03_preparing_the_model_data

September 29, 2021

1 Preparing Alpha Factors and Features to predict Stock Returns

1.1 Imports & Settings

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

[2]:
```
%matplotlib inline

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats import pearsonr, spearmanr
from talib import RSI, BBANDS, MACD, ATR
```

[3]:
```
MONTH = 21
YEAR = 12 * MONTH
```

[4]:
```
START = '2013-01-01'
END = '2017-12-31'
```

[5]:
```
sns.set_style('whitegrid')
idx = pd.IndexSlice
```

1.2 Loading Quandl Wiki Stock Prices & Meta Data

[6]:
```
ohlcv = ['adj_open', 'adj_close', 'adj_low', 'adj_high', 'adj_volume']
```

[7]:
```
DATA_STORE = '../data/assets.h5'
```

[8]:
```
with pd.HDFStore(DATA_STORE) as store:
    prices = (store['quandl/wiki/prices']
              .loc[idx[START:END, :], ohlcv]
              .rename(columns=lambda x: x.replace('adj_', ''))
```

```
                .assign(volume=lambda x: x.volume.div(1000))
                .swaplevel()
                .sort_index())

    stocks = (store['us_equities/stocks']
                .loc[:, ['marketcap', 'ipoyear', 'sector']])
```

1.3 Remove stocks with few observations

[9]:
```
# want at least 2 years of data
min_obs = 2 * YEAR

# have this much per ticker
nobs = prices.groupby(level='ticker').size()

# keep those that exceed the limit
keep = nobs[nobs > min_obs].index

prices = prices.loc[idx[keep, :], :]
```

1.3.1 Align price and meta data

[10]:
```
stocks = stocks[~stocks.index.duplicated() & stocks.sector.notnull()]
stocks.sector = stocks.sector.str.lower().str.replace(' ', '_')
stocks.index.name = 'ticker'
```

[11]:
```
shared = (prices.index.get_level_values('ticker').unique()
          .intersection(stocks.index))
stocks = stocks.loc[shared, :]
prices = prices.loc[idx[shared, :], :]
```

[12]:
```
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2904233 entries, ('A', Timestamp('2013-01-02 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-29 00:00:00'))
Data columns (total 5 columns):
 #   Column  Non-Null Count    Dtype
---  ------  --------------    -----
 0   open    2904233 non-null  float64
 1   close   2904233 non-null  float64
 2   low     2904233 non-null  float64
 3   high    2904233 non-null  float64
 4   volume  2904233 non-null  float64
dtypes: float64(5)
memory usage: 122.6+ MB
```

[13]:
```
stocks.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2348 entries, A to ZUMZ
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   marketcap  2345 non-null   float64
 1   ipoyear    1026 non-null   float64
 2   sector     2348 non-null   object
dtypes: float64(2), object(1)
memory usage: 73.4+ KB
```

[14]:
```
stocks.sector.value_counts()
```

[14]:
```
consumer_services        440
finance                  393
technology               297
health_care              297
capital_goods            227
basic_industries         138
consumer_non-durables    126
energy                   123
public_utilities         105
consumer_durables         78
miscellaneous             69
transportation            55
Name: sector, dtype: int64
```

Optional: persist intermediate results:

[15]:
```
# with pd.HDFStore('tmp.h5') as store:
#     store.put('prices', prices)
#     store.put('stocks', stocks)
```

[16]:
```
# with pd.HDFStore('tmp.h5') as store:
#     prices = store['prices']
#     stocks = store['stocks']
```

1.4 Compute Rolling Average Dollar Volume

[17]:
```
# compute dollar volume to determine universe
prices['dollar_vol'] = prices[['close', 'volume']].prod(axis=1)
```

[18]:
```
prices['dollar_vol_1m'] = (prices.dollar_vol.groupby('ticker')
                           .rolling(window=21, level='date')
                           .mean()).values
```

[19]:
```python
prices.info(show_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2904233 entries, ('A', Timestamp('2013-01-02 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-29 00:00:00'))
Data columns (total 7 columns):
 #   Column         Non-Null Count    Dtype
---  ------         --------------    -----
 0   open           2904233 non-null  float64
 1   close          2904233 non-null  float64
 2   low            2904233 non-null  float64
 3   high           2904233 non-null  float64
 4   volume         2904233 non-null  float64
 5   dollar_vol     2904233 non-null  float64
 6   dollar_vol_1m  2857273 non-null  float64
dtypes: float64(7)
memory usage: 166.9+ MB
```

[20]:
```python
prices['dollar_vol_rank'] = (prices.groupby('date')
                              .dollar_vol_1m
                              .rank(ascending=False))
```

[21]:
```python
prices.info(show_counts=True)
```

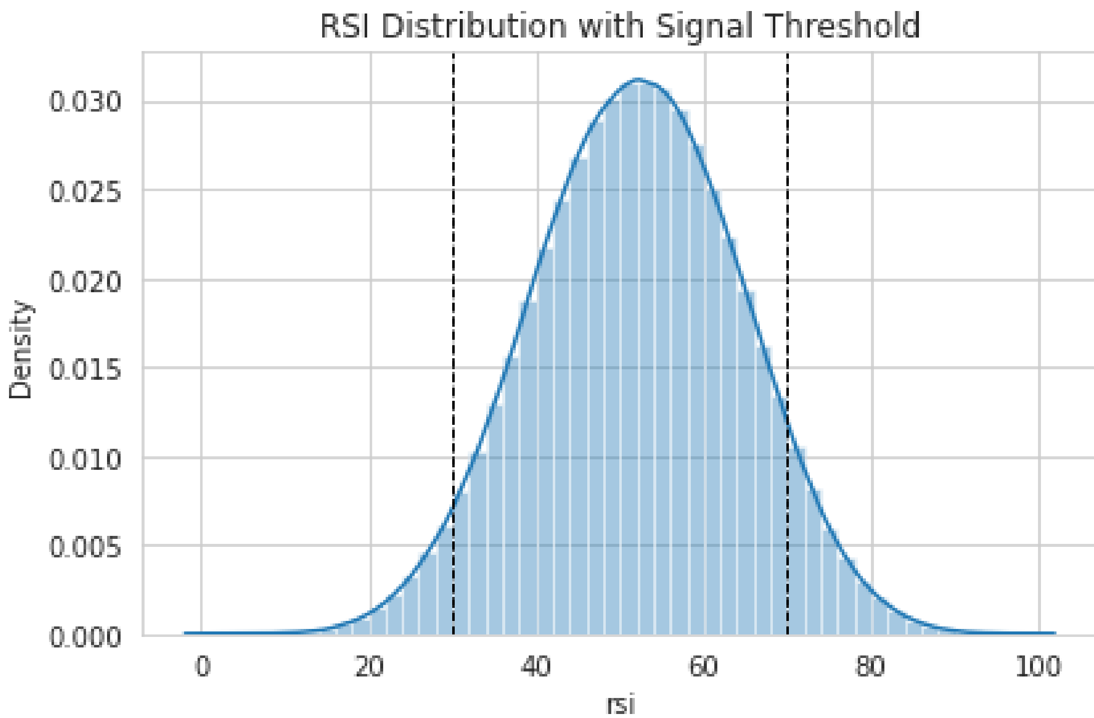
```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2904233 entries, ('A', Timestamp('2013-01-02 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-29 00:00:00'))
Data columns (total 8 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   open             2904233 non-null  float64
 1   close            2904233 non-null  float64
 2   low              2904233 non-null  float64
 3   high             2904233 non-null  float64
 4   volume           2904233 non-null  float64
 5   dollar_vol       2904233 non-null  float64
 6   dollar_vol_1m    2857273 non-null  float64
 7   dollar_vol_rank  2857273 non-null  float64
dtypes: float64(8)
memory usage: 189.1+ MB
```

1.5 Add some Basic Factors

1.5.1 Compute the Relative Strength Index

[22]:
```python
prices['rsi'] = prices.groupby(level='ticker').close.apply(RSI)
```

[23]:
```
ax = sns.distplot(prices.rsi.dropna())
ax.axvline(30, ls='--', lw=1, c='k')
ax.axvline(70, ls='--', lw=1, c='k')
ax.set_title('RSI Distribution with Signal Threshold')
plt.tight_layout();
```



1.5.2 Compute Bollinger Bands

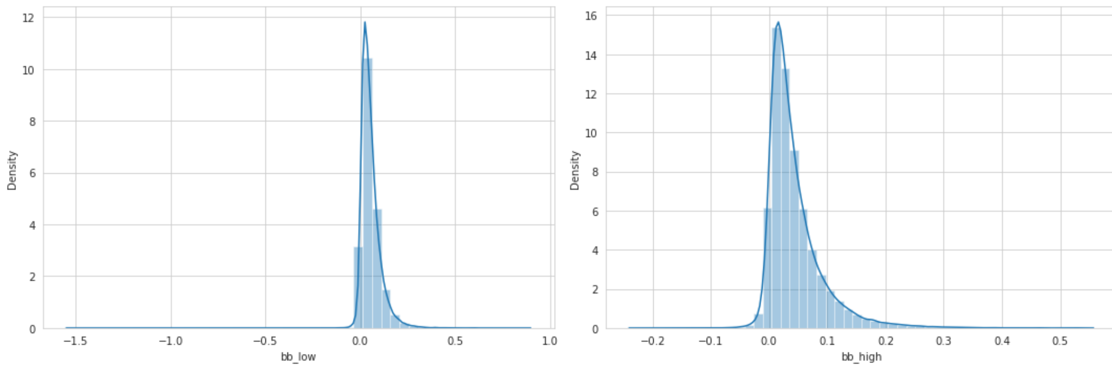
[24]:
```
def compute_bb(close):
    high, mid, low = BBANDS(close, timeperiod=20)
    return pd.DataFrame({'bb_high': high, 'bb_low': low}, index=close.index)
```

[25]:
```
prices = (prices.join(prices
                      .groupby(level='ticker')
                      .close
                      .apply(compute_bb)))
```

[26]:
```
prices['bb_high'] = prices.bb_high.sub(prices.close).div(prices.bb_high).
 ↪apply(np.log1p)
prices['bb_low'] = prices.close.sub(prices.bb_low).div(prices.close).apply(np.
 ↪log1p)
```

[27]:

```
fig, axes = plt.subplots(ncols=2, figsize=(15, 5))
sns.distplot(prices.loc[prices.dollar_vol_rank<100, 'bb_low'].dropna(),␣
↪ax=axes[0])
sns.distplot(prices.loc[prices.dollar_vol_rank<100, 'bb_high'].dropna(),␣
↪ax=axes[1])
plt.tight_layout();
```



1.5.3 Compute Average True Range

[28]:

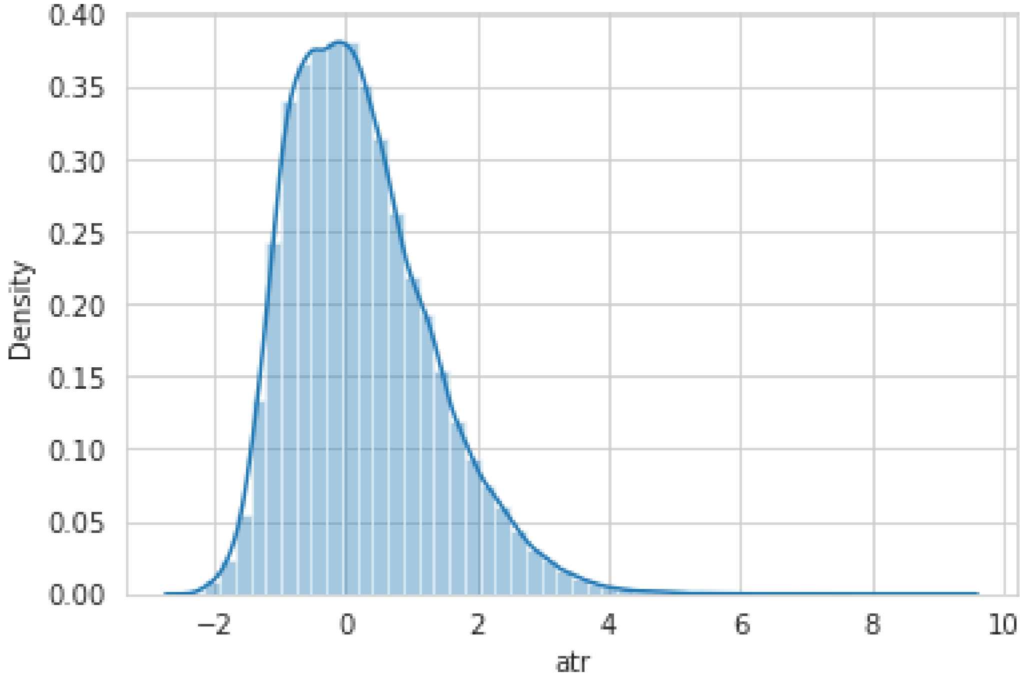
```
def compute_atr(stock_data):
    df = ATR(stock_data.high, stock_data.low,
             stock_data.close, timeperiod=14)
    return df.sub(df.mean()).div(df.std())
```

[29]:

```
prices['atr'] = (prices.groupby('ticker', group_keys=False)
                   .apply(compute_atr))
```

[30]:

```
sns.distplot(prices[prices.dollar_vol_rank<50].atr.dropna());
```



1.5.4 Compute Moving Average Convergence/Divergence

[31]:
```
def compute_macd(close):
    macd = MACD(close)[0]
    return (macd - np.mean(macd))/np.std(macd)
```

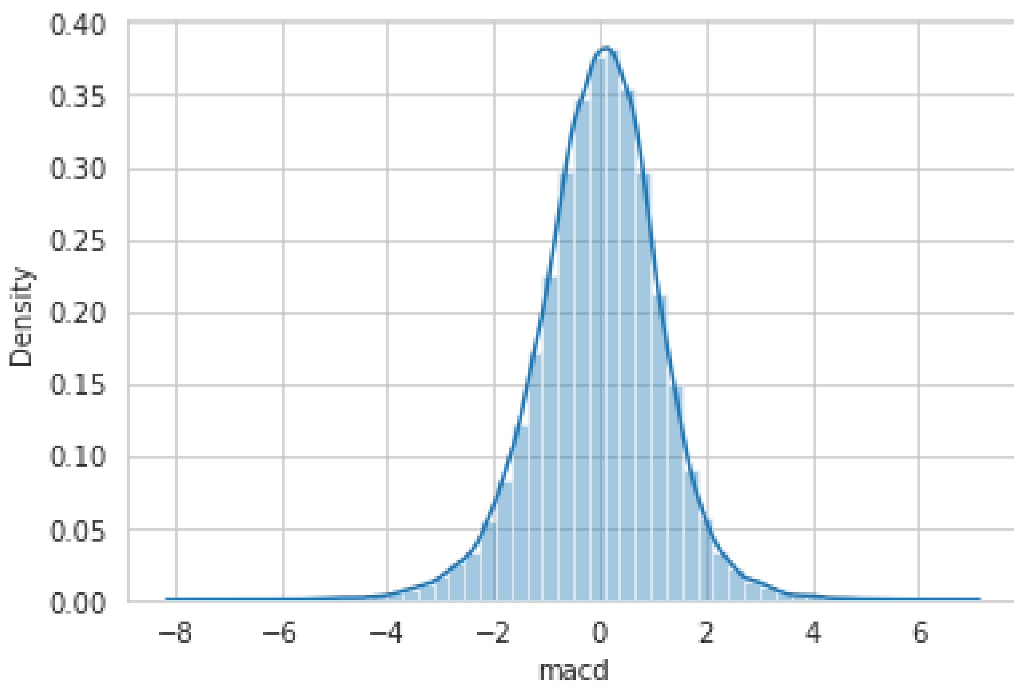
[32]:
```
prices['macd'] = (prices
                  .groupby('ticker', group_keys=False)
                  .close
                  .apply(compute_macd))
```

[33]:
```
prices.macd.describe(percentiles=[.001, .01, .02, .03, .04, .05, .95, .96, .97,␣
 ↪.98, .99, .999]).apply(lambda x: f'{x:,.1f}')
```

[33]:
```
count    2,826,749.0
mean            -0.0
std              1.0
min            -10.5
0.1%            -4.1
1%              -2.6
2%              -2.2
3%              -2.0
4%              -1.8
5%              -1.6
```

```
50%             0.0
95%             1.6
96%             1.7
97%             1.9
98%             2.1
99%             2.6
99.9%           4.0
max             8.7
Name: macd, dtype: object
```

[34]:
```
sns.distplot(prices[prices.dollar_vol_rank<100].macd.dropna());
```



1.6 Compute Lagged Returns

[35]:
```
lags = [1, 5, 10, 21, 42, 63]
```

[36]:
```
returns = prices.groupby(level='ticker').close.pct_change()
percentiles=[.0001, .001, .01]
percentiles+= [1-p for p in percentiles]
returns.describe(percentiles=percentiles).iloc[2:].to_frame('percentiles').
 ↪style.format(lambda x: f'{x:,.2%}')
```

[36]:
```
<pandas.io.formats.style.Styler at 0x7fc45043cd90>
```

[37]:
```python
q = 0.0001
```

1.6.1 Winsorize outliers

[38]:
```python
for lag in lags:
    prices[f'return_{lag}d'] = (prices.groupby(level='ticker').close
                                .pct_change(lag)
                                .pipe(lambda x: x.clip(lower=x.quantile(q),
                                                       upper=x.quantile(1 - q)))
                                .add(1)
                                .pow(1 / lag)
                                .sub(1)
                                )
```

1.6.2 Shift lagged returns

[39]:
```python
for t in [1, 2, 3, 4, 5]:
    for lag in [1, 5, 10, 21]:
        prices[f'return_{lag}d_lag{t}'] = (prices.groupby(level='ticker')
                                           [f'return_{lag}d'].shift(t * lag))
```

1.7 Compute Forward Returns

[40]:
```python
for t in [1, 5, 10, 21]:
    prices[f'target_{t}d'] = prices.groupby(level='ticker')[f'return_{t}d'].
 ↪shift(-t)
```

1.8 Combine Price and Meta Data

[41]:
```python
prices = prices.join(stocks[['sector']])
```

1.9 Create time and sector dummy variables

[42]:
```python
prices['year'] = prices.index.get_level_values('date').year
prices['month'] = prices.index.get_level_values('date').month
```

[43]:
```python
prices.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2904233 entries, ('A', Timestamp('2013-01-02 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-29 00:00:00'))
Data columns (total 46 columns):
 #   Column           Non-Null Count    Dtype
---  ------           --------------    -----
 0   open             2904233 non-null  float64
 1   close            2904233 non-null  float64
```

```
 2   low              2904233 non-null  float64
 3   high             2904233 non-null  float64
 4   volume           2904233 non-null  float64
 5   dollar_vol       2904233 non-null  float64
 6   dollar_vol_1m    2857273 non-null  float64
 7   dollar_vol_rank  2857273 non-null  float64
 8   rsi              2871361 non-null  float64
 9   bb_high          2859618 non-null  float64
 10  bb_low           2859585 non-null  float64
 11  atr              2871361 non-null  float64
 12  macd             2826749 non-null  float64
 13  return_1d        2901885 non-null  float64
 14  return_5d        2892493 non-null  float64
 15  return_10d       2880753 non-null  float64
 16  return_21d       2854925 non-null  float64
 17  return_42d       2805617 non-null  float64
 18  return_63d       2756309 non-null  float64
 19  return_1d_lag1   2899537 non-null  float64
 20  return_5d_lag1   2880753 non-null  float64
 21  return_10d_lag1  2857273 non-null  float64
 22  return_21d_lag1  2805617 non-null  float64
 23  return_1d_lag2   2897189 non-null  float64
 24  return_5d_lag2   2869013 non-null  float64
 25  return_10d_lag2  2833793 non-null  float64
 26  return_21d_lag2  2756309 non-null  float64
 27  return_1d_lag3   2894841 non-null  float64
 28  return_5d_lag3   2857273 non-null  float64
 29  return_10d_lag3  2810313 non-null  float64
 30  return_21d_lag3  2707001 non-null  float64
 31  return_1d_lag4   2892493 non-null  float64
 32  return_5d_lag4   2845533 non-null  float64
 33  return_10d_lag4  2786833 non-null  float64
 34  return_21d_lag4  2657693 non-null  float64
 35  return_1d_lag5   2890145 non-null  float64
 36  return_5d_lag5   2833793 non-null  float64
 37  return_10d_lag5  2763353 non-null  float64
 38  return_21d_lag5  2608385 non-null  float64
 39  target_1d        2901885 non-null  float64
 40  target_5d        2892493 non-null  float64
 41  target_10d       2880753 non-null  float64
 42  target_21d       2854925 non-null  float64
 43  sector           2904233 non-null  object
 44  year             2904233 non-null  int64
 45  month            2904233 non-null  int64
dtypes: float64(43), int64(2), object(1)
memory usage: 1.1+ GB
```

[44]:
```
prices.assign(sector=pd.factorize(prices.sector, sort=True)[0]).to_hdf('data.
↪h5', 'model_data/no_dummies')
```

[45]:
```
prices = pd.get_dummies(prices,
                        columns=['year', 'month', 'sector'],
                        prefix=['year', 'month', ''],
                        prefix_sep=['_', '_', ''],
                        drop_first=True)
```

[46]:
```
prices.info(null_counts=True)
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2904233 entries, ('A', Timestamp('2013-01-02 00:00:00')) to ('ZUMZ',
Timestamp('2017-12-29 00:00:00'))
Data columns (total 69 columns):
 #   Column               Non-Null Count    Dtype
---  ------               --------------    -----
 0   open                 2904233 non-null  float64
 1   close                2904233 non-null  float64
 2   low                  2904233 non-null  float64
 3   high                 2904233 non-null  float64
 4   volume               2904233 non-null  float64
 5   dollar_vol           2904233 non-null  float64
 6   dollar_vol_1m        2857273 non-null  float64
 7   dollar_vol_rank      2857273 non-null  float64
 8   rsi                  2871361 non-null  float64
 9   bb_high              2859618 non-null  float64
 10  bb_low               2859585 non-null  float64
 11  atr                  2871361 non-null  float64
 12  macd                 2826749 non-null  float64
 13  return_1d            2901885 non-null  float64
 14  return_5d            2892493 non-null  float64
 15  return_10d           2880753 non-null  float64
 16  return_21d           2854925 non-null  float64
 17  return_42d           2805617 non-null  float64
 18  return_63d           2756309 non-null  float64
 19  return_1d_lag1       2899537 non-null  float64
 20  return_5d_lag1       2880753 non-null  float64
 21  return_10d_lag1      2857273 non-null  float64
 22  return_21d_lag1      2805617 non-null  float64
 23  return_1d_lag2       2897189 non-null  float64
 24  return_5d_lag2       2869013 non-null  float64
 25  return_10d_lag2      2833793 non-null  float64
 26  return_21d_lag2      2756309 non-null  float64
 27  return_1d_lag3       2894841 non-null  float64
 28  return_5d_lag3       2857273 non-null  float64
 29  return_10d_lag3      2810313 non-null  float64
```

```
 30  return_21d_lag3        2707001 non-null  float64
 31  return_1d_lag4         2892493 non-null  float64
 32  return_5d_lag4         2845533 non-null  float64
 33  return_10d_lag4        2786833 non-null  float64
 34  return_21d_lag4        2657693 non-null  float64
 35  return_1d_lag5         2890145 non-null  float64
 36  return_5d_lag5         2833793 non-null  float64
 37  return_10d_lag5        2763353 non-null  float64
 38  return_21d_lag5        2608385 non-null  float64
 39  target_1d              2901885 non-null  float64
 40  target_5d              2892493 non-null  float64
 41  target_10d             2880753 non-null  float64
 42  target_21d             2854925 non-null  float64
 43  year_2014              2904233 non-null  uint8
 44  year_2015              2904233 non-null  uint8
 45  year_2016              2904233 non-null  uint8
 46  year_2017              2904233 non-null  uint8
 47  month_2                2904233 non-null  uint8
 48  month_3                2904233 non-null  uint8
 49  month_4                2904233 non-null  uint8
 50  month_5                2904233 non-null  uint8
 51  month_6                2904233 non-null  uint8
 52  month_7                2904233 non-null  uint8
 53  month_8                2904233 non-null  uint8
 54  month_9                2904233 non-null  uint8
 55  month_10               2904233 non-null  uint8
 56  month_11               2904233 non-null  uint8
 57  month_12               2904233 non-null  uint8
 58  capital_goods          2904233 non-null  uint8
 59  consumer_durables      2904233 non-null  uint8
 60  consumer_non-durables  2904233 non-null  uint8
 61  consumer_services      2904233 non-null  uint8
 62  energy                 2904233 non-null  uint8
 63  finance                2904233 non-null  uint8
 64  health_care            2904233 non-null  uint8
 65  miscellaneous          2904233 non-null  uint8
 66  public_utilities       2904233 non-null  uint8
 67  technology             2904233 non-null  uint8
 68  transportation         2904233 non-null  uint8
dtypes: float64(43), uint8(26)
memory usage: 1.1+ GB
```

1.10 Store Model Data

[47]:
```
prices.to_hdf('data.h5', 'model_data')
```

1.11 Explore Data

1.11.1 Plot Factors

[48]:
```
target = 'target_5d'
top100 = prices[prices.dollar_vol_rank<100].copy()
```

1.11.2 RSI

[49]:
```
top100.loc[:, 'rsi_signal'] = pd.cut(top100.rsi, bins=[0, 30, 70, 100])
```

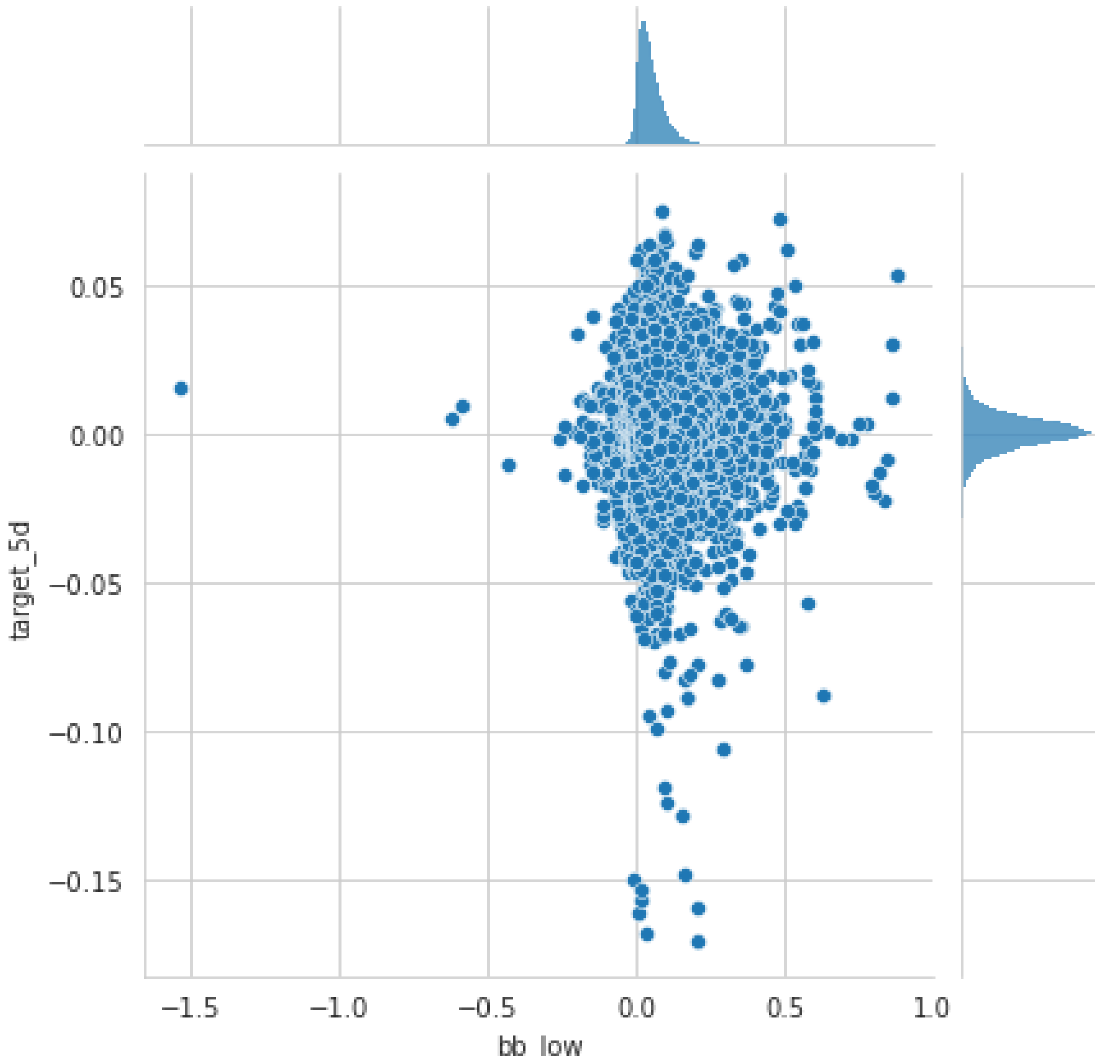
[50]:
```
top100.groupby('rsi_signal')['target_5d'].describe()
```

[50]:
```
               count      mean       std       min       25%       50%  \
rsi_signal
(0, 30]       4209.0  0.001126  0.010457 -0.067138 -0.003606  0.001051
(30, 70]    107244.0  0.000446  0.007711 -0.170571 -0.003054  0.000650
(70, 100]    10634.0  0.000018  0.006354 -0.087857 -0.002818  0.000145

                 75%       max
rsi_signal
(0, 30]     0.006156  0.061889
(30, 70]    0.004246  0.075653
(70, 100]   0.003121  0.058570
```

1.11.3 Bollinger Bands

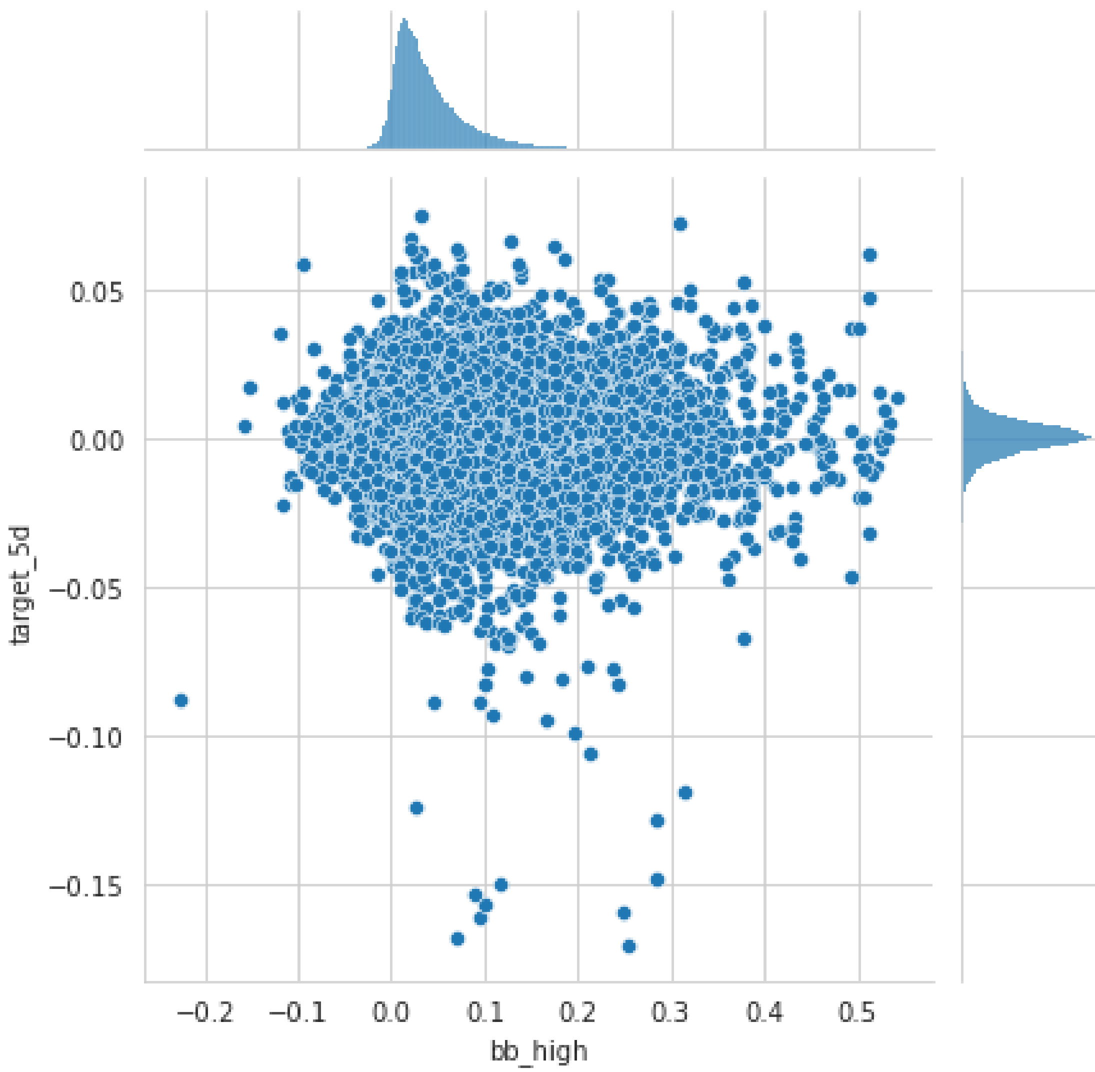
[51]:
```
metric = 'bb_low'
j=sns.jointplot(x=metric, y=target, data=top100)

df = top100[[metric, target]].dropna()
r, p = spearmanr(df[metric], df[target])
print(f'{r:,.2%} ({p:.2%})')
```

```
-2.68% (0.00%)
```



[52]:
```
metric = 'bb_high'
j=sns.jointplot(x=metric, y=target, data=top100)

df = top100[[metric, target]].dropna()
r, p = spearmanr(df[metric], df[target])
print(f'{r:,.2%} ({p:.2%})')
```

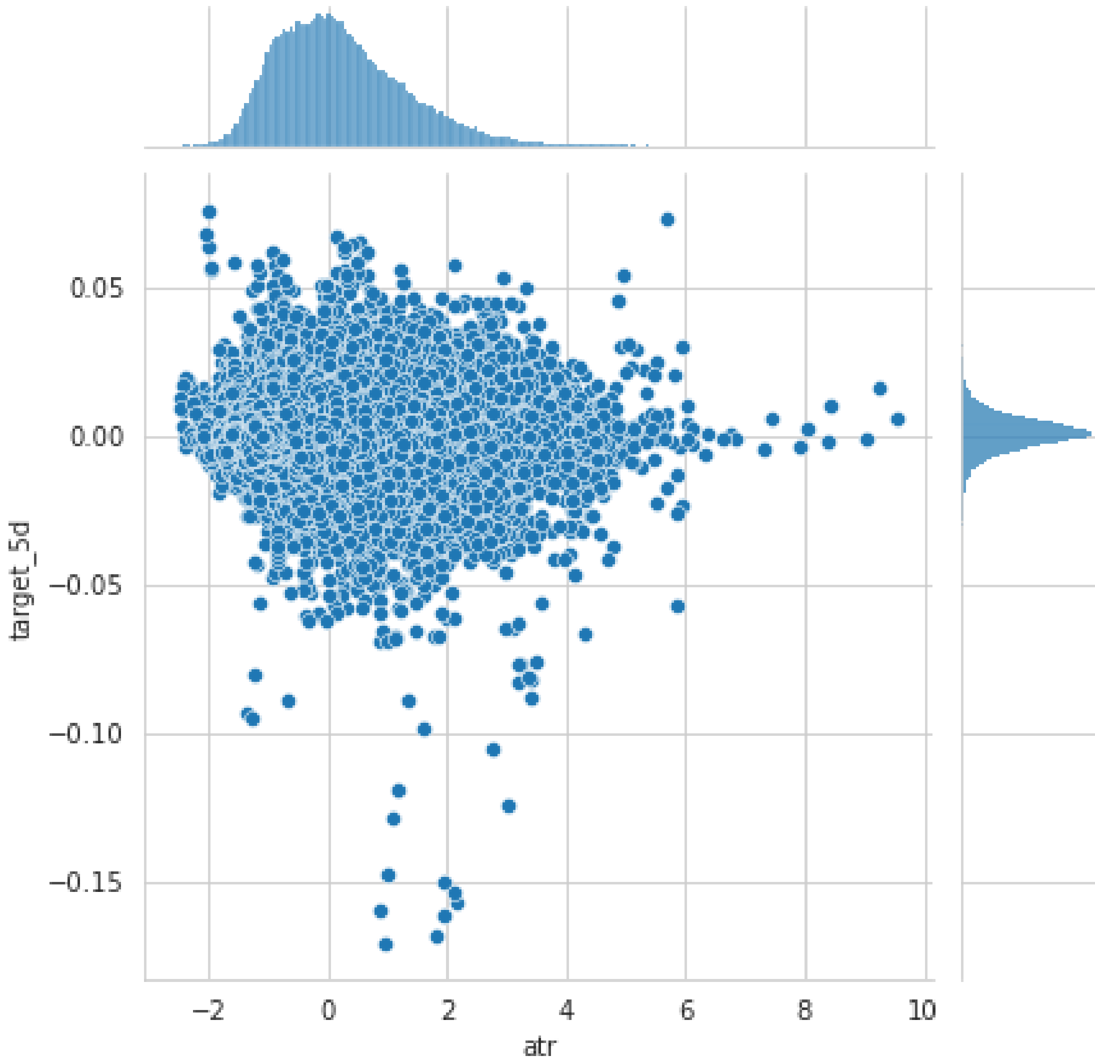
```
4.21% (0.00%)
```



1.11.4 ATR

[53]:
```
metric = 'atr'
j=sns.jointplot(x=metric, y=target, data=top100)

df = top100[[metric, target]].dropna()
r, p = spearmanr(df[metric], df[target])
print(f'{r:,.2%} ({p:.2%})')
```

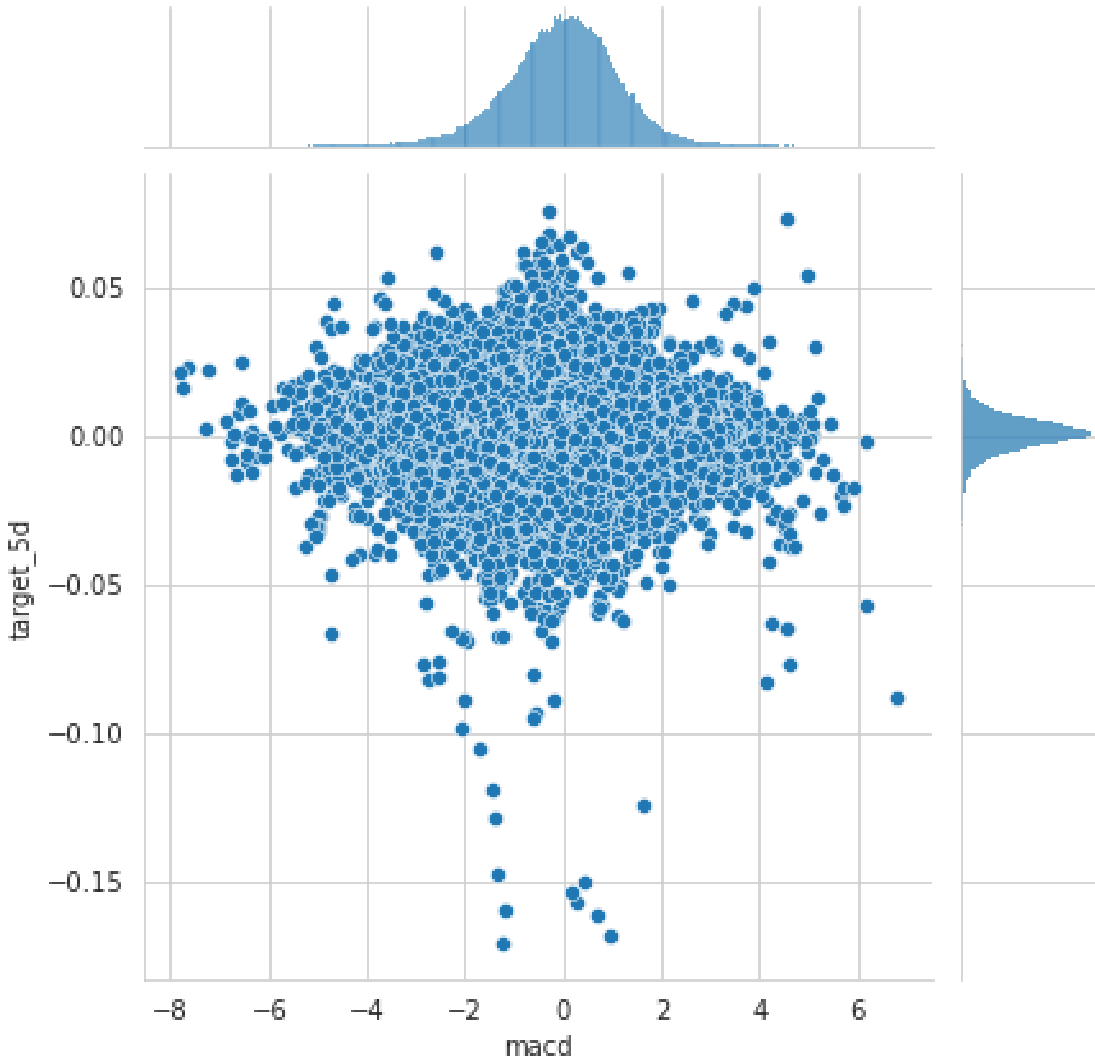
```
0.07% (80.08%)
```



1.11.5 MACD

[54]:
```
metric = 'macd'
j=sns.jointplot(x=metric, y=target, data=top100)

df = top100[[metric, target]].dropna()
r, p = spearmanr(df[metric], df[target])
print(f'{r:,.2%} ({p:.2%})')
```

```
-4.72% (0.00%)
```



0.05
0.00
−0.05
−0.10
−0.15
target_5d
−8
−6
−4
−2
0
2
4
6
macd