11_intraday_model

September 29, 2021

1 Intraday Strategy, Part 2: Model Training & Signal Evaluation

In this notebook, we load the high-quality NASDAQ100 minute-bar trade-and-quote data generously provided by Algoseek (available here) and use the features engineered in the last notebook to train gradient boosting model that predicts the returns for the NASDAQ100 stocks over the next 1-minute bar.

> Note that we will assume throughout that we can always buy (sell) at the first (last) trade price for a given bar at no cost and without market impact. This does certainly not reflect market reality, and is rather due to the challenges of simulating a trading strategy at this much higher intraday frequency in a realistic manner using open-source tools.

Note also that this section has slightly changed from the version published in the book to permit replication using the Algoseek data sample.

1.1 Imports & Settings

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

[2]:
```
%matplotlib inline

import sys, os
from pathlib import Path
from time import time
from tqdm import tqdm

import numpy as np
import pandas as pd

from scipy.stats import spearmanr
import lightgbm as lgb

import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns
```

Ensuring we can import `utils.py` in the repo's root directory:

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

[64]:
```
sns.set_style('whitegrid')
idx = pd.IndexSlice
deciles = np.arange(.1, 1, .1)
```

[5]:
```
# where we stored the features engineered in the previous notebook
data_store = 'data/algoseek.h5'
```

[6]:
```
# where we'll store the model results
result_store = 'data/intra_day.h5'
```

[7]:
```
# here we save the trained models
model_path = Path('models/intraday')
if not model_path.exists():
    model_path.mkdir(parents=True)
```

1.2 Load Model Data

[8]:
```
data = pd.read_hdf(data_store, 'model_data2')
```

[9]:
```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 30875649 entries, ('AAL', Timestamp('2015-01-02 09:30:00')) to
('YHOO', Timestamp('2017-06-16 15:59:00'))
Data columns (total 22 columns):
 #   Column          Non-Null Count     Dtype
---  ------          --------------     -----
 0   minute          30875649 non-null  int64
 1   ret1min         30612848 non-null  float64
 2   ret2min         30302846 non-null  float64
 3   ret3min         30220887 non-null  float64
 4   ret4min         30141503 non-null  float64
 5   ret5min         30063236 non-null  float64
 6   ret6min         29983969 non-null  float64
 7   ret7min         29903822 non-null  float64
 8   ret8min         29824607 non-null  float64
 9   ret9min         29745431 non-null  float64
 10  ret10min        29666821 non-null  float64
 11  fwd1min         30875649 non-null  float64
 12  rup             30083777 non-null  float64
 13  rdown           30083777 non-null  float64
 14  BOP             30612848 non-null  float64
 15  CCI             28517773 non-null  float64
 16  MFI             30873719 non-null  float64
```

```
 17  STOCHRSI        30871639 non-null  float64
 18  slowd           30873302 non-null  float64
 19  slowk           30873302 non-null  float64
 20  NATR            30873719 non-null  float64
 21  trades_bid_ask  30083777 non-null  float64
dtypes: float64(21), int64(1)
memory usage: 5.2+ GB
```

[10]:
```
data.sample(frac=.1).describe(percentiles=np.arange(.1, 1, .1))
```

[10]:
```
             minute       ret1min       ret2min       ret3min       ret4min  \
count  3.087565e+06  3.061353e+06  3.030366e+06  3.022232e+06  3.014597e+06
mean   1.944517e+02 -2.933200e-06 -1.869810e-06 -1.598179e-06 -1.981696e-06
std    1.127876e+02  8.522094e-04  1.143481e-03  1.364755e-03  1.554875e-03
min    0.000000e+00 -1.244796e-01 -8.829405e-02 -1.060236e-01 -1.327945e-01
10%    3.800000e+01 -7.494558e-04 -1.048584e-03 -1.268377e-03 -1.454229e-03
20%    7.700000e+01 -4.105090e-04 -5.929791e-04 -7.232152e-04 -8.290892e-04
30%    1.160000e+02 -2.308225e-04 -3.375865e-04 -4.100041e-04 -4.732608e-04
40%    1.550000e+02 -9.680542e-05 -1.555210e-04 -1.871257e-04 -2.161311e-04
50%    1.940000e+02  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
60%    2.340000e+02  9.104980e-05  1.499700e-04  1.805591e-04  2.082899e-04
70%    2.730000e+02  2.255130e-04  3.308337e-04  4.010963e-04  4.651163e-04
80%    3.120000e+02  4.033559e-04  5.854801e-04  7.150892e-04  8.195378e-04
90%    3.510000e+02  7.384155e-04  1.041016e-03  1.264733e-03  1.447178e-03
max    3.890000e+02  9.877805e-02  1.051307e-01  1.034375e-01  1.911828e-01

            ret5min       ret6min       ret7min       ret8min       ret9min  \
count  3.006284e+06  2.998549e+06  2.990669e+06  2.982548e+06  2.974617e+06
mean  -1.142065e-06  3.964908e-08  8.709935e-07  1.473304e-06  8.600771e-07
std    1.717925e-03  1.863826e-03  1.994273e-03  2.115630e-03  2.235502e-03
min   -1.545420e-01 -1.956444e-01 -2.158158e-01 -1.726063e-01 -2.157102e-01
10%   -1.616089e-03 -1.762741e-03 -1.897606e-03 -2.026686e-03 -2.142857e-03
20%   -9.218753e-04 -1.004307e-03 -1.081334e-03 -1.153403e-03 -1.218621e-03
30%   -5.260389e-04 -5.755245e-04 -6.196361e-04 -6.601532e-04 -6.987242e-04
40%   -2.398082e-04 -2.604845e-04 -2.820079e-04 -3.003003e-04 -3.175107e-04
50%    0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
60%    2.328158e-04  2.537642e-04  2.754062e-04  2.960551e-04  3.132832e-04
70%    5.172414e-04  5.666289e-04  6.132654e-04  6.540222e-04  6.938020e-04
80%    9.140768e-04  9.963062e-04  1.073346e-03  1.147301e-03  1.214083e-03
90%    1.610306e-03  1.759015e-03  1.891895e-03  2.018163e-03  2.133207e-03
max    1.327160e-01  2.006452e-01  1.245827e-01  1.317181e-01  1.121233e-01

       …           rup         rdown           BOP           CCI  \
count  …  3.008146e+06  3.008146e+06  3.061353e+06  2.851720e+06
mean   …  5.109800e-01  5.258520e-01 -2.657472e-03  1.926504e-01
std    …  7.497976e+00  3.099559e+01  6.268154e-01  1.088541e+02
min    …  0.000000e+00  0.000000e+00 -1.000000e+00 -4.666667e+02
```

```
10%    …  0.000000e+00  0.000000e+00 -9.000000e-01 -1.377555e+02
20%    …  9.638554e-02  9.944259e-02 -6.644518e-01 -9.983731e+01
30%    …  1.976744e-01  2.017393e-01 -4.508475e-01 -6.917500e+01
40%    …  2.857143e-01  2.916667e-01 -1.826087e-01 -3.702543e+01
50%    …  3.701016e-01  3.759077e-01  0.000000e+00  4.377638e-01
60%    …  4.578505e-01  4.638802e-01  1.666667e-01  3.785810e+01
70%    …  5.551150e-01  5.599337e-01  4.428571e-01  6.964201e+01
80%    …  6.792615e-01  6.823138e-01  6.538462e-01  9.985441e+01
90%    …  8.656430e-01  8.662695e-01  9.000000e-01  1.375000e+02
max    …  5.500000e+03  5.000100e+04  1.000000e+00  4.666667e+02

                MFI      STOCHRSI         slowd         slowk          NATR  \
count  3.087377e+06  3.087164e+06  3.087329e+06  3.087329e+06  3.087377e+06
mean   4.995851e+01  4.996170e+01  5.026232e+01  5.025505e+01  9.574717e-02
std    1.969340e+01  3.548760e+01  2.770983e+01  2.860330e+01  7.538252e-02
min   -1.837897e-08  0.000000e+00 -3.910354e-12 -5.092223e-12  2.026288e-07
10%    2.395492e+01  0.000000e+00  1.250572e+01  1.122968e+01  4.014445e-02
20%    3.237073e+01  9.771635e+00  2.094136e+01  1.994344e+01  4.871973e-02
30%    3.883638e+01  2.365167e+01  3.006536e+01  2.936605e+01  5.665948e-02
40%    4.452486e+01  3.687606e+01  3.997666e+01  3.958910e+01  6.520095e-02
50%    4.989353e+01  4.993994e+01  5.029630e+01  5.008741e+01  7.514502e-02
60%    5.529671e+01  6.304218e+01  6.069305e+01  6.111111e+01  8.752835e-02
70%    6.100298e+01  7.622753e+01  7.055556e+01  7.123016e+01  1.040583e-01
80%    6.753297e+01  9.012224e+01  7.961905e+01  8.057127e+01  1.289437e-01
90%    7.610552e+01  1.000000e+02  8.790211e+01  8.905852e+01  1.755765e-01
max    1.000000e+02  1.000000e+02  1.000000e+02  1.000000e+02  3.459402e+01

       trades_bid_ask
count    3.008146e+06
mean    -7.094037e-03
std      2.717903e+01
min     -2.630100e+04
10%     -7.299035e-01
20%     -4.601227e-01
30%     -2.782861e-01
40%     -1.309554e-01
50%      0.000000e+00
60%      1.036810e-01
70%      2.516316e-01
80%      4.365163e-01
90%      7.094017e-01
max      2.500100e+04

[14 rows x 22 columns]
```

1.3 Model Training

1.3.1 Helper functions

[11]:
```
class MultipleTimeSeriesCV:
    """Generates tuples of train_idx, test_idx pairs
    Assumes the MultiIndex contains levels 'symbol' and 'date'
    purges overlapping outcomes"""

    def __init__(self,
                 n_splits=3,
                 train_period_length=126,
                 test_period_length=21,
                 lookahead=None,
                 date_idx='date',
                 shuffle=False):
        self.n_splits = n_splits
        self.lookahead = lookahead
        self.test_length = test_period_length
        self.train_length = train_period_length
        self.shuffle = shuffle
        self.date_idx = date_idx

    def split(self, X, y=None, groups=None):
        unique_dates = X.index.get_level_values(self.date_idx).unique()
        days = sorted(unique_dates, reverse=True)
        split_idx = []
        for i in range(self.n_splits):
            test_end_idx = i * self.test_length
            test_start_idx = test_end_idx + self.test_length
            train_end_idx = test_start_idx + self.lookahead - 1
            train_start_idx = train_end_idx + self.train_length + self.
↪lookahead - 1
            split_idx.append([train_start_idx, train_end_idx,
                              test_start_idx, test_end_idx])

        dates = X.reset_index()[[self.date_idx]]
        for train_start, train_end, test_start, test_end in split_idx:

            train_idx = dates[(dates[self.date_idx] > days[train_start])
                              & (dates[self.date_idx] <= days[train_end])].index
            test_idx = dates[(dates[self.date_idx] > days[test_start])
                             & (dates[self.date_idx] <= days[test_end])].index
            if self.shuffle:
                np.random.shuffle(list(train_idx))
            yield train_idx.to_numpy(), test_idx.to_numpy()

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

```
        return self.n_splits
```

[12]:
```
def get_fi(model):
    fi = model.feature_importance(importance_type='gain')
    return (pd.Series(fi / fi.sum(),
                      index=model.feature_name()))
```

1.3.2 Categorical Variables

[13]:
```
data['stock_id'] = pd.factorize(data.index.get_level_values('ticker'),␣
 ↪sort=True)[0]
```

[14]:
```
categoricals = ['stock_id']
```

1.3.3 Custom Metric

[15]:
```
def ic_lgbm(preds, train_data):
    """Custom IC eval metric for lightgbm"""
    is_higher_better = True
    return 'ic', spearmanr(preds, train_data.get_label())[0], is_higher_better
```

1.3.4 Cross-validation setup

[16]:
```
DAY = 390   # number of minute bars in a trading day of 6.5 hrs (9:30 - 15:59)
MONTH = 21  # trading days
```

[17]:
```
def get_cv(n_splits=23):
    return MultipleTimeSeriesCV(n_splits=n_splits,
                                lookahead=1,
                                test_period_length=MONTH * DAY,       # test␣
 ↪for 1 month
                                train_period_length=12 * MONTH * DAY,  # train␣
 ↪for 1 year
                                date_idx='date_time')
```

Show train/validation periods:

[18]:
```
for i, (train_idx, test_idx) in enumerate(get_cv().split(X=data)):
    train_dates = data.iloc[train_idx].index.unique('date_time')
    test_dates = data.iloc[test_idx].index.unique('date_time')
    print(train_dates.min(), train_dates.max(), test_dates.min(), test_dates.
 ↪max())
```

```
2016-11-29 15:59:00 2017-11-29 15:59:00 2017-11-30 09:30:00 2017-12-29 15:59:00
2016-10-28 15:47:00 2017-10-30 15:58:00 2017-10-30 15:59:00 2017-11-29 15:59:00
2016-09-29 15:47:00 2017-09-29 15:58:00 2017-09-29 15:59:00 2017-10-30 15:58:00
```

```
2016-08-30 15:47:00 2017-08-30 15:58:00 2017-08-30 15:59:00 2017-09-29 15:58:00
2016-08-01 15:47:00 2017-08-01 15:58:00 2017-08-01 15:59:00 2017-08-30 15:58:00
2016-06-30 15:47:00 2017-06-30 15:58:00 2017-06-30 15:59:00 2017-08-01 15:58:00
2016-06-01 15:47:00 2017-06-01 15:58:00 2017-06-01 15:59:00 2017-06-30 15:58:00
2016-05-02 15:47:00 2017-05-02 15:58:00 2017-05-02 15:59:00 2017-06-01 15:58:00
2016-04-01 15:47:00 2017-03-31 15:58:00 2017-03-31 15:59:00 2017-05-02 15:58:00
2016-03-02 15:47:00 2017-03-02 15:58:00 2017-03-02 15:59:00 2017-03-31 15:58:00
2016-02-01 15:47:00 2017-01-31 15:58:00 2017-01-31 15:59:00 2017-03-02 15:58:00
2015-12-30 15:47:00 2016-12-29 15:58:00 2016-12-29 15:59:00 2017-01-31 15:58:00
2015-11-30 15:23:00 2016-11-29 15:58:00 2016-11-29 15:59:00 2016-12-29 15:58:00
2015-10-29 15:09:00 2016-10-28 15:46:00 2016-10-28 15:47:00 2016-11-29 15:58:00
2015-09-30 15:09:00 2016-09-29 15:46:00 2016-09-29 15:47:00 2016-10-28 15:46:00
2015-08-31 15:09:00 2016-08-30 15:46:00 2016-08-30 15:47:00 2016-09-29 15:46:00
2015-07-31 15:09:00 2016-08-01 15:46:00 2016-08-01 15:47:00 2016-08-30 15:46:00
2015-07-01 15:09:00 2016-06-30 15:46:00 2016-06-30 15:47:00 2016-08-01 15:46:00
2015-06-02 15:09:00 2016-06-01 15:46:00 2016-06-01 15:47:00 2016-06-30 15:46:00
2015-05-01 15:09:00 2016-05-02 15:46:00 2016-05-02 15:47:00 2016-06-01 15:46:00
2015-04-01 15:09:00 2016-04-01 15:46:00 2016-04-01 15:47:00 2016-05-02 15:46:00
2015-03-03 15:09:00 2016-03-02 15:46:00 2016-03-02 15:47:00 2016-04-01 15:46:00
2015-01-30 15:09:00 2016-02-01 15:46:00 2016-02-01 15:47:00 2016-03-02 15:46:00
```

1.3.5 Train model

[19]:
```python
label = sorted(data.filter(like='fwd').columns)
features = data.columns.difference(label).tolist()
label = label[0]
```

[48]:
```python
params = dict(objective='regression',
              metric=['rmse'],
              device='gpu',
              max_bin=63,
              gpu_use_dp=False,
              num_leaves=16,
              min_data_in_leaf=500,
              feature_fraction=.8,
              verbose=-1)
```

[49]:
```python
num_boost_round = 250
```

[50]:
```python
cv = get_cv(n_splits=23) # we have enough data for 23 different test periods
```

[51]:
```python
def get_scores(result):
    return pd.DataFrame({'train': result['training']['ic'],
                         'valid': result['valid_1']['ic']})
```

The following model-training loop will take more than 10 hours to run and also consumes substantial memory. If you run into resource constraints, you can modify the code, e.g., by: 1. Only loading data required for one iteration. 2. Shortening the training period to require less than one year.

You can also speed up the process by using fewer `n_splits`, which implies longer test periods.

```
[52]: start = time()
for fold, (train_idx, test_idx) in enumerate(cv.split(X=data), 1):
    # create lgb train set
    train_set = data.iloc[train_idx, :]
    lgb_train = lgb.Dataset(data=train_set.drop(label, axis=1),
                            label=train_set[label],
                            categorical_feature=categoricals)

    # create lgb test set
    test_set = data.iloc[test_idx, :]
    lgb_test = lgb.Dataset(data=test_set.drop(label, axis=1),
                           label=test_set[label],
                           categorical_feature=categoricals,
                           reference=lgb_train)

    # train model
    evals_result = {}
    model = lgb.train(params=params,
                      train_set=lgb_train,
                      valid_sets=[lgb_train, lgb_test],
                      feval=ic_lgbm,
                      num_boost_round=num_boost_round,
                      evals_result=evals_result,
                      verbose_eval=50)
    model.save_model((model_path / f'{fold:02}.txt').as_posix())

    # get train/valid ic scores
    scores = get_scores(evals_result)
    scores.to_hdf(result_store, f'ic/{fold:02}')

    # get feature importance
    fi = get_fi(model)
    fi.to_hdf(result_store, f'fi/{fold:02}')

    # generate validation predictions
    X_test = test_set.loc[:, model.feature_name()]
    y_test = test_set.loc[:, [label]]
    y_test['pred'] = model.predict(X_test)
    y_test.to_hdf(result_store, f'predictions/{fold:02}')

    # compute average IC per minute
    by_minute = y_test.groupby(test_set.index.get_level_values('date_time'))
    daily_ic = by_minute.apply(lambda x: spearmanr(x[label], x.pred)[0]).mean()
    print(f'\nFold: {fold:02} | {format_time(time()-start)} | IC per minute:␣
 ↪{daily_ic:.2%}\n')
```

```
[50]    training's rmse: 0.0006962      training's ic: 0.038731 valid_1's rmse:
0.000816226     valid_1's ic: 0.0543727
[100]   training's rmse: 0.000695586    training's ic: 0.04416  valid_1's rmse:
0.000815993     valid_1's ic: 0.0552591
[150]   training's rmse: 0.000695027    training's ic: 0.046986 valid_1's rmse:
0.000815898     valid_1's ic: 0.0557145
[200]   training's rmse: 0.000694592    training's ic: 0.04948  valid_1's rmse:
0.000815859     valid_1's ic: 0.0561737
[250]   training's rmse: 0.000694165    training's ic: 0.0517389
valid_1's rmse: 0.000815865     valid_1's ic: 0.0558025
```

Fold: 01 | 00:17:46 | IC per minute: 5.59%

```
[50]    training's rmse: 0.000699973    training's ic: 0.0376039
valid_1's rmse: 0.000847957     valid_1's ic: 0.0416495
[100]   training's rmse: 0.000699303    training's ic: 0.0426195
valid_1's rmse: 0.000847627     valid_1's ic: 0.043379
[150]   training's rmse: 0.000698748    training's ic: 0.0457404
valid_1's rmse: 0.000847548     valid_1's ic: 0.043617
[200]   training's rmse: 0.000698298    training's ic: 0.0482473
valid_1's rmse: 0.000847537     valid_1's ic: 0.0440953
[250]   training's rmse: 0.000697857    training's ic: 0.0506102
valid_1's rmse: 0.000847582     valid_1's ic: 0.0439462
```

Fold: 02 | 00:35:29 | IC per minute: 4.45%

```
[50]    training's rmse: 0.000698592    training's ic: 0.0370533
valid_1's rmse: 0.000706335     valid_1's ic: 0.0404773
[100]   training's rmse: 0.000697869    training's ic: 0.0418831
valid_1's rmse: 0.000706128     valid_1's ic: 0.0413394
[150]   training's rmse: 0.000697354    training's ic: 0.0452553
valid_1's rmse: 0.000706085     valid_1's ic: 0.0411713
[200]   training's rmse: 0.000696885    training's ic: 0.0479669
valid_1's rmse: 0.000706038     valid_1's ic: 0.0413983
[250]   training's rmse: 0.000696456    training's ic: 0.0503778
valid_1's rmse: 0.000706054     valid_1's ic: 0.0412612
```

Fold: 03 | 00:57:48 | IC per minute: 4.45%

```
[50]    training's rmse: 0.000701553    training's ic: 0.0363031
valid_1's rmse: 0.000669637     valid_1's ic: 0.0326244
[100]   training's rmse: 0.000700849    training's ic: 0.0413249
valid_1's rmse: 0.000669565     valid_1's ic: 0.0339486
[150]   training's rmse: 0.000700357    training's ic: 0.0447981
valid_1's rmse: 0.000669562     valid_1's ic: 0.0343703
[200]   training's rmse: 0.000699884    training's ic: 0.0476104
valid_1's rmse: 0.000669583     valid_1's ic: 0.0349983
[250]   training's rmse: 0.000699484    training's ic: 0.0501712
```

```
valid_1's rmse: 0.000669543     valid_1's ic: 0.0355025

Fold: 04 | 01:24:05 | IC per minute: 3.83%

[50]    training's rmse: 0.000697019    training's ic: 0.0354982
valid_1's rmse: 0.000697012     valid_1's ic: 0.0247309
[100]   training's rmse: 0.000696274    training's ic: 0.0410205
valid_1's rmse: 0.000696904     valid_1's ic: 0.0271854
[150]   training's rmse: 0.000695755    training's ic: 0.044584 valid_1's rmse:
0.000696912     valid_1's ic: 0.0276005
[200]   training's rmse: 0.000695313    training's ic: 0.0474853
valid_1's rmse: 0.000696927     valid_1's ic: 0.0285591
[250]   training's rmse: 0.000694863    training's ic: 0.0498696
valid_1's rmse: 0.000696917     valid_1's ic: 0.0285991

Fold: 05 | 01:50:23 | IC per minute: 3.13%

[50]    training's rmse: 0.00069678     training's ic: 0.0350113
valid_1's rmse: 0.000701348     valid_1's ic: 0.0275999
[100]   training's rmse: 0.00069605     training's ic: 0.0406079
valid_1's rmse: 0.000701289     valid_1's ic: 0.0297336
[150]   training's rmse: 0.000695473    training's ic: 0.0441527
valid_1's rmse: 0.000701216     valid_1's ic: 0.0307175
[200]   training's rmse: 0.000694997    training's ic: 0.0471703
valid_1's rmse: 0.000701244     valid_1's ic: 0.0314352
[250]   training's rmse: 0.000694559    training's ic: 0.0492445
valid_1's rmse: 0.000701273     valid_1's ic: 0.0314369

Fold: 06 | 02:16:28 | IC per minute: 3.34%

[50]    training's rmse: 0.000702829    training's ic: 0.0337797
valid_1's rmse: 0.000744246     valid_1's ic: 0.0246692
[100]   training's rmse: 0.00070212     training's ic: 0.0385954
valid_1's rmse: 0.000744224     valid_1's ic: 0.0264151
[150]   training's rmse: 0.000701593    training's ic: 0.0430637
valid_1's rmse: 0.000744229     valid_1's ic: 0.0275546
[200]   training's rmse: 0.000701114    training's ic: 0.0458159
valid_1's rmse: 0.000744281     valid_1's ic: 0.0282104
[250]   training's rmse: 0.000700721    training's ic: 0.0482636
valid_1's rmse: 0.000744313     valid_1's ic: 0.0283922

Fold: 07 | 02:42:44 | IC per minute: 3.28%

[50]    training's rmse: 0.000722509    training's ic: 0.0334184
valid_1's rmse: 0.00062052      valid_1's ic: 0.032487
[100]   training's rmse: 0.000721876    training's ic: 0.038585 valid_1's rmse:
0.000620422     valid_1's ic: 0.0333264
[150]   training's rmse: 0.000721342    training's ic: 0.0423346
```

```
valid_1's rmse: 0.000620373     valid_1's ic: 0.0332792
[200]   training's rmse: 0.000720854    training's ic: 0.0453648
valid_1's rmse: 0.000620391     valid_1's ic: 0.0344978
[250]   training's rmse: 0.00072039     training's ic: 0.0475421
valid_1's rmse: 0.000620433     valid_1's ic: 0.0349232

Fold: 08 | 03:08:25 | IC per minute: 3.70%

[50]    training's rmse: 0.000752768    training's ic: 0.0325142
valid_1's rmse: 0.0005842       valid_1's ic: 0.0271741
[100]   training's rmse: 0.000751985    training's ic: 0.0374633
valid_1's rmse: 0.000584136     valid_1's ic: 0.0283447
[150]   training's rmse: 0.000751343    training's ic: 0.0407396
valid_1's rmse: 0.000584099     valid_1's ic: 0.0289354
[200]   training's rmse: 0.000750835    training's ic: 0.0439565
valid_1's rmse: 0.000584126     valid_1's ic: 0.0294128
[250]   training's rmse: 0.00075033     training's ic: 0.0460732
valid_1's rmse: 0.000584183     valid_1's ic: 0.0293556

Fold: 09 | 03:34:14 | IC per minute: 3.21%

[50]    training's rmse: 0.000772983    training's ic: 0.0315982
valid_1's rmse: 0.00063351      valid_1's ic: 0.0269043
[100]   training's rmse: 0.000772305    training's ic: 0.0370821
valid_1's rmse: 0.000633424     valid_1's ic: 0.0295316
[150]   training's rmse: 0.000771751    training's ic: 0.0402892
valid_1's rmse: 0.000633369     valid_1's ic: 0.0301651
[200]   training's rmse: 0.000771242    training's ic: 0.0432137
valid_1's rmse: 0.000633349     valid_1's ic: 0.0312183
[250]   training's rmse: 0.000770771    training's ic: 0.0455847
valid_1's rmse: 0.000633325     valid_1's ic: 0.0315627

Fold: 10 | 04:00:30 | IC per minute: 2.98%

[50]    training's rmse: 0.000832092    training's ic: 0.0325253
valid_1's rmse: 0.000653653     valid_1's ic: 0.026781
[100]   training's rmse: 0.000831323    training's ic: 0.0377314
valid_1's rmse: 0.000653568     valid_1's ic: 0.0289015
[150]   training's rmse: 0.000830753    training's ic: 0.0411433
valid_1's rmse: 0.000653586     valid_1's ic: 0.0291601
[200]   training's rmse: 0.000830191    training's ic: 0.043913 valid_1's rmse:
0.000653599     valid_1's ic: 0.0301002
[250]   training's rmse: 0.000829674    training's ic: 0.0465464
valid_1's rmse: 0.000653658     valid_1's ic: 0.0303744

Fold: 11 | 04:26:17 | IC per minute: 2.94%

[50]    training's rmse: 0.000877395    training's ic: 0.0320049
```

```
valid_1's rmse: 0.000721517     valid_1's ic: 0.0240198
[100]   training's rmse: 0.000876658    training's ic: 0.0374841
valid_1's rmse: 0.00072146      valid_1's ic: 0.026157
[150]   training's rmse: 0.000876046    training's ic: 0.0408182
valid_1's rmse: 0.000721393     valid_1's ic: 0.0272646
[200]   training's rmse: 0.000875495    training's ic: 0.0441758
valid_1's rmse: 0.000721363     valid_1's ic: 0.0281185
[250]   training's rmse: 0.000875026    training's ic: 0.0467237
valid_1's rmse: 0.00072137      valid_1's ic: 0.028905

Fold: 12 | 04:52:49 | IC per minute: 3.04%

[50]    training's rmse: 0.000886972    training's ic: 0.0326955
valid_1's rmse: 0.000749551     valid_1's ic: 0.0260998
[100]   training's rmse: 0.000886233    training's ic: 0.0374855
valid_1's rmse: 0.00074944      valid_1's ic: 0.0283205
[150]   training's rmse: 0.000885641    training's ic: 0.0409926
valid_1's rmse: 0.000749411     valid_1's ic: 0.029227
[200]   training's rmse: 0.000885103    training's ic: 0.0439042
valid_1's rmse: 0.000749372     valid_1's ic: 0.0297628
[250]   training's rmse: 0.000884651    training's ic: 0.0465908
valid_1's rmse: 0.000749306     valid_1's ic: 0.0307105

Fold: 13 | 05:18:51 | IC per minute: 3.01%

[50]    training's rmse: 0.000892264    training's ic: 0.0326621
valid_1's rmse: 0.00088496      valid_1's ic: 0.0215666
[100]   training's rmse: 0.000891562    training's ic: 0.0366921
valid_1's rmse: 0.000884886     valid_1's ic: 0.0220376
[150]   training's rmse: 0.000890964    training's ic: 0.0397876
valid_1's rmse: 0.000884839     valid_1's ic: 0.0227016
[200]   training's rmse: 0.000890451    training's ic: 0.0430167
valid_1's rmse: 0.000884803     valid_1's ic: 0.0235889
[250]   training's rmse: 0.000889943    training's ic: 0.0452669
valid_1's rmse: 0.000884774     valid_1's ic: 0.0240788

Fold: 14 | 05:45:07 | IC per minute: 2.86%

[50]    training's rmse: 0.000921495    training's ic: 0.0325343
valid_1's rmse: 0.000688911     valid_1's ic: 0.0223877
[100]   training's rmse: 0.00092084     training's ic: 0.0366749
valid_1's rmse: 0.000688793     valid_1's ic: 0.0239436
[150]   training's rmse: 0.000920176    training's ic: 0.0401455
valid_1's rmse: 0.00068875      valid_1's ic: 0.0249856
[200]   training's rmse: 0.000919602    training's ic: 0.0432488
valid_1's rmse: 0.000688764     valid_1's ic: 0.0256182
[250]   training's rmse: 0.000919108    training's ic: 0.0458315
valid_1's rmse: 0.000688732     valid_1's ic: 0.0265407
```

```
Fold: 15 | 06:11:36 | IC per minute: 2.68%

[50]    training's rmse: 0.000940675    training's ic: 0.0333497
valid_1's rmse: 0.00070608      valid_1's ic: 0.0200963
[100]   training's rmse: 0.000939891    training's ic: 0.0377662
valid_1's rmse: 0.000706092     valid_1's ic: 0.020633
[150]   training's rmse: 0.000939188    training's ic: 0.0414858
valid_1's rmse: 0.000706075     valid_1's ic: 0.021742
[200]   training's rmse: 0.000938638    training's ic: 0.0441729
valid_1's rmse: 0.00070609      valid_1's ic: 0.0223267
[250]   training's rmse: 0.000938117    training's ic: 0.0468418
valid_1's rmse: 0.000706121     valid_1's ic: 0.0225305

Fold: 16 | 06:38:11 | IC per minute: 2.44%

[50]    training's rmse: 0.000985282    training's ic: 0.0324179
valid_1's rmse: 0.000640303     valid_1's ic: 0.0209769
[100]   training's rmse: 0.00098423     training's ic: 0.0362766
valid_1's rmse: 0.000640323     valid_1's ic: 0.0216562
[150]   training's rmse: 0.000983366    training's ic: 0.0396048
valid_1's rmse: 0.000640393     valid_1's ic: 0.0223887
[200]   training's rmse: 0.000982623    training's ic: 0.042354 valid_1's rmse:
0.000640399     valid_1's ic: 0.0228008
[250]   training's rmse: 0.000981903    training's ic: 0.0447996
valid_1's rmse: 0.000640409     valid_1's ic: 0.0235311

Fold: 17 | 07:04:30 | IC per minute: 2.60%

[50]    training's rmse: 0.000992882    training's ic: 0.0330731
valid_1's rmse: 0.000698768     valid_1's ic: 0.0178816
[100]   training's rmse: 0.000991763    training's ic: 0.0369799
valid_1's rmse: 0.000698784     valid_1's ic: 0.0188669
[150]   training's rmse: 0.000990925    training's ic: 0.0401558
valid_1's rmse: 0.00069884      valid_1's ic: 0.0197579
[200]   training's rmse: 0.00099016     training's ic: 0.0430659
valid_1's rmse: 0.00069889      valid_1's ic: 0.0204069
[250]   training's rmse: 0.000989494    training's ic: 0.0454836
valid_1's rmse: 0.000698912     valid_1's ic: 0.021086

Fold: 18 | 07:23:22 | IC per minute: 2.47%

[50]    training's rmse: 0.000981605    training's ic: 0.0333102
valid_1's rmse: 0.000807922     valid_1's ic: 0.0192318
[100]   training's rmse: 0.000980441    training's ic: 0.0371727
valid_1's rmse: 0.000807994     valid_1's ic: 0.0198469
[150]   training's rmse: 0.000979597    training's ic: 0.040212 valid_1's rmse:
0.000808115     valid_1's ic: 0.0198447
```

```
[200]   training's rmse: 0.000978876    training's ic: 0.0429504
valid_1's rmse: 0.000808122     valid_1's ic: 0.0202568
[250]   training's rmse: 0.000978225    training's ic: 0.0454618
valid_1's rmse: 0.000808137     valid_1's ic: 0.0204947

Fold: 19 | 07:42:22 | IC per minute: 2.58%

[50]    training's rmse: 0.000971273    training's ic: 0.0343452
valid_1's rmse: 0.00084749      valid_1's ic: 0.0205258
[100]   training's rmse: 0.000970176    training's ic: 0.0383209
valid_1's rmse: 0.000847495     valid_1's ic: 0.0222474
[150]   training's rmse: 0.000969198    training's ic: 0.0409799
valid_1's rmse: 0.000847536     valid_1's ic: 0.0226757
[200]   training's rmse: 0.000968461    training's ic: 0.0437774
valid_1's rmse: 0.000847519     valid_1's ic: 0.0232256
[250]   training's rmse: 0.000967769    training's ic: 0.0463843
valid_1's rmse: 0.000847529     valid_1's ic: 0.0236719

Fold: 20 | 08:00:44 | IC per minute: 2.79%

[50]    training's rmse: 0.000956095    training's ic: 0.0343668
valid_1's rmse: 0.00093566      valid_1's ic: 0.0210374
[100]   training's rmse: 0.000955025    training's ic: 0.0392049
valid_1's rmse: 0.000935819     valid_1's ic: 0.022133
[150]   training's rmse: 0.000954102    training's ic: 0.0422933
valid_1's rmse: 0.0009359       valid_1's ic: 0.0228522
[200]   training's rmse: 0.000953454    training's ic: 0.0448814
valid_1's rmse: 0.000935966     valid_1's ic: 0.0233652
[250]   training's rmse: 0.000952775    training's ic: 0.0473471
valid_1's rmse: 0.000936005     valid_1's ic: 0.0231158

Fold: 21 | 08:19:21 | IC per minute: 2.43%

[50]    training's rmse: 0.000945276    training's ic: 0.0343428
valid_1's rmse: 0.000878341     valid_1's ic: 0.0227607
[100]   training's rmse: 0.000944164    training's ic: 0.0389748
valid_1's rmse: 0.000878351     valid_1's ic: 0.0246803
[150]   training's rmse: 0.000943245    training's ic: 0.0416026
valid_1's rmse: 0.00087842      valid_1's ic: 0.0257048
[200]   training's rmse: 0.000942459    training's ic: 0.0444224
valid_1's rmse: 0.000878479     valid_1's ic: 0.0260882
[250]   training's rmse: 0.000941729    training's ic: 0.0464706
valid_1's rmse: 0.000878522     valid_1's ic: 0.0260996

Fold: 22 | 08:38:07 | IC per minute: 2.97%

[50]    training's rmse: 0.000901678    training's ic: 0.0344405
valid_1's rmse: 0.00124889      valid_1's ic: 0.0247168
```

```
[100]   training's rmse: 0.000900504    training's ic: 0.0387862
valid_1's rmse: 0.00124921      valid_1's ic: 0.0242162
[150]   training's rmse: 0.000899561    training's ic: 0.0426923
valid_1's rmse: 0.00124947      valid_1's ic: 0.0241308
[200]   training's rmse: 0.00089887     training's ic: 0.045369 valid_1's rmse:
0.00124959      valid_1's ic: 0.0242198
[250]   training's rmse: 0.000898202    training's ic: 0.0477219
valid_1's rmse: 0.00124973      valid_1's ic: 0.0247126

Fold: 23 | 08:56:41 | IC per minute: 3.17%
```

1.4 Signal Evaluation

[112]:
```python
with pd.HDFStore(result_store) as store:
    pred_keys = [k[1:] for k in store.keys() if k[1:].startswith('pred')]
    cv_predictions = pd.concat([store[k] for k in pred_keys]).sort_index()
```

[113]:
```python
cv_predictions.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 19648064 entries, ('AAL', Timestamp('2016-02-01 15:47:00')) to
('YHOO', Timestamp('2017-06-16 15:59:00'))
Data columns (total 2 columns):
 #   Column   Non-Null Count     Dtype
---  ------   --------------     -----
 0   fwd1min  19648064 non-null  float64
 1   pred     19648064 non-null  float64
dtypes: float64(2)
memory usage: 399.0+ MB
```

[114]:
```python
time_stamp = cv_predictions.index.get_level_values('date_time')
dates = sorted(np.unique(time_stamp.date))
```

We have out-of-sample predictions for 484 days from February 2016 through December 2017:

[116]:
```python
print(f'# Days: {len(dates)} | First: {dates[0]} | Last: {dates[-1]}')
```

```
# Days: 484 | First: 2016-02-01 | Last: 2017-12-29
```

We only use minutes with at least 100 predictions:

[117]:
```python
n = cv_predictions.groupby('date_time').size()
```

There are ~700 periods, equivalent to a bit over a single trading day (0.67% of all periods in the sample), with fewer than 100 predictions over the 23 test months:

[120]:
```python
incomplete_minutes = n[n<100].index
```

[124]:
```
print(f'{len(incomplete_minutes)} ({len(incomplete_minutes)/len(n):.2%})')
```

```
1255 (0.67%)
```

[125]:
```
cv_predictions = cv_predictions[~time_stamp.isin(incomplete_minutes)]
```

[126]:
```
cv_predictions.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 19571774 entries, ('AAL', Timestamp('2016-02-01 15:47:00')) to
('YHOO', Timestamp('2017-06-16 15:59:00'))
Data columns (total 2 columns):
 #   Column   Non-Null Count     Dtype
---  ------   --------------     -----
 0   fwd1min  19571774 non-null  float64
 1   pred     19571774 non-null  float64
dtypes: float64(2)
memory usage: 397.4+ MB
```

1.4.1 Information Coefficient

Across all periods

[127]:
```
ic = spearmanr(cv_predictions.fwd1min, cv_predictions.pred)[0]
```

By minute We are making new predictions every minute, so it makes sense to look at the average performance across all short-term forecasts:

[132]:
```
minutes = cv_predictions.index.get_level_values('date_time')
by_minute = cv_predictions.groupby(minutes)
```

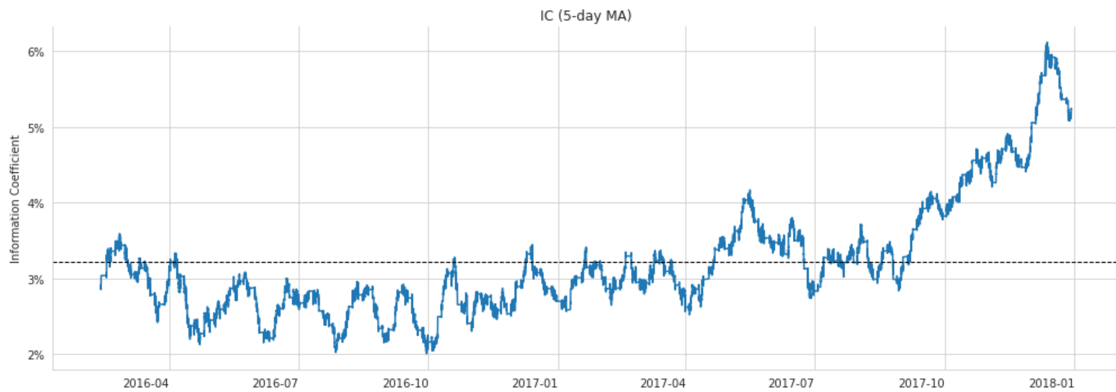
[129]:
```
ic_by_minute = by_minute.apply(lambda x: spearmanr(x.fwd1min, x.pred)[0])

minute_ic_mean = ic_by_minute.mean()
minute_ic_median = ic_by_minute.median()

print(f'\nAll periods: {ic:6.2%} | By Minute: {minute_ic_mean: 6.2%} (Median:␣
 ↪{minute_ic_median: 6.2%})')
```

```

All periods:  2.96% | By Minute:  3.21% (Median:  3.23%)
```

Plotted as a five-day rolling average, we see that the IC was mostly below the out-of-sample period mean, and increased during the last quarter of 2017 (as reflected in the validation results we observed while training the model).

[279]:
```
ax = ic_by_minute.rolling(5*650).mean().plot(figsize=(14, 5), title='IC (5-day␣
 ↪MA)', rot=0)
ax.axhline(minute_ic_mean, ls='--', lw=1, c='k')
```

```
ax.yaxis.set_major_formatter(FuncFormatter(lambda y, _: '{:.0%}'.format(y)))
ax.set_ylabel('Information Coefficient')
ax.set_xlabel('')
sns.despine()
plt.tight_layout()
```



1.4.2 Vectorized backtest of a naive strategey: financial performance by signal quantile

Alphalens does not work with minute-data, so we need to compute our own signal performance measures.

Unfortunately, Zipline's Pipeline also doesn't work for minute-data and Backtrader takes a very long time with such a large dataset. Hence, instead of an event-driven backtest of entry/exit rules as in previous examples, we can only create a rough sketch of the financial performance of a naive trading strategy driven by the model's predictions using vectorized backtesting (see Chapter 8 on the ML4T workflow. As we will see below, this does not produce particularly helpful results.

This naive strategy invests in equal-weighted portfolios of the stocks in each decile under the following assumptions (mentioned at the beginning of this notebook: 1. Based on the predictions using inputs from the current and previous bars, we can enter positions at the first trade price in the following minute bar 2. We exit all positions at the last price in that following minute bar 3. There are no trading cost or market impact (slippage) of our trades (but we can check how sensitive the results would be).

Average returns by minute bar and signal quantile To this end, we compute the quintiles and deciles of the model's `fwd1min` predictions for each minute:

[133]:
```
by_minute = cv_predictions.groupby(minutes, group_keys=False)
```

[134]:
```
labels = list(range(1, 6))
cv_predictions['quintile'] = by_minute.apply(lambda x: pd.qcut(x.pred, q=5,␣
↪labels=labels).astype(int))
```

```
[135]: labels = list(range(1, 11))
cv_predictions['decile'] = by_minute.apply(lambda x: pd.qcut(x.pred, q=10,␣
 ↪labels=labels).astype(int))
```

```
[136]: cv_predictions.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 19571774 entries, ('AAL', Timestamp('2016-02-01 15:47:00')) to
('YHOO', Timestamp('2017-06-16 15:59:00'))
Data columns (total 4 columns):
 #   Column    Non-Null Count     Dtype
---  ------    --------------     -----
 0   fwd1min   19571774 non-null  float64
 1   pred      19571774 non-null  float64
 2   quintile  19571774 non-null  int64
 3   decile    19571774 non-null  int64
dtypes: float64(2), int64(2)
memory usage: 696.1+ MB
```

Descriptive statistics of intraday returns by quintile and decile of model predictions Next, we compute the average one-minute returns for each quintile / decile and minute.

```
[319]: def compute_intraday_returns_by_quantile(predictions, quantile='quintile'):
    by_quantile = cv_predictions.reset_index().groupby(['date_time', quantile])
    return by_quantile.fwd1min.mean().unstack(quantile).sort_index()
```

```
[330]: intraday_returns = {'quintile':␣
 ↪compute_intraday_returns_by_quantile(cv_predictions),
                    'decile':␣
 ↪compute_intraday_returns_by_quantile(cv_predictions, quantile='decile')}
```

```
[334]: def summarize_intraday_returns(returns):
    summary = returns.describe(deciles)
    return pd.concat([summary.iloc[:1].applymap(lambda x: f'{x:,.0f}'),
                      summary.iloc[1:].applymap(lambda x: f'{x:.4%}')])
```

The returns per minute, averaged over the 23-months period, increase by quintile/decile and range from -.3 (-.4) to .27 (.37) basis points for the bottom and top quintile (decile), respectively. While this aligns with the finding of a weakly positive rank correlation coefficient, it also suggests that such small gains are unlikely to survive the impact of trading costs.

```
[335]: summary = summarize_intraday_returns(intraday_returns['quintile'])
summary
```

[335]:

quintile	1	2	3	4	5
count	187,115	187,115	187,115	187,115	187,115
mean	-0.0030%	-0.0011%	-0.0002%	0.0007%	0.0027%

```
std         0.0368%   0.0308%   0.0300%   0.0306%   0.0366%
min        -0.6316%  -0.4878%  -0.4880%  -0.5088%  -0.5918%
10%        -0.0397%  -0.0325%  -0.0307%  -0.0300%  -0.0326%
20%        -0.0234%  -0.0190%  -0.0178%  -0.0170%  -0.0177%
30%        -0.0145%  -0.0114%  -0.0105%  -0.0097%  -0.0094%
40%        -0.0080%  -0.0057%  -0.0049%  -0.0042%  -0.0032%
50%        -0.0023%  -0.0007%  -0.0000%   0.0008%   0.0024%
60%         0.0033%   0.0042%   0.0048%   0.0057%   0.0079%
70%         0.0096%   0.0098%   0.0104%   0.0113%   0.0144%
80%         0.0179%   0.0171%   0.0176%   0.0186%   0.0230%
90%         0.0328%   0.0300%   0.0302%   0.0317%   0.0383%
max         0.8794%   0.4456%   0.7358%   0.7256%   0.9139%
```

[336]:
```python
summary = summarize_intraday_returns(intraday_returns['decile'])
summary
```

[336]:
```
decile          1         2         3         4         5         6         7   \
count     187,115   187,115   187,115   187,115   187,115   187,115   187,115
mean     -0.0040%  -0.0020%  -0.0013%  -0.0009%  -0.0003%  -0.0000%   0.0005%
std       0.0448%   0.0369%   0.0342%   0.0333%   0.0328%   0.0329%   0.0332%
min      -0.7406%  -1.2023%  -0.5405%  -0.5460%  -0.9286%  -0.9563%  -0.5948%
10%      -0.0485%  -0.0392%  -0.0365%  -0.0351%  -0.0341%  -0.0338%  -0.0332%
20%      -0.0288%  -0.0233%  -0.0215%  -0.0208%  -0.0200%  -0.0198%  -0.0192%
30%      -0.0180%  -0.0142%  -0.0130%  -0.0124%  -0.0119%  -0.0116%  -0.0111%
40%      -0.0101%  -0.0074%  -0.0066%  -0.0061%  -0.0057%  -0.0054%  -0.0050%
50%      -0.0031%  -0.0015%  -0.0010%  -0.0006%  -0.0001%   0.0002%   0.0005%
60%       0.0038%   0.0045%   0.0047%   0.0049%   0.0053%   0.0056%   0.0060%
70%       0.0116%   0.0110%   0.0110%   0.0111%   0.0115%   0.0118%   0.0123%
80%       0.0218%   0.0196%   0.0193%   0.0192%   0.0195%   0.0198%   0.0204%
90%       0.0395%   0.0348%   0.0334%   0.0332%   0.0331%   0.0337%   0.0343%
max       0.8348%   1.0942%   0.5067%   0.7221%   0.7832%   1.3252%   1.0380%

decile          8         9        10
count     187,115   187,115   187,115
mean      0.0010%   0.0017%   0.0037%
std       0.0339%   0.0365%   0.0448%
min      -0.6565%  -0.5173%  -1.1758%
10%      -0.0331%  -0.0340%  -0.0389%
20%      -0.0191%  -0.0192%  -0.0210%
30%      -0.0109%  -0.0107%  -0.0112%
40%      -0.0046%  -0.0043%  -0.0037%
50%       0.0009%   0.0015%   0.0030%
60%       0.0065%   0.0073%   0.0098%
70%       0.0128%   0.0139%   0.0175%
80%       0.0211%   0.0225%   0.0280%
90%       0.0353%   0.0376%   0.0471%
max       1.3348%   1.3651%   1.1961%
```

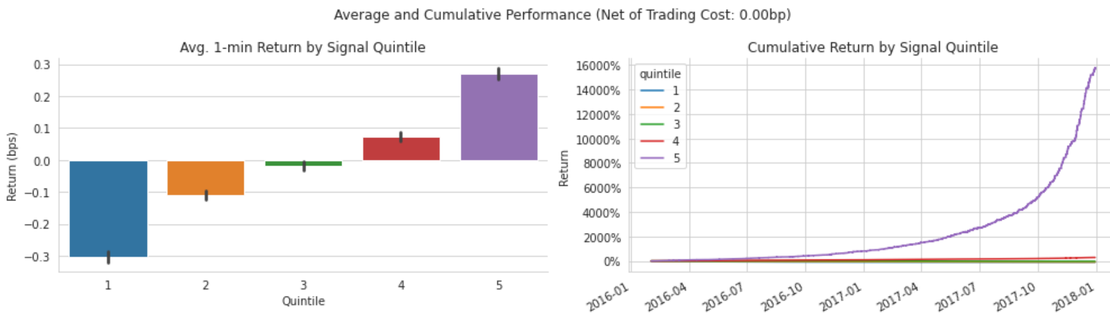
Cumulative Performance by Quantile To simulate the performance of our naive strategy that trades all available stocks every minute, we simply assume that we can reinvest (including potential gains/losses) every minute. To check for the sensitivity with respect for trading cost, we can assume they are a constant number (fraction) of basis points, and subtract this number from the minute-bar returns.

[367]:
```
def plot_cumulative_performance(returns, quantile='quintile',␣
↪trading_costs_bp=0):
    """Plot average return by quantile (in bp) as well as cumulative return,
        both net of trading costs (provided as basis points; 1bp = 0.01%)
    """

    fig, axes = plt.subplots(figsize=(14, 4), ncols=2)

    sns.barplot(y='fwd1min', x=quantile,
                data=returns[quantile].mul(10000).sub(trading_costs_bp).stack().
↪to_frame(
                    'fwd1min').reset_index(),
                ax=axes[0])
    axes[0].set_title(f'Avg. 1-min Return by Signal {quantile.capitalize()}')
    axes[0].set_ylabel('Return (bps)')
    axes[0].set_xlabel(quantile.capitalize())

    title = f'Cumulative Return by Signal {quantile.capitalize()}'
    (returns[quantile].sort_index().add(1).sub(trading_costs_bp/10000).
↪cumprod().sub(1)
     .plot(ax=axes[1], title=title))

    axes[1].yaxis.set_major_formatter(
        FuncFormatter(lambda y, _: '{:.0%}'.format(y)))
    axes[1].set_xlabel('')
    axes[1].set_ylabel('Return')
    fig.suptitle(f'Average and Cumulative Performance (Net of Trading Cost:␣
↪{trading_costs_bp:.2f}bp)')

    sns.despine()
    fig.tight_layout()
```

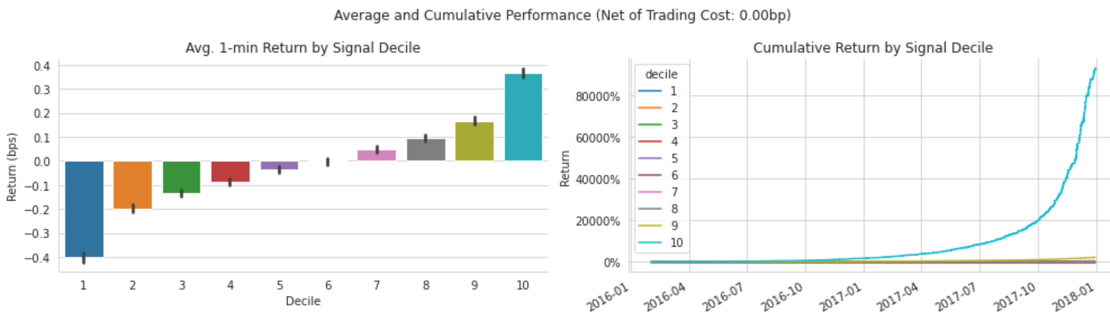
Without trading costs, the compounding of even fairly small gains leads to extremely large cumulative profits for the top quantile. However, these disappear as soon as we allow for minuscule trading costs that reduce the average quantile return close to zero.

Without trading costs

[368]:
```
plot_cumulative_performance(intraday_returns, 'quintile', trading_costs_bp=0)
```

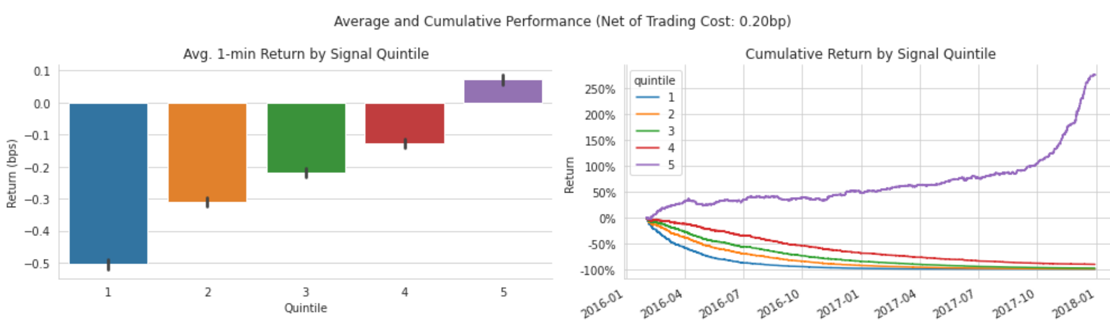


[369]:
```
plot_cumulative_performance(intraday_returns, 'decile', trading_costs_bp=0)
```

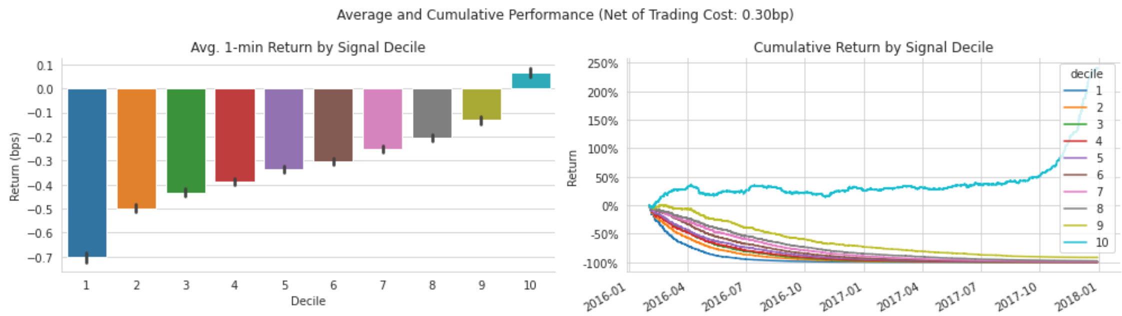


With extremely low trading costs

[370]:
```
# assuming costs of a fraction of a basis point, close to the average return of␣
↪the top quantile
plot_cumulative_performance(intraday_returns, 'quintile', trading_costs_bp=.2)
```



[371]:
```
plot_cumulative_performance(intraday_returns, 'decile', trading_costs_bp=.3)
```



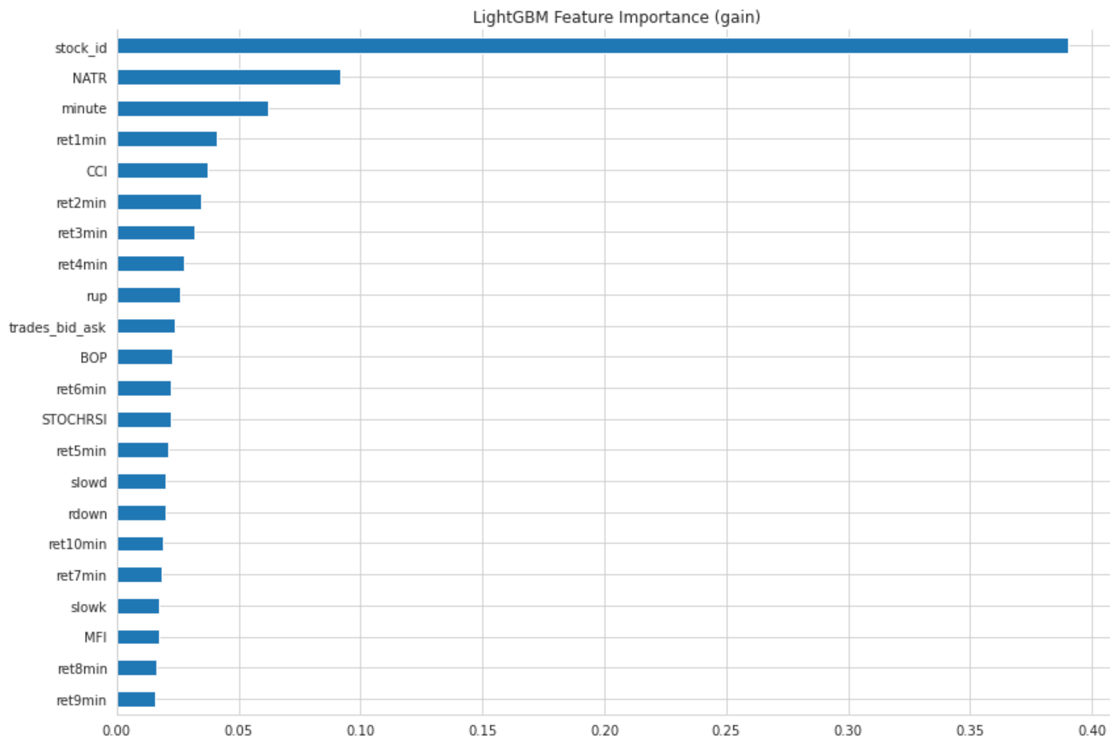
1.4.3 Feature Importance

We'll take a quick look at the features that most contributed to improving the IC across the 23 folds:

[235]:
```
with pd.HDFStore(result_store) as store:
    fi_keys = [k[1:] for k in store.keys() if k[1:].startswith('fi')]
    fi = pd.concat([store[k].to_frame(i) for i, k in enumerate(fi_keys, 1)],␣
↪axis=1)
```

The top features from a conventional feature importance perspective are the ticker, followed by NATR, minute of the day, latest 1m return and the CCI:

[254]:
```
fi.mean(1).nsmallest(25).plot.barh(figsize=(12, 8), title='LightGBM Feature␣
↪Importance (gain)')
sns.despine()
plt.tight_layout();
```



Explore with greater accuracy and in more detail how feature values affect predictions using SHAP values as demonstrated in various other notebooks in this Chapter and the appendix!

1.5 Conclusion

We have seen that a relatively simple gradient boosting model is able to achieve fairly consistent predictive performance that is significantly better than a random guess even on a very short horizon.

However, the resulting economic gains of our naive strategy of frequently buying/(short-)selling the top/bottome quantiles are too small to overcome the inevitable transaction costs. On the one hand, this demonstrates the challenges of extracting value from a predictive signal. On the other hand, it shows that we need a more sophisticated backtesting platform so that we can even begin to design and evaluate a more sophisticated strategy that requires far fewer trades to exploit the signal in our ML predictions.

In addition, we would also want to work on improving the model by adding more informative feature, e.g. based on the quote/trade info contained in the Algoseek data, or by fine-tuning our model architecture and hyperparameter settings.