01_gbm_baseline

September 29, 2021

1 Adaptive and Gradient Boosting

In this notebook, we demonstrate the use of AdaBoost and gradient boosting, incuding several state-of-the-art implementations of this very powerful and flexible algorithm that greatly speed up training.

We use the stock return dataset with a few engineered factors created in Chapter 4 on Alpha Factor Research in the notebook feature_engineering.

1.1 Imports and Settings

[1]:
```
%matplotlib inline

import warnings
import os
from datetime import datetime
from pathlib import Path
import quandl
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import seaborn as sns
import graphviz

from xgboost import XGBClassifier, XGBRegressor
from lightgbm import LGBMClassifier, LGBMRegressor
from catboost import CatBoostClassifier, CatBoostRegressor
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier
from sklearn.ensemble.partial_dependence import partial_dependence,␣
↪plot_partial_dependence
from sklearn.externals import joblib
```

```
from sklearn.metrics import roc_auc_score, roc_curve, mean_squared_error,␣
↪precision_recall_curve
```

[2]:
```
results_path = Path('results')
if not results_path.exists():
    results_path.mkdir(exist_ok=True)
```

[3]:
```
warnings.filterwarnings('ignore')
sns.set_style("whitegrid")
idx = pd.IndexSlice
np.random.seed(42)
```

1.2 Prepare Data

1.2.1 Get source

We use the `engineered_features` dataset created in Chapter 4, Alpha Factor Research

Set data store location:

[4]:
```
DATA_STORE = '../data/assets.h5'
```

[5]:
```
def get_data(start='2000', end='2018', task='classification', holding_period=1,␣
↪dropna=False):

    idx = pd.IndexSlice
    target = f'target_{holding_period}m'
    with pd.HDFStore(DATA_STORE) as store:
        df = store['engineered_features']

    if start is not None and end is not None:
        df = df.loc[idx[:, start: end], :]
    if dropna:
        df = df.dropna()

    y = (df[target]>0).astype(int)
    X = df.drop([c for c in df.columns if c.startswith('target')], axis=1)
    return y, X
```

1.2.2 Factorize Categories

Define columns with categorical data:

[6]:
```
cat_cols = ['year', 'month', 'age', 'msize', 'sector']
```

Integer-encode categorical columns:

[7]:
```
def factorize_cats(df, cats=['sector']):
    cat_cols = ['year', 'month', 'age', 'msize'] + cats
    for cat in cats:
        df[cat] = pd.factorize(df[cat])[0]
    df.loc[:, cat_cols] = df.loc[:, cat_cols].fillna(-1)
    return df
```

1.2.3 One-Hot Encoding

Create dummy variables from categorical columns if needed:

[8]:
```
def get_one_hot_data(df, cols=cat_cols[:-1]):
    df = pd.get_dummies(df,
                        columns=cols + ['sector'],
                        prefix=cols + [''],
                        prefix_sep=['_'] * len(cols) + [''])
    return df.rename(columns={c: c.replace('.0', '') for c in df.columns})
```

1.2.4 Get Holdout Set

Create holdout test set to estimate generalization error after cross-validation:

[9]:
```
def get_holdout_set(target, features, period=6):
    idx = pd.IndexSlice
    label = target.name
    dates = np.sort(y.index.get_level_values('date').unique())
    cv_start, cv_end = dates[0], dates[-period - 2]
    holdout_start, holdout_end = dates[-period - 1], dates[-1]

    df = features.join(target.to_frame())
    train = df.loc[idx[:, cv_start: cv_end], :]
    y_train, X_train = train[label], train.drop(label, axis=1)

    test = df.loc[idx[:, holdout_start: holdout_end], :]
    y_test, X_test = test[label], test.drop(label, axis=1)
    return y_train, X_train, y_test, X_test
```

1.3 Load Data

The algorithms in this chapter use a dataset generated in Chapter 4 on Alpha Factor Research in the notebook feature-engineering that needs to be executed first.

[10]:
```
y, features = get_data()
X_dummies = get_one_hot_data(features)
X_factors = factorize_cats(features)
```

```
[11]: y_clean, features_clean = get_data(dropna=True)
X_dummies_clean = get_one_hot_data(features_clean)
X_factors_clean = factorize_cats(features_clean)
```

1.4 Cross-Validation Setup

1.4.1 Custom Time Series KFold Generator

Custom Time Series KFold generator introduced in Chapter 10 on Decision Trees and Random Forests.

```
[12]: class OneStepTimeSeriesSplit:
    """Generates tuples of train_idx, test_idx pairs
    Assumes the index contains a level labeled 'date'"""

    def __init__(self, n_splits=3, test_period_length=1, shuffle=False):
        self.n_splits = n_splits
        self.test_period_length = test_period_length
        self.shuffle = shuffle

    @staticmethod
    def chunks(l, n):
        for i in range(0, len(l), n):
            yield l[i:i + n]

    def split(self, X, y=None, groups=None):
        unique_dates = (X.index
                        .get_level_values('date')
                        .unique()
                        .sort_values(ascending=False)
                        [:self.n_splits*self.test_period_length])

        dates = X.reset_index()[['date']]
        for test_date in self.chunks(unique_dates, self.test_period_length):
            train_idx = dates[dates.date < min(test_date)].index
            test_idx = dates[dates.date.isin(test_date)].index
            if self.shuffle:
                np.random.shuffle(list(train_idx))
            yield train_idx, test_idx

    def get_n_splits(self, X, y, groups=None):
        return self.n_splits
```

```
[13]: cv = OneStepTimeSeriesSplit(n_splits=12, test_period_length=1, shuffle=True)
```

1.4.2 CV Metrics

Define some metrics for use with cross-validation:

[14]:
```python
metrics = {'balanced_accuracy': 'Accuracy' ,
           'roc_auc': 'AUC',
           'neg_log_loss': 'Log Loss',
           'f1_weighted': 'F1',
           'precision_weighted': 'Precision',
           'recall_weighted': 'Recall'
}
```

Helper function that runs cross-validation for the various algorithms.

[15]:
```python
def run_cv(clf, X=X_dummies, y=y, metrics=metrics, cv=cv, fit_params=None):
    return cross_validate(estimator=clf,
                          X=X,
                          y=y,
                          scoring=list(metrics.keys()),
                          cv=cv,
                          return_train_score=True,
                          n_jobs=-1,
                          verbose=1,
                          fit_params=fit_params)
```

1.4.3 CV Result Handler Functions

The following helper functions manipulate and plot the cross-validation results to produce the outputs below.

[16]:
```python
def stack_results(scores):
    columns = pd.MultiIndex.from_tuples(
        [tuple(m.split('_', 1)) for m in scores.keys()],
        names=['Dataset', 'Metric'])
    data = np.array(list(scores.values())).T
    df = (pd.DataFrame(data=data,
                       columns=columns)
          .iloc[:, 2:])
    results = pd.melt(df, value_name='Value')
    results.Metric = results.Metric.apply(lambda x: metrics.get(x))
    results.Dataset = results.Dataset.str.capitalize()
    return results
```

[17]:
```python
def plot_result(df, model=None):
    m = list(metrics.values())
    g = sns.catplot(x='Dataset',
                    y='Value',
                    hue='Dataset',
                    col='Metric',
                    data=df,
                    col_order=m,
                    order=['Train', 'Test'],
```

```
                    kind="box",
                    col_wrap=3,
                    sharey=False,
                    height=4, aspect=1.2)
    df = df.groupby(['Metric', 'Dataset']).Value.mean().unstack().loc[m]
    for i, ax in enumerate(g.axes.flat):
        s = f"Train: {df.loc[m[i], 'Train']:>7.4f}\nTest:  {df.loc[m[i],␣
↪'Test'] :>7.4f}"
        ax.text(0.05, 0.85, s, fontsize=10, transform=ax.transAxes,
                bbox=dict(facecolor='white', edgecolor='grey',␣
↪boxstyle='round,pad=0.5'))
    g.fig.suptitle(model, fontsize=16)
    g.fig.subplots_adjust(top=.9);
```

1.5 Baseline Classifier

`sklearn` provides the DummyClassifier that makes predictions using simple rule and is useful as a simple baseline to compare with the other (real) classifiers we use below.

The `stratified` rule generates predictions based on the training set's class distribution, i.e. always predicts the most frequent class.

[18]:
```
dummy_clf = DummyClassifier(strategy='stratified',
                            random_state=42)
```

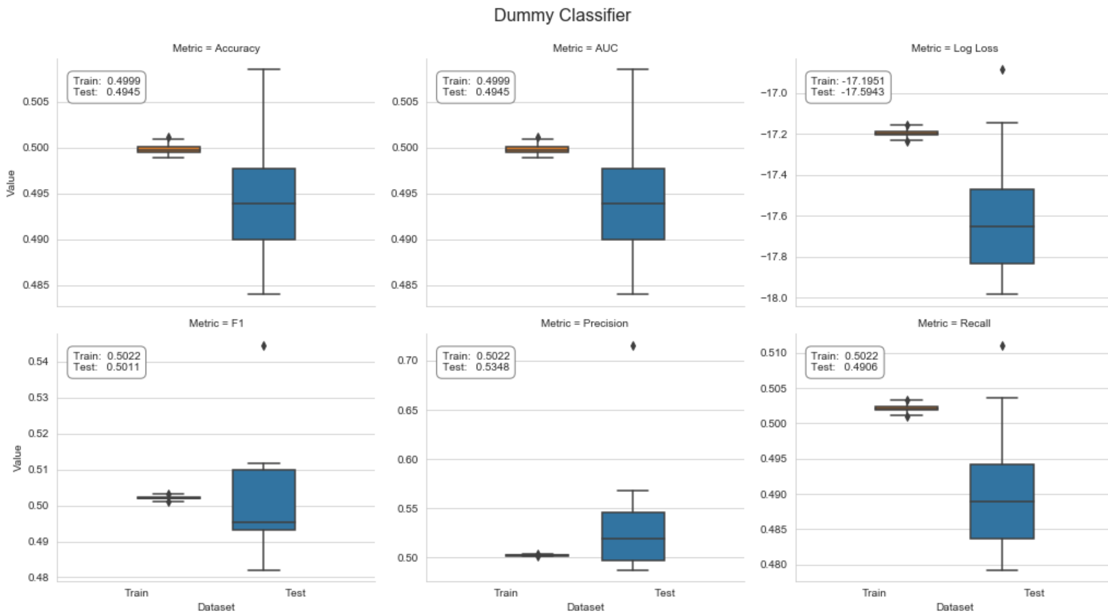
[19]:
```
fname = 'results/dummy_cv_result.joblib'
if not Path(fname).exists():
    dummy_cv_result = run_cv(dummy_clf)
    joblib.dump(dummy_cv_result, fname)
else:
    dummy_cv_result = joblib.load(fname)
```

Unsurprisingly, it produces results near the AUC threshold for arbitrary predictions of 0.5:

[20]:
```
dummy_result = stack_results(dummy_cv_result)
dummy_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[20]:
```
Dataset         Test      Train
Metric
AUC         0.494516   0.499862
Accuracy    0.494516   0.499862
F1          0.501068   0.502171
Log Loss  -17.594264 -17.195080
Precision   0.534767   0.502186
Recall      0.490601   0.502157
```

[21]:
```
plot_result(dummy_result, model='Dummy Classifier')
```



1.6 RandomForest

For comparison, we train a `RandomForestClassifier` as presented in Chapter 10 on Decision Trees and Random Forests.

1.6.1 Configure

[22]:
```
rf_clf = RandomForestClassifier(n_estimators=200,            # will change␣
 ↪from 10 to 100 in version 0.22
                                criterion='gini',
                                max_depth=None,
                                min_samples_split=2,
                                min_samples_leaf=1,
                                min_weight_fraction_leaf=0.0,
                                max_features='auto',
                                max_leaf_nodes=None,
                                min_impurity_decrease=0.0,
                                min_impurity_split=None,
                                bootstrap=True,
                                oob_score=True,
                                n_jobs=-1,
                                random_state=42,
                                verbose=1)
```

1.6.2 Cross-validate

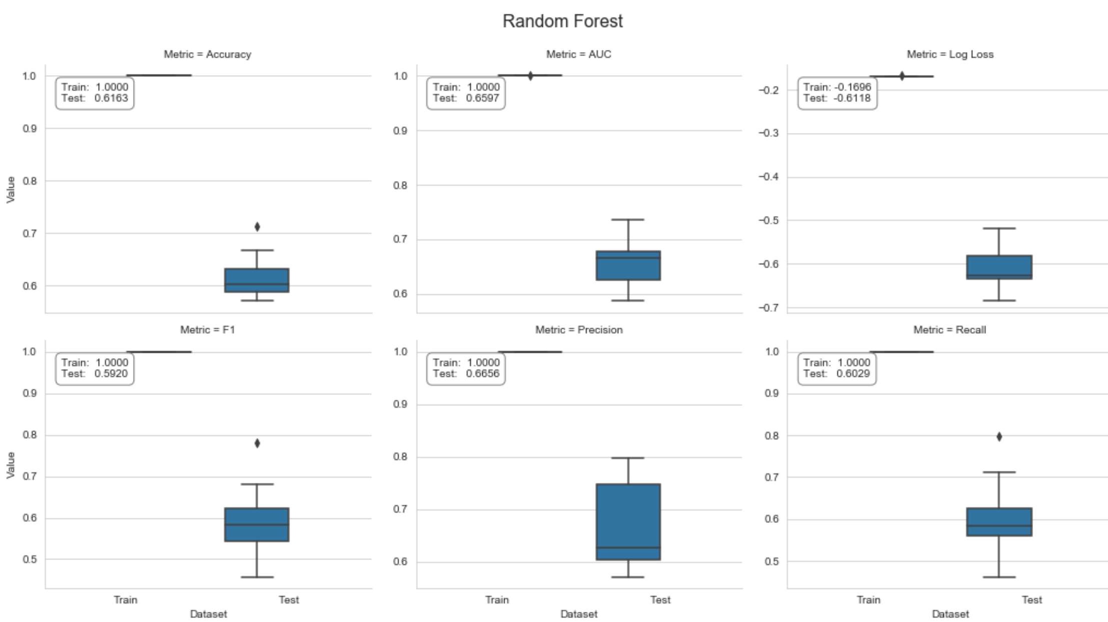
[23]:
```python
fname = 'results/rf_cv_result.joblib'
if not Path(fname).exists():
    rf_cv_result = run_cv(rf_clf, y=y_clean, X=X_dummies_clean)
    joblib.dump(rf_cv_result, fname)
else:
    rf_cv_result = joblib.load(fname)
```

1.6.3 Plot Results

[24]:
```python
rf_result = stack_results(rf_cv_result)
rf_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[24]:
```
Dataset         Test     Train
Metric
AUC         0.659692  1.000000
Accuracy    0.616270  1.000000
F1          0.592029  1.000000
Log Loss   -0.611774 -0.169561
Precision   0.665563  1.000000
Recall      0.602865  1.000000
```

[25]:
```python
plot_result(rf_result, model='Random Forest')
```



1.7 sklearn: AdaBoost

As part of its ensemble module, sklearn provides an AdaBoostClassifier implementation that supports two or more classes. The code examples for this section are in the notebook gbm_baseline that compares the performance of various algorithms with a dummy classifier that always predicts the most frequent class.

1.7.1 Base Estimator

We need to first define a base_estimator as a template for all ensemble members and then configure the ensemble itself. We'll use the default DecisionTreeClassifier with max_depth=1—that is, a stump with a single split. The complexity of the base_estimator is a key tuning parameter because it depends on the nature of the data.

As demonstrated in the previous chapter, changes to `max_depth` should be combined with appropriate regularization constraints using adjustments to, for example, `min_samples_split`:

[26]:
```
base_estimator = DecisionTreeClassifier(criterion='gini',
                                        splitter='best',
                                        max_depth=1,
                                        min_samples_split=2,
                                        min_samples_leaf=20,
                                        min_weight_fraction_leaf=0.0,
                                        max_features=None,
                                        random_state=None,
                                        max_leaf_nodes=None,
                                        min_impurity_decrease=0.0,
                                        min_impurity_split=None,
                                        class_weight=None,
                                        presort=False)
```

1.7.2 AdaBoost Configuration

In the second step, we'll design the ensemble. The n_estimators parameter controls the number of weak learners and the learning_rate determines the contribution of each weak learner, as shown in the following code. By default, weak learners are decision tree stumps:

[27]:
```
ada_clf = AdaBoostClassifier(base_estimator=base_estimator,
                             n_estimators=200,
                             learning_rate=1.0,
                             algorithm='SAMME.R',
                             random_state=42)
```

The main tuning parameters that are responsible for good results are `n_estimators` and the base estimator complexity because the depth of the tree controls the extent of the interaction among the features.

1.7.3 Cross-validate

We will cross-validate the AdaBoost ensemble using a custom 12-fold rolling time-series split to predict 1 month ahead for the last 12 months in the sample, using all available prior data for training, as shown in the following code:

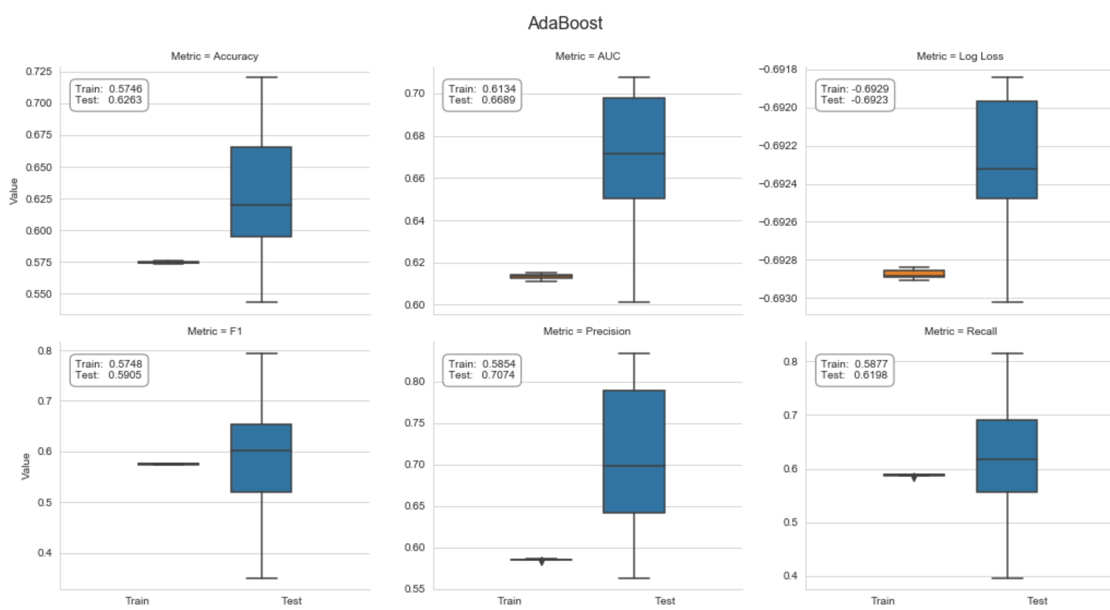
[28]:
```
fname = 'results/ada_cv_result.joblib'
if not Path(fname).exists():
    ada_cv_result = run_cv(ada_clf, y=y_clean, X=X_dummies_clean)
    joblib.dump(ada_cv_result, fname)
else:
    ada_cv_result = joblib.load(fname)
```

1.7.4 Plot Result

[29]:
```
ada_result = stack_results(ada_cv_result)
ada_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[29]:
```
Dataset         Test     Train
Metric
AUC         0.668890  0.613425
Accuracy    0.626251  0.574614
F1          0.590490  0.574779
Log Loss   -0.692288 -0.692875
Precision   0.707423  0.585429
Recall      0.619776  0.587690
```

[30]:
```
plot_result(ada_result, model='AdaBoost')
```



1.8 GradientBoostingClassifier

The ensemble module of sklearn contains an implementation of gradient boosting trees for regression and classification, both binary and multiclass.

1.8.1 Configure

The following GradientBoostingClassifier initialization code illustrates the key tuning parameters that we previously introduced, in addition to those that we are familiar with from looking at standalone decision tree models.

The available loss functions include the exponential loss that leads to the AdaBoost algorithm and the deviance that corresponds to the logistic regression for probabilistic outputs.

The `friedman_mse` node quality measure is a variation on the mean squared error that includes an improvement score (see GitHub references for links to original papers), as shown in the following code:

[31]:
```
gb_clf = GradientBoostingClassifier(loss='deviance',                # deviance␣
 ↪= logistic reg; exponential: AdaBoost
                                    learning_rate=0.1,              # shrinks␣
 ↪the contribution of each tree
                                    n_estimators=100,               # number of␣
 ↪boosting stages
                                    subsample=1.0,                  # fraction␣
 ↪of samples used t fit base learners
                                    criterion='friedman_mse',       # measures␣
 ↪the quality of a split
                                    min_samples_split=2,
                                    min_samples_leaf=1,
                                    min_weight_fraction_leaf=0.0,   # min.␣
 ↪fraction of sum of weights
                                    max_depth=3,                    # opt value␣
 ↪depends on interaction
                                    min_impurity_decrease=0.0,
                                    min_impurity_split=None,
                                    init=None,
                                    random_state=None,
                                    max_features=None,
                                    verbose=0,
                                    max_leaf_nodes=None,
                                    warm_start=False,
                                    presort='auto',
                                    validation_fraction=0.1,
                                    n_iter_no_change=None,
                                    tol=0.0001)
```

1.8.2 Cross-validate

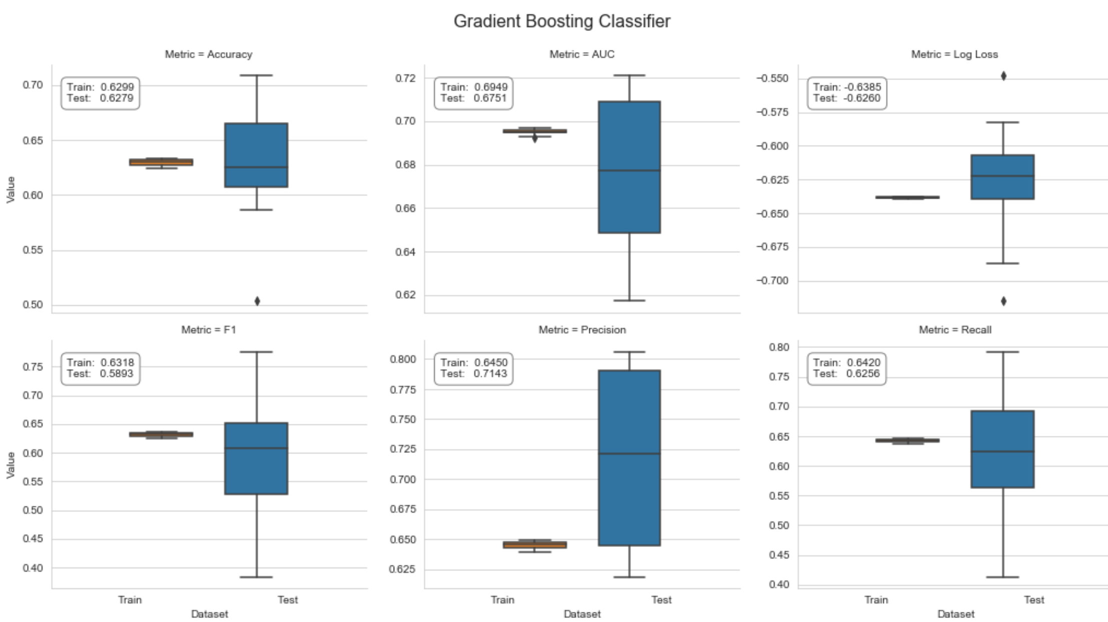
[32]:
```
fname = 'results/gb_cv_result.joblib'
if not Path(fname).exists():
    gb_cv_result = run_cv(gb_clf, y=y_clean, X=X_dummies_clean)
    joblib.dump(gb_cv_result, fname)
else:
    gb_cv_result = joblib.load(fname)
```

1.8.3 Plot Results

[33]:
```
gb_result = stack_results(gb_cv_result)
gb_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[33]:
```
Dataset         Test     Train
Metric
AUC         0.675116  0.694941
Accuracy    0.627907  0.629854
F1          0.589335  0.631810
Log Loss   -0.626003 -0.638505
Precision   0.714278  0.645043
Recall      0.625646  0.642046
```

[34]:
```
plot_result(gb_result, model='Gradient Boosting Classifier')
```



1.8.4 Partial Dependence Plot

[35]:
```
gb_clf.fit(y=y_clean, X=X_dummies_clean)
```

[35]:
```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=1.0, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
```

[36]:
```
# mean accuracy
gb_clf.score(X=X_dummies_clean, y=y_clean)
```

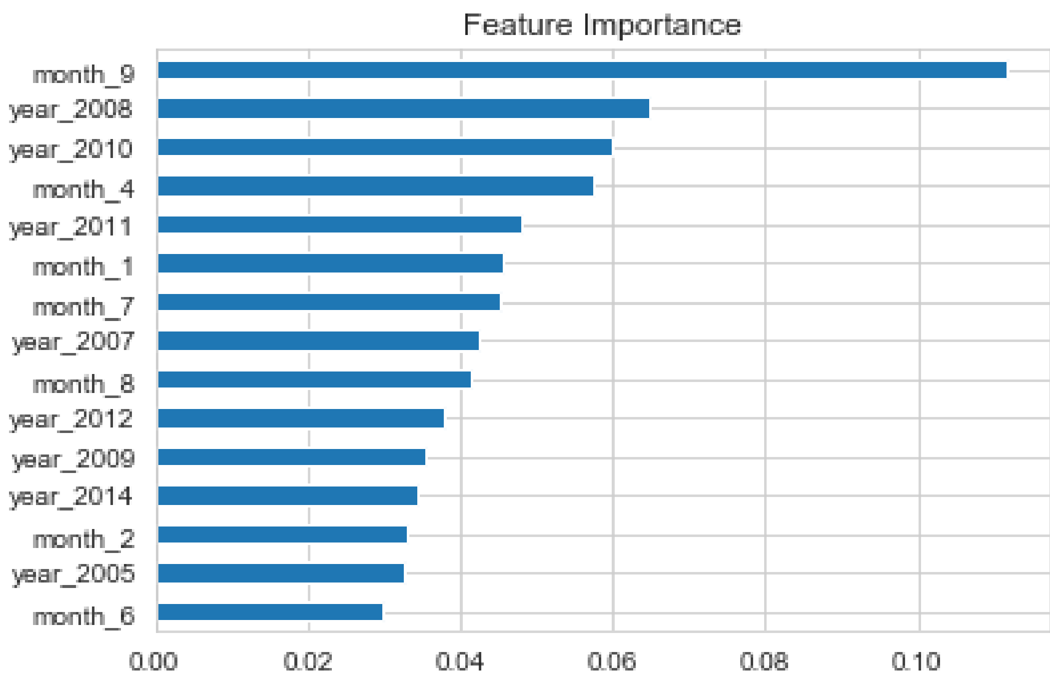
[36]: 0.6404773585987626

[37]:
```
y_score = gb_clf.predict_proba(X_dummies_clean)[:, 1]
roc_auc_score(y_score=y_score, y_true=y_clean)
```

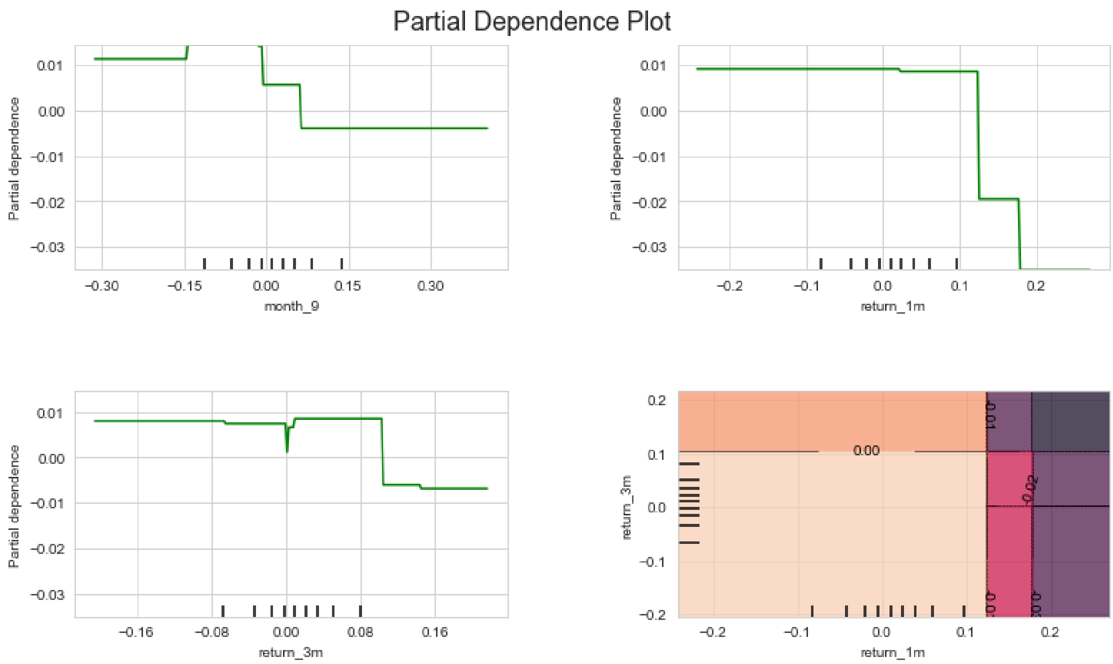
[37]: 0.6893357756405963

Feature Importance

[38]:
```
(pd.Series(gb_clf.feature_importances_,
           index=X_dummies_clean.columns)
 .sort_values(ascending=False)
 .head(15)).sort_values().plot.barh(title='Feature Importance');
```

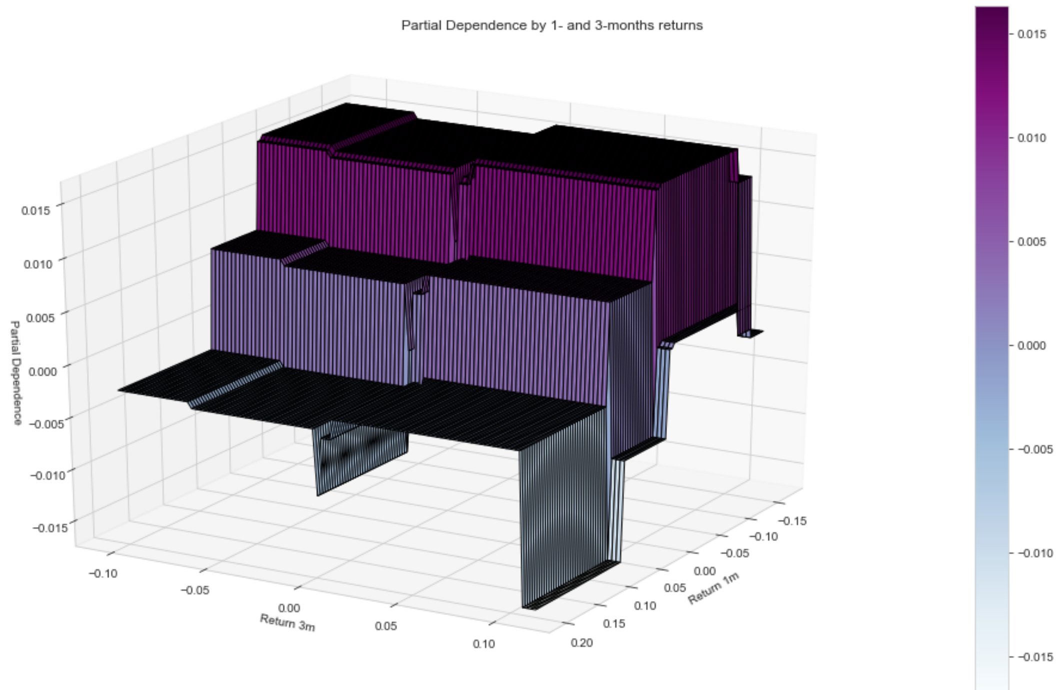


[39]:
```
fig, axes = plot_partial_dependence(gbrt=gb_clf,
                                    X=X_dummies_clean,
                                    features=['month_9', 'return_1m',␣
 ↪'return_3m', ('return_1m', 'return_3m')],
                                    feature_names=['month_9','return_1m',␣
 ↪'return_3m'],
                                    percentiles=(0.01, 0.99),
                                    n_jobs=-1,
                                    n_cols=2,
                                    grid_resolution=250)
fig.suptitle('Partial Dependence Plot', fontsize=18)
fig.tight_layout()
fig.set_size_inches(12, 7)
```



[40]:
```
targets = ['return_1m', 'return_3m']
target_feature = [X_dummies_clean.columns.get_loc(t) for t in targets]
pdp, axes = partial_dependence(gb_clf,
                               target_feature,
                               X=X_dummies_clean,
                               grid_resolution=100)

XX, YY = np.meshgrid(axes[0], axes[1])
Z = pdp[0].reshape(list(map(np.size, axes))).T

fig = plt.figure(figsize=(14, 8))
ax = Axes3D(fig)
surf = ax.plot_surface(XX, YY, Z,
                       rstride=1,
                       cstride=1,
                       cmap=plt.cm.BuPu,
                       edgecolor='k')
ax.set_xlabel(' '.join(targets[0].split('_')).capitalize())
ax.set_ylabel(' '.join(targets[1].split('_')).capitalize())
ax.set_zlabel('Partial Dependence')
ax.view_init(elev=22, azim=30)

fig.colorbar(surf)
fig.suptitle('Partial Dependence by 1- and 3-months returns')
fig.tight_layout()
```

```
fig.savefig('partial_plot', dpi=300);
```



1.9 XGBoost

See XGBoost docs for details on parameters and usage.

1.9.1 Configure

[41]:
```
xgb_clf = XGBClassifier(max_depth=3,                    # Maximum tree depth for␣
 ↪base learners.
                        learning_rate=0.1,             # Boosting learning rate␣
 ↪(xgb's "eta")
                        n_estimators=100,              # Number of boosted trees␣
 ↪to fit.
                        silent=True,                   # Whether to print␣
 ↪messages while running
                        objective='binary:logistic',   # Task and objective or␣
 ↪custom objective function
                        booster='gbtree',              # Select booster: gbtree,␣
 ↪gblinear or dart
#                         tree_method='gpu_hist',
                        n_jobs=-1,                     # Number of parallel␣
 ↪threads
```

```
                       gamma=0,                     # Min loss reduction for␣
↪further splits
                       min_child_weight=1,          # Min sum of sample␣
↪weight(hessian) needed
                       max_delta_step=0,            # Max delta step for each␣
↪tree's weight estimation
                       subsample=1,                 # Subsample ratio of␣
↪training samples
                       colsample_bytree=1,          # Subsample ratio of cols␣
↪for each tree
                       colsample_bylevel=1,         # Subsample ratio of cols␣
↪for each split
                       reg_alpha=0,                 # L1 regularization term␣
↪on weights
                       reg_lambda=1,                # L2 regularization term␣
↪on weights
                       scale_pos_weight=1,          # Balancing class weights
                       base_score=0.5,              # Initial prediction␣
↪score; global bias
                       random_state=42)             # random seed
```

1.9.2 Cross-validate

[42]:
```
fname = 'results/xgb_cv_result.joblib'
if not Path(fname).exists():
    xgb_cv_result = run_cv(xgb_clf)
    joblib.dump(xgb_cv_result, fname)
else:
    xgb_cv_result = joblib.load(fname)
```

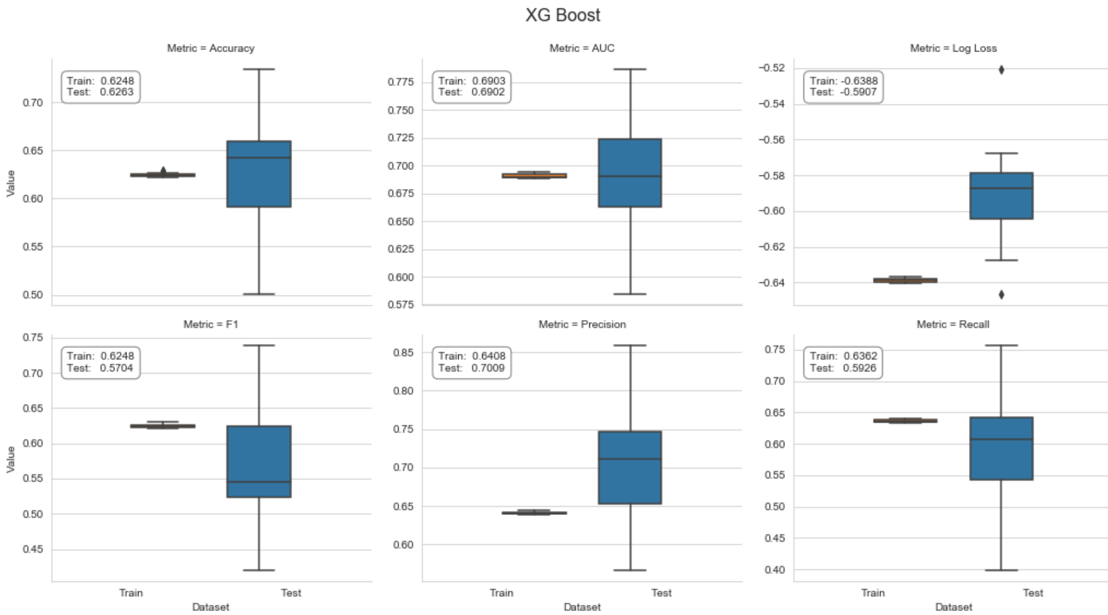
1.9.3 Plot Results

[43]:
```
xbg_result = stack_results(xgb_cv_result)
xbg_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[43]:

Dataset Metric	Test	Train
AUC	0.690214	0.690331
Accuracy	0.626261	0.624804
F1	0.570426	0.624806
Log Loss	-0.590711	-0.638768
Precision	0.700872	0.640821
Recall	0.592593	0.636230

[44]:
```
plot_result(xbg_result, model='XG Boost')
```



[45]:
```
xgb_clf.fit(X=X_dummies, y=y)
```

[45]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
        colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
        max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
        n_jobs=-1, nthread=None, objective='binary:logistic',
        random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
        seed=None, silent=True, subsample=1)
```

[46]:
```
fi = pd.Series(xgb_clf.feature_importances_, index=X_dummies.columns)
```

[47]:
```
fi[fi>0].sort_values(ascending=False)
```

[47]:
```
year_2008          0.054534
month_4            0.050602
year_2010          0.041430
year_2012          0.039757
month_9            0.039299
year_2007          0.037836
month_7            0.033265
year_2011          0.032926
year_2005          0.031873
year_2014          0.031700
month_8            0.030093
month_10           0.029192
year_2015          0.028653
month_5            0.026768
```

```
year_2003            0.026737
month_6              0.026244
month_1              0.026009
year_2018            0.024712
year_2013            0.023958
month_11             0.023091
year_2002            0.022950
month_12             0.021967
year_2004            0.021956
month_2              0.021665
year_2016            0.021070
year_2009            0.021010
year_2017            0.020547
month_3              0.016647
momentum_12          0.011454
return_12m           0.010553
return_6m            0.010244
return_1m_t-3        0.009592
return_1m_t-6        0.008697
return_1m_t-4        0.008140
return_2m            0.007653
return_1m_t-2        0.007380
return_3m            0.007291
return_1m_t-5        0.007066
CMA                  0.006816
age_5                0.005803
return_1m            0.005731
momentum_9           0.005605
msize_1              0.005375
momentum_2           0.005295
Health Care          0.004494
RMW                  0.004481
momentum_3_12        0.004194
SMB                  0.003891
return_9m            0.003780
return_1m_t-1        0.003524
Public Utilities     0.003251
Energy               0.003126
momentum_3           0.003038
msize_10             0.002805
momentum_6           0.002791
Finance              0.002748
Mkt-RF               0.002721
Technology           0.002414
year_2001            0.002396
msize_6              0.001158
dtype: float32
```

1.10 LightGBM

See LightGBM docs for details on parameters and usage.

1.10.1 Configure

[48]:
```
lgb_clf = LGBMClassifier(boosting_type='gbdt',
#                          device='gpu',
                         objective='binary',          # learning task
                         metric='auc',
                         num_leaves=31,               # Maximum tree leaves for␣
 ↪base learners.
                         max_depth=-1,                # Maximum tree depth for␣
 ↪base learners, -1 means no limit.
                         learning_rate=0.1,          # Adaptive lr via callback␣
 ↪override in .fit() method
                         n_estimators=100,            # Number of boosted trees␣
 ↪to fit
                         subsample_for_bin=200000,    # Number of samples for␣
 ↪constructing bins.
                         class_weight=None,           # dict, 'balanced' or None
                         min_split_gain=0.0,          # Minimum loss reduction␣
 ↪for further split
                         min_child_weight=0.001,      # Minimum sum of instance␣
 ↪weight(hessian)
                         min_child_samples=20,        # Minimum number of data␣
 ↪need in a child(leaf)
                         subsample=1.0,               # Subsample ratio of␣
 ↪training samples
                         subsample_freq=0,            # Frequency of␣
 ↪subsampling, <=0: disabled
                         colsample_bytree=1.0,        # Subsampling ratio of␣
 ↪features
                         reg_alpha=0.0,               # L1 regularization term␣
 ↪on weights
                         reg_lambda=0.0,              # L2 regularization term␣
 ↪on weights
                         random_state=42,             # Random number seed;␣
 ↪default: C++ seed
                         n_jobs=-1,                   # Number of parallel␣
 ↪threads.
                         silent=False,
                         importance_type='gain',      # default: 'split' or␣
 ↪'gain'
                        )
```

1.10.2 Cross-Validate

Using categorical features

[49]:
```
fname = 'results/lgb_factor_cv_result.joblib'
if not Path(fname).exists():
    lgb_factor_cv_result = run_cv(lgb_clf, X=X_factors, fit_params={'categorical_feature': cat_cols})
    joblib.dump(lgb_factor_cv_result, fname)
else:
    lgb_factor_cv_result = joblib.load(fname)
```

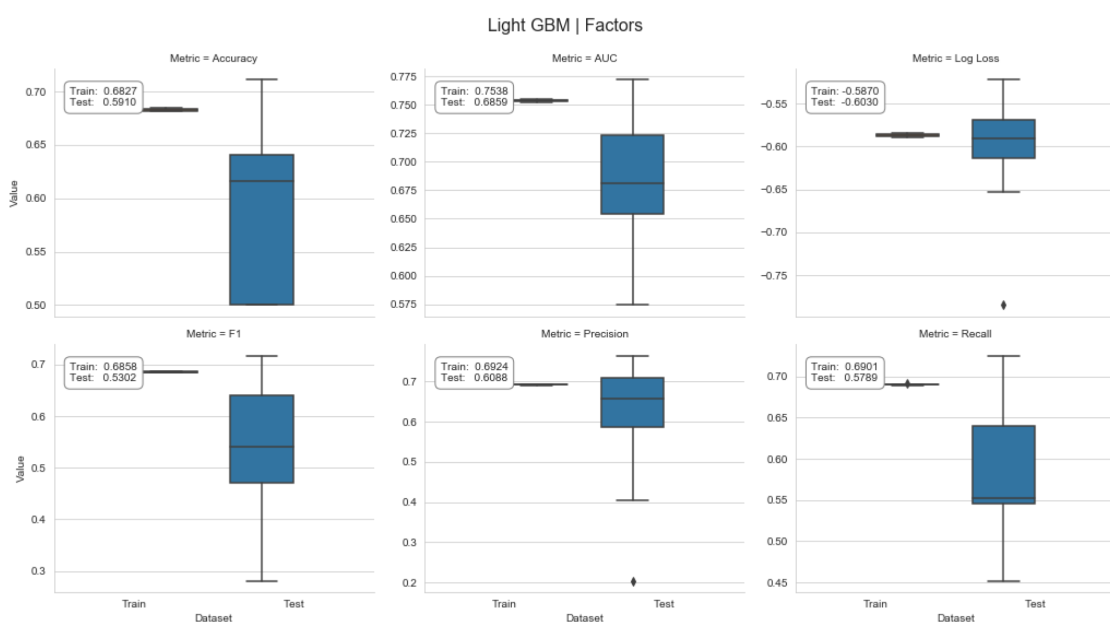
Plot Results

[50]:
```
lgb_factor_result = stack_results(lgb_factor_cv_result)
lgb_factor_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[50]:

Dataset / Metric	Test	Train
AUC	0.685903	0.753829
Accuracy	0.591003	0.682658
F1	0.530207	0.685766
Log Loss	-0.603009	-0.587044
Precision	0.608764	0.692368
Recall	0.578861	0.690098

[51]:
```
plot_result(lgb_factor_result, model='Light GBM | Factors')
```



Using dummy variables

[52]:
```
fname = 'results/lgb_dummy_cv_result.joblib'
if not Path(fname).exists():
    lgb_dummy_cv_result = run_cv(lgb_clf)
    joblib.dump(lgb_dummy_cv_result, fname)
else:
    lgb_dummy_cv_result = joblib.load(fname)
```

Plot results

[53]:
```
lgb_dummy_result = stack_results(lgb_dummy_cv_result)
lgb_dummy_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[53]:

Dataset Metric	Test	Train
AUC	0.690086	0.747246
Accuracy	0.624242	0.675954
F1	0.570777	0.678493
Log Loss	-0.581760	-0.594757
Precision	0.655675	0.690174
Recall	0.599825	0.685142

1.11 Catboost

See CatBoost docs for details on parameters and usage.

1.11.1 Configure

[66]:
```
cat_clf = CatBoostClassifier()
cat_cv_result = run_cv(cat_clf, X=X_factors, fit_params={'cat_features':␣
↪cat_cols_idx})
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  10 out of  12 | elapsed: 33.6min remaining:  6.7min
[Parallel(n_jobs=-1)]: Done  12 out of  12 | elapsed: 33.7min finished
```

1.11.2 Cross-Validate

[62]:
```
s = pd.Series(X_factors.columns.tolist())
cat_cols_idx = s[s.isin(cat_cols)].index.tolist()
```

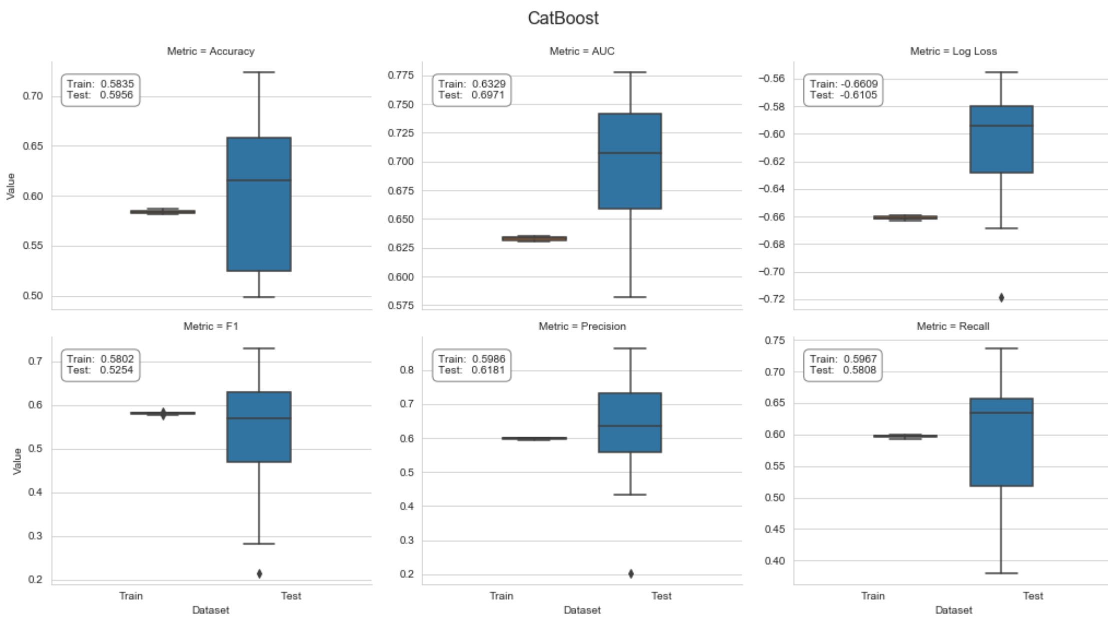
[63]:
```
fname = 'results/cat_cv_result.joblib'
if not Path(fname).exists():
    cat_cv_result = run_cv(cat_clf, X=X_factors, fit_params={'cat_features':␣
↪cat_cols_idx})
    joblib.dump(cat_cv_result, fname)
else:
    cat_cv_result = joblib.load(fname)
```

1.11.3 Plot Results

[64]:
```python
cat_result = stack_results(cat_cv_result)
cat_result.groupby(['Metric', 'Dataset']).Value.mean().unstack()
```

[64]:
```
Dataset         Test     Train
Metric
AUC         0.697064  0.632887
Accuracy    0.595647  0.583538
F1          0.525387  0.580220
Log Loss   -0.610451 -0.660919
Precision   0.618131  0.598573
Recall      0.580783  0.596744
```

[67]:
```python
plot_result(cat_result, model='CatBoost')
```



1.12 Compare Results

[68]:
```python
results = {'Baseline': dummy_result,
           'Random Forest': rf_result,
           'AdaBoost': ada_result,
           'Gradient Booster': gb_result,
           'XG Boost': xbg_result,
           'LightGBM Dummies': lgb_dummy_result,
           'LightGBM Factors': lgb_factor_result,
           'CatBoost': cat_result}
df = pd.DataFrame()
```

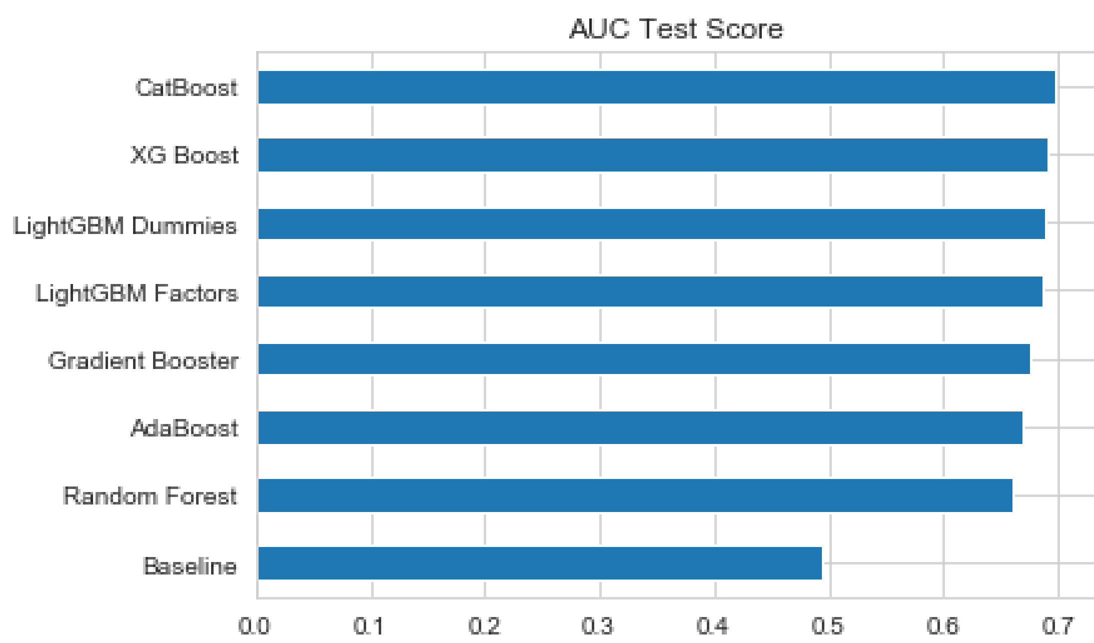
```python
for model, result in results.items():
    df = pd.concat([df, result.groupby(['Metric', 'Dataset']
                                        ).Value.mean().unstack()['Test'].
 ↪to_frame(model)], axis=1)

df.T.sort_values('AUC', ascending=False)
```

[68]:

Metric	AUC	Accuracy	F1	Log Loss	Precision	Recall
CatBoost	0.697064	0.595647	0.525387	-0.610451	0.618131	0.580783
XG Boost	0.690214	0.626261	0.570426	-0.590711	0.700872	0.592593
LightGBM Dummies	0.690086	0.624242	0.570777	-0.581760	0.655675	0.599825
LightGBM Factors	0.685903	0.591003	0.530207	-0.603009	0.608764	0.578861
Gradient Booster	0.675116	0.627907	0.589335	-0.626003	0.714278	0.625646
AdaBoost	0.668890	0.626251	0.590490	-0.692288	0.707423	0.619776
Random Forest	0.659692	0.616270	0.592029	-0.611774	0.665563	0.602865
Baseline	0.494516	0.494516	0.501068	-17.594264	0.534767	0.490601

[69]:

```python
df.T['AUC'].sort_values().plot.barh(title='AUC Test Score');
```



[ ]:

```python
fig, ax = plt.subplots(figsize=(14, 8))
auc = pd.concat([v.loc[(v.Dataset=='Test') & (v.Metric=='AUC'), 'Value'].
 ↪to_frame('AUC').assign(Model=k)
                 for k, v in results.items()])
auc = auc[auc.Model != 'Baseline']
sns.barplot(x='Model', y='AUC', data=auc, ax=ax)
ax.set_ylim(.5, .8);
```