test_CatBoost

December 22, 2021

1 Training CatBoostClassifier Model on Processed Data with CPU, GPU

[1]:
```
#import usefull DataStructures
import pandas as pd
import numpy as np
from scipy.stats import uniform

#import plotting libraries
import matplotlib.pyplot as plt
import seaborn as sns
from prettytable import PrettyTable

#import Misc Libraries
import os
import gc
import pickle
import warnings
warnings.filterwarnings('ignore')
from datetime import datetime

#for 100% jupyter notebook cell width
from IPython.core.display import display, HTML
display(HTML("<style>.container { width: 100% !important; }</style>"))

#sklearn
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import roc_auc_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import roc_curve
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
```

```
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.calibration import CalibratedClassifierCV

#other modelling libraries
from bayes_opt import BayesianOptimization #https://github.com/fmfn/
↪BayesianOptimization, https://machinelearningmastery.com/
↪what-is-bayesian-optimization/
import xgboost as xgb
from xgboost import XGBClassifier
from xgboost import XGBRegressor

import lightgbm as lgb
from lightgbm import LGBMClassifier
from lightgbm import LGBMRegressor
from catboost import CatBoostClassifier
```

<IPython.core.display.HTML object>

[2]:
```
#loading saved processed data from part 2
train_data = pickle.load( open( "./data/pre_modelling_train.pkl", "rb" ) )
test_data = pickle.load( open( "./data/pre_modelling_test.pkl", "rb" ) )
target_train = pickle.load( open( "./data/pre_modelling_target_train.pkl", "rb"␣
↪) )
skid_test = pickle.load( open( "./data/pre_modelling_skid_test.pkl", "rb" ) )
```

[3]:
```
#standardizing the data
scaler = StandardScaler()
x_train_std = scaler.fit_transform(train_data)
x_test_std = scaler.fit_transform(test_data)
y_train = target_train

#replacing nan values with 0
x_train_std[np.isnan(x_train_std)] = 0
x_test_std[np.isnan(x_test_std)] = 0
```

[45]:
```
class cat_boosting:
    '''
    Class for Boosting Ensembles and displaying results. Contains 6 methods:

        1. init method
        2. train method
        3. proba_to_class method
        4. tune_threshold method
        5. results method
        6. feat_importance_show
```

```
    '''

    def __init__(self, x_train, y_train, x_test, params, num_folds = 3,␣
↪random_state = 33,
                 verbose = True, save_model_to_pickle = False):
        '''
        Function to initialize the class members.

        Inputs:
            self
            x_train: DataFrame
                Training DataFrame
            y_train: DataFrame
                Training Class labels
            x_test: DataFrame
                Test DataFrame
            params: dict
                Parameters for the boosting ensemble
            num_folds: int, default = 3
                Number of folds for k-Fold Cross Validation
            random_state: int, default = 33
                Random State for Splitting the data for K-Fold Cross Validation
            verbose: bool, default = True
                Whether to keep verbosity or not
            save_model_to_pickle: bool, default = False
                Whether to save the model to pickle file or not

        Returns:
            None
        '''

        self.x_train = x_train
        self.y_train = y_train
        self.x_test = x_test
        self.params = params
        self.num_folds = num_folds
        self.stratified_cv = StratifiedKFold(n_splits = num_folds, shuffle =␣
↪True, random_state = random_state)
        self.verbose = verbose
        self.save_model = save_model_to_pickle

    def train(self, booster, verbose = 400, early_stopping = 200, pickle_name =␣
↪'', plot_flag = False):
        '''
        Function to train the Classifier on given parameters. It fits the␣
↪classifier for each fold, and for
```

```
        Cross Validation, uses Out-of-Fold Predictions. The test predictions␣
↪are averaged predictions over each fold.

        Inputs:
            self
            booster: str
                Whether the booster is 'xgboost' or 'lightgbm' or 'catboost'
            verbose: int, default = 400
                Number of boosting rounds for printint boosting results.
            early_stopping: int, default = 200
                Number of boosting rounds to look for early stopping
            pickle_name: str, default = ''
                The string to add to end of pickle file of model, if any

        Returns:
            None
        '''

        self.train_preds_proba_mean = np.zeros(self.x_train.shape[0])
        #out-of-fold cv predictions
        self.cv_preds_proba = np.zeros(self.x_train.shape[0])
        self.test_preds_proba_mean = np.zeros(self.x_test.shape[0])
        #best threshold will be
        self.best_threshold_train = 0
        self.feature_importance = pd.DataFrame()
        self.feature_importance['features'] = self.x_train.columns
        self.feature_importance['gain'] = np.zeros(self.x_train.shape[1])

        if self.verbose:
            print(f"Fitting the {booster} on Training Data with {self.
↪num_folds} fold cross validation, and using Out-Of-Folds Predictions for␣
↪Cross-Validation")
            start = datetime.now()

        for fold_number, (train_indices, cv_indices) in enumerate(self.
↪stratified_cv.split(self.x_train, self.y_train), 1):
            if self.verbose:
                print(f"\n\tFold Number {fold_number}\n")

            x_tr = self.x_train.iloc[train_indices]
            y_tr = self.y_train.iloc[train_indices]
            x_cv = self.x_train.iloc[cv_indices]
            y_cv = self.y_train.iloc[cv_indices]

            if booster == 'xgboost':
                clf = XGBClassifier(**self.params)
            elif booster == 'lightgbm':
```

```
                clf = LGBMClassifier(**self.params)
            else: #catboost
                clf = CatBoostClassifier(**self.params)


            clf.fit(x_tr, y_tr, eval_set = [(x_tr, y_tr), (x_cv, y_cv)],
                     verbose = verbose, early_stopping_rounds = 200, plot =␣
↪plot_flag)

            if booster == 'xgboost':
                self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr, ntree_limit = clf.get_booster().best_ntree_limit)[:, 1] /
↪ (self.num_folds - 1)
                self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv,␣
↪ntree_limit = clf.get_booster().best_ntree_limit)[:,1]
                self.test_preds_proba_mean += clf.predict_proba(self.x_test,␣
↪ntree_limit = clf.get_booster().best_ntree_limit)[:,1] / self.num_folds

                #feature importance
                gain_fold = clf.get_booster().get_score(importance_type =␣
↪'gain')
                feat_imp = pd.DataFrame()
                feat_imp['features'] = gain_fold.keys()
                feat_imp['gain'] = gain_fold.values()

            elif booster == 'lightgbm': #lightgbm
                self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr, num_iteration = clf.best_iteration_)[:,1] / (self.
↪num_folds - 1)
                self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv,␣
↪num_iteration = clf.best_iteration_)[:,1]
                self.test_preds_proba_mean += clf.predict_proba(self.x_test,␣
↪num_iteration = clf.best_iteration_)[:,1] / self.num_folds

                #feature importance
                gain_fold = clf.booster_.
↪feature_importance(importance_type='gain')
                feat_imp = pd.DataFrame()
                feat_imp['features'] = self.x_train.columns
                feat_imp['gain'] = gain_fold
            else: #catboost
                # self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr,
                #                                                              ␣
↪ ntree_start = clf.best_iteration_,
```

```
                #                                                              ␣
↪ ntree_end = clf.best_iteration_ + 1)[:,1] / (self.num_folds - 1)
                # self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv,␣
↪ntree_start = clf.best_iteration_,
                #                                                              ␣
↪ ntree_end = clf.best_iteration_ + 1)[:,1]
                # self.test_preds_proba_mean += clf.predict_proba(self.x_test,␣
↪ntree_start = clf.best_iteration_,
                #                                                              ␣
↪ ntree_end = clf.best_iteration_ + 1)[:,1] / self.num_folds
                self.train_preds_proba_mean[train_indices] = clf.
↪predict_proba(x_tr)[:,1] / (self.num_folds - 1)
                self.cv_preds_proba[cv_indices] = clf.predict_proba(x_cv)[:,1]
                self.test_preds_proba_mean += clf.predict_proba(self.x_test)[:
↪,1] / self.num_folds
                #feature importance
                gain_fold = clf.feature_importances_
                feat_imp = pd.DataFrame()
                feat_imp['features'] = self.x_train.columns
                feat_imp['gain'] = gain_fold


            #tuning the threshold for optimal TPR and FPR from ROC Curve
            self.best_threshold_train += self.tune_threshold(self.
↪y_train[train_indices], self.train_preds_proba_mean[train_indices]) / self.
↪num_folds
            #concatenating the feature importance of each fold to original df
            self.feature_importance = pd.concat([self.feature_importance,␣
↪feat_imp], axis = 0)

            if self.save_model:
                #saving the model into a pickle file
                with open(f'./data/
↪clf_{booster}_fold_{fold_number}_model_{pickle_name}.pkl', 'wb') as f:
                    pickle.dump(clf, f)

        #mean feature importance averaged over all folds
        self.feature_importance = self.feature_importance.groupby('features',␣
↪as_index = False).mean()
        #sorting the feature importance
        self.feature_importance = self.feature_importance.sort_values(by =␣
↪'gain', ascending = False)

        if self.verbose:
            print("Done.")
            print(f"Time elapsed = {datetime.now() - start}")
```

```python
        gc.collect()

    def proba_to_class(self, proba, threshold):
        '''
        Function to convert a given probability to class label based on a␣
↪threshold value.

        Inputs:
            self
            proba: numpy array
                Probabilities of class label = 1
            threshold: int
                Threshold probability to be considered as Positive or Negative␣
↪Class Label

        Returns:
            Converted Class Label
        '''

        return np.where(proba >= threshold, 1, 0)

    def tune_threshold(self, true_labels, predicted_probas):
        '''
        Function to find the optimal threshold for maximizing the TPR and␣
↪minimizing the FPR from ROC-AUC Curve.
        This is found out by using the J Statistic, which is J = TPR - FPR.
        Reference: https://machinelearningmastery.com/
↪threshold-moving-for-imbalanced-classification/

        Inputs:
            self
            true_labels: numpy array or pandas series
                True Class Labels
            predicted_probas: numpy array
                Predicted Probability of Positive Class label

        Returns:
            Threshold probability.
        '''

        fpr, tpr, threshold = roc_curve(true_labels, predicted_probas)
        j_stat = tpr - fpr
        index_for_best_threshold = np.argmax(j_stat)

        return threshold[index_for_best_threshold]
```

```
    def results(self, roc_auc = True, precision_recall = True, show_conf_matrix␣
↪= True, cv_test_distribution = False):
        '''
        Function to display the final results of Train, CV and Test Dataset.

        Inputs:
            self

        Returns:
            None
        '''

        #getting the crisp class labels
        self.train_preds_class = self.proba_to_class(self.
↪train_preds_proba_mean, self.best_threshold_train)
        self.cv_preds_class = self.proba_to_class(self.cv_preds_proba, self.
↪best_threshold_train)
        self.test_preds_class = self.proba_to_class(self.test_preds_proba_mean,␣
↪self.best_threshold_train)
        print("=" * 100)
        print("Train Results:")
        print(f"\nThe best selected Threshold as per the J-Statistic, which is␣
↪J = TPR - FPR, is = {self.best_threshold_train}\n")
        if roc_auc:
            print(f"\tROC-AUC Score = {roc_auc_score(self.y_train, self.
↪train_preds_proba_mean)}")
        if precision_recall:
            print(f"\tPrecision Score = {precision_score(self.y_train, self.
↪train_preds_class)}")
            print(f"\tRecall Score = {recall_score(self.y_train, self.
↪train_preds_class)}")
        print("CV Results:")
        if roc_auc:
            print(f"\tROC-AUC Score = {roc_auc_score(self.y_train, self.
↪cv_preds_proba)}")
        if precision_recall:
            print(f"\tPrecision Score = {precision_score(self.y_train, self.
↪cv_preds_class)}")
            print(f"\tRecall Score = {recall_score(self.y_train, self.
↪cv_preds_class)}")

        if show_conf_matrix:
            print('=' * 100)
            print("Confusion, Precision and Recall Matrix on CV data:")
            conf_mat = confusion_matrix(self.y_train, self.cv_preds_class)
```

```
            conf_mat = pd.DataFrame(conf_mat, columns =␣
↪['Predicted_0','Predicted_1'], index = ['Actual_0','Actual_1'])
            plt.figure(figsize = (7,6))
            plt.title('Confusion Matrix Heatmap')
            sns.heatmap(conf_mat, annot = True, fmt = 'g', linewidth = 0.5,␣
↪annot_kws = {'size' : 15})
            plt.show()

        if cv_test_distribution:
            print('=' * 100)
            print("Distribution of Original Class Labels and Predicted CV and␣
↪Test Class Labels")
            plt.figure(figsize = (20,6))
            plt.subplot(1,3,1)
            plt.title('Class Distribution of Original Dataset')
            sns.countplot(self.y_train)
            plt.subplot(1,3,2)
            plt.title('Class Distribution of predicted Class Labels on CV')
            sns.countplot(self.cv_preds_class)
            plt.subplot(1,3,3)
            plt.title('Class Distribution of predicted Test Dataset')
            sns.countplot(self.test_preds_class)
            plt.show()
        print('=' * 100)

        gc.collect()

    def feat_importances_show(self, num_features, figsize = (10,15)):
        '''
        Function to display the top most important features.

        Inputs:
            self
            num_features: int
                Number of top features importances to display
            figsize: tuple, default = (10,15)
                Size of figure to be displayed

        Returns:
            None
        '''

        plt.figure(figsize = figsize)
        sns.barplot(self.feature_importance['gain'].iloc[:num_features],
                    self.feature_importance['features'].iloc[:num_features],␣
↪orient = 'h')
        plt.title(f'Top {num_features} features as per classifier')
```

```
        plt.xlabel('Feature Importance')
        plt.ylabel('Feature Names')
        plt.grid()
        plt.show()
        print('=' * 100)

        gc.collect()
```

1.1 Test CPU

[31]:
```
params = {
    'learning_rate' : 0.01,
    'eval_metric': 'AUC',
    'n_estimators' : 1000,
    'max_depth' : 5,
    'min_child_samples' : 80,
    'colsample_bylevel' : 0.5699318202360774,
    'reg_lambda' : 0.03564525547115141,
    'random_state' : 42
}
```

[32]:
```
X_train, X_validation, y_train, y_validation = train_test_split(train_data,␣
 ↪target_train, train_size=0.8, random_state=42)

clf = CatBoostClassifier(**params)

clf.fit(X_train, y_train, eval_set=[(X_train, y_train), (X_validation,␣
 ↪y_validation)],
                 verbose_eval = 50, early_stopping_rounds = 100, plot=True)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))
```

```
0:      test: 0.6940571 test1: 0.6882441        best: 0.6882441 (0)     total:
204ms    remaining: 3m 23s
50:     test: 0.7584303 test1: 0.7549618        best: 0.7552215 (48)    total:
11s      remaining: 3m 23s
100:    test: 0.7663035 test1: 0.7621045        best: 0.7621177 (98)    total:
21.6s    remaining: 3m 12s
150:    test: 0.7714174 test1: 0.7672110        best: 0.7672110 (150)   total:
32.3s    remaining: 3m 1s
200:    test: 0.7759023 test1: 0.7718879        best: 0.7718879 (200)   total:
42.9s    remaining: 2m 50s
250:    test: 0.7790657 test1: 0.7752858        best: 0.7752858 (250)   total:
54s      remaining: 2m 41s
300:    test: 0.7817454 test1: 0.7779051        best: 0.7779051 (300)   total:
1m 4s    remaining: 2m 30s
```

```
350:    test: 0.7836677 test1: 0.7798549        best: 0.7798549 (350)   total:
1m 15s   remaining: 2m 20s
400:    test: 0.7857428 test1: 0.7818167        best: 0.7818167 (400)   total:
1m 26s   remaining: 2m 9s
450:    test: 0.7874039 test1: 0.7832623        best: 0.7832623 (450)   total:
1m 37s   remaining: 1m 59s
500:    test: 0.7888124 test1: 0.7845510        best: 0.7845510 (500)   total:
1m 48s   remaining: 1m 48s
550:    test: 0.7901469 test1: 0.7856906        best: 0.7856906 (550)   total:
1m 59s   remaining: 1m 37s
600:    test: 0.7912733 test1: 0.7866257        best: 0.7866257 (600)   total:
2m 10s   remaining: 1m 26s
650:    test: 0.7924491 test1: 0.7875334        best: 0.7875334 (650)   total:
2m 21s   remaining: 1m 15s
700:    test: 0.7934635 test1: 0.7883336        best: 0.7883336 (700)   total:
2m 32s   remaining: 1m 5s
750:    test: 0.7945026 test1: 0.7891089        best: 0.7891089 (750)   total:
2m 43s   remaining: 54.1s
800:    test: 0.7954016 test1: 0.7897317        best: 0.7897317 (800)   total:
2m 54s   remaining: 43.2s
850:    test: 0.7963606 test1: 0.7904411        best: 0.7904411 (850)   total:
3m 4s    remaining: 32.4s
900:    test: 0.7971055 test1: 0.7908813        best: 0.7908813 (900)   total:
3m 15s   remaining: 21.5s
950:    test: 0.7979118 test1: 0.7914456        best: 0.7914456 (950)   total:
3m 27s   remaining: 10.7s
999:    test: 0.7986561 test1: 0.7919191        best: 0.7919191 (999)   total:
3m 37s   remaining: 0us

bestTest = 0.7919190983
bestIteration = 999
```

[32]:
```
<catboost.core.CatBoostClassifier at 0x135ac341e80>
```

[33]:
```
clf.best_iteration_
```

[33]:
```
999
```

[34]:
```
clf.predict_proba(X_validation, ntree_start = clf.best_iteration_, ntree_end =
 ↪clf.best_iteration_ + 1)
```

[34]:
```
array([[0.50004502, 0.49995498],
       [0.49999731, 0.50000269],
       [0.499619  , 0.500381  ],
       …,
       [0.49999731, 0.50000269],
       [0.50004502, 0.49995498],
```

```
[0.49999731, 0.50000269]])
```

[40]:
```
a = clf.predict_proba(X_validation)
```

[44]:
```
print(f'min: {min(a[:,0])}')
print(f'max: {max(a[:,0])}')
print(f'min: {min(a[:,1])}')
print(f'max: {max(a[:,1])}')
```

```
min: 0.010361315036407581
max: 0.996864928944795
min: 0.0031350710552050074
max: 0.9896386849635924
```

[36]:
```
clf.get_feature_importance().max()
```

[36]:
```
36.92717332660058
```

[39]:
```
clf.feature_importances_
```

[39]:
```
array([0.        , 0.08483556, 0.00587416, …, 0.        , 0.        ,
       0.        ])
```

1.2 Boosting method

[46]:
```
cb_boosting = cat_boosting(train_data, target_train, test_data, params,␣
 ↪random_state = 98, save_model_to_pickle = True)
cb_boosting.train(booster = 'catboost')
```

```
Fitting the catboost on Training Data with 3 fold cross validation, and using
Out-Of-Folds Predictions for Cross-Validation

        Fold Number 1

0:      test: 0.7024532 test1: 0.7080920        best: 0.7080920 (0)     total:
171ms    remaining: 2m 51s
400:    test: 0.7843553 test1: 0.7862527        best: 0.7862527 (400)   total:
1m 15s   remaining: 1m 52s
800:    test: 0.7950115 test1: 0.7937132        best: 0.7937132 (800)   total:
2m 30s   remaining: 37.5s
999:    test: 0.7985316 test1: 0.7956759        best: 0.7956759 (999)   total:
3m 7s    remaining: 0us

bestTest = 0.7956759314
bestIteration = 999


        Fold Number 2
```

```
0:      test: 0.6617842 test1: 0.6594850        best: 0.6594850 (0)     total:
145ms    remaining: 2m 24s
400:    test: 0.7854983 test1: 0.7809740        best: 0.7809740 (400)   total:
1m 13s   remaining: 1m 50s
800:    test: 0.7955595 test1: 0.7895085        best: 0.7895085 (800)   total:
2m 29s   remaining: 37.1s
999:    test: 0.7989058 test1: 0.7918125        best: 0.7918125 (999)   total:
3m 6s    remaining: 0us

bestTest = 0.7918124544
bestIteration = 999



        Fold Number 3

0:      test: 0.6545629 test1: 0.6550703        best: 0.6550703 (0)     total:
161ms    remaining: 2m 41s
400:    test: 0.7869335 test1: 0.7807095        best: 0.7807095 (400)   total:
1m 14s   remaining: 1m 52s
800:    test: 0.7971602 test1: 0.7883884        best: 0.7883884 (800)   total:
2m 29s   remaining: 37s
999:    test: 0.8005148 test1: 0.7904606        best: 0.7904606 (999)   total:
3m 5s    remaining: 0us

bestTest = 0.7904605979
bestIteration = 999

Done.
Time elapsed = 0:16:47.365003
```

[21]:
```
# ###with plot
# cb_boosting = cat_boosting(train_data, target_train, test_data, params,␣
↪random_state = 98, save_model_to_pickle = True)
# cb_boosting.train(booster = 'catboost', plot_flag=True)
```

```
Fitting the catboost on Training Data with 3 fold cross validation, and using
Out-Of-Folds Predictions for Cross-Validation

        Fold Number 1


MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

0:      test: 0.7024532 test1: 0.7080920        best: 0.7080920 (0)     total:
171ms    remaining: 2m 50s
400:    test: 0.7843553 test1: 0.7862527        best: 0.7862527 (400)   total:
1m 16s   remaining: 1m 54s
800:    test: 0.7950115 test1: 0.7937132        best: 0.7937132 (800)   total:
```

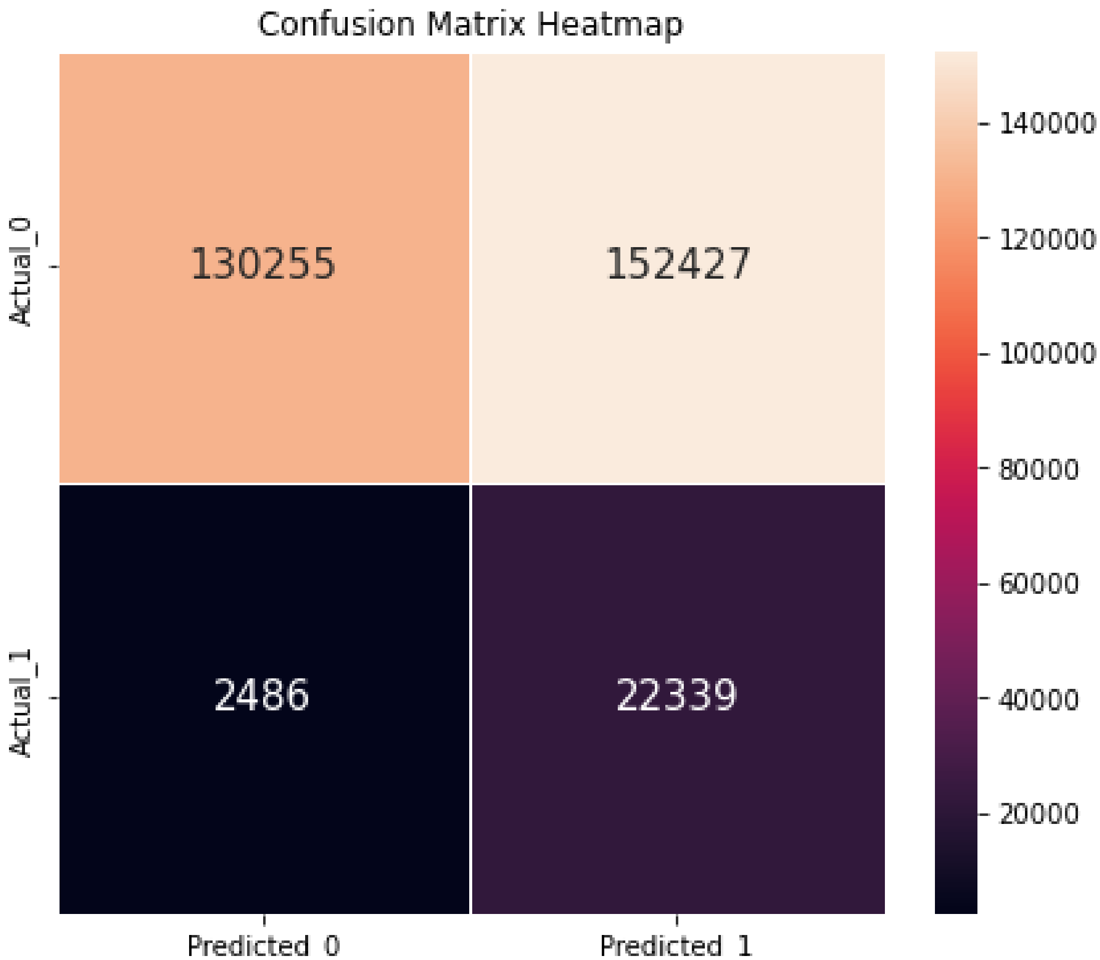
```
2m 32s   remaining: 37.9s
999:    test: 0.7985316 test1: 0.7956759        best: 0.7956759 (999)   total:
3m 11s   remaining: 0us

bestTest = 0.7956759314
bestIteration = 999


        Fold Number 2


MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

0:      test: 0.6617842 test1: 0.6594850        best: 0.6594850 (0)     total:
165ms    remaining: 2m 44s
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_3940/3697511157.py in <module>
      1 cb_boosting = cat_boosting(train_data, target_train, test_data, params,␣
 ↪random_state = 98, save_model_to_pickle = True)
----> 2 cb_boosting.train(booster = 'catboost', plot_flag=True)

~\AppData\Local\Temp/ipykernel_3940/1208348369.py in train(self, booster,␣
 ↪verbose, early_stopping, pickle_name, plot_flag)
     99
    100
--> 101             clf.fit(x_tr, y_tr, eval_set = [(x_tr, y_tr), (x_cv, y_cv)]

    102                      verbose = verbose, early_stopping_rounds = 200,␣
 ↪plot = plot_flag)
    103

D:\chengxu\Anaconda\lib\site-packages\catboost\core.py in fit(self, X, y,␣
 ↪cat_features, text_features, embedding_features, sample_weight, baseline,␣
 ↪use_best_model, eval_set, verbose, logging_level, plot, column_description,␣
 ↪verbose_eval, metric_period, silent, early_stopping_rounds, save_snapshot,␣
 ↪snapshot_file, snapshot_interval, init_model, callbacks, log_cout, log_cerr)
   4714             CatBoostClassifier.
 ↪_check_is_compatible_loss(params['loss_function'])
   4715
-> 4716         self._fit(X, y, cat_features, text_features, embedding_features ␣
 ↪None, sample_weight, None, None, None, None, baseline, use_best_model,

   4717                   eval_set, verbose, logging_level, plot,␣
 ↪column_description, verbose_eval, metric_period,
   4718                   silent, early_stopping_rounds, save_snapshot,␣
 ↪snapshot_file, snapshot_interval, init_model, callbacks, log_cout, log_cerr)
```

```
D:\chengxu\Anaconda\lib\site-packages\catboost\core.py in _fit(self, X, y,␣
↪cat_features, text_features, embedding_features, pairs, sample_weight,␣
↪group_id, group_weight, subgroup_id, pairs_weight, baseline, use_best_model,␣
↪eval_set, verbose, logging_level, plot, column_description, verbose_eval,␣
↪metric_period, silent, early_stopping_rounds, save_snapshot, snapshot_file,␣
↪snapshot_interval, init_model, callbacks, log_cout, log_cerr)
   2035         with log_fixup(log_cout, log_cerr), \
   2036             plot_wrapper(plot, [_get_train_dir(self.get_params())]):
-> 2037             self._train(

   2038                 train_pool,
   2039                 train_params["eval_sets"],

D:\chengxu\Anaconda\lib\site-packages\catboost\core.py in _train(self,␣
↪train_pool, test_pool, params, allow_clear_pool, init_model)
   1462
   1463     def _train(self, train_pool, test_pool, params, allow_clear_pool,␣
↪init_model):
-> 1464         self._object._train(train_pool, test_pool, params,␣
↪allow_clear_pool, init_model._object if init_model else None)
   1465         self._set_trained_model_attributes()
   1466

_catboost.pyx in _catboost._CatBoost._train()

_catboost.pyx in _catboost._CatBoost._train()

KeyboardInterrupt:
```

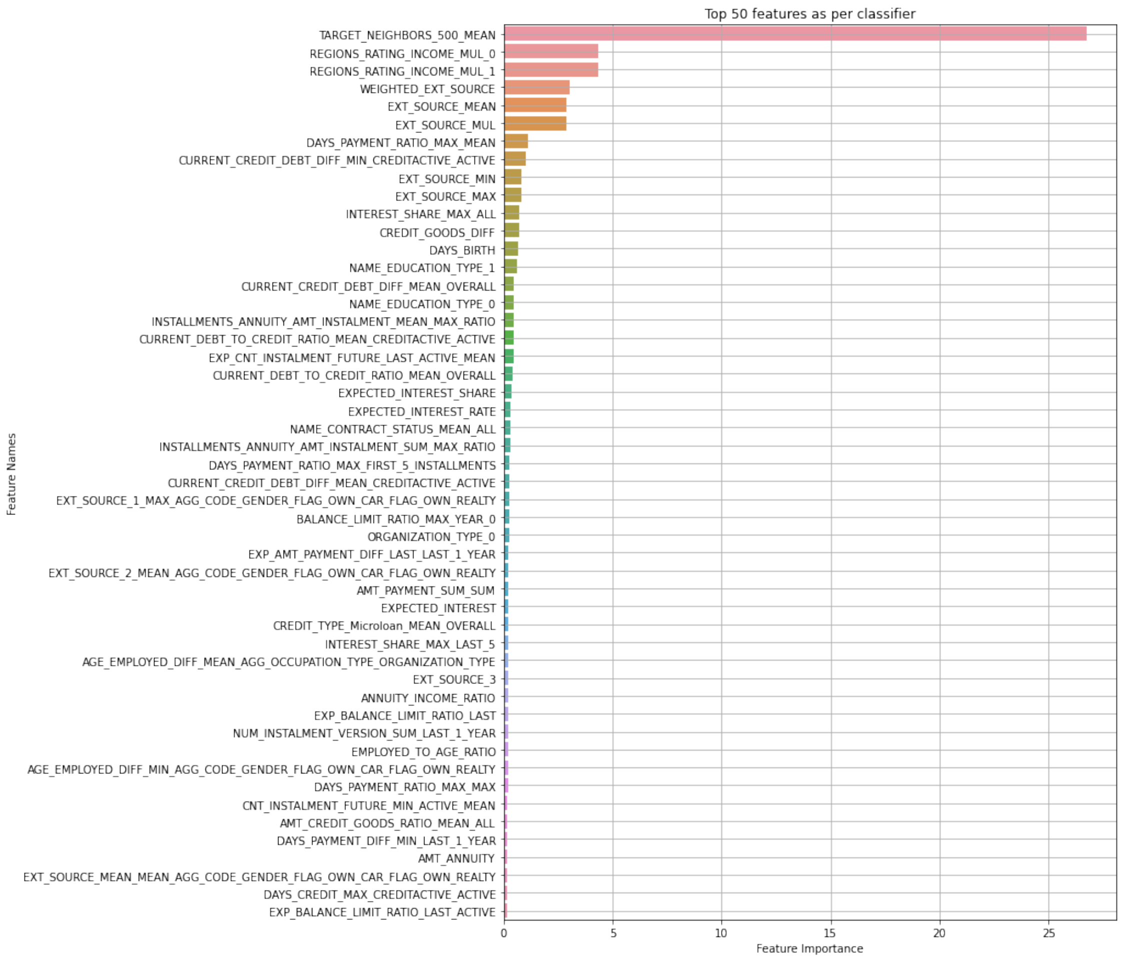
[47]:
```
#displaying the results and metrics
cb_boosting.results()
```

```
================================================================================
====================
Train Results:

The best selected Threshold as per the J-Statistic, which is J = TPR - FPR, is =
0.0405867135435595054

        ROC-AUC Score = 0.7991647011566586
        Precision Score = 0.18450191999024768
        Recall Score = 0.7316012084592145
CV Results:
        ROC-AUC Score = 0.7926123874329822
        Precision Score = 0.12782234530743966
        Recall Score = 0.8998590130916415
================================================================================
====================
Confusion, Precision and Recall Matrix on CV data:
```



==
====================

[48]:
```
#displaying top 50 important features
cb_boosting.feat_importances_show(50)
```




```
================================================================================
====================
```

[ ]:

```

```

1.3 Test GPU

after some search on the internet, I think `"atboost_options.cpp:612: Error: rsm on GPU is supported for pairwise modes only"` is a bug, so stop trying this case on GPU now.

colsample_bylevel=0.57 caused the above error.

[4]:

```
params = {
    'task_type': 'GPU',
    'eval_metric': 'AUC',
    'n_estimators' : 10000,
    'learning_rate' : 0.01,
    'max_depth' : 5,
    'min_child_samples' : 80,
```

```
    'reg_lambda' : 0.03564525547115141,
    'random_state' : 42
}
```

[5]:

```
X_train, X_validation, y_train, y_validation = train_test_split(train_data,␣
↪target_train, train_size=0.8, random_state=42)

clf_gpu = CatBoostClassifier(**params)

clf_gpu.fit(X_train, y_train, eval_set=(X_validation, y_validation),
                 verbose_eval = 200, early_stopping_rounds = 100, plot=True)
```

```
MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

0:      learn: 0.7374999        test: 0.7310336 best: 0.7310336 (0)     total:
24.7ms   remaining: 4m 6s
200:    learn: 0.7815136        test: 0.7771608 best: 0.7771608 (200)   total:
5.22s    remaining: 4m 14s
400:    learn: 0.7887281        test: 0.7839294 best: 0.7839294 (400)   total:
10.5s    remaining: 4m 10s
600:    learn: 0.7938392        test: 0.7880316 best: 0.7880316 (600)   total:
15.6s    remaining: 4m 4s
800:    learn: 0.7978637        test: 0.7908291 best: 0.7908291 (800)   total:
20.8s    remaining: 3m 58s
1000:   learn: 0.8010053        test: 0.7926714 best: 0.7926714 (1000)  total:
25.9s    remaining: 3m 52s
1200:   learn: 0.8037855        test: 0.7941756 best: 0.7941756 (1200)  total:
31s      remaining: 3m 46s
1400:   learn: 0.8061350        test: 0.7951680 best: 0.7951680 (1400)  total:
35.9s    remaining: 3m 40s
1600:   learn: 0.8084269        test: 0.7960042 best: 0.7960042 (1600)  total:
40.9s    remaining: 3m 34s
1800:   learn: 0.8104979        test: 0.7967569 best: 0.7967569 (1800)  total:
45.8s    remaining: 3m 28s
2000:   learn: 0.8126208        test: 0.7974707 best: 0.7974724 (1999)  total:
50.8s    remaining: 3m 22s
2200:   learn: 0.8145652        test: 0.7981249 best: 0.7981335 (2198)  total:
55.7s    remaining: 3m 17s
2400:   learn: 0.8164235        test: 0.7985342 best: 0.7985342 (2400)  total:
1m       remaining: 3m 12s
2600:   learn: 0.8182155        test: 0.7989728 best: 0.7989730 (2599)  total:
1m 5s    remaining: 3m 6s
2800:   learn: 0.8199943        test: 0.7993891 best: 0.7993891 (2800)  total:
1m 10s   remaining: 3m 1s
3000:   learn: 0.8216785        test: 0.7997618 best: 0.7997618 (3000)  total:
1m 15s   remaining: 2m 56s
```

```
3200:   learn: 0.8233958        test: 0.8001505 best: 0.8001505 (3200)  total:
1m 20s   remaining: 2m 51s
3400:   learn: 0.8249927        test: 0.8004469 best: 0.8004469 (3400)  total:
1m 25s   remaining: 2m 46s
3600:   learn: 0.8265725        test: 0.8006648 best: 0.8006675 (3590)  total:
1m 30s   remaining: 2m 41s
3800:   learn: 0.8281254        test: 0.8008833 best: 0.8008837 (3798)  total:
1m 35s   remaining: 2m 36s
4000:   learn: 0.8296616        test: 0.8010972 best: 0.8010993 (3998)  total:
1m 41s   remaining: 2m 31s
4200:   learn: 0.8311698        test: 0.8013049 best: 0.8013070 (4196)  total:
1m 45s   remaining: 2m 26s
4400:   learn: 0.8326520        test: 0.8015103 best: 0.8015104 (4399)  total:
1m 51s   remaining: 2m 21s
4600:   learn: 0.8341025        test: 0.8016108 best: 0.8016118 (4596)  total:
1m 56s   remaining: 2m 16s
4800:   learn: 0.8355027        test: 0.8017629 best: 0.8017633 (4790)  total:
2m 1s    remaining: 2m 11s
5000:   learn: 0.8368742        test: 0.8018548 best: 0.8018548 (5000)  total:
2m 6s    remaining: 2m 6s
5200:   learn: 0.8382441        test: 0.8020157 best: 0.8020179 (5199)  total:
2m 11s   remaining: 2m
5400:   learn: 0.8395865        test: 0.8021098 best: 0.8021098 (5400)  total:
2m 16s   remaining: 1m 55s
5600:   learn: 0.8409414        test: 0.8022474 best: 0.8022507 (5588)  total:
2m 21s   remaining: 1m 50s
5800:   learn: 0.8422177        test: 0.8023926 best: 0.8023926 (5800)  total:
2m 26s   remaining: 1m 45s
6000:   learn: 0.8435318        test: 0.8025001 best: 0.8025024 (5987)  total:
2m 31s   remaining: 1m 40s
6200:   learn: 0.8447956        test: 0.8026737 best: 0.8026737 (6200)  total:
2m 36s   remaining: 1m 35s
6400:   learn: 0.8460547        test: 0.8028385 best: 0.8028412 (6397)  total:
2m 41s   remaining: 1m 30s
6600:   learn: 0.8473146        test: 0.8029287 best: 0.8029346 (6587)  total:
2m 46s   remaining: 1m 25s
6800:   learn: 0.8485467        test: 0.8030444 best: 0.8030504 (6796)  total:
2m 51s   remaining: 1m 20s
7000:   learn: 0.8497840        test: 0.8031321 best: 0.8031321 (7000)  total:
2m 56s   remaining: 1m 15s
7200:   learn: 0.8510396        test: 0.8032120 best: 0.8032140 (7199)  total:
3m 1s    remaining: 1m 10s
7400:   learn: 0.8522313        test: 0.8032809 best: 0.8032834 (7397)  total:
3m 6s    remaining: 1m 5s
7600:   learn: 0.8534546        test: 0.8034166 best: 0.8034193 (7599)  total:
3m 10s   remaining: 1m
7800:   learn: 0.8545764        test: 0.8034737 best: 0.8034774 (7795)  total:
3m 16s   remaining: 55.3s
```

```
8000:   learn: 0.8557383        test: 0.8035545 best: 0.8035590 (7954)  total:
3m 20s   remaining: 50.2s
8200:   learn: 0.8568818        test: 0.8036433 best: 0.8036433 (8198)  total:
3m 25s   remaining: 45.2s
8400:   learn: 0.8580528        test: 0.8037110 best: 0.8037190 (8391)  total:
3m 30s   remaining: 40.1s
8600:   learn: 0.8591834        test: 0.8037611 best: 0.8037616 (8583)  total:
3m 35s   remaining: 35.1s
8800:   learn: 0.8602805        test: 0.8038218 best: 0.8038218 (8800)  total:
3m 40s   remaining: 30.1s
9000:   learn: 0.8613597        test: 0.8039020 best: 0.8039076 (8997)  total:
3m 45s   remaining: 25.1s
bestTest = 0.803907603
bestIteration = 8997
Shrink model to first 8998 iterations.
```

[5]: `<catboost.core.CatBoostClassifier at 0x1c16e407640>`

[ ]:
```
clf_gpu.predict_proba(test_data)[:,1]
```

[6]:
```
clf_gpu_model_df = pd.DataFrame({'SK_ID_CURR': skid_test, 'TARGET' : clf_gpu.
 ↪predict_proba(test_data)[:,1]})
clf_gpu_model_df['SK_ID_CURR'] = clf_gpu_model_df['SK_ID_CURR'].astype(int)
clf_gpu_model_df.to_csv('./submissions/catboost_gpu_model.csv',index = False)
```

Model	Private Score	Public Score
CatBoost_GPU_Model	0.78860	0.79378

1.4 Grid search

unssucced: kernel died

[ ]:
```

X_train, X_validation, y_train, y_validation = train_test_split(train_data,␣
 ↪target_train, train_size=0.8, random_state=42)

clf_gpu = CatBoostClassifier(task_type='GPU', eval_metric='AUC',␣
 ↪n_estimators=10000, random_state=42)

grid_params = {'n_estimators': [2000, 40000, 6000, 8000, 10000],
            'learning_rate': list(np.arange(0.01, 0.1, 0.01)),
            'max_depth': list(range(15,25)),
            'min_child_samples': list(range(5,80)),
            'reg_lambda': list(np.arange(0.1, 0.31, 0.1))}

grid_search_result = clf_gpu.grid_search(grid_params, X=X_train, y=y_train,␣
 ↪plot=True)
```

```
# randm = RandomizedSearchCV(estimator=clf_gpu, param_distributions =␣
↪grid_params,
#                                 cv = 5, n_iter = 10, n_jobs=2, verbose=True)
# randm.fit(train_data, target_train)
```

MetricVisualizer(layout=Layout(align_self='stretch', height='500px'))

1.5 Hyperparameter tuning on GPU

unssucced: kernel died

[6]:
```
def cbc_evaluation(learning_rate, max_depth, min_child_samples, reg_lambda):
    '''
    Objective function for Bayesian Optimization of CatBoost's Hyperparamters.␣
↪Takes the hyperparameters as input, and
    returns the Cross-Validation AUC as output.

    Inputs: Hyperparamters to be tuned.
        learning_rate, max_depth, min_child_samples, reg_lambda

    Returns:
        CV ROC-AUC Score
    '''
    params = {
        'task_type': 'GPU',
        'eval_metric': 'AUC',
        'n_estimators' : 10000,
        'learning_rate' : learning_rate,
        'max_depth' : int(round(max_depth)),
        'min_child_samples' : int(round(min_child_samples)),
        'reg_lambda' : reg_lambda,
        'random_state' : 42
    }

    #defining the Cross-Validation Strategegry
    stratified_cv = StratifiedKFold(n_splits = 3, shuffle = True, random_state␣
↪= 33)
    cv_preds = np.zeros(train_data.shape[0])

    #iterating over each fold, training the model, and making Out of Fold␣
↪Predictions
    for train_indices, cv_indices in stratified_cv.split(train_data,␣
↪target_train):

        x_tr = train_data.iloc[train_indices]
        y_tr = target_train.iloc[train_indices]
```

```
        x_cv = train_data.iloc[cv_indices]
        y_cv = target_train.iloc[cv_indices]

        cbc = CatBoostClassifier(**params)
        cbc.fit(x_tr, y_tr, eval_set= (x_cv,y_cv), verbose = False,␣
↪early_stopping_rounds = 200)

        cv_preds[cv_indices] = cbc.predict_proba(x_cv)[:,1]
        gc.collect()

    return roc_auc_score(target_train, cv_preds)
```

[ ]:

```
#defining the optimizer and the hyperparameters along with ranges of values.
bopt_cbc =  BayesianOptimization(cbc_evaluation, {
                                                   'learning_rate': (0.01, 0.1),
                                                   'max_depth' : (5,15),
                                                   'min_child_samples' : (5,80),
                                                   'reg_lambda' : (0.001, 0.3)},
                                 random_state = 55)

bopt_cbc.maximize(n_iter = 6, init_points = 4) #cost time:

#the package has bug: kernel died when start tuning
```

```
|   iter    |  target   | learni… | max_depth | min_ch… | reg_la… |
-------------------------------------------------------------------------
```

[ ]: