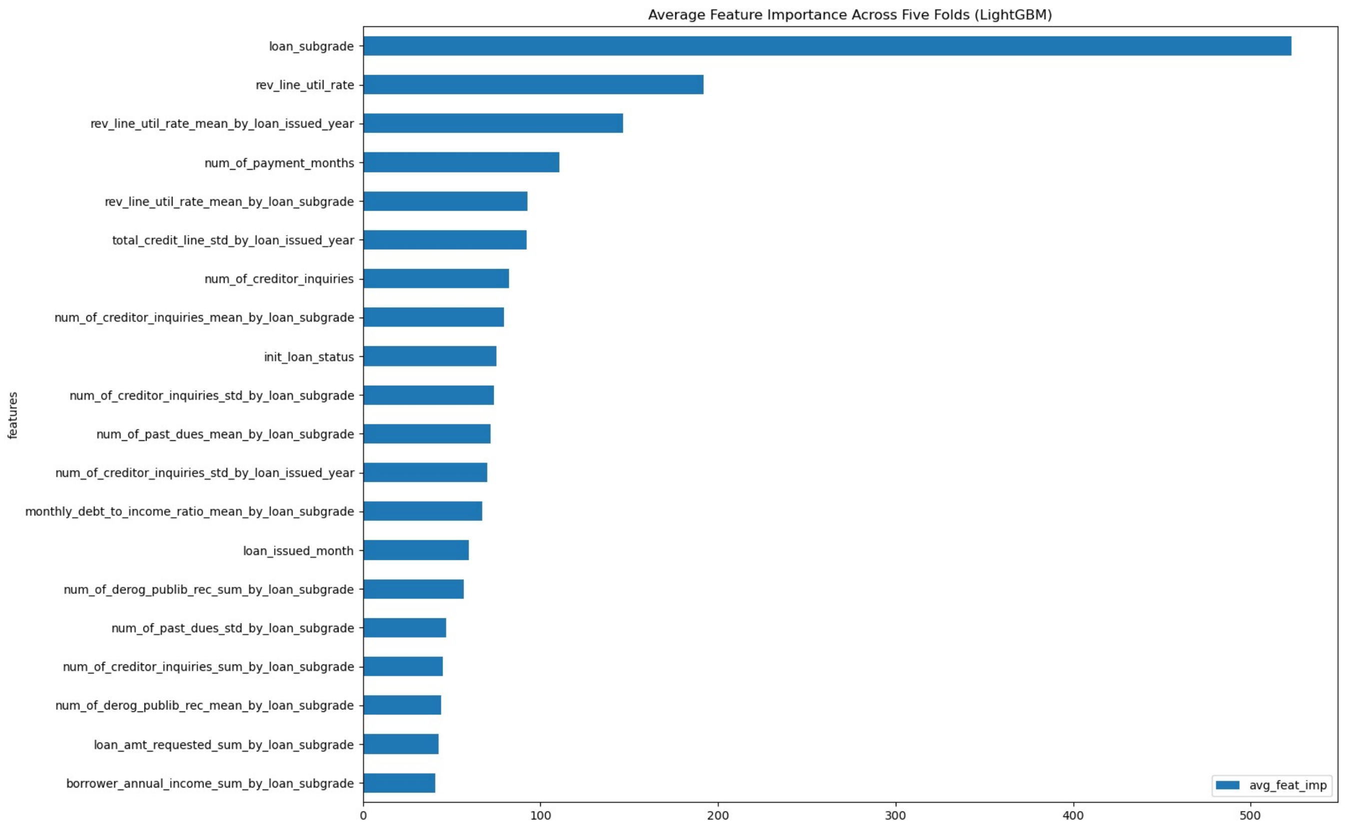
```
Start processing fold 1...
```

Out[66]:
```
['../output/models/lightgbm/preprocessor_fold_1.joblib']
```

```
        Training until validation scores don't improve for 200 rounds
        [50]    train's rmse: 3.15877   valid's rmse: 3.18044
        [100]   train's rmse: 2.442     valid's rmse: 2.50662
        [150]   train's rmse: 2.0306    valid's rmse: 2.20206
        [200]   train's rmse: 1.79768   valid's rmse: 2.08868
        [250]   train's rmse: 1.66129   valid's rmse: 2.05533
        [300]   train's rmse: 1.57837   valid's rmse: 2.05621
        [350]   train's rmse: 1.52252   valid's rmse: 2.06422
        [400]   train's rmse: 1.48046   valid's rmse: 2.07768
        [450]   train's rmse: 1.45079   valid's rmse: 2.08082
Out[66]: <lightgbm.basic.Booster at 0x7f22ec491040>

Out[66]: ['../output/models/lightgbm/eval_fold_1.joblib']
        Predicting for fold 1...
        Start processing fold 2...
Out[66]: ['../output/models/lightgbm/preprocessor_fold_2.joblib']
        Training until validation scores don't improve for 200 rounds
        [50]    train's rmse: 3.15987   valid's rmse: 3.14101
        [100]   train's rmse: 2.4468    valid's rmse: 2.45851
        [150]   train's rmse: 2.03853   valid's rmse: 2.14168
        [200]   train's rmse: 1.80417   valid's rmse: 2.02628
        [250]   train's rmse: 1.66945   valid's rmse: 2.00035
        [300]   train's rmse: 1.58584   valid's rmse: 2.00402
        [350]   train's rmse: 1.5317    valid's rmse: 2.01464
        [400]   train's rmse: 1.48987   valid's rmse: 2.02046
        [450]   train's rmse: 1.45823   valid's rmse: 2.0195
Out[66]: <lightgbm.basic.Booster at 0x7f22fe77b070>

Out[66]: ['../output/models/lightgbm/eval_fold_2.joblib']
        Predicting for fold 2...
        Start processing fold 3...
Out[66]: ['../output/models/lightgbm/preprocessor_fold_3.joblib']
        Training until validation scores don't improve for 200 rounds
        [50]    train's rmse: 3.16028   valid's rmse: 3.12902
        [100]   train's rmse: 2.44853   valid's rmse: 2.44402
        [150]   train's rmse: 2.03809   valid's rmse: 2.12483
        [200]   train's rmse: 1.80589   valid's rmse: 1.99557
        [250]   train's rmse: 1.66739   valid's rmse: 1.95735
        [300]   train's rmse: 1.58758   valid's rmse: 1.96054
        [350]   train's rmse: 1.53206   valid's rmse: 1.96208
        [400]   train's rmse: 1.48973   valid's rmse: 1.97646
        [450]   train's rmse: 1.45691   valid's rmse: 1.9839
        Early stopping, best iteration is:
        [256]   train's rmse: 1.65545   valid's rmse: 1.95659
Out[66]: <lightgbm.basic.Booster at 0x7f23072c5730>

Out[66]: ['../output/models/lightgbm/eval_fold_3.joblib']
        Predicting for fold 3...
        Start processing fold 4...
Out[66]: ['../output/models/lightgbm/preprocessor_fold_4.joblib']
        Training until validation scores don't improve for 200 rounds
        [50]    train's rmse: 3.15984   valid's rmse: 3.14697
        [100]   train's rmse: 2.44539   valid's rmse: 2.47591
        [150]   train's rmse: 2.03673   valid's rmse: 2.17032
        [200]   train's rmse: 1.80254   valid's rmse: 2.0478
        [250]   train's rmse: 1.66627   valid's rmse: 2.02398
        [300]   train's rmse: 1.58329   valid's rmse: 2.03934
        [350]   train's rmse: 1.52493   valid's rmse: 2.05101
        [400]   train's rmse: 1.48307   valid's rmse: 2.05466
Out[66]: <lightgbm.basic.Booster at 0x7f2307c34490>

Out[66]: ['../output/models/lightgbm/eval_fold_4.joblib']
        Predicting for fold 4...
        Start processing fold 5...
Out[66]: ['../output/models/lightgbm/preprocessor_fold_5.joblib']
        Training until validation scores don't improve for 200 rounds
        [50]    train's rmse: 3.15796   valid's rmse: 3.11707
        [100]   train's rmse: 2.43985   valid's rmse: 2.45579
        [150]   train's rmse: 2.02856   valid's rmse: 2.18495
        [200]   train's rmse: 1.79659   valid's rmse: 2.11167
        [250]   train's rmse: 1.66124   valid's rmse: 2.10853
        [300]   train's rmse: 1.57794   valid's rmse: 2.13395
        [350]   train's rmse: 1.524     valid's rmse: 2.16732
        [400]   train's rmse: 1.48257   valid's rmse: 2.17625
Out[66]: <lightgbm.basic.Booster at 0x7f22ec4a8c10>

Out[66]: ['../output/models/lightgbm/eval_fold_5.joblib']
        Predicting for fold 5...
```

Feature Importance

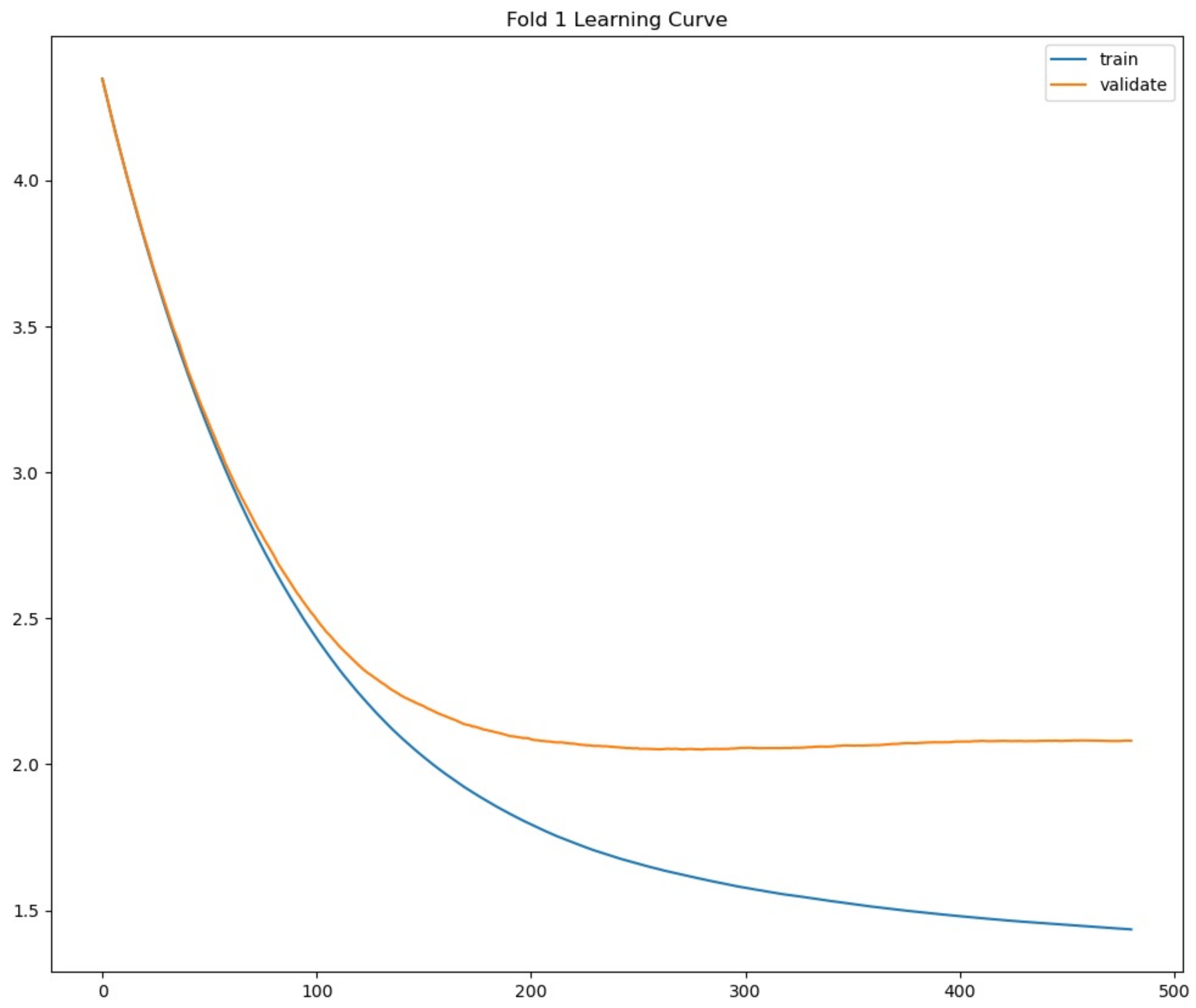
```
In [67]: # Join feature importance
feat_imp_lightgbm = reduce(lambda x, y: pd.merge(x, y, on='features', how='left'), feat_imp_lightgbm)
feat_imp_lightgbm['avg_feat_imp'] = feat_imp_lightgbm.iloc[:, 1:].apply(lambda row: row.mean(), axis=1)

# Plot top feature importance
feat_imp_lightgbm.sort_values(by='avg_feat_imp', ascending=True).iloc[-20:].plot(
    kind='barh', x='features', y='avg_feat_imp',
    figsize=(15, 12),
    title='Average Feature Importance Across Five Folds (LightGBM)'
)
plt.show();
```



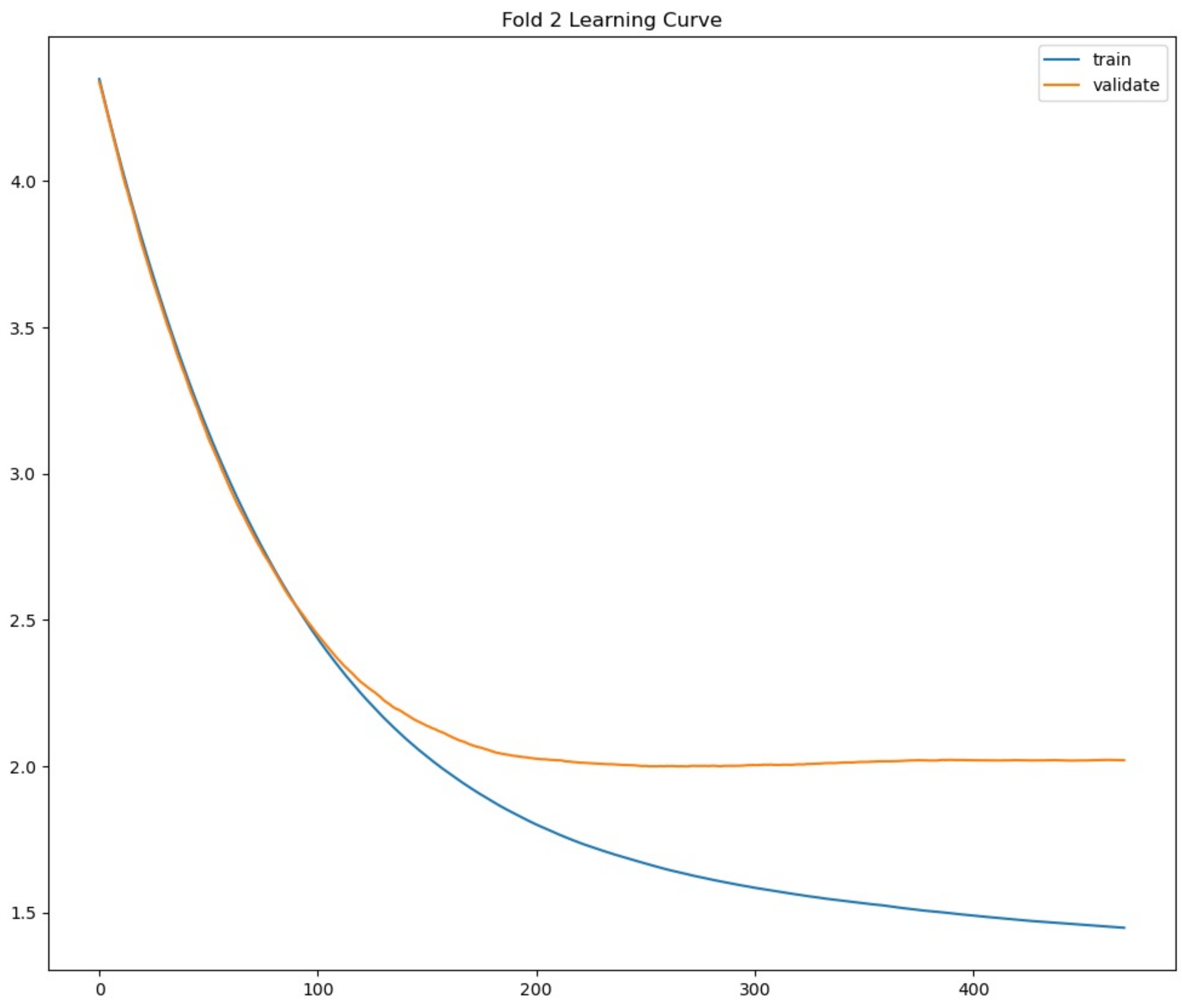
Learning Curves

```
In [68]: for fold in range(5):
    eval_result = joblib.load(model_path + f'lightgbm/eval_fold_{fold + 1}.joblib')
    plt.plot(eval_result['train']['rmse'], label='train');
    plt.plot(eval_result['valid']['rmse'], label='validate');
    plt.legend();
    plt.title(f'Fold {fold + 1} Learning Curve');
    plt.show();
```

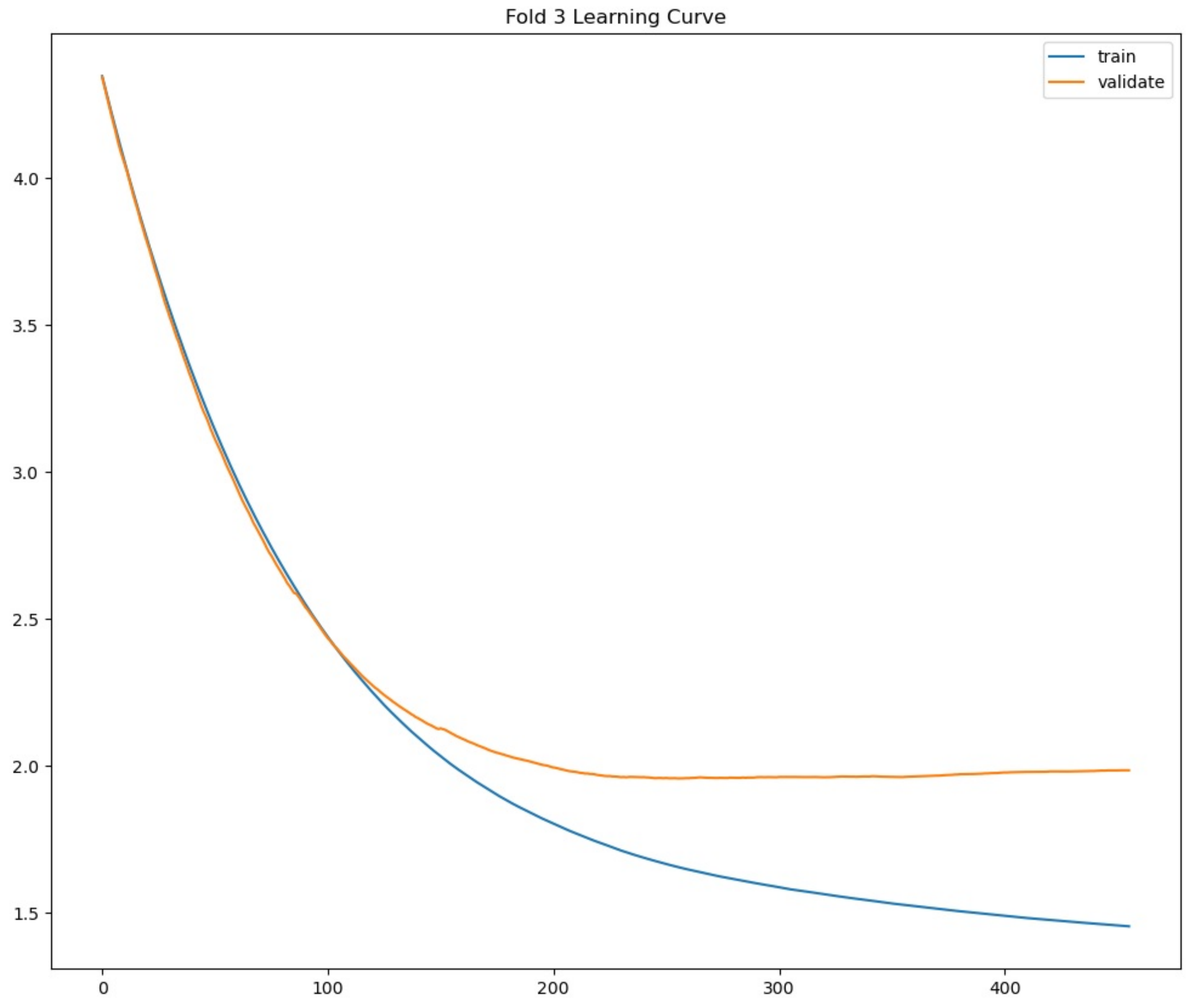
```
Out[68]: [<matplotlib.lines.Line2D at 0x7f22fe2e8910>]

Out[68]: [<matplotlib.lines.Line2D at 0x7f22fe2e8f10>]

Out[68]: <matplotlib.legend.Legend at 0x7f22fe2e8ee0>

Out[68]: Text(0.5, 1.0, 'Fold 1 Learning Curve')
```



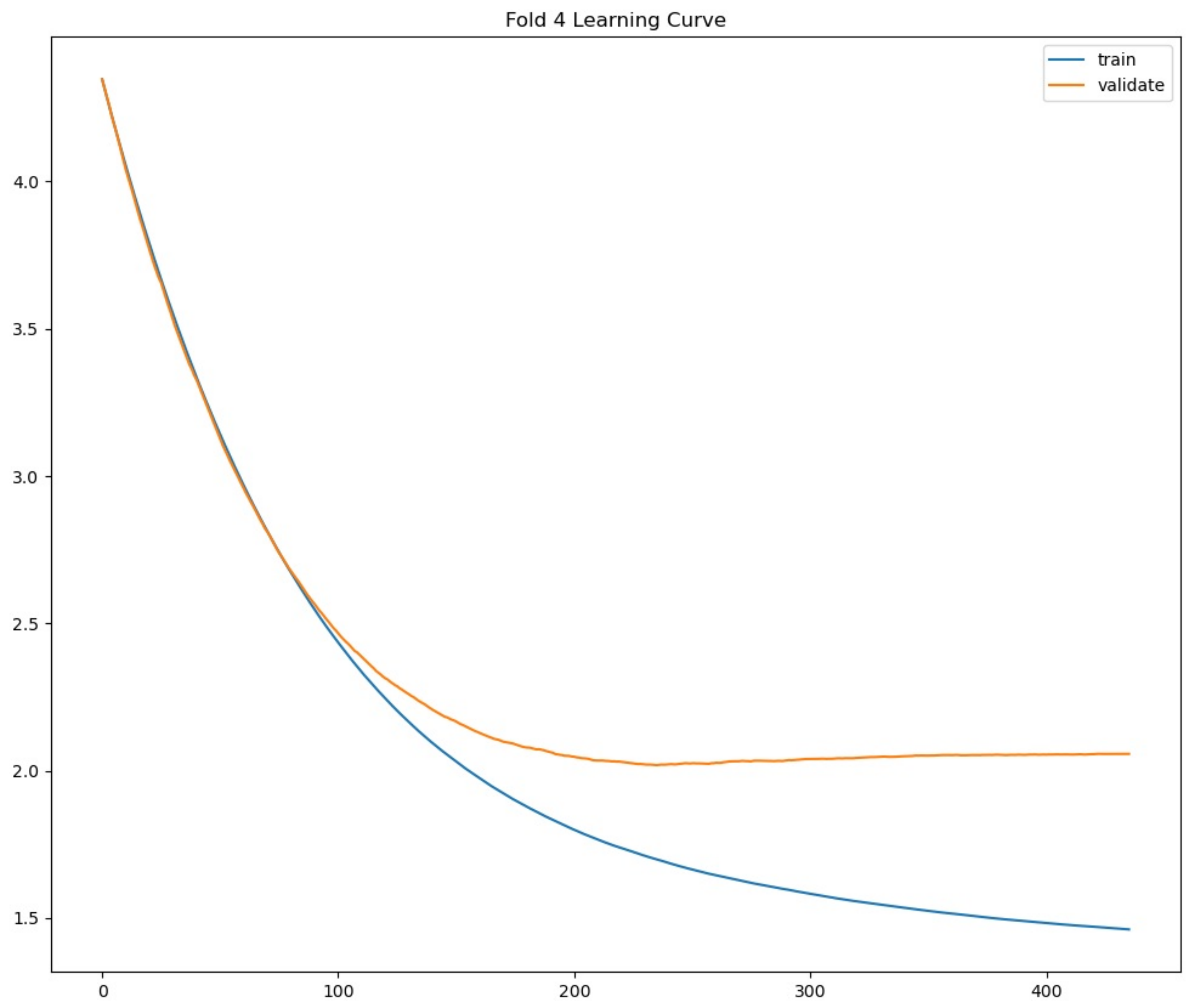
```
Out[68]: [<matplotlib.lines.Line2D at 0x7f22fe2f5a60>]

Out[68]: [<matplotlib.lines.Line2D at 0x7f231daaedc0>]

Out[68]: <matplotlib.legend.Legend at 0x7f22fe2f5340>

Out[68]: Text(0.5, 1.0, 'Fold 2 Learning Curve')
```



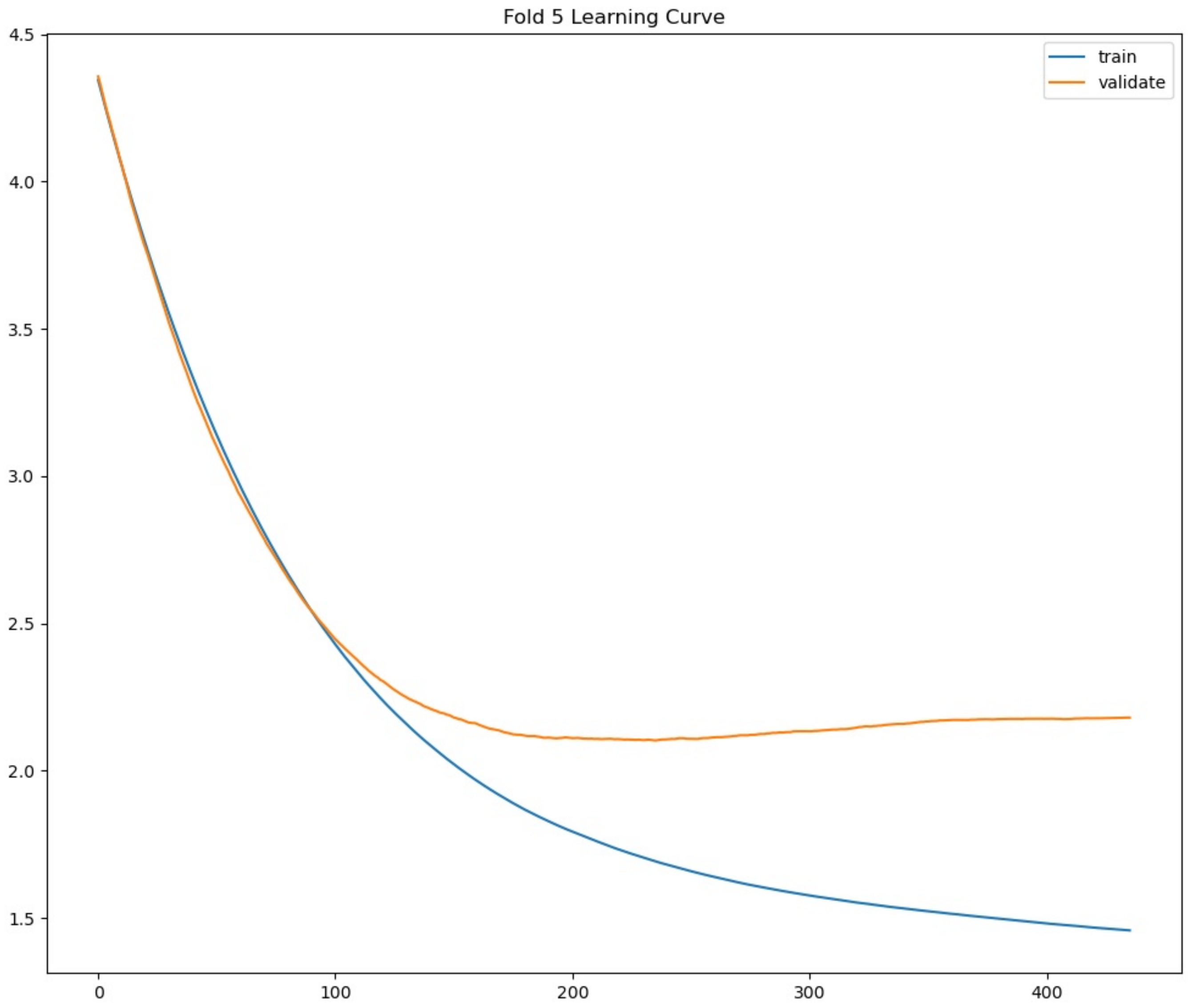
```
Out[68]: [<matplotlib.lines.Line2D at 0x7f22ee6e4640>]
Out[68]: [<matplotlib.lines.Line2D at 0x7f22fee46fa0>]
Out[68]: <matplotlib.legend.Legend at 0x7f22fee46880>
Out[68]: Text(0.5, 1.0, 'Fold 3 Learning Curve')
```



```
Out[68]: [<matplotlib.lines.Line2D at 0x7f2307856220>]

Out[68]: [<matplotlib.lines.Line2D at 0x7f2307855e80>]

Out[68]: <matplotlib.legend.Legend at 0x7f2307855040>

Out[68]: Text(0.5, 1.0, 'Fold 4 Learning Curve')
```



```
Out[68]: [<matplotlib.lines.Line2D at 0x7f230dd28ee0>]

Out[68]: [<matplotlib.lines.Line2D at 0x7f230dd28460>]

Out[68]: <matplotlib.legend.Legend at 0x7f230dd28f10>

Out[68]: Text(0.5, 1.0, 'Fold 5 Learning Curve')
```



Performance on Validation Sets

In [69]:
```
oof_lightgbm_rmse = []
target_frame = cudf.DataFrame(index=['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max'])

for key in oof_lightgbm:

    oof_lightgbm_rmse.append(
        mean_squared_error(oof_lightgbm[key]['target'], oof_lightgbm[key]['predictions'], squared=False)
    )
    print(f'Finished computing rmse for {key}')

    target_frame[f'{key}_target_descriptive_stats'] = cudf.Series(oof_lightgbm[key]['target']).describe()
    print(f'Finished computing descriptive stats for {key} target')
```

```
Finished computing rmse for fold_1
Finished computing descriptive stats for fold_1 target
Finished computing rmse for fold_2
Finished computing descriptive stats for fold_2 target
Finished computing rmse for fold_3
Finished computing descriptive stats for fold_3 target
Finished computing rmse for fold_4
Finished computing descriptive stats for fold_4 target
Finished computing rmse for fold_5
Finished computing descriptive stats for fold_5 target
```

In [70]:
```
cudf.Series(oof_lightgbm_rmse).describe()
```

Out[70]:
```
count    5.000000
mean     2.025601
std      0.055010
min      1.956591
25%      1.999203
50%      2.018575
75%      2.050838
max      2.102796
dtype: float64
```

In [71]:
```
target_frame
```

Out[71]:

	fold_1_target_descriptive_stats	fold_2_target_descriptive_stats	fold_3_target_descriptive_stats	fold_4_target_descriptive_stats	fold_5_tar
count	67798.00000	67798.000000	67798.000000	67797.000000	
mean	13.94996	13.935819	13.954786	13.931679	
std	4.37422	4.369764	4.379598	4.378819	
min	5.42000	5.420000	5.420000	5.420000	
25%	10.99000	10.990000	10.990000	10.990000	
50%	13.79000	13.680000	13.680000	13.680000	
75%	16.78000	16.780000	16.780000	16.780000	
max	26.06000	26.060000	26.060000	26.060000	

Interestingly, for both LightGBM and CatBoost, the validation errors converges to around 2 percentage points, while XGBoost was able to reduce the validation error rates below 2 percentage points. Still, it may be that XGBoost was simply able to fine-tune the models based on the validation set; therefore, to improve generalization on unseen data, we will bag the three gradient boosting machines to create a meta-learner.

Ensemble Weighted Averaging

We will generate predictions for each of the three gradient boosted machines and average their predictions:

- XGBoost

In [89]:
```
pred_xgboost = np.zeros(X_test.shape[0])

for fold in range(5):

    # Instantiate booster
    model_xgboost = xgb.Booster()
    # Load model
    model_xgboost.load_model(model_path + f'xgboost/model_fold_{fold + 1}.xgb')
    # Transform test data using fold preprocessor
    print(f'Preprocessing fold {fold + 1}...')
    fold_X_test = joblib.load(model_path + f'xgboost/preprocessor_fold_{fold + 1}.joblib').transform(X_test)
    # Make predictions on test set
    print(f'Predicting for fold {fold + 1}...')
    pred_xgboost += model_xgboost.predict(xgb.DMatrix(fold_X_test))
pred_xgboost /= 5
pred_xgboost
```

```
Preprocessing fold 1...
Predicting for fold 1...
Preprocessing fold 2...
Predicting for fold 2...
Preprocessing fold 3...
Predicting for fold 3...
Preprocessing fold 4...
Predicting for fold 4...
Preprocessing fold 5...
Predicting for fold 5...
```

Out[89]:
```
array([15.15944023,  6.61361198, 14.25195141, ..., 16.88702888,
       14.72674465, 13.8499157 ])
```

- CatBoost:

In [97]:
```
pred_catboost = np.zeros(X_test.shape[0])

for fold in range(5):

    # Instantiate booster
    model_catboost = cb.CatBoostRegressor()
    # Load model
    model_catboost.load_model(model_path + f'catboost/model_fold_{fold + 1}.cbm')
    # Transform test data using fold preprocessor
    print(f'Preprocessing fold {fold + 1}...')
    fold_X_test = joblib.load(model_path + f'catboost/preprocessor_fold_{fold + 1}.joblib').transform(X_test)
    # Make predictions on test set
    print(f'Predicting for fold {fold + 1}...')
    pred_catboost += model_catboost.predict(fold_X_test)
pred_catboost /= 5
pred_catboost
```

```
Out[97]: <catboost.core.CatBoostRegressor at 0x7f2362bfa820>

         Preprocessing fold 1...
         Predicting for fold 1...

Out[97]: <catboost.core.CatBoostRegressor at 0x7f231a30cf40>

         Preprocessing fold 2...
         Predicting for fold 2...

Out[97]: <catboost.core.CatBoostRegressor at 0x7f230dd202b0>

         Preprocessing fold 3...
         Predicting for fold 3...

Out[97]: <catboost.core.CatBoostRegressor at 0x7f235769ba90>

         Preprocessing fold 4...
         Predicting for fold 4...

Out[97]: <catboost.core.CatBoostRegressor at 0x7f2361fec4c0>

         Preprocessing fold 5...
         Predicting for fold 5...

Out[97]: array([17.2385936 ,  9.72445119, 16.22936023, ..., 16.0668276 ,
                16.35841502, 14.75556931])
```

- LightGBM

In [98]:
```
pred_lightgbm = np.zeros(X_test.shape[0])

for fold in range(5):

    # Instantiate booster
    model_lightgbm = lgb.Booster(model_file = model_path + f'lightgbm/model_fold_{fold + 1}.txt')
    # Transform test data using fold preprocessor
    print(f'Preprocessing fold {fold + 1}...')
    fold_X_test = joblib.load(model_path + f'lightgbm/preprocessor_fold_{fold + 1}.joblib').transform(X_test)
    # Make predictions on test set
    print(f'Predicting for fold {fold + 1}...')
    pred_lightgbm += model_lightgbm.predict(fold_X_test)
pred_lightgbm /= 5
pred_lightgbm
```

```
Preprocessing fold 1...
Predicting for fold 1...
Preprocessing fold 2...
Predicting for fold 2...
Preprocessing fold 3...
Predicting for fold 3...
Preprocessing fold 4...
Predicting for fold 4...
Preprocessing fold 5...
Predicting for fold 5...

Out[98]: array([15.81290531,  8.98502879, 15.04477182, ..., 17.69637397,
                15.16434433, 14.48658767])
```

Computing Weights For Averaging

We will use weights that are inversely related to validation RMSE--- the lower the validation RMSE of the model, the higher the weights the predictions of that model recieves.

In [129…
```
model_rsme = np.array([np.mean(oof_xgboost_rmse), np.mean(oof_catboost_rmse), np.mean(oof_lightgbm_rmse)])
model_rsme
```

Out[129]:
```
array([1.58097789, 1.91714624, 2.02560063])
```

The model weights are the inverse of these errors:

In [133…
```
model_weights = 1 / (model_rsme / model_rsme.sum())
model_weights
```

Out[133]:
```
array([3.49386592, 2.88122243, 2.72695648])
```

Generate matrix of predictions ($80, 000 \times 3$) where each row vector is a training example and each column vector is a vector of predictions:

In [155…
```
predictions = np.column_stack((pred_xgboost, pred_catboost, pred_lightgbm))
predictions
```

Out[155]:
```
array([[15.15944023, 17.2385936 , 15.81290531],
       [ 6.61361198,  9.72445119,  8.98502879],
       [14.25195141, 16.22936023, 15.04477182],
       ...,
       [16.88702888, 16.0668276 , 17.69637397],
       [14.72674465, 16.35841502, 15.16434433],
       [13.8499157 , 14.75556931, 14.48658767]])
```

Take the weighted average:

In [158…
```
avg_predictions = np.average(predictions, axis=1, weights=model_weights)
avg_predictions
```

Out[158]:
```
array([16.01336639,  8.3088102 , 15.11542127, ..., 16.86987521,
       15.37434864, 14.32734317])
```

Finally, we attach the identification columns and write the output to disk:

In [160…
```
final_output = pd.DataFrame({
    'id_loan': X_test['id_loan'],
    'id_borrower': X_test['id_borrower'],
    'predicted_interest_rate': avg_predictions
})
final_output
```

Out[160]:

	id_loan	id_borrower	predicted_interest_rate
0	44409194.0	47416907.0	16.013366
1	44017917.0	47034722.0	8.308810
2	44259158.0	47306871.0	15.115421
3	44429213.0	47476932.0	16.124419
4	44299188.0	47346901.0	12.716305
...	...	...	...
79995	38272852.0	41056632.0	9.004351
79996	38232598.0	41016384.0	18.758735
79997	38282597.0	41066378.0	16.869875
79998	38232613.0	41016400.0	15.374349
79999	38262186.0	41045946.0	14.327343

80000 rows × 3 columns

Write To S3

In [165…
```
with io.StringIO() as csv_buffer:

    final_output.to_csv(csv_buffer, index=False)

    response = s3.put_object(
        Bucket=AWS_S3_BUCKET, Key='Loan Prediction/Loan Results from Yang Wu 12373055.csv', Body=csv_buffer.getv
    )

    status = response.get("ResponseMetadata", {}).get("HTTPStatusCode")

    if status == 200:
        print(f"Successful S3 put_object response. Status - {status}")
    else:
        print(f"Unsuccessful S3 put_object response. Status - {status}")
```

```
Successful S3 put_object response. Status - 200
```