04_japanese_equity_features

September 29, 2021

1 Japanese Equity Data - Feature Engineering

1.1 Imports & Settings

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

[2]:
```
%matplotlib inline

from pathlib import Path

import numpy as np
import pandas as pd
import talib

import matplotlib.pyplot as plt
import seaborn as sns
```

[3]:
```
sns.set_style('white')
```

[4]:
```
idx = pd.IndexSlice
```

1.2 Get Data

1.2.1 Stooq Japanese Equity data 2014-2019

[5]:
```
DATA_DIR = Path('..', 'data')
```

[6]:
```
prices = (pd.read_hdf(DATA_DIR / 'assets.h5', 'stooq/jp/tse/stocks/prices')
          .loc[idx[:, '2010': '2019'], :]
          .loc[lambda df: ~df.index.duplicated(), :])
```

[7]:
```
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 7491767 entries, ('1301.JP', Timestamp('2010-01-04 00:00:00')) to
('9997.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 5 columns):
```

```
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   open    7491767 non-null  float64
 1   high    7491767 non-null  float64
 2   low     7491767 non-null  float64
 3   close   7491767 non-null  float64
 4   volume  7491767 non-null  int64
dtypes: float64(4), int64(1)
memory usage: 314.7+ MB
```

[8]:
```
before = len(prices.index.unique('ticker').unique())
```

1.2.2 Remove symbols with missing values

[9]:
```
prices = (prices.unstack('ticker')
         .sort_index()
         .ffill(limit=5)
         .dropna(axis=1)
         .stack('ticker')
         .swaplevel())
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 5578822 entries, ('1301.JP', Timestamp('2010-01-04 00:00:00')) to
('9997.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 5 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   open    5578822 non-null  float64
 1   high    5578822 non-null  float64
 2   low     5578822 non-null  float64
 3   close   5578822 non-null  float64
 4   volume  5578822 non-null  float64
dtypes: float64(5)
memory usage: 234.3+ MB
```

[10]:
```
after = len(prices.index.unique('ticker').unique())
print(f'Before: {before:,.0f} after: {after:,.0f}')
```

```
Before: 3,664 after: 2,278
```

1.2.3 Keep most traded symbols

[11]:
```
dv = prices.close.mul(prices.volume)
keep = dv.groupby('ticker').median().nlargest(1000).index.tolist()
```

[13]:
```
prices = prices.loc[idx[keep, :], :]
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2449000 entries, ('9984.JP', Timestamp('2010-01-04 00:00:00')) to
('8107.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 5 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   open    2449000 non-null  float64
 1   high    2449000 non-null  float64
 2   low     2449000 non-null  float64
 3   close   2449000 non-null  float64
 4   volume  2449000 non-null  float64
dtypes: float64(5)
memory usage: 103.0+ MB
```

1.3 Feature Engineering

1.3.1 Compute period returns

[14]:
```
intervals = [1, 5, 10, 21, 63]
```

[15]:
```
returns = []
by_ticker = prices.groupby(level='ticker').close
for t in intervals:
    returns.append(by_ticker.pct_change(t).to_frame(f'ret_{t}'))
returns = pd.concat(returns, axis=1)
```

[16]:
```
returns.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2449000 entries, ('9984.JP', Timestamp('2010-01-04 00:00:00')) to
('8107.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 5 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   ret_1   2448000 non-null  float64
 1   ret_5   2444000 non-null  float64
 2   ret_10  2439000 non-null  float64
 3   ret_21  2428000 non-null  float64
 4   ret_63  2386000 non-null  float64
dtypes: float64(5)
memory usage: 103.0+ MB
```

1.3.2 Remove outliers

[20]:
```
max_ret_by_sym = returns.groupby(level='ticker').max()
```

[21]:
```
percentiles = [0.001, .005, .01, .025, .05, .1]
percentiles += [1-p for p in percentiles]
max_ret_by_sym.describe(percentiles=sorted(percentiles)[6:])
```

[21]:

	ret_1	ret_5	ret_10	ret_21	ret_63
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	0.170931	0.348342	0.468836	0.620602	1.015105
std	0.083577	0.293201	0.527677	0.802252	1.498513
min	0.066825	0.105314	0.106831	0.130860	0.204482
50%	0.150563	0.252961	0.307507	0.389720	0.638036
90%	0.268196	0.608058	0.837042	1.061642	1.740919
95%	0.340981	0.934732	1.381340	1.643186	2.573712
97.5%	0.379277	1.319257	2.042933	2.889063	4.228995
99%	0.471767	1.668250	3.283656	4.457870	8.028316
99.5%	0.555778	1.958242	3.590300	5.666164	9.627482
99.9%	0.789489	2.166924	4.385537	8.049485	17.754458
max	0.826025	2.402364	5.336406	9.085616	22.067797

[22]:
```
quantiles = max_ret_by_sym.quantile(.95)
to_drop = []
for ret, q in quantiles.items():
    to_drop.extend(max_ret_by_sym[max_ret_by_sym[ret]>q].index.tolist())
```

[23]:
```
to_drop = pd.Series(to_drop).value_counts()
to_drop = to_drop[to_drop > 1].index.tolist()
len(to_drop)
```

[23]: 59

[24]:
```
prices = prices.drop(to_drop, level='ticker')
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2304509 entries, ('9984.JP', Timestamp('2010-01-04 00:00:00')) to
('8107.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 5 columns):
 #   Column  Dtype
---  ------  -----
 0   open    float64
 1   high    float64
 2   low     float64
 3   close   float64
 4   volume  float64
dtypes: float64(5)
```

```
memory usage: 96.9+ MB
```

1.3.3 Calculate relative return percentiles

[25]:
```
returns = []
by_sym = prices.groupby(level='ticker').close
for t in intervals:
    ret = by_sym.pct_change(t)
    rel_perc = (ret.groupby(level='date')
                .apply(lambda x: pd.qcut(x, q=20, labels=False,␣
 ↪duplicates='drop')))
    returns.extend([ret.to_frame(f'ret_{t}'), rel_perc.
 ↪to_frame(f'ret_rel_perc_{t}')])
returns = pd.concat(returns, axis=1)
```

1.3.4 Technical Indicators

Percentage Price Oscillator

[26]:
```
ppo = prices.groupby(level='ticker').close.apply(talib.PPO).to_frame('PPO')
```

Normalized Average True Range

[27]:
```
natr = prices.groupby(level='ticker', group_keys=False).apply(lambda x: talib.
 ↪NATR(x.high, x.low, x.close)).to_frame('NATR')
```

Relative Strength Indicator

[28]:
```
rsi = prices.groupby(level='ticker').close.apply(talib.RSI).to_frame('RSI')
```

Bollinger Bands

[29]:
```
def get_bollinger(x):
    u, m, l = talib.BBANDS(x)
    return pd.DataFrame({'u': u, 'm': m, 'l': l})
```

[30]:
```
bbands = prices.groupby(level='ticker').close.apply(get_bollinger)
```

1.3.5 Combine Features

[31]:
```
data = pd.concat([prices, returns, ppo, natr, rsi, bbands], axis=1)
```

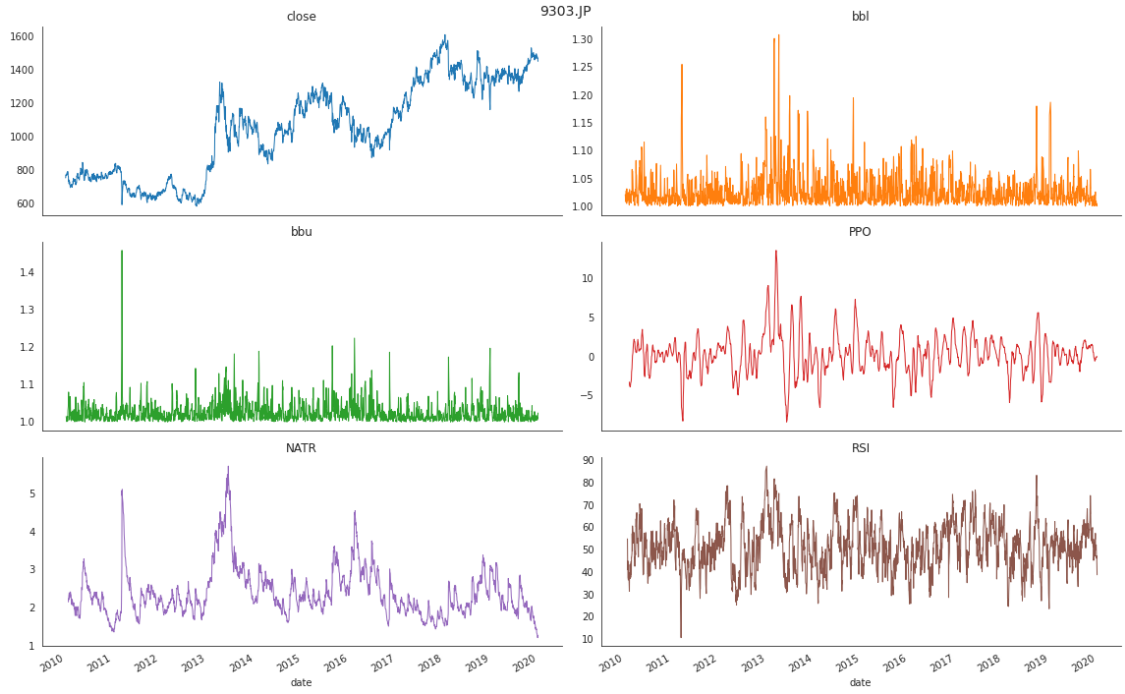
[32]:
```
data['bbl'] = data.close.div(data.l)
data['bbu'] = data.u.div(data.close)
data = data.drop(['u', 'm', 'l'], axis=1)
```

[33]:
```
data.bbu.corr(data.bbl, method='spearman')
```

[33]: -0.1598831761711913

1.3.6 Plot Indicators for randomly sample ticker

[34]:
```
indicators = ['close', 'bbl', 'bbu', 'PPO', 'NATR', 'RSI']
ticker = np.random.choice(data.index.get_level_values('ticker'))
(data.loc[idx[ticker, :], indicators].reset_index('ticker', drop=True)
 .plot(lw=1, subplots=True, figsize=(16, 10), title=indicators, layout=(3, 2),␣
 ↪legend=False))
plt.suptitle(ticker, fontsize=14)
sns.despine()
plt.tight_layout()
plt.subplots_adjust(top=.95)
```



[35]:
```
data = data.drop(prices.columns, axis=1)
```

1.3.7 Create time period indicators

[36]:
```
dates = data.index.get_level_values('date')
data['weekday'] = dates.weekday
data['month'] = dates.month
data['year'] = dates.year
```

1.4 Compute forward returns

[37]:
```
outcomes = []
by_ticker = data.groupby('ticker')
for t in intervals:
    k = f'fwd_ret_{t:02}'
    outcomes.append(k)
    data[k] = by_ticker[f'ret_{t}'].shift(-t)
```

[38]:
```
data.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2304509 entries, ('1332.JP', Timestamp('2010-01-04 00:00:00')) to
('9990.JP', Timestamp('2019-12-30 00:00:00'))
Data columns (total 23 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   ret_1            2303568 non-null  float64
 1   ret_rel_perc_1   2303568 non-null  float64
 2   ret_5            2299804 non-null  float64
 3   ret_rel_perc_5   2299804 non-null  float64
 4   ret_10           2295099 non-null  float64
 5   ret_rel_perc_10  2295099 non-null  float64
 6   ret_21           2284748 non-null  float64
 7   ret_rel_perc_21  2284748 non-null  float64
 8   ret_63           2245226 non-null  float64
 9   ret_rel_perc_63  2245226 non-null  float64
 10  PPO              2280984 non-null  float64
 11  NATR             2291335 non-null  float64
 12  RSI              2291335 non-null  float64
 13  bbl              2300745 non-null  float64
 14  bbu              2300745 non-null  float64
 15  weekday          2304509 non-null  int64
 16  month            2304509 non-null  int64
 17  year             2304509 non-null  int64
 18  fwd_ret_01       2303568 non-null  float64
 19  fwd_ret_05       2299804 non-null  float64
 20  fwd_ret_10       2295099 non-null  float64
 21  fwd_ret_21       2284748 non-null  float64
 22  fwd_ret_63       2245226 non-null  float64
dtypes: float64(20), int64(3)
memory usage: 413.3+ MB
```

[39]:
```
data.to_hdf('data.h5', 'stooq/japan/equities')
```