06_evaluate_trading_signals

September 29, 2021

1 Long-Short Strategy, Part 3: Evaluating our Boosting Model Signals

In this section, we'll start designing, implementing, and evaluating a trading strategy for US equities driven by daily return forecasts produced by gradient boosting models.

As in the previous examples, we'll lay out a framework and build a specific example that you can adapt to run your own experiments. There are numerous aspects that you can vary, from the asset class and investment universe to more granular aspects like the features, holding period, or trading rules. See, for example, the **Alpha Factor Library** in the Appendix for numerous additional features.

We'll keep the trading strategy simple and only use a single ML signal; a real-life application will likely use multiple signals from different sources, such as complementary ML models trained on different datasets or with different lookahead or lookback periods. It would also use sophisticated risk management, from simple stop-loss to value-at-risk analysis.

Six notebooks cover our workflow sequence:

1. preparing_the_model_data: we engineer a few simple features from the Quandl Wiki data
2. trading_signals_with_lightgbm_and_catboost: we tune hyperparameters for LightGBM and CatBoost to select a model, using 2015/16 as our validation period.
3. `evaluate_trading_signals` (this noteboook): we compare the cross-validation performance using various metrics to select the best model.
4. model_interpretation: we take a closer look at the drivers behind the best model's predictions.
5. making_out_of_sample_predictions: we generate predictions for our out-of-sample test period 2017.
6. backtesting_with_zipline: evaluate the historical performance of a long-short strategy based on our predictive signals using Zipline.

Cross-validation of numerous configurations has produced a large number of results. Now, we need to evaluate the predictive performance to identify the model that generates the most reliable and profitable signals for our prospective trading strategy.

1.1 Imports & Settings

[1]:
```
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
%matplotlib inline

from time import time
from io import StringIO
import sys, os
import warnings
from pathlib import Path
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns

import lightgbm as lgb

from scipy.stats import spearmanr, pearsonr

from alphalens import plotting
from alphalens import performance as perf
from alphalens.utils import get_clean_factor_and_forward_returns,␣
↪rate_of_return, std_conversion
from alphalens.tears import (create_summary_tear_sheet,
                             create_full_tear_sheet)
```

[3]:
```
sys.path.insert(1, os.path.join(sys.path[0], '..'))
from utils import MultipleTimeSeriesCV
```

[4]:
```
sns.set_style('whitegrid')
```

[5]:
```
YEAR = 252
idx = pd.IndexSlice
```

[6]:
```
scope_params = ['lookahead', 'train_length', 'test_length']
daily_ic_metrics = ['daily_ic_mean', 'daily_ic_mean_n', 'daily_ic_median',␣
↪'daily_ic_median_n']
lgb_train_params = ['learning_rate', 'num_leaves', 'feature_fraction',␣
↪'min_data_in_leaf']
catboost_train_params = ['max_depth', 'min_child_samples']
```

[7]:
```
results_path = Path('results', 'us_stocks')
if not results_path.exists():
    results_path.mkdir(parents=True)
```

1.2 Collect Data

We produced a larger number of LightGBM models because it runs an order of magnitude faster than CatBoost and will demonstrate some evaluation strategies accordingly.

1.2.1 LightGBM

Summary Metrics by Fold First, we collect the summary metrics computed for each fold and hyperparameter combination:

[8]:
```
with pd.HDFStore(results_path / 'tuning_lgb.h5') as store:
    for i, key in enumerate(
        [k[1:] for k in store.keys() if k[1:].startswith('metrics')]):
        _, t, train_length, test_length = key.split('/')[:4]
        attrs = {
            'lookahead': t,
            'train_length': train_length,
            'test_length': test_length
        }
        s = store[key].to_dict()
        s.update(attrs)
        if i == 0:
            lgb_metrics = pd.Series(s).to_frame(i)
        else:
            lgb_metrics[i] = pd.Series(s)

id_vars = scope_params + lgb_train_params + daily_ic_metrics
lgb_metrics = pd.melt(lgb_metrics.T.drop('t', axis=1),
                      id_vars=id_vars,
                      value_name='ic',
                      var_name='boost_rounds').dropna().apply(pd.to_numeric)
```

[9]:
```
lgb_metrics.to_hdf('data/model_tuning.h5', 'lgb/metrics')
lgb_metrics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2457 entries, 0 to 2456
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   lookahead          2457 non-null   int64
 1   train_length       2457 non-null   int64
 2   test_length        2457 non-null   int64
 3   learning_rate      2457 non-null   float64
 4   num_leaves         2457 non-null   float64
 5   feature_fraction   2457 non-null   float64
 6   min_data_in_leaf   2457 non-null   float64
 7   daily_ic_mean      2457 non-null   float64
 8   daily_ic_mean_n    2457 non-null   float64
 9   daily_ic_median    2457 non-null   float64
 10  daily_ic_median_n  2457 non-null   float64
 11  boost_rounds       2457 non-null   int64
 12  ic                 2457 non-null   float64
```

```
dtypes: float64(9), int64(4)
memory usage: 268.7 KB
```

[10]:
```
lgb_metrics.groupby(scope_params).size()
```

[10]:
```
lookahead  train_length  test_length
1          756           63             351
           1134          63             486
5          756           63             324
           1134          63             486
21         756           63             324
           1134          63             486
dtype: int64
```

Information Coefficient by Day Next, we retrieve the IC per day computed during cross-validation:

[11]:
```
int_cols = ['lookahead', 'train_length', 'test_length', 'boost_rounds']
```

[12]:
```
lgb_ic = []
with pd.HDFStore(results_path / 'tuning_lgb.h5') as store:
    keys = [k[1:] for k in store.keys()]
    for key in keys:
        _, t, train_length, test_length = key.split('/')[:4]
        if key.startswith('daily_ic'):
            df = (store[key]
                   .drop(['boosting', 'objective', 'verbose'], axis=1)
                  .assign(lookahead=t,
                          train_length=train_length,
                          test_length=test_length))
            lgb_ic.append(df)
    lgb_ic = pd.concat(lgb_ic).reset_index()
```

[13]:
```
id_vars = ['date'] + scope_params + lgb_train_params
lgb_ic = pd.melt(lgb_ic,
                 id_vars=id_vars,
                 value_name='ic',
                 var_name='boost_rounds').dropna()
lgb_ic.loc[:, int_cols] = lgb_ic.loc[:, int_cols].astype(int)
```

[14]:
```
lgb_ic.to_hdf('data/model_tuning.h5', 'lgb/ic')
lgb_ic.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1564369 entries, 0 to 1788695
Data columns (total 10 columns):
 #   Column          Non-Null Count    Dtype
---  ------          --------------    -----
```

```
 0   date               1564369 non-null  datetime64[ns]
 1   lookahead          1564369 non-null  int64
 2   train_length       1564369 non-null  int64
 3   test_length        1564369 non-null  int64
 4   learning_rate      1564369 non-null  float64
 5   num_leaves         1564369 non-null  int64
 6   feature_fraction   1564369 non-null  float64
 7   min_data_in_leaf   1564369 non-null  int64
 8   boost_rounds       1564369 non-null  int64
 9   ic                 1564369 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(6)
memory usage: 131.3 MB
```

[15]:
```
lgb_daily_ic = lgb_ic.groupby(id_vars[1:] + ['boost_rounds']).ic.mean().
 ↪to_frame('ic').reset_index()
lgb_daily_ic.to_hdf('data/model_tuning.h5', 'lgb/daily_ic')
lgb_daily_ic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3105 entries, 0 to 3104
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   lookahead         3105 non-null   int64
 1   train_length      3105 non-null   int64
 2   test_length       3105 non-null   int64
 3   learning_rate     3105 non-null   float64
 4   num_leaves        3105 non-null   int64
 5   feature_fraction  3105 non-null   float64
 6   min_data_in_leaf  3105 non-null   int64
 7   boost_rounds      3105 non-null   int64
 8   ic                3105 non-null   float64
dtypes: float64(3), int64(6)
memory usage: 218.4 KB
```

[16]:
```
lgb_ic = pd.read_hdf('data/model_tuning.h5', 'lgb/ic')
lgb_daily_ic = pd.read_hdf('data/model_tuning.h5', 'lgb/daily_ic')
```

1.2.2 CatBoost

We proceed similarly for CatBoost:

Summary Metrics

[17]:
```
with pd.HDFStore(results_path / 'tuning_catboost.h5') as store:
    for i, key in enumerate(
            [k[1:] for k in store.keys() if k[1:].startswith('metrics')]):
        _, t, train_length, test_length = key.split('/')[:4]
```

```
        attrs = {
            'lookahead'    : t,
            'train_length': train_length,
            'test_length' : test_length
        }
        s = store[key].to_dict()
        s.update(attrs)
        if i == 0:
            catboost_metrics = pd.Series(s).to_frame(i)
        else:
            catboost_metrics[i] = pd.Series(s)

id_vars = scope_params + catboost_train_params + daily_ic_metrics
catboost_metrics = pd.melt(catboost_metrics.T.drop('t', axis=1),
                           id_vars=id_vars,
                           value_name='ic',
                           var_name='boost_rounds').dropna().apply(pd.
 ↪to_numeric)
```

[18]:
```
catboost_metrics.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1176 entries, 0 to 1175
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   lookahead          1176 non-null   int64
 1   train_length       1176 non-null   int64
 2   test_length        1176 non-null   int64
 3   max_depth          1176 non-null   float64
 4   min_child_samples  1176 non-null   float64
 5   daily_ic_mean      1176 non-null   float64
 6   daily_ic_mean_n    1176 non-null   float64
 7   daily_ic_median    1176 non-null   float64
 8   daily_ic_median_n  1176 non-null   float64
 9   boost_rounds       1176 non-null   int64
 10  ic                 1176 non-null   float64
dtypes: float64(7), int64(4)
memory usage: 110.2 KB
```

[19]:
```
catboost_metrics.groupby(scope_params).size()
```

[19]:
```
lookahead  train_length  test_length
1          252           21             168
           756           63             168
           1134          63             168
5          252           21             168
```

```
            756          63             168
21          252          63             168
            756          63             168
dtype: int64
```

Daily Information Coefficient

[20]:
```
catboost_ic = []
with pd.HDFStore(results_path / 'tuning_catboost.h5') as store:
    keys = [k[1:] for k in store.keys()]
    for key in keys:
        _, t, train_length, test_length = key.split('/')[:4]
        if key.startswith('daily_ic'):
            df = (store[key].drop('task_type', axis=1)
                  .assign(lookahead=t,
                          train_length=train_length,
                          test_length=test_length))
            catboost_ic.append(df)
    catboost_ic = pd.concat(catboost_ic).reset_index()
```

[21]:
```
id_vars = ['date'] + scope_params + catboost_train_params
catboost_ic = pd.melt(catboost_ic,
                      id_vars=id_vars,
                      value_name='ic',
                      var_name='boost_rounds').dropna()
catboost_ic.loc[:, int_cols] = catboost_ic.loc[:, int_cols].astype(int)
```

[22]:
```
catboost_ic.to_hdf('data/model_tuning.h5', 'catboost/ic')
catboost_ic.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 592704 entries, 0 to 592703
Data columns (total 8 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   date               592704 non-null  datetime64[ns]
 1   lookahead          592704 non-null  int64
 2   train_length       592704 non-null  int64
 3   test_length        592704 non-null  int64
 4   max_depth          592704 non-null  int64
 5   min_child_samples  592704 non-null  int64
 6   boost_rounds       592704 non-null  int64
 7   ic                 592704 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(6)
memory usage: 40.7 MB
```

```
[23]: catboost_daily_ic = catboost_ic.groupby(id_vars[1:] + ['boost_rounds']).ic.
       ↪mean().to_frame('ic').reset_index()
      catboost_daily_ic.to_hdf('data/model_tuning.h5', 'catboost/daily_ic')
      catboost_daily_ic.info()
```

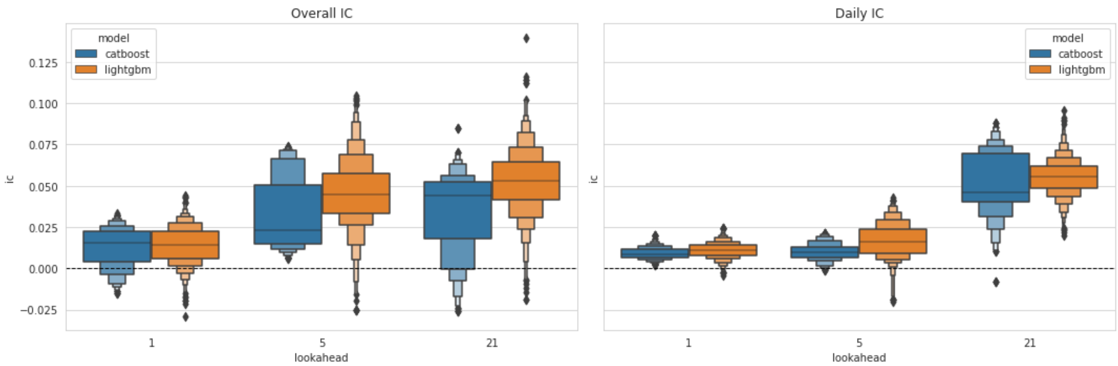
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1176 entries, 0 to 1175
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   lookahead          1176 non-null   int64
 1   train_length       1176 non-null   int64
 2   test_length        1176 non-null   int64
 3   max_depth          1176 non-null   int64
 4   min_child_samples  1176 non-null   int64
 5   boost_rounds       1176 non-null   int64
 6   ic                 1176 non-null   float64
dtypes: float64(1), int64(6)
memory usage: 64.4 KB
```

```
[24]: catboost_ic = pd.read_hdf('data/model_tuning.h5', 'catboost/ic')
      catboost_daily_ic = pd.read_hdf('data/model_tuning.h5', 'catboost/daily_ic')
```

1.3 Validation Performance: Daily vs Overall Information Coefficient

The following image shows that that LightGBM (in orange) performs (slightly) better than CatBoost, especially for longer horizons. This is not an entirely fair comparison because we ran more configurations for LightGBM, which also, unsurprisingly, shows a wider dispersion of outcomes:

```
[25]: fig, axes = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
      sns.boxenplot(x='lookahead', y='ic', hue='model',
                    data=catboost_metrics.assign(model='catboost')
                    .append(lgb_metrics.assign(model='lightgbm')), ax=axes[0])
      axes[0].axhline(0, ls='--', lw=1, c='k')
      axes[0].set_title('Overall IC')
      sns.boxenplot(x='lookahead', y='ic', hue='model',
                    data=catboost_daily_ic.assign(model='catboost')
                    .append(lgb_daily_ic.assign(model='lightgbm')), ax=axes[1])
      axes[1].axhline(0, ls='--', lw=1, c='k')
      axes[1].set_title('Daily IC')
      fig.tight_layout()
```



1.4 HyperParameter Impact: Linear Regression

Next, we'd like to understand if there's a systematic, statistical relationship between the hyperparameters and the outcomes across daily predictions. To this end, we will run a linear regression using the various LightGBM hyperparameter settings as dummy variables and the daily validation IC as the outcome.

The below chart shows the coefficient estimates and their confidence intervals for 1- and 21-day forecast horizons. - For the shorter horizon, a longer lookback period, a higher learning rate, and deeper trees (more leaf nodes) have a positive impact. - For the longer horizon, the picture is a little less clear: shorter trees do better, but the lookback period is not significant. A higher feature sampling rate also helps. In both cases, a larger ensemble does better.

Note that these results apply to this specific example only.

[29]:
```
lin_reg = {}
for t in [1, 21]:
    df_ = lgb_ic[lgb_ic.lookahead==t]
    y, X = df_.ic, df_.drop(['ic'], axis=1)
    X = sm.add_constant(pd.get_dummies(X, columns=X.columns, drop_first=True))
    model = sm.OLS(endog=y, exog=X)
    lin_reg[t] = model.fit()
    s = lin_reg[t].summary()
    coefs = pd.read_csv(StringIO(s.tables[1].as_csv())).rename(columns=lambda x:
 ↪ x.strip())
    coefs.columns = ['variable', 'coef', 'std_err', 't', 'p_value', 'ci_low',␣
 ↪'ci_high']
    coefs.to_csv(f'results/linreg_result_{t:02}.csv', index=False)
```

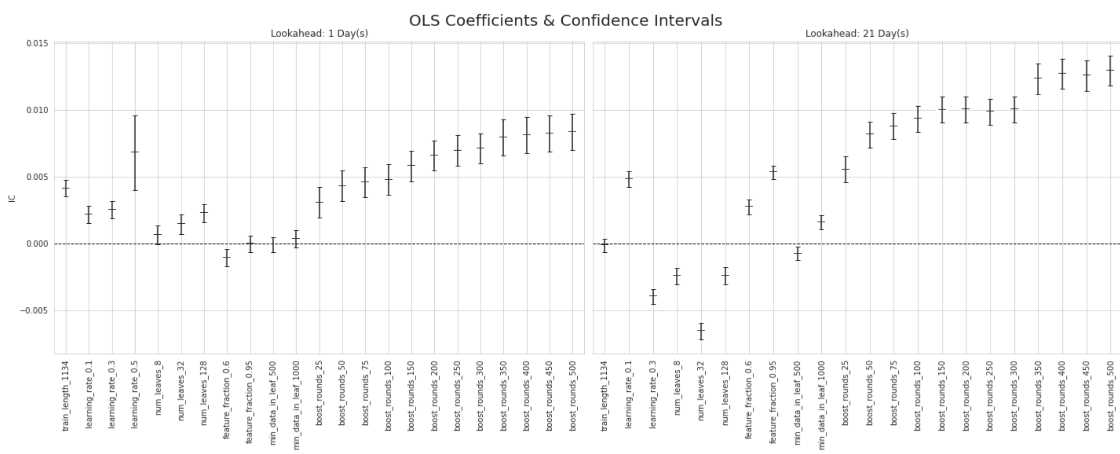
[30]:
```
def visualize_lr_result(model, ax):
    ci = model.conf_int()
    errors = ci[1].sub(ci[0]).div(2)

    coefs = (model.params.to_frame('coef').assign(error=errors)
             .reset_index().rename(columns={'index': 'variable'}))
```

```
    coefs = coefs[~coefs['variable'].str.startswith('date')&(coefs.variable!
↪='const')]

    coefs.plot(x='variable', y='coef', kind='bar',
               ax=ax, color='none', capsize=3,
               yerr='error', legend=False)
    ax.set_ylabel('IC')
    ax.set_xlabel('')
    ax.scatter(x=pd.np.arange(len(coefs)), marker='_', s=120, y=coefs['coef'],␣
↪color='black')
    ax.axhline(y=0, linestyle='--', color='black', linewidth=1)
    ax.xaxis.set_ticks_position('none')
```

[31]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20, 8), sharey=True)
axes = axes.flatten()
for i, t in enumerate([1, 21]):
    visualize_lr_result(lin_reg[t], axes[i])
    axes[i].set_title(f'Lookahead: {t} Day(s)')
fig.suptitle('OLS Coefficients & Confidence Intervals', fontsize=20)
fig.tight_layout()
fig.subplots_adjust(top=.92);
```



1.5 Cross-validation Result: Best Hyperparameters

1.5.1 LightGBM

The top-performing LightGBM models use the following parameters for the three different prediction horizons.

[32]:
```
group_cols = scope_params + lgb_train_params + ['boost_rounds']
lgb_daily_ic.groupby('lookahead', group_keys=False).apply(lambda x: x.
↪nlargest(3, 'ic'))
```

[32]:

	lookahead	train_length	test_length	learning_rate	num_leaves
595	1	1134	63	0.01	128
596	1	1134	63	0.01	128
610	1	1134	63	0.01	128
1569	5	1134	63	0.10	4
1568	5	1134	63	0.10	4
1570	5	1134	63	0.10	4
2260	21	756	63	0.10	128
2261	21	756	63	0.10	128
2262	21	756	63	0.10	128

	feature_fraction	min_data_in_leaf	boost_rounds	ic
595	0.95	250	400	0.024674
596	0.95	250	450	0.024292
610	0.95	500	500	0.024198
1569	0.30	500	400	0.042814
1568	0.30	500	350	0.041771
1570	0.30	500	450	0.041151
2260	0.95	1000	25	0.095405
2261	0.95	1000	50	0.091278
2262	0.95	1000	75	0.089669

[33]:

```
lgb_metrics.groupby('lookahead', group_keys=False).apply(lambda x: x.
↪nlargest(3, 'ic'))
lgb_metrics.groupby('lookahead', group_keys=False).apply(lambda x: x.
↪nlargest(3, 'ic')).to_csv('results/best_lgb_model.csv', index=False)
```

[34]:

```
lgb_metrics.groupby('lookahead', group_keys=False).apply(lambda x: x.
↪nlargest(3, 'daily_ic_mean'))
```

[34]:

	lookahead	train_length	test_length	learning_rate	num_leaves
267	1	1134	63	0.01	128.0
540	1	1134	63	0.01	128.0
813	1	1134	63	0.01	128.0
63	5	1134	63	0.10	4.0
336	5	1134	63	0.10	4.0
609	5	1134	63	0.10	4.0
120	21	756	63	0.10	128.0
393	21	756	63	0.10	128.0
666	21	756	63	0.10	128.0

	feature_fraction	min_data_in_leaf	daily_ic_mean	daily_ic_mean_n
267	0.95	250.0	0.024674	400.0
540	0.95	250.0	0.024674	400.0
813	0.95	250.0	0.024674	400.0
63	0.30	500.0	0.042814	400.0
336	0.30	500.0	0.042814	400.0

```
609                0.30             500.0       0.042814            400.0
120                0.95            1000.0       0.095405             25.0
393                0.95            1000.0       0.095405             25.0
666                0.95            1000.0       0.095405             25.0

     daily_ic_median  daily_ic_median_n  boost_rounds        ic
267         0.023807              500.0            10 -0.002447
540         0.023807              500.0            25 -0.000077
813         0.023807              500.0            50 -0.000030
63          0.038330              500.0            10  0.055980
336         0.038330              500.0            25  0.055506
609         0.038330              500.0            50  0.045449
120         0.099453               25.0            10  0.082795
393         0.099453               25.0            25  0.076064
666         0.099453               25.0            50  0.072365
```

1.5.2 CatBoost

[35]:
```
group_cols = scope_params + catboost_train_params + ['boost_rounds']
catboost_daily_ic.groupby('lookahead', group_keys=False).apply(lambda x: x.
 ↪nlargest(3, 'ic'))
```

[35]:
```
      lookahead  train_length  test_length  max_depth  min_child_samples  \
341           1          1134           63          3                 20
355           1          1134           63          3                250
369           1          1134           63          3                500
679           5           756           63          3                 20
693           5           756           63          3                250
707           5           756           63          3                500
1051         21           756           63          5                 20
1065         21           756           63          5                250
1079         21           756           63          5                500

      boost_rounds        ic
341            200  0.019974
355            200  0.019974
369            200  0.019973
679            400  0.021375
693            400  0.021375
707            400  0.021375
1051            25  0.088109
1065            25  0.088109
1079            25  0.088109
```

[36]:
```
catboost_metrics.groupby('lookahead', group_keys=False).apply(lambda x: x.
 ↪nlargest(3, 'ic'))
```

[36]:

	lookahead	train_length	test_length	max_depth	min_child_samples
920	1	1134	63	5.0	500.0
836	1	1134	63	5.0	500.0
1172	1	1134	63	5.0	500.0
935	5	756	63	3.0	500.0
1102	5	756	63	3.0	250.0
513	5	756	63	3.0	20.0
33	21	756	63	3.0	20.0
34	21	756	63	3.0	250.0
35	21	756	63	3.0	500.0

	daily_ic_mean	daily_ic_mean_n	daily_ic_median	daily_ic_median_n
920	0.015616	10.0	0.016628	10.0
836	0.015616	10.0	0.016628	10.0
1172	0.015616	10.0	0.016628	10.0
935	0.021375	400.0	0.021886	600.0
1102	0.021375	400.0	0.021290	300.0
513	0.021375	400.0	0.021886	600.0
33	0.077041	500.0	0.094301	300.0
34	0.077041	500.0	0.094301	300.0
35	0.076753	500.0	0.094931	300.0

	boost_rounds	ic
920	700	0.032989
836	600	0.032336
1172	1000	0.032125
935	800	0.073752
1102	1000	0.073468
513	300	0.073285
33	10	0.085074
34	10	0.085074
35	10	0.085074

[37]:

```
catboost_metrics.groupby('lookahead', group_keys=False).apply(lambda x: x.
↪nlargest(3, 'daily_ic_mean'))
```

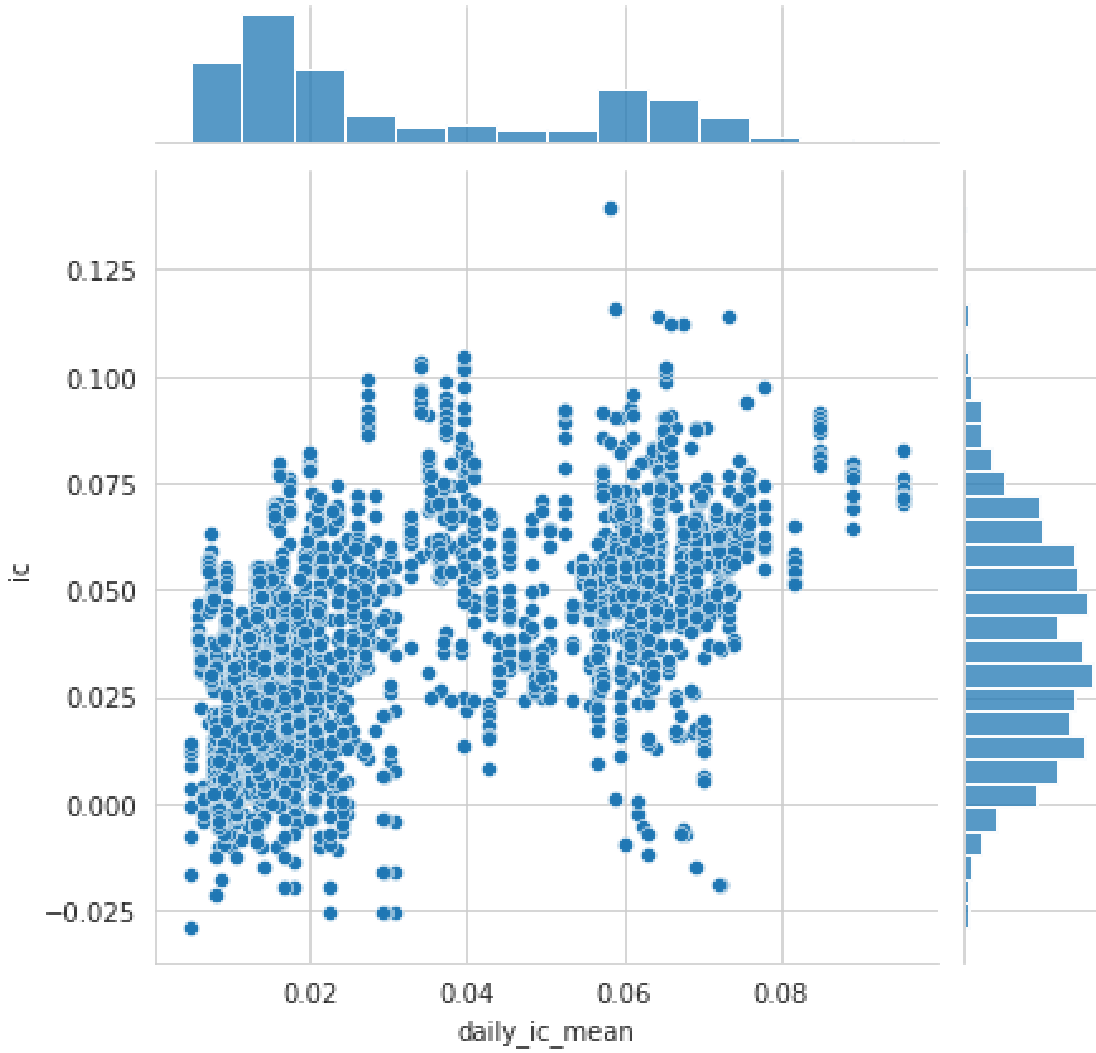
[37]:

	lookahead	train_length	test_length	max_depth	min_child_samples
81	1	1134	63	3.0	20.0
82	1	1134	63	3.0	250.0
165	1	1134	63	3.0	20.0
9	5	756	63	3.0	20.0
10	5	756	63	3.0	250.0
11	5	756	63	3.0	500.0
30	21	756	63	5.0	20.0
31	21	756	63	5.0	250.0
32	21	756	63	5.0	500.0

```
     daily_ic_mean  daily_ic_mean_n  daily_ic_median  daily_ic_median_n  \
81        0.019974            200.0         0.019573              300.0
82        0.019974            200.0         0.019452              300.0
165       0.019974            200.0         0.019573              300.0
9         0.021375            400.0         0.021886              600.0
10        0.021375            400.0         0.021290              300.0
11        0.021375            400.0         0.021886              600.0
30        0.088109             25.0         0.098979               50.0
31        0.088109             25.0         0.098979               50.0
32        0.088109             25.0         0.098979               50.0

     boost_rounds        ic
81             10  0.011191
82             10  0.011191
165            25  0.013491
9              10  0.012467
10             10  0.012467
11             10  0.012467
30             10 -0.004620
31             10 -0.004620
32             10 -0.004620
```

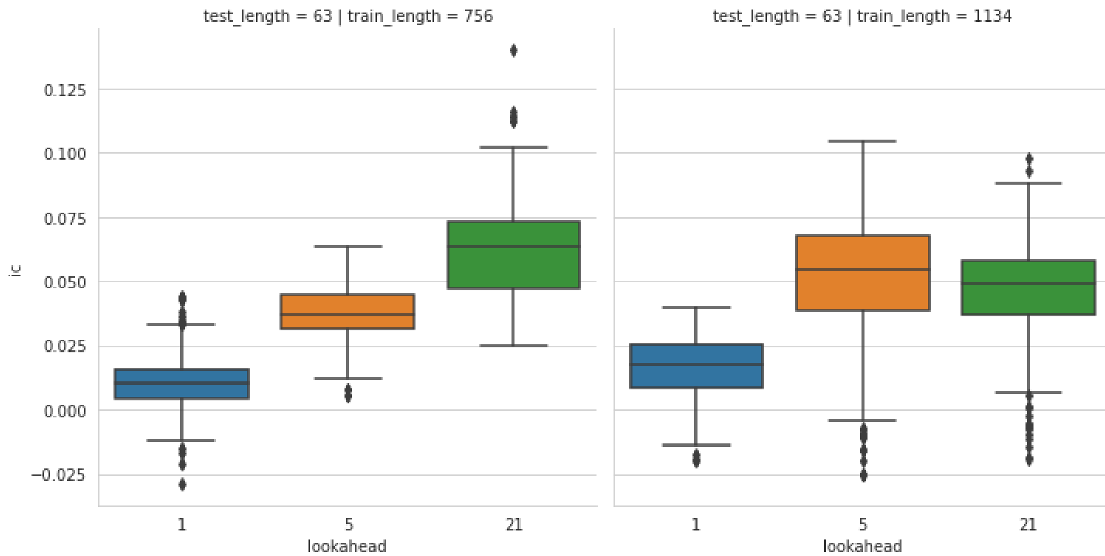
[39]:
```
sns.jointplot(x=lgb_metrics.daily_ic_mean,y=lgb_metrics.ic);
```



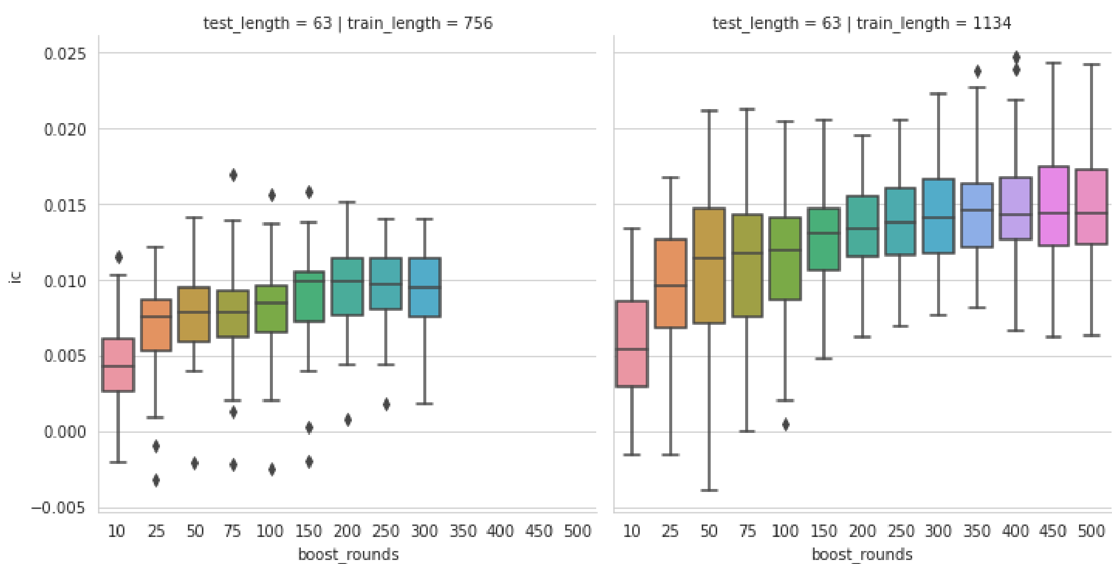
1.5.3 Visualization

LightGBM

[40]:
```
g = sns.catplot(x='lookahead', y='ic',
                col='train_length', row='test_length',
                data=lgb_metrics,
                kind='box')
```

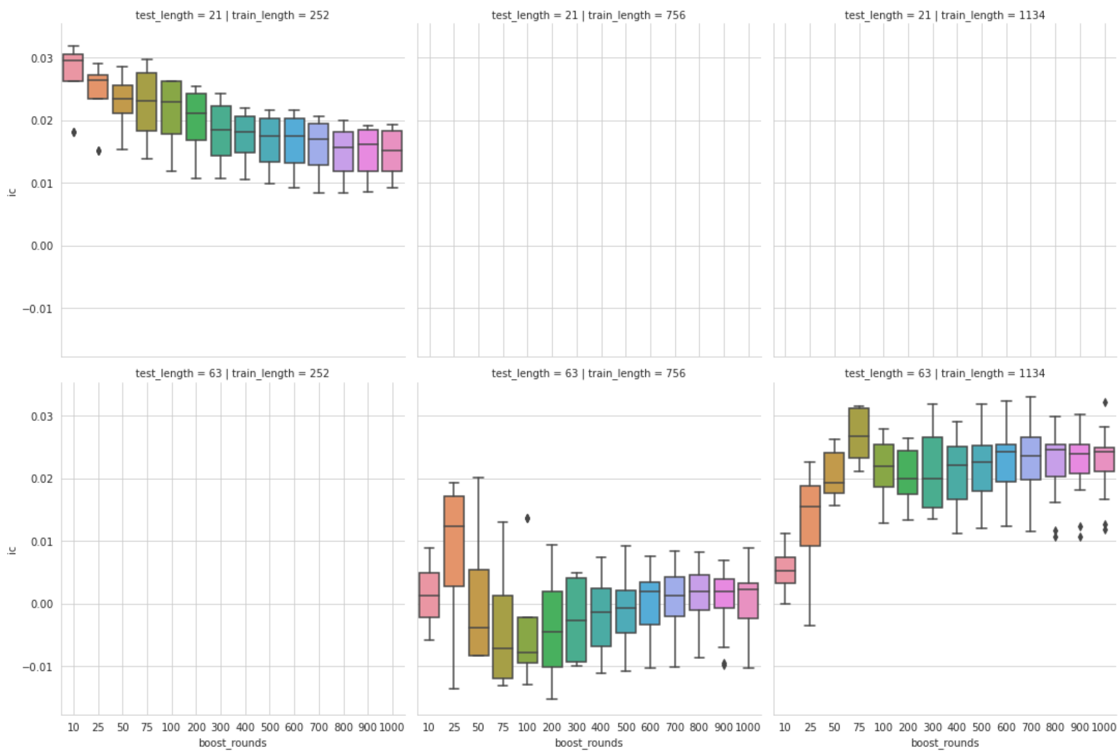


[41]:
```
t=1
g=sns.catplot(x='boost_rounds',
              y='ic',
              col='train_length',
              row='test_length',
              data=lgb_daily_ic[lgb_daily_ic.lookahead == t],
              kind='box')
```

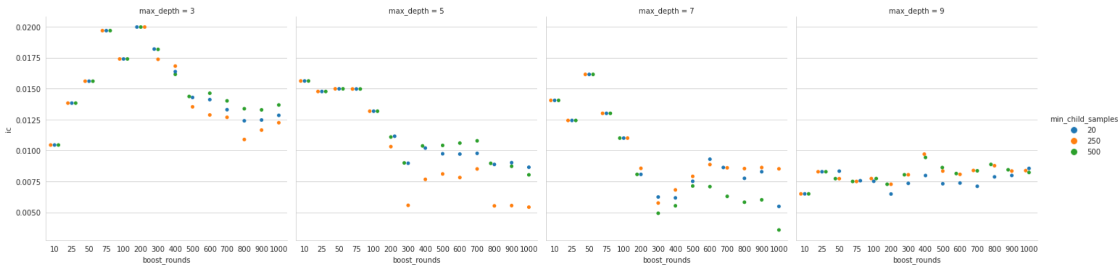


CatBoost Some figures are empty because we did not run those parameter combinations.

[42]:
```
t = 1
g=sns.catplot(x='boost_rounds',
            y='ic',
            col='train_length',
            row='test_length',
            data=catboost_metrics[catboost_metrics.lookahead == t],
            kind='box')
```



[43]:
```
t = 1
train_length = 1134
test_length = 63
g = sns.catplot(
    x='boost_rounds',
    y='ic',
    col='max_depth',
    hue='min_child_samples',
    data=catboost_daily_ic[(catboost_daily_ic.lookahead == t) &
                          (catboost_daily_ic.train_length == train_length) &
                          (catboost_daily_ic.test_length == test_length)],
    kind='swarm')
```



1.6 AlphaLens Analysis - Validation Performance

1.6.1 LightGBM

Select Parameters

[44]:
```
lgb_daily_ic = pd.read_hdf('data/model_tuning.h5', 'lgb/daily_ic')
lgb_daily_ic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3105 entries, 0 to 3104
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   lookahead         3105 non-null   int64
 1   train_length      3105 non-null   int64
 2   test_length       3105 non-null   int64
 3   learning_rate     3105 non-null   float64
 4   num_leaves        3105 non-null   int64
 5   feature_fraction  3105 non-null   float64
 6   min_data_in_leaf  3105 non-null   int64
 7   boost_rounds      3105 non-null   int64
 8   ic                3105 non-null   float64
dtypes: float64(3), int64(6)
memory usage: 242.6 KB
```

[45]:
```
def get_lgb_params(data, t=5, best=0):
    param_cols = scope_params[1:] + lgb_train_params + ['boost_rounds']
    df = data[data.lookahead==t].sort_values('ic', ascending=False).iloc[best]
    return df.loc[param_cols]
```

[46]:
```
def get_lgb_key(t, p):
    key = f'{t}/{int(p.train_length)}/{int(p.test_length)}/{p.learning_rate}/'
    return key + f'{int(p.num_leaves)}/{p.feature_fraction}/{int(p.
↪min_data_in_leaf)}'
```

[47]:
```
best_params = get_lgb_params(lgb_daily_ic, t=1, best=0)
best_params
```

[47]:
```
train_length          1134.00
test_length             63.00
learning_rate            0.01
num_leaves             128.00
feature_fraction         0.95
min_data_in_leaf       250.00
boost_rounds           400.00
Name: 595, dtype: float64
```

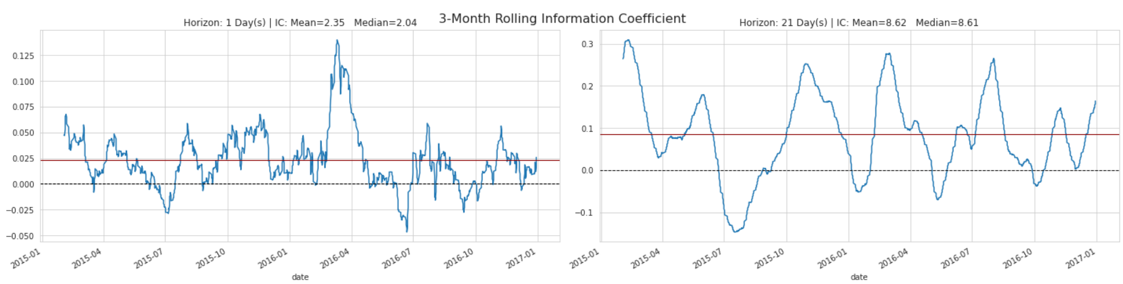
[48]:
```
best_params.to_hdf('data.h5', 'best_params')
```

Plot rolling IC

[49]:
```
def select_ic(params, ic_data, lookahead):
    return ic_data.loc[(ic_data.lookahead == lookahead) &
                       (ic_data.train_length == params.train_length) &
                       (ic_data.test_length == params.test_length) &
                       (ic_data.learning_rate == params.learning_rate) &
                       (ic_data.num_leaves == params.num_leaves) &
                       (ic_data.feature_fraction == params.feature_fraction) &
                       (ic_data.boost_rounds == params.boost_rounds), ['date',␣
↪'ic']].set_index('date')
```

[50]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20, 5))
axes = axes.flatten()
for i, t in enumerate([1, 21]):
    params = get_lgb_params(lgb_daily_ic, t=t)
    data = select_ic(params, lgb_ic, lookahead=t).sort_index()
    rolling = data.rolling(63).ic.mean().dropna()
    avg = data.ic.mean()
    med = data.ic.median()
    rolling.plot(ax=axes[i], title=f'Horizon: {t} Day(s) | IC: Mean={avg*100:.
↪2f}   Median={med*100:.2f}')
    axes[i].axhline(avg, c='darkred', lw=1)
    axes[i].axhline(0, ls='--', c='k', lw=1)

fig.suptitle('3-Month Rolling Information Coefficient', fontsize=16)
fig.tight_layout()
fig.subplots_adjust(top=0.92);
```



Get Predictions for Validation Period We retrieve the predictions for the 10 validation runs:

[51]:
```
lookahead = 1
topn = 10
for best in range(topn):
    best_params = get_lgb_params(lgb_daily_ic, t=lookahead, best=best)
    key = get_lgb_key(lookahead, best_params)
    rounds = str(int(best_params.boost_rounds))
    if best == 0:
        best_predictions = pd.read_hdf(results_path / 'tuning_lgb.h5',␣
↪'predictions/' + key)
        best_predictions = best_predictions[rounds].to_frame(best)
    else:
        best_predictions[best] = pd.read_hdf(results_path / 'tuning_lgb.h5',
                                             'predictions/' + key)[rounds]
best_predictions = best_predictions.sort_index()
```

[52]:
```
best_predictions.to_hdf('data/predictions.h5', f'lgb/train/{lookahead:02}')
best_predictions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 501310 entries, ('A', Timestamp('2015-01-02 00:00:00')) to ('ZION',
Timestamp('2016-12-30 00:00:00'))
Data columns (total 10 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   0       501310 non-null  float64
 1   1       501310 non-null  float64
 2   2       501310 non-null  float64
 3   3       501310 non-null  float64
 4   4       501310 non-null  float64
 5   5       501310 non-null  float64
 6   6       501310 non-null  float64
 7   7       501310 non-null  float64
 8   8       501310 non-null  float64
 9   9       501310 non-null  float64
dtypes: float64(10)
memory usage: 40.2+ MB
```

Get Trade Prices Using next available prices.

[53]:
```
def get_trade_prices(tickers):
    idx = pd.IndexSlice
    DATA_STORE = '../data/assets.h5'
```

```
    prices = (pd.read_hdf(DATA_STORE, 'quandl/wiki/prices').swaplevel().
 ↪sort_index())
    prices.index.names = ['symbol', 'date']
    return (prices.loc[idx[tickers, '2015': '2017'], 'adj_open']
            .unstack('symbol')
            .sort_index()
            .shift(-1)
            .tz_localize('UTC'))
```

[54]:
```
test_tickers = best_predictions.index.get_level_values('symbol').unique()
```

[55]:
```
trade_prices = get_trade_prices(test_tickers)
trade_prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 755 entries, 2015-01-02 00:00:00+00:00 to 2017-12-29
00:00:00+00:00
Columns: 995 entries, A to ZION
dtypes: float64(995)
memory usage: 5.7 MB
```

[56]:
```
# persist result in case we want to rerun:
trade_prices.to_hdf('data/model_tuning.h5', 'trade_prices/model_selection')
trade_prices = pd.read_hdf('data/model_tuning.h5', 'trade_prices/
 ↪model_selection')
```

We average the top five models and provide the corresponding prices to Alphalens, in order to compute the mean period-wise return earned on an equal-weighted portfolio invested in the daily factor quintiles for various holding periods:

[57]:
```
factor = best_predictions.iloc[:, :5].mean(1).dropna().tz_localize('UTC',␣
 ↪level='date').swaplevel()
```

Create AlphaLens Inputs

[58]:
```
factor_data = get_clean_factor_and_forward_returns(factor=factor,
                                                   prices=trade_prices,
                                                   quantiles=5,
                                                   periods=(1, 5, 10, 21))
```

```
Dropped 0.0% entries from factor data: 0.0% in forward returns computation and
0.0% in binning phase (set max_loss=0 to see potentially suppressed Exceptions).
max_loss is 35.0%, not exceeded: OK!
```

Compute Alphalens metrics

[59]:
```
mean_quant_ret_bydate, std_quant_daily = perf.mean_return_by_quantile(
    factor_data,
```

```
    by_date=True,
    by_group=False,
    demeaned=True,
    group_adjust=False,
)
```

[60]:
```
factor_returns = perf.factor_returns(factor_data)
```

[61]:
```
mean_quant_ret, std_quantile = perf.mean_return_by_quantile(factor_data,
                                                            by_group=False,
                                                            demeaned=True)




mean_quant_rateret = mean_quant_ret.apply(rate_of_return, axis=0,
                                          base_period=mean_quant_ret.columns[0])
```

[62]:
```
mean_quant_ret_bydate, std_quant_daily = perf.mean_return_by_quantile(
    factor_data,
    by_date=True,
    by_group=False,
    demeaned=True,
    group_adjust=False,
)

mean_quant_rateret_bydate = mean_quant_ret_bydate.apply(
    rate_of_return,
    base_period=mean_quant_ret_bydate.columns[0],
)

compstd_quant_daily = std_quant_daily.apply(std_conversion,
                                            base_period=std_quant_daily.
 ↪columns[0])

alpha_beta = perf.factor_alpha_beta(factor_data,
                                    demeaned=True)

mean_ret_spread_quant, std_spread_quant = perf.compute_mean_returns_spread(
    mean_quant_rateret_bydate,
    factor_data["factor_quantile"].max(),
    factor_data["factor_quantile"].min(),
    std_err=compstd_quant_daily,
)
```

[63]:
```
mean_ret_spread_quant.mean().mul(10000).to_frame('Mean Period Wise Spread␣
 ↪(bps)').join(alpha_beta.T).T
```

[63]:
```
                                    1D        5D       10D       21D
Mean Period Wise Spread (bps)  12.165432  6.951403  4.946450  4.407920
Ann. alpha                      0.175933  0.077596  0.044649  0.037394
beta                            0.089060  0.151587  0.191898  0.198344
```

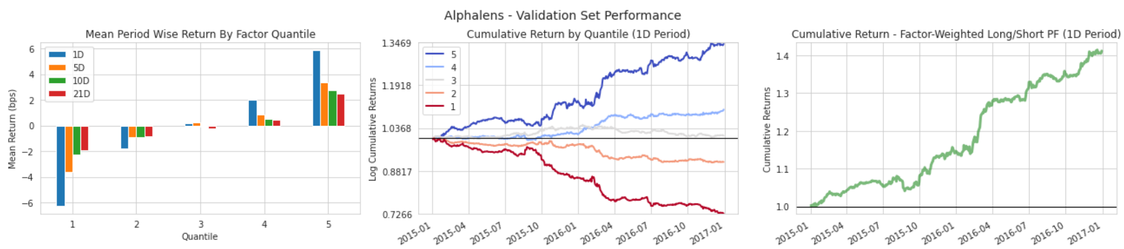
[64]:
```
fig, axes = plt.subplots(ncols=3, figsize=(18, 4))


plotting.plot_quantile_returns_bar(mean_quant_rateret, ax=axes[0])
plt.setp(axes[0].xaxis.get_majorticklabels(), rotation=0)
axes[0].set_xlabel('Quantile')

plotting.plot_cumulative_returns_by_quantile(mean_quant_ret_bydate['1D'],
                                             freq=pd.tseries.offsets.BDay(),
                                             period='1D',
                                             ax=axes[1])
axes[1].set_title('Cumulative Return by Quantile (1D Period)')

title = "Cumulative Return - Factor-Weighted Long/Short PF (1D Period)"
plotting.plot_cumulative_returns(factor_returns['1D'],
                                 period='1D',
                                 freq=pd.tseries.offsets.BDay(),
                                 title=title,
                                 ax=axes[2])

fig.suptitle('Alphalens - Validation Set Performance', fontsize=14)
fig.tight_layout()
fig.subplots_adjust(top=.85);
```



Summary Tearsheet

[65]:
```
create_summary_tear_sheet(factor_data)
```

Quantiles Statistics

```
                      min       max      mean       std   count    count %
factor_quantile
1               -0.043323  0.007629 -0.002025  0.003269  100296  20.006822
```

2	-0.013078	0.010640	-0.000747	0.002936	100247	19.997048
3	-0.008825	0.012310	-0.000009	0.002950	100223	19.992260
4	-0.008289	0.017452	0.000698	0.003072	100247	19.997048
5	-0.007450	0.052497	0.002109	0.003811	100296	20.006822

Returns Analysis

	1D	5D	10D	21D
Ann. alpha	0.176	0.078	0.045	0.037
beta	0.089	0.152	0.192	0.198
Mean Period Wise Return Top Quantile (bps)	5.884	3.375	2.742	2.496
Mean Period Wise Return Bottom Quantile (bps)	-6.282	-3.603	-2.240	-1.946
Mean Period Wise Spread (bps)	12.165	6.951	4.946	4.408

Information Analysis

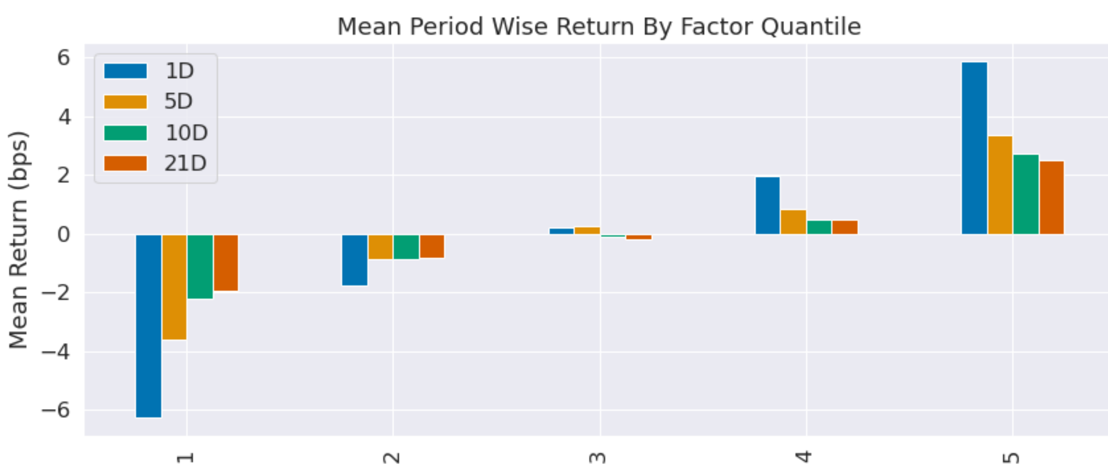
	1D	5D	10D	21D
IC Mean	0.020	0.021	0.022	0.034
IC Std.	0.126	0.136	0.141	0.140
Risk-Adjusted IC	0.162	0.158	0.156	0.246
t-stat(IC)	3.638	3.545	3.501	5.515
p-value(IC)	0.000	0.000	0.001	0.000
IC Skew	0.065	0.249	0.246	0.087
IC Kurtosis	0.970	1.544	0.567	0.740

Turnover Analysis

	1D	5D	10D	21D
Quantile 1 Mean Turnover	0.634	0.654	0.721	0.770
Quantile 2 Mean Turnover	0.751	0.756	0.779	0.790
Quantile 3 Mean Turnover	0.763	0.769	0.783	0.791
Quantile 4 Mean Turnover	0.752	0.756	0.777	0.795
Quantile 5 Mean Turnover	0.622	0.640	0.695	0.738

	1D	5D	10D	21D
Mean Factor Rank Autocorrelation	0.309	0.283	0.164	0.071

<Figure size 432x288 with 0 Axes>



[66]:
```
create_full_tear_sheet(factor_data)
```

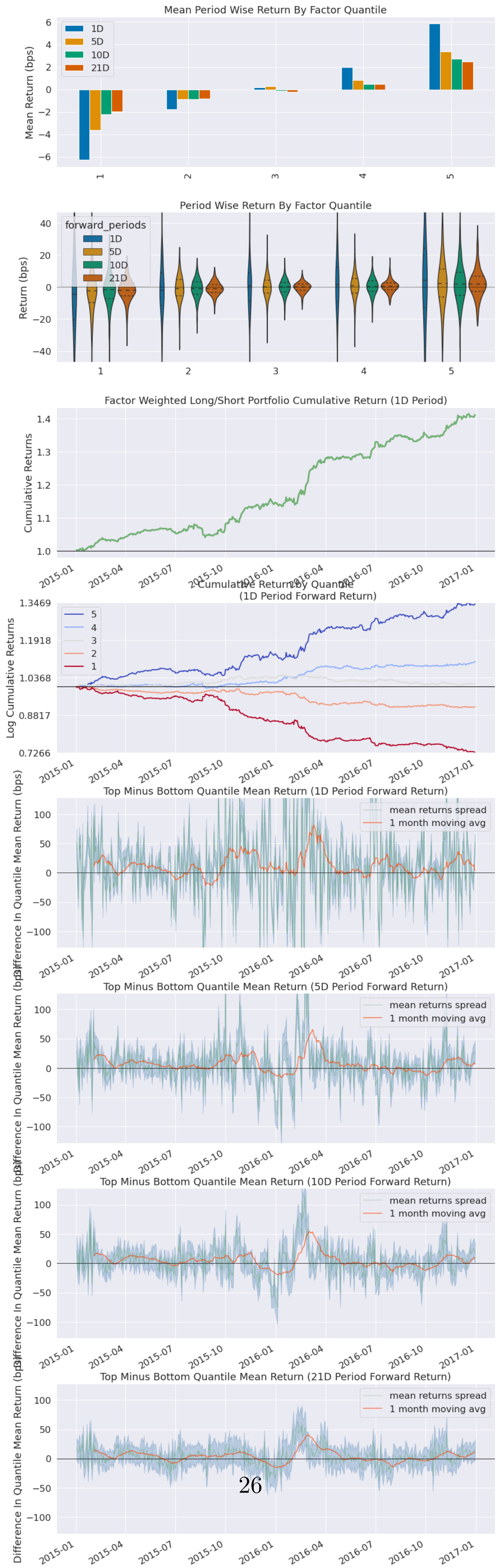
Quantiles Statistics

	min	max	mean	std	count	count %
factor_quantile						
1	-0.043323	0.007629	-0.002025	0.003269	100296	20.006822
2	-0.013078	0.010640	-0.000747	0.002936	100247	19.997048
3	-0.008825	0.012310	-0.000009	0.002950	100223	19.992260
4	-0.008289	0.017452	0.000698	0.003072	100247	19.997048
5	-0.007450	0.052497	0.002109	0.003811	100296	20.006822

Returns Analysis

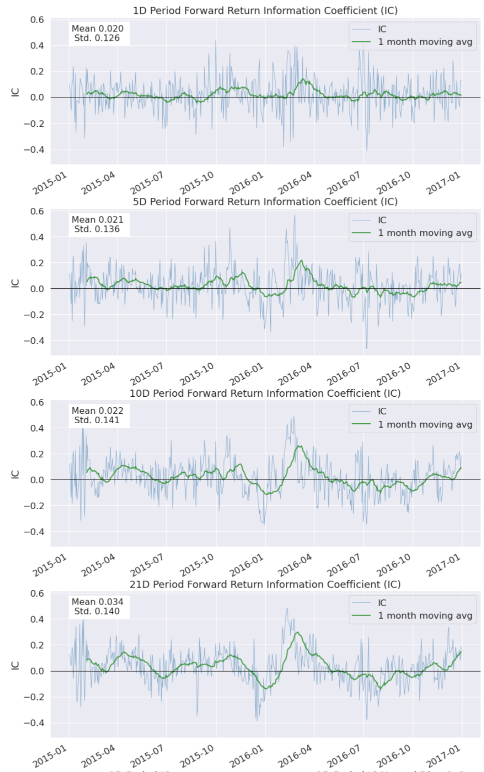
	1D	5D	10D	21D
Ann. alpha	0.176	0.078	0.045	0.037
beta	0.089	0.152	0.192	0.198
Mean Period Wise Return Top Quantile (bps)	5.884	3.375	2.742	2.496
Mean Period Wise Return Bottom Quantile (bps)	-6.282	-3.603	-2.240	-1.946
Mean Period Wise Spread (bps)	12.165	6.951	4.946	4.408

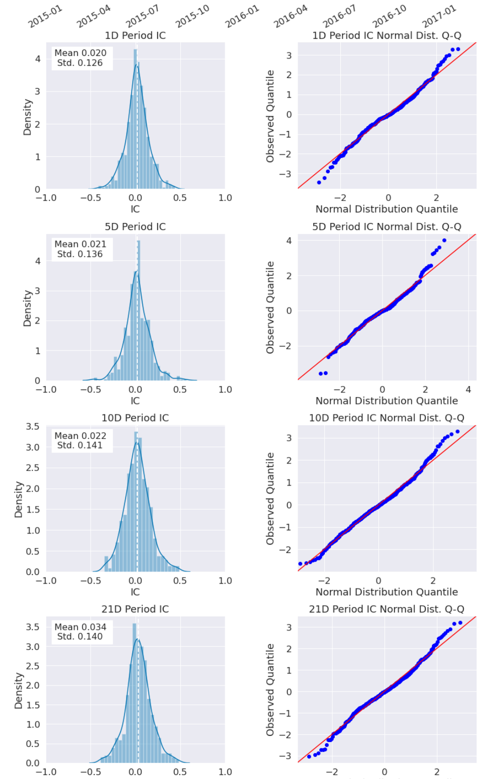
<Figure size 432x288 with 0 Axes>

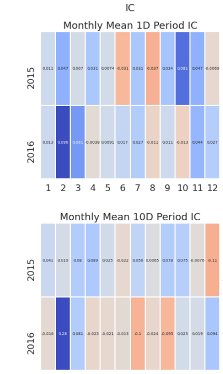

Mean Period Wise Return By Factor Quantile
Mean Return (bps)
1D
5D
10D
21D
Period Wise Return By Factor Quantile
forward_periods
Return (bps)
Factor Weighted Long/Short Portfolio Cumulative Return (1D Period)
Cumulative Returns
Cumulative Return by Quantile
(1D Period Forward Return)
Log Cumulative Returns
Top Minus Bottom Quantile Mean Return (1D Period Forward Return)
Difference In Quantile Mean Return (bps)
mean returns spread
1 month moving avg
Top Minus Bottom Quantile Mean Return (5D Period Forward Return)
Top Minus Bottom Quantile Mean Return (10D Period Forward Return)
Top Minus Bottom Quantile Mean Return (21D Period Forward Return)

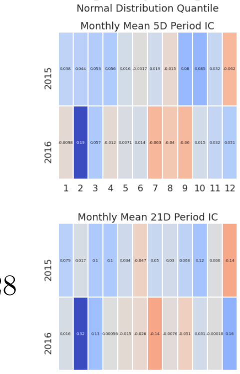
Information Analysis

	1D	5D	10D	21D
IC Mean	0.020	0.021	0.022	0.034
IC Std.	0.126	0.136	0.141	0.140
Risk-Adjusted IC	0.162	0.158	0.156	0.246
t-stat(IC)	3.638	3.545	3.501	5.515
p-value(IC)	0.000	0.000	0.001	0.000
IC Skew	0.065	0.249	0.246	0.087
IC Kurtosis	0.970	1.544	0.567	0.740


1D Period Forward Return Information Coefficient (IC)
Mean 0.020
Std. 0.126
IC
1 month moving avg
5D Period Forward Return Information Coefficient (IC)
Mean 0.021
Std. 0.136
10D Period Forward Return Information Coefficient (IC)
Mean 0.022
Std. 0.141
21D Period Forward Return Information Coefficient (IC)
Mean 0.034
Std. 0.140


1D Period IC
1D Period IC Normal Dist. Q-Q
5D Period IC
5D Period IC Normal Dist. Q-Q
10D Period IC
10D Period IC Normal Dist. Q-Q
21D Period IC
21D Period IC Normal Dist. Q-Q
Density
Observed Quantile
Normal Distribution Quantile

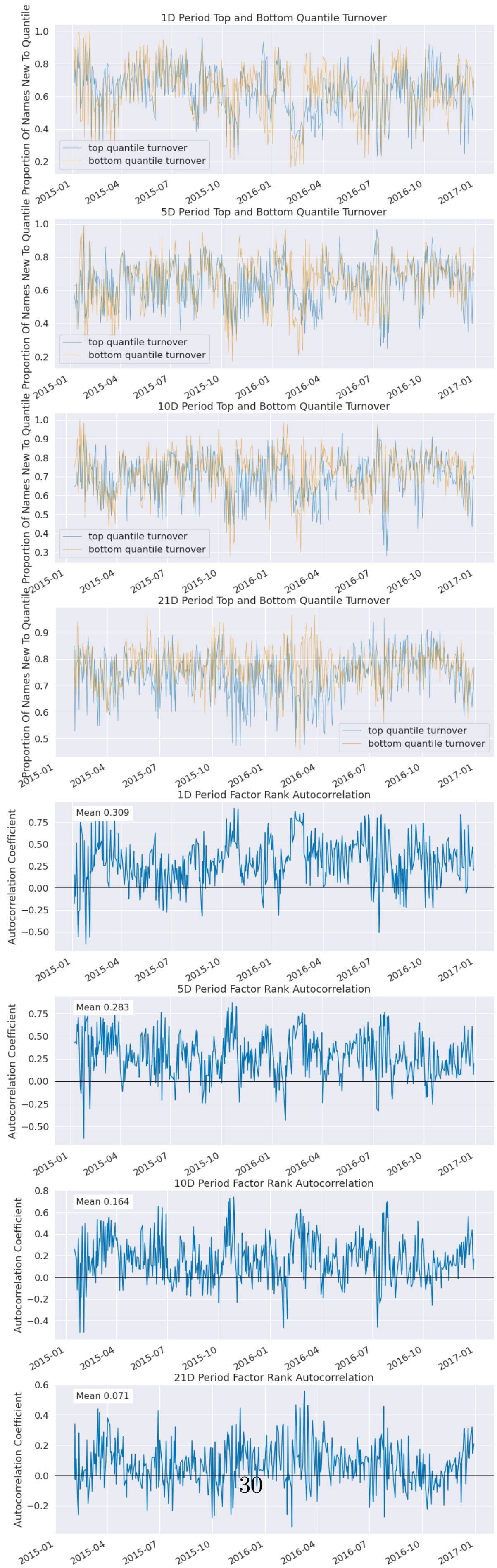

Monthly Mean 1D Period IC
Monthly Mean 10D Period IC


Monthly Mean 5D Period IC
Monthly Mean 21D Period IC

Turnover Analysis

	1D	5D	10D	21D
Quantile 1 Mean Turnover	0.634	0.654	0.721	0.770
Quantile 2 Mean Turnover	0.751	0.756	0.779	0.790
Quantile 3 Mean Turnover	0.763	0.769	0.783	0.791
Quantile 4 Mean Turnover	0.752	0.756	0.777	0.795
Quantile 5 Mean Turnover	0.622	0.640	0.695	0.738

	1D	5D	10D	21D
Mean Factor Rank Autocorrelation	0.309	0.283	0.164	0.071


1D Period Top and Bottom Quantile Turnover
Proportion Of Names New To Quantile
top quantile turnover
bottom quantile turnover
5D Period Top and Bottom Quantile Turnover
Proportion Of Names New To Quantile
top quantile turnover
bottom quantile turnover
10D Period Top and Bottom Quantile Turnover
Proportion Of Names New To Quantile
top quantile turnover
bottom quantile turnover
21D Period Top and Bottom Quantile Turnover
Proportion Of Names New To Quantile
top quantile turnover
bottom quantile turnover
1D Period Factor Rank Autocorrelation
Autocorrelation Coefficient
Mean 0.309
5D Period Factor Rank Autocorrelation
Autocorrelation Coefficient
Mean 0.283
10D Period Factor Rank Autocorrelation
Autocorrelation Coefficient
Mean 0.164
21D Period Factor Rank Autocorrelation
Autocorrelation Coefficient
Mean 0.071

1.6.2 CatBoost

Select Parameters

[67]:
```
catboost_daily_ic = pd.read_hdf('data/model_tuning.h5', 'catboost/daily_ic')
catboost_daily_ic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1176 entries, 0 to 1175
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   lookahead          1176 non-null   int64
 1   train_length       1176 non-null   int64
 2   test_length        1176 non-null   int64
 3   max_depth          1176 non-null   int64
 4   min_child_samples  1176 non-null   int64
 5   boost_rounds       1176 non-null   int64
 6   ic                 1176 non-null   float64
dtypes: float64(1), int64(6)
memory usage: 73.5 KB
```

[68]:
```
def get_cb_params(data, t=5, best=0):
    param_cols = scope_params[1:] + catboost_train_params + ['boost_rounds']
    df = data[data.lookahead==t].sort_values('ic', ascending=False).iloc[best]
    return df.loc[param_cols]
```

[69]:
```
def get_cb_key(t, p):
    key = f'{t}/{int(p.train_length)}/{int(p.test_length)}/'
    return key + f'{int(p.max_depth)}/{int(p.min_child_samples)}'
```

[70]:
```
best_params = get_cb_params(catboost_daily_ic, t=1, best=0)
best_params
```

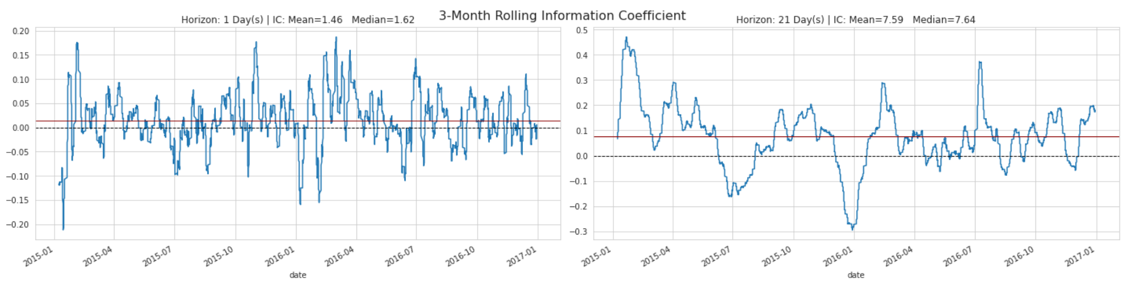
[70]:
```
train_length         1134.0
test_length            63.0
max_depth               3.0
min_child_samples     250.0
boost_rounds          200.0
Name: 355, dtype: float64
```

[71]:
```
def select_cb_ic(params, ic_data, lookahead):
    return ic_data.loc[(ic_data.lookahead == lookahead) &
                       (ic_data.train_length == params.train_length) &
                       (ic_data.test_length == params.test_length) &
                       (ic_data.max_depth == params.max_depth) &
```

```
                        (ic_data.min_child_samples == params.min_child_samples)].
↪set_index('date')
```

[72]:
```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(20, 5))
axes = axes.flatten()
for i, t in enumerate([1, 21]):
    params = get_cb_params(catboost_daily_ic, t=t)
    data = select_cb_ic(params, catboost_ic, lookahead=t).sort_index()
    rolling = data.rolling(63).ic.mean().dropna()
    avg = data.ic.mean()
    med = data.ic.median()
    rolling.plot(ax=axes[i], title=f'Horizon: {t} Day(s) | IC: Mean={avg*100:.
↪2f}   Median={med*100:.2f}')
    axes[i].axhline(avg, c='darkred', lw=1)
    axes[i].axhline(0, ls='--', c='k', lw=1)

fig.suptitle('3-Month Rolling Information Coefficient', fontsize=16)
fig.tight_layout()
fig.subplots_adjust(top=0.92);
```



Get Predictions

[73]:
```
lookahead = 1
topn = 10
for best in range(topn):
    best_params = get_cb_params(catboost_daily_ic, t=lookahead, best=best)
    key = get_cb_key(lookahead, best_params)
    rounds = str(int(best_params.boost_rounds))
    if best == 0:
        best_predictions = pd.read_hdf(results_path / 'tuning_catboost.h5',␣
↪'predictions/' + key)
        best_predictions = best_predictions[rounds].to_frame(best)
    else:
        best_predictions[best] = pd.read_hdf(results_path / 'tuning_catboost.
↪h5',
                                             'predictions/' + key)[rounds]
```

```
best_predictions = best_predictions.sort_index()
```

[74]:
```
best_predictions.to_hdf('data/predictions.h5', f'catboost/train/{lookahead:02}')
best_predictions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 501310 entries, ('A', Timestamp('2015-01-02 00:00:00')) to ('ZION',
Timestamp('2016-12-30 00:00:00'))
Data columns (total 10 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   0       501310 non-null  float64
 1   1       501310 non-null  float64
 2   2       501310 non-null  float64
 3   3       501310 non-null  float64
 4   4       501310 non-null  float64
 5   5       501310 non-null  float64
 6   6       501310 non-null  float64
 7   7       501310 non-null  float64
 8   8       501310 non-null  float64
 9   9       501310 non-null  float64
dtypes: float64(10)
memory usage: 40.2+ MB
```

Get Trade Prices Using next available prices.

[75]:
```
def get_trade_prices(tickers):
    idx = pd.IndexSlice
    DATA_STORE = '../data/assets.h5'
    prices = (pd.read_hdf(DATA_STORE, 'quandl/wiki/prices').swaplevel().
 ↪sort_index())
    prices.index.names = ['symbol', 'date']
    return (prices.loc[idx[tickers, '2015': '2017'], 'adj_open']
            .unstack('symbol')
            .sort_index()
            .shift(-1)
            .tz_localize('UTC'))
```

[76]:
```
test_tickers = best_predictions.index.get_level_values('symbol').unique()
```

[77]:
```
trade_prices = get_trade_prices(test_tickers)
trade_prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 755 entries, 2015-01-02 00:00:00+00:00 to 2017-12-29
00:00:00+00:00
Columns: 995 entries, A to ZION
```

```
dtypes: float64(995)
memory usage: 5.7 MB
```

[78]:
```python
# only generate once to save time
trade_prices.to_hdf('data/model_tuning.h5', 'trade_prices/model_selection')
```

[79]:
```python
trade_prices = pd.read_hdf('data/model_tuning.h5', 'trade_prices/
 ↪model_selection')
```

[80]:
```python
factor = best_predictions.iloc[:, :5].mean(1).dropna().tz_localize('UTC',␣
 ↪level='date').swaplevel()
```

Create AlphaLens Inputs

[81]:
```python
factor_data = get_clean_factor_and_forward_returns(factor=factor,
                                                   prices=trade_prices,
                                                   quantiles=5,
                                                   periods=(1, 5, 10, 21))
```

```
Dropped 0.0% entries from factor data: 0.0% in forward returns computation and
0.0% in binning phase (set max_loss=0 to see potentially suppressed Exceptions).
max_loss is 35.0%, not exceeded: OK!
```

Summary Tearsheet

[82]:
```python
create_summary_tear_sheet(factor_data)
```

Quantiles Statistics

factor_quantile	min	max	mean	std	count	count %
1	-0.048616	0.008704	-0.001321	0.004333	100296	20.006822
2	-0.017568	0.011154	0.000004	0.003696	100247	19.997048
3	-0.012403	0.015290	0.000651	0.003633	100223	19.992260
4	-0.011378	0.022721	0.001284	0.003775	100247	19.997048
5	-0.010400	0.047750	0.002889	0.004981	100296	20.006822

Returns Analysis

	1D	5D	10D	21D
Ann. alpha	0.176	0.077	0.057	0.049
beta	0.086	0.150	0.147	0.189
Mean Period Wise Return Top Quantile (bps)	6.103	4.049	3.508	3.207
Mean Period Wise Return Bottom Quantile (bps)	-6.037	-2.994	-2.581	-2.698
Mean Period Wise Spread (bps)	12.140	7.020	6.066	5.885

Information Analysis

	1D	5D	10D	21D
IC Mean	0.019	0.026	0.033	0.054
IC Std.	0.124	0.136	0.139	0.134

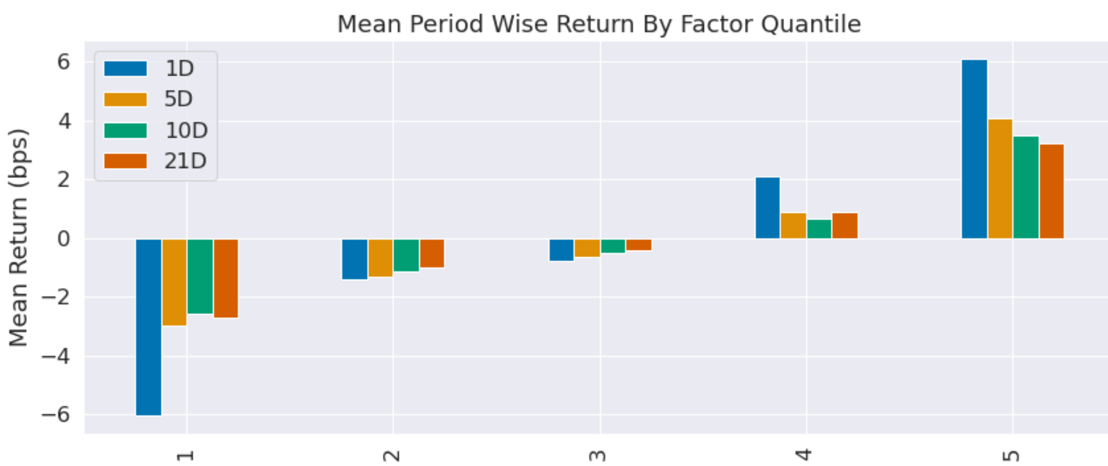
Risk-Adjusted IC	0.152	0.193	0.236	0.401
t-stat(IC)	3.423	4.324	5.299	9.010
p-value(IC)	0.001	0.000	0.000	0.000
IC Skew	-0.073	0.041	0.205	0.231
IC Kurtosis	0.297	0.495	0.058	0.074

Turnover Analysis

	1D	5D	10D	21D
Quantile 1 Mean Turnover	0.524	0.630	0.689	0.756
Quantile 2 Mean Turnover	0.692	0.748	0.764	0.784
Quantile 3 Mean Turnover	0.719	0.765	0.776	0.785
Quantile 4 Mean Turnover	0.689	0.745	0.765	0.787
Quantile 5 Mean Turnover	0.525	0.616	0.667	0.739

	1D	5D	10D	21D
Mean Factor Rank Autocorrelation	0.482	0.328	0.222	0.085

<Figure size 432x288 with 0 Axes>



[83]:
```
create_full_tear_sheet(factor_data)
```

Quantiles Statistics

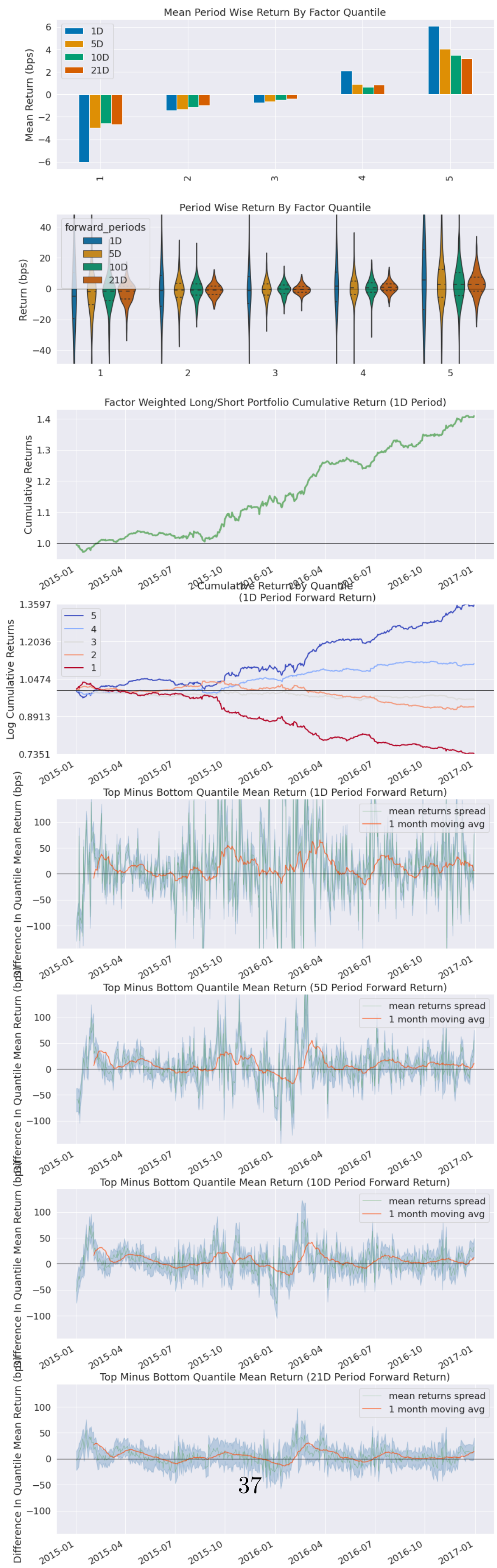
	min	max	mean	std	count	count %
factor_quantile						
1	-0.048616	0.008704	-0.001321	0.004333	100296	20.006822
2	-0.017568	0.011154	0.000004	0.003696	100247	19.997048
3	-0.012403	0.015290	0.000651	0.003633	100223	19.992260
4	-0.011378	0.022721	0.001284	0.003775	100247	19.997048
5	-0.010400	0.047750	0.002889	0.004981	100296	20.006822

Returns Analysis

	1D	5D	10D	21D

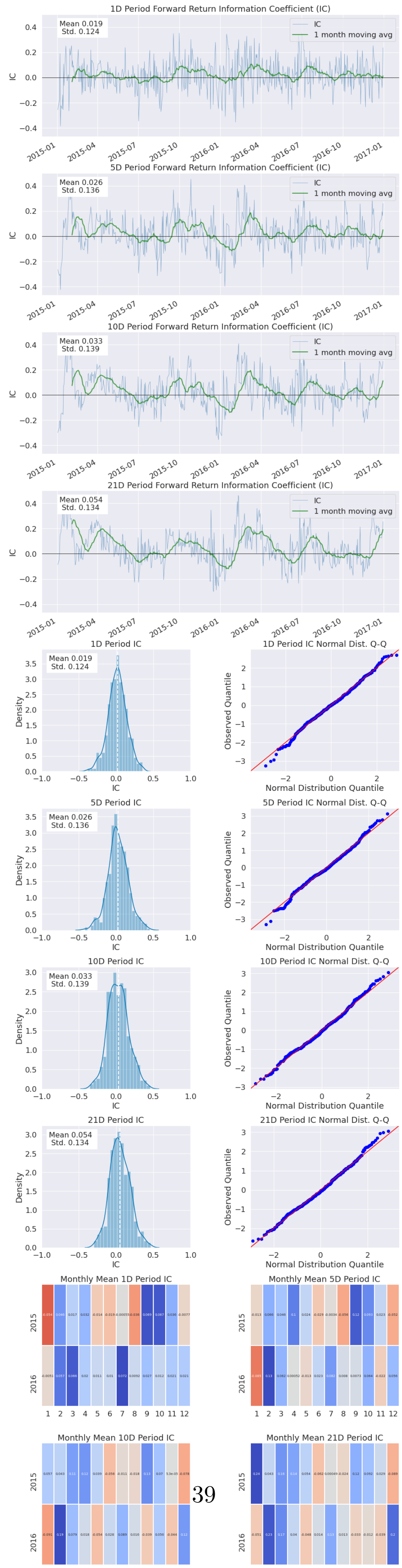
```
Ann. alpha                                    0.176  0.077  0.057  0.049
beta                                          0.086  0.150  0.147  0.189
Mean Period Wise Return Top Quantile (bps)    6.103  4.049  3.508  3.207
Mean Period Wise Return Bottom Quantile (bps) -6.037 -2.994 -2.581 -2.698
Mean Period Wise Spread (bps)                12.140  7.020  6.066  5.885
```

```
<Figure size 432x288 with 0 Axes>
```


Mean Period Wise Return By Factor Quantile
Mean Return (bps)
1D
5D
10D
21D
Period Wise Return By Factor Quantile
Return (bps)
forward_periods
Factor Weighted Long/Short Portfolio Cumulative Return (1D Period)
Cumulative Returns
Cumulative Return by Quantile
(1D Period Forward Return)
Log Cumulative Returns
Top Minus Bottom Quantile Mean Return (1D Period Forward Return)
Top Minus Bottom Quantile Mean Return (5D Period Forward Return)
Top Minus Bottom Quantile Mean Return (10D Period Forward Return)
Top Minus Bottom Quantile Mean Return (21D Period Forward Return)
Difference In Quantile Mean Return (bps)
mean returns spread
1 month moving avg

Information Analysis

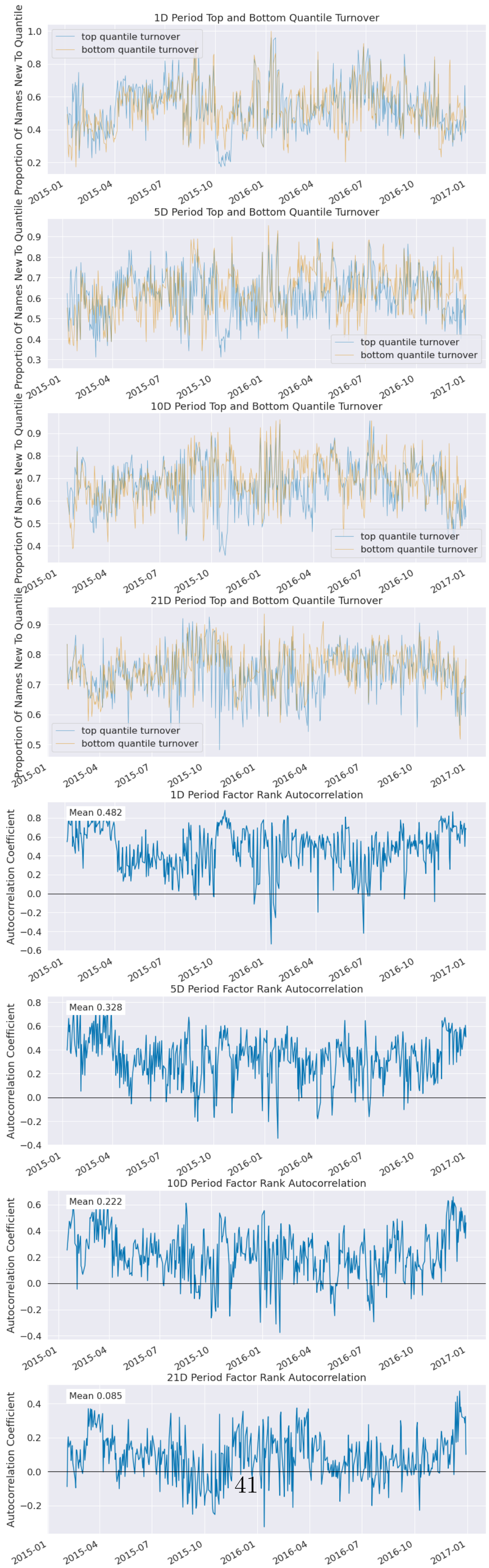
	1D	5D	10D	21D
IC Mean	0.019	0.026	0.033	0.054
IC Std.	0.124	0.136	0.139	0.134
Risk-Adjusted IC	0.152	0.193	0.236	0.401
t-stat(IC)	3.423	4.324	5.299	9.010
p-value(IC)	0.001	0.000	0.000	0.000
IC Skew	-0.073	0.041	0.205	0.231
IC Kurtosis	0.297	0.495	0.058	0.074


1D Period Forward Return Information Coefficient (IC)
Mean 0.019
Std. 0.124
IC
1 month moving avg
5D Period Forward Return Information Coefficient (IC)
Mean 0.026
Std. 0.136
10D Period Forward Return Information Coefficient (IC)
Mean 0.033
Std. 0.139
21D Period Forward Return Information Coefficient (IC)
Mean 0.054
Std. 0.134
1D Period IC
1D Period IC Normal Dist. Q-Q
5D Period IC
5D Period IC Normal Dist. Q-Q
10D Period IC
10D Period IC Normal Dist. Q-Q
21D Period IC
21D Period IC Normal Dist. Q-Q
Density
Observed Quantile
Normal Distribution Quantile
Monthly Mean 1D Period IC
Monthly Mean 5D Period IC
Monthly Mean 10D Period IC
Monthly Mean 21D Period IC

Turnover Analysis

	1D	5D	10D	21D
Quantile 1 Mean Turnover	0.524	0.630	0.689	0.756
Quantile 2 Mean Turnover	0.692	0.748	0.764	0.784
Quantile 3 Mean Turnover	0.719	0.765	0.776	0.785
Quantile 4 Mean Turnover	0.689	0.745	0.765	0.787
Quantile 5 Mean Turnover	0.525	0.616	0.667	0.739

	1D	5D	10D	21D
Mean Factor Rank Autocorrelation	0.482	0.328	0.222	0.085


1D Period Top and Bottom Quantile Turnover
top quantile turnover
bottom quantile turnover
5D Period Top and Bottom Quantile Turnover
10D Period Top and Bottom Quantile Turnover
21D Period Top and Bottom Quantile Turnover
Proportion Of Names New To Quantile
1D Period Factor Rank Autocorrelation
Mean 0.482
5D Period Factor Rank Autocorrelation
Mean 0.328
10D Period Factor Rank Autocorrelation
Mean 0.222
21D Period Factor Rank Autocorrelation
Mean 0.085
Autocorrelation Coefficient
2015-01
2015-04
2015-07
2015-10
2016-01
2016-04
2016-07
2016-10
2017-01