01_feature_engineering

September 29, 2021

1 How to transform data into factors

Based on a conceptual understanding of key factor categories, their rationale and popular metrics, a key task is to identify new factors that may better capture the risks embodied by the return drivers laid out previously, or to find new ones.

In either case, it will be important to compare the performance of innovative factors to that of known factors to identify incremental signal gains.

We create the dataset here and store it in our data folder to facilitate reuse in later chapters.

1.1 Imports & Settings

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

[2]:
```
%matplotlib inline

from datetime import datetime
import pandas as pd
import pandas_datareader.data as web

# replaces pyfinance.ols.PandasRollingOLS (no longer maintained)
from statsmodels.regression.rolling import RollingOLS
import statsmodels.api as sm

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

[3]:
```
sns.set_style('whitegrid')
idx = pd.IndexSlice
```

1.2 Get Data

The `assets.h5` store can be generated using the the notebook create_datasets in the data directory in the root directory of this repo for instruction to download the following dataset.

We load the Quandl stock price datasets covering the US equity markets 2000-18 using `pd.IndexSlice` to perform a slice operation on the `pd.MultiIndex`, select the adjusted close price and unpivot the column to convert the DataFrame to wide format with tickers in the columns and timestamps in the rows:

Set data store location:

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

[5]:
```
START = 2000
END = 2018
```

[6]:
```
with pd.HDFStore(DATA_STORE) as store:
    prices = (store['quandl/wiki/prices']
              .loc[idx[str(START):str(END), :], 'adj_close']
              .unstack('ticker'))
    stocks = store['us_equities/stocks'].loc[:, ['marketcap', 'ipoyear',␣
 ↪'sector']]
```

[7]:
```
prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4706 entries, 2000-01-03 to 2018-03-27
Columns: 3199 entries, A to ZUMZ
dtypes: float64(3199)
memory usage: 114.9 MB
```

[8]:
```
stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 6834 entries, PIH to ZYME
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   marketcap  5766 non-null   float64
 1   ipoyear    3038 non-null   float64
 2   sector     5288 non-null   object
dtypes: float64(2), object(1)
memory usage: 213.6+ KB
```

1.2.1 Keep data with stock info

Remove `stocks` duplicates and align index names for later joining.

[9]:
```
stocks = stocks[~stocks.index.duplicated()]
stocks.index.name = 'ticker'
```

Get tickers with both price information and metdata

[10]:
```
shared = prices.columns.intersection(stocks.index)
```

```
[11]: stocks = stocks.loc[shared, :]
      stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2412 entries, A to ZUMZ
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   marketcap  2407 non-null   float64
 1   ipoyear    1065 non-null   float64
 2   sector     2372 non-null   object
dtypes: float64(2), object(1)
memory usage: 75.4+ KB
```

```
[12]: prices = prices.loc[:, shared]
      prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4706 entries, 2000-01-03 to 2018-03-27
Columns: 2412 entries, A to ZUMZ
dtypes: float64(2412)
memory usage: 86.6 MB
```

```
[13]: assert prices.shape[1] == stocks.shape[0]
```

1.3 Create monthly return series

To reduce training time and experiment with strategies for longer time horizons, we convert the business-daily data to month-end frequency using the available adjusted close price:

```
[14]: monthly_prices = prices.resample('M').last()
```

To capture time series dynamics that reflect, for example, momentum patterns, we compute historical returns using the method `.pct_change(n_periods)`, that is, returns over various monthly periods as identified by lags.

We then convert the wide result back to long format with the `.stack()` method, use `.pipe()` to apply the `.clip()` method to the resulting `DataFrame`, and winsorize returns at the [1%, 99%] levels; that is, we cap outliers at these percentiles.

Finally, we normalize returns using the geometric average. After using `.swaplevel()` to change the order of the `MultiIndex` levels, we obtain compounded monthly returns for six periods ranging from 1 to 12 months:

```
[15]: monthly_prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 219 entries, 2000-01-31 to 2018-03-31
Freq: M
```

```
Columns: 2412 entries, A to ZUMZ
dtypes: float64(2412)
memory usage: 4.0 MB
```

[16]:
```
outlier_cutoff = 0.01
data = pd.DataFrame()
lags = [1, 2, 3, 6, 9, 12]
for lag in lags:
    data[f'return_{lag}m'] = (monthly_prices
                           .pct_change(lag)
                           .stack()
                           .pipe(lambda x: x.clip(lower=x.
 ↪quantile(outlier_cutoff),
                                                  upper=x.
 ↪quantile(1-outlier_cutoff)))
                           .add(1)
                           .pow(1/lag)
                           .sub(1)
                           )
data = data.swaplevel().dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 399525 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 6 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   return_1m   399525 non-null  float64
 1   return_2m   399525 non-null  float64
 2   return_3m   399525 non-null  float64
 3   return_6m   399525 non-null  float64
 4   return_9m   399525 non-null  float64
 5   return_12m  399525 non-null  float64
dtypes: float64(6)
memory usage: 19.9+ MB
```

1.4 Drop stocks with less than 10 yrs of returns

[17]:
```
min_obs = 120
nobs = data.groupby(level='ticker').size()
keep = nobs[nobs>min_obs].index

data = data.loc[idx[keep,:], :]
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
```

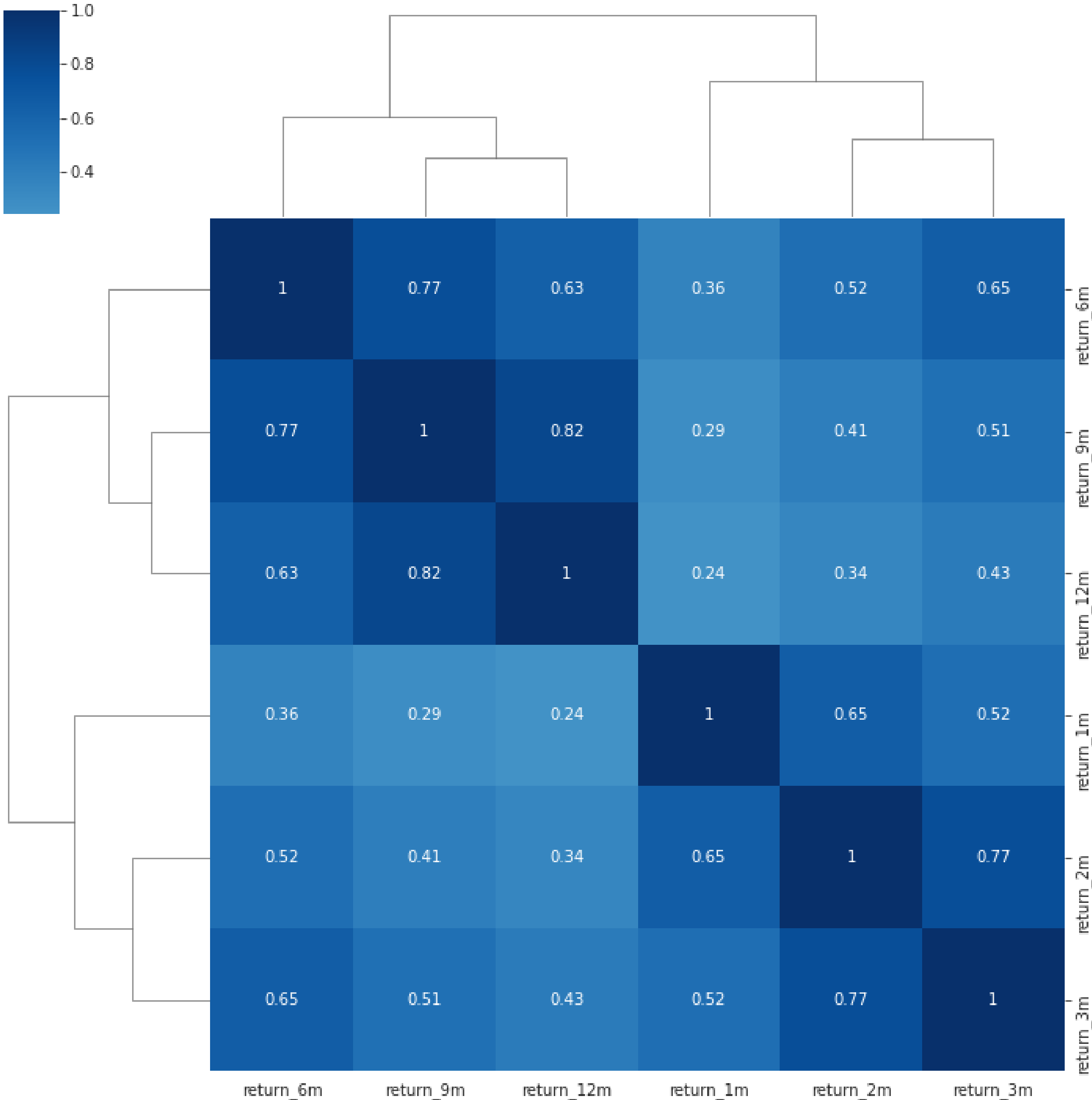
```
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 6 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   return_1m   360752 non-null  float64
 1   return_2m   360752 non-null  float64
 2   return_3m   360752 non-null  float64
 3   return_6m   360752 non-null  float64
 4   return_9m   360752 non-null  float64
 5   return_12m  360752 non-null  float64
dtypes: float64(6)
memory usage: 18.0+ MB
```

[18]:
```python
data.describe()
```

[18]:
```
            return_1m      return_2m      return_3m      return_6m  \
count  360752.000000  360752.000000  360752.000000  360752.000000
mean        0.012255       0.009213       0.008181       0.007025
std         0.114236       0.081170       0.066584       0.048474
min        -0.329564      -0.255452      -0.214783      -0.162063
25%        -0.046464      -0.030716      -0.023961      -0.014922
50%         0.009448       0.009748       0.009744       0.009378
75%         0.066000       0.049249       0.042069       0.031971
max         0.430943       0.281819       0.221789       0.154555

            return_9m     return_12m
count  360752.000000  360752.000000
mean        0.006552       0.006296
std         0.039897       0.034792
min        -0.131996      -0.114283
25%        -0.011182      -0.009064
50%         0.008982       0.008726
75%         0.027183       0.024615
max         0.124718       0.106371
```

[19]:
```python
# cmap = sns.diverging_palette(10, 220, as_cmap=True)
sns.clustermap(data.corr('spearman'), annot=True, center=0, cmap='Blues');
```



We are left with 1,670 tickers.

[20]:
```
data.index.get_level_values('ticker').nunique()
```

[20]: 1838

1.5 Rolling Factor Betas

We will introduce the Fama—French data to estimate the exposure of assets to common risk factors using linear regression in Chapter 9, Time Series Models.

The five Fama—French factors, namely market risk, size, value, operating profitability, and investment have been shown empirically to explain asset returns and are commonly used to assess the risk/return profile of portfolios. Hence, it is natural to include past factor exposures as financial features in models that aim to predict future returns.

We can access the historical factor returns using the `pandas-datareader` and estimate historical exposures using the `RollingOLS` rolling linear regression functionality in the `statsmodels` library as follows:

Use Fama-French research factors to estimate the factor exposures of the stock in the dataset to the 5 factors market risk, size, value, operating profitability and investment.

[21]:
```
factors = ['Mkt-RF', 'SMB', 'HML', 'RMW', 'CMA']
factor_data = web.DataReader('F-F_Research_Data_5_Factors_2x3', 'famafrench',␣
 ↪start='2000')[0].drop('RF', axis=1)
factor_data.index = factor_data.index.to_timestamp()
factor_data = factor_data.resample('M').last().div(100)
factor_data.index.name = 'date'
factor_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 254 entries, 2000-01-31 to 2021-02-28
Freq: M
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Mkt-RF  254 non-null    float64
 1   SMB     254 non-null    float64
 2   HML     254 non-null    float64
 3   RMW     254 non-null    float64
 4   CMA     254 non-null    float64
dtypes: float64(5)
memory usage: 11.9 KB
```

[22]:
```
factor_data = factor_data.join(data['return_1m']).sort_index()
factor_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 6 columns):
 #   Column     Non-Null Count   Dtype
---  ------     --------------   -----
 0   Mkt-RF     360752 non-null  float64
 1   SMB        360752 non-null  float64
 2   HML        360752 non-null  float64
 3   RMW        360752 non-null  float64
 4   CMA        360752 non-null  float64
 5   return_1m  360752 non-null  float64
dtypes: float64(6)
memory usage: 18.0+ MB
```

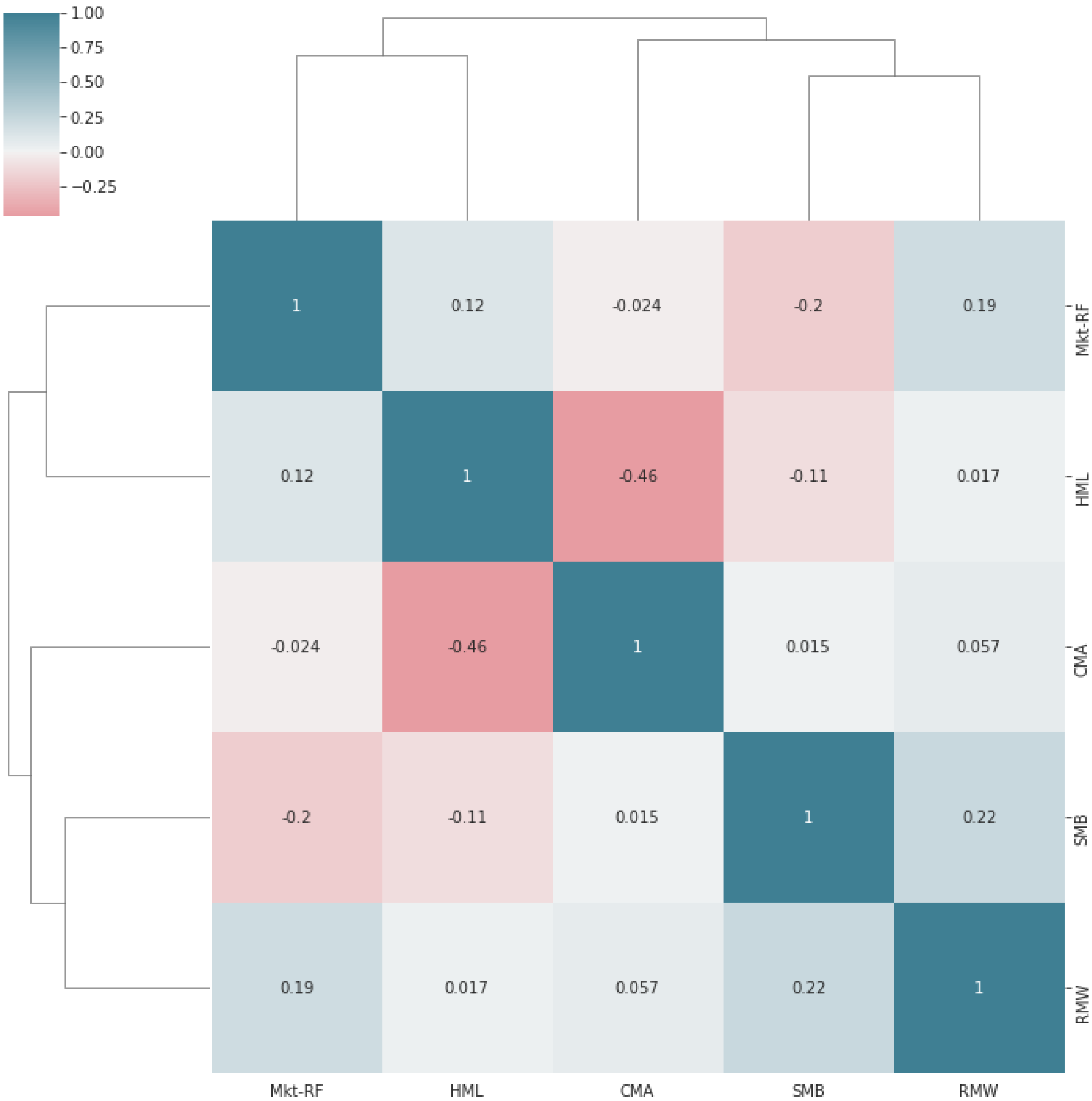
[23]:
```python
T = 24
betas = (factor_data.groupby(level='ticker',
                             group_keys=False)
         .apply(lambda x: RollingOLS(endog=x.return_1m,
                                     exog=sm.add_constant(x.drop('return_1m', axis=1)),
                                     window=min(T, x.shape[0]-1))
                .fit(params_only=True)
                .params
                .drop('const', axis=1)))
```

[24]:
```python
betas.describe().join(betas.sum(1).describe().to_frame('total'))
```

[24]:

	Mkt-RF	SMB	HML	RMW	CMA	total
count	318478.000000	318478.000000	318478.000000	318478.000000	318478.000000	360752.000000
mean	0.981855	0.628163	0.128131	-0.059253	0.013774	1.494318
std	0.918800	1.248071	1.615972	1.919938	2.182730	3.291402
min	-9.922641	-10.212033	-17.654894	-22.925165	-18.182706	-31.429456
25%	0.465445	-0.114605	-0.710399	-0.979216	-1.086919	0.000000
50%	0.932070	0.542998	0.101903	0.039229	0.032834	1.214277
75%	1.447381	1.303487	0.955263	0.955362	1.140431	3.145515
max	10.916430	10.373043	14.558920	17.413382	17.626042	33.316296

[25]:
```python
cmap = sns.diverging_palette(10, 220, as_cmap=True)
sns.clustermap(betas.corr(), annot=True, cmap=cmap, center=0);
```



[26]:
```
data = (data
        .join(betas
              .groupby(level='ticker')
              .shift()))
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 11 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   return_1m   360752 non-null  float64
```

```
 1   return_2m   360752 non-null  float64
 2   return_3m   360752 non-null  float64
 3   return_6m   360752 non-null  float64
 4   return_9m   360752 non-null  float64
 5   return_12m  360752 non-null  float64
 6   Mkt-RF      316640 non-null  float64
 7   SMB         316640 non-null  float64
 8   HML         316640 non-null  float64
 9   RMW         316640 non-null  float64
 10  CMA         316640 non-null  float64
dtypes: float64(11)
memory usage: 39.8+ MB
```

1.5.1 Impute mean for missing factor betas

[27]:
```
data.loc[:, factors] = data.groupby('ticker')[factors].apply(lambda x: x.
 ↪fillna(x.mean()))
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 11 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   return_1m   360752 non-null  float64
 1   return_2m   360752 non-null  float64
 2   return_3m   360752 non-null  float64
 3   return_6m   360752 non-null  float64
 4   return_9m   360752 non-null  float64
 5   return_12m  360752 non-null  float64
 6   Mkt-RF      360752 non-null  float64
 7   SMB         360752 non-null  float64
 8   HML         360752 non-null  float64
 9   RMW         360752 non-null  float64
 10  CMA         360752 non-null  float64
dtypes: float64(11)
memory usage: 39.8+ MB
```

1.6 Momentum factors

We can use these results to compute momentum factors based on the difference between returns over longer periods and the most recent monthly return, as well as for the difference between 3 and 12 month returns as follows:

[28]:
```
for lag in [2,3,6,9,12]:
    data[f'momentum_{lag}'] = data[f'return_{lag}m'].sub(data.return_1m)
data[f'momentum_3_12'] = data[f'return_12m'].sub(data.return_3m)
```

1.7 Date Indicators

[29]:
```
dates = data.index.get_level_values('date')
data['year'] = dates.year
data['month'] = dates.month
```

1.8 Lagged returns

To use lagged values as input variables or features associated with the current observations, we use the .shift() method to move historical returns up to the current period:

[30]:
```
for t in range(1, 7):
    data[f'return_1m_t-{t}'] = data.groupby(level='ticker').return_1m.shift(t)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 25 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   return_1m       360752 non-null  float64
 1   return_2m       360752 non-null  float64
 2   return_3m       360752 non-null  float64
 3   return_6m       360752 non-null  float64
 4   return_9m       360752 non-null  float64
 5   return_12m      360752 non-null  float64
 6   Mkt-RF          360752 non-null  float64
 7   SMB             360752 non-null  float64
 8   HML             360752 non-null  float64
 9   RMW             360752 non-null  float64
 10  CMA             360752 non-null  float64
 11  momentum_2      360752 non-null  float64
 12  momentum_3      360752 non-null  float64
 13  momentum_6      360752 non-null  float64
 14  momentum_9      360752 non-null  float64
 15  momentum_12     360752 non-null  float64
 16  momentum_3_12   360752 non-null  float64
 17  year            360752 non-null  int64
 18  month           360752 non-null  int64
 19  return_1m_t-1   358914 non-null  float64
 20  return_1m_t-2   357076 non-null  float64
 21  return_1m_t-3   355238 non-null  float64
 22  return_1m_t-4   353400 non-null  float64
 23  return_1m_t-5   351562 non-null  float64
 24  return_1m_t-6   349724 non-null  float64
dtypes: float64(23), int64(2)
memory usage: 78.3+ MB
```

1.9 Target: Holding Period Returns

Similarly, to compute returns for various holding periods, we use the normalized period returns computed previously and shift them back to align them with the current financial features

[31]:
```
for t in [1,2,3,6,12]:
    data[f'target_{t}m'] = data.groupby(level='ticker')[f'return_{t}m'].
 ↪shift(-t)
```

[32]:
```
cols = ['target_1m',
        'target_2m',
        'target_3m',
        'return_1m',
        'return_2m',
        'return_3m',
        'return_1m_t-1',
        'return_1m_t-2',
        'return_1m_t-3']

data[cols].dropna().sort_index().head(10)
```

[32]:
```
                   target_1m  target_2m  target_3m  return_1m  return_2m  \
ticker date
A      2001-04-30  -0.140220  -0.087246  -0.098192   0.269444   0.040966
       2001-05-31  -0.031008  -0.076414  -0.075527  -0.140220   0.044721
       2001-06-30  -0.119692  -0.097014  -0.155847  -0.031008  -0.087246
       2001-07-31  -0.073750  -0.173364  -0.080114  -0.119692  -0.076414
       2001-08-31  -0.262264  -0.083279   0.009593  -0.073750  -0.097014
       2001-09-30   0.139130   0.181052   0.134010  -0.262264  -0.173364
       2001-10-31   0.224517   0.131458   0.108697   0.139130  -0.083279
       2001-11-30   0.045471   0.054962   0.045340   0.224517   0.181052
       2001-12-31   0.064539   0.045275   0.070347   0.045471   0.131458
       2002-01-31   0.026359   0.073264  -0.003306   0.064539   0.054962

                   return_3m  return_1m_t-1  return_1m_t-2  return_1m_t-3
ticker date
A      2001-04-30  -0.105747      -0.146389      -0.329564      -0.003653
       2001-05-31  -0.023317       0.269444      -0.146389      -0.329564
       2001-06-30   0.018842      -0.140220       0.269444      -0.146389
       2001-07-31  -0.098192      -0.031008      -0.140220       0.269444
       2001-08-31  -0.075527      -0.119692      -0.031008      -0.140220
       2001-09-30  -0.155847      -0.073750      -0.119692      -0.031008
       2001-10-31  -0.080114      -0.262264      -0.073750      -0.119692
       2001-11-30   0.009593       0.139130      -0.262264      -0.073750
       2001-12-31   0.134010       0.224517       0.139130      -0.262264
       2002-01-31   0.108697       0.045471       0.224517       0.139130
```

[33]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 30 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   return_1m       360752 non-null  float64
 1   return_2m       360752 non-null  float64
 2   return_3m       360752 non-null  float64
 3   return_6m       360752 non-null  float64
 4   return_9m       360752 non-null  float64
 5   return_12m      360752 non-null  float64
 6   Mkt-RF          360752 non-null  float64
 7   SMB             360752 non-null  float64
 8   HML             360752 non-null  float64
 9   RMW             360752 non-null  float64
 10  CMA             360752 non-null  float64
 11  momentum_2      360752 non-null  float64
 12  momentum_3      360752 non-null  float64
 13  momentum_6      360752 non-null  float64
 14  momentum_9      360752 non-null  float64
 15  momentum_12     360752 non-null  float64
 16  momentum_3_12   360752 non-null  float64
 17  year            360752 non-null  int64
 18  month           360752 non-null  int64
 19  return_1m_t-1   358914 non-null  float64
 20  return_1m_t-2   357076 non-null  float64
 21  return_1m_t-3   355238 non-null  float64
 22  return_1m_t-4   353400 non-null  float64
 23  return_1m_t-5   351562 non-null  float64
 24  return_1m_t-6   349724 non-null  float64
 25  target_1m       358914 non-null  float64
 26  target_2m       357076 non-null  float64
 27  target_3m       355238 non-null  float64
 28  target_6m       349724 non-null  float64
 29  target_12m      338696 non-null  float64
dtypes: float64(28), int64(2)
memory usage: 92.1+ MB
```

1.10 Create age proxy

We use quintiles of IPO year as a proxy for company age.

[34]:
```
data = (data
        .join(pd.qcut(stocks.ipoyear, q=5, labels=list(range(1, 6)))
              .astype(float)
              .fillna(0)
              .astype(int)
```

```
                 .to_frame('age')))
data.age = data.age.fillna(-1)
```

1.11 Create dynamic size proxy

We use the marketcap information from the NASDAQ ticker info to create a size proxy.

[35]:
```
stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2412 entries, A to ZUMZ
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   marketcap  2407 non-null   float64
 1   ipoyear    1065 non-null   float64
 2   sector     2372 non-null   object
dtypes: float64(2), object(1)
memory usage: 139.9+ KB
```

Market cap information is tied to currrent prices. We create an adjustment factor to have the values reflect lower historical prices for each individual stock:

[36]:
```
size_factor = (monthly_prices
               .loc[data.index.get_level_values('date').unique(),
                    data.index.get_level_values('ticker').unique()]
               .sort_index(ascending=False)
               .pct_change()
               .fillna(0)
               .add(1)
               .cumprod())
size_factor.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 207 entries, 2018-03-31 to 2001-01-31
Columns: 1838 entries, A to ZUMZ
dtypes: float64(1838)
memory usage: 2.9 MB
```

[37]:
```
msize = (size_factor
         .mul(stocks
              .loc[size_factor.columns, 'marketcap'])).dropna(axis=1, how='all')
```

1.11.1 Create Size indicator as deciles per period

Compute size deciles per month:

[38]:
```python
data['msize'] = (msize
                 .apply(lambda x: pd.qcut(x, q=10, labels=list(range(1, 11)))
                        .astype(int), axis=1)
                 .stack()
                 .swaplevel())
data.msize = data.msize.fillna(-1)
```

1.12 Combine data

[39]:
```python
data = data.join(stocks[['sector']])
data.sector = data.sector.fillna('Unknown')
```

[40]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 33 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   return_1m       360752 non-null  float64
 1   return_2m       360752 non-null  float64
 2   return_3m       360752 non-null  float64
 3   return_6m       360752 non-null  float64
 4   return_9m       360752 non-null  float64
 5   return_12m      360752 non-null  float64
 6   Mkt-RF          360752 non-null  float64
 7   SMB             360752 non-null  float64
 8   HML             360752 non-null  float64
 9   RMW             360752 non-null  float64
 10  CMA             360752 non-null  float64
 11  momentum_2      360752 non-null  float64
 12  momentum_3      360752 non-null  float64
 13  momentum_6      360752 non-null  float64
 14  momentum_9      360752 non-null  float64
 15  momentum_12     360752 non-null  float64
 16  momentum_3_12   360752 non-null  float64
 17  year            360752 non-null  int64
 18  month           360752 non-null  int64
 19  return_1m_t-1   358914 non-null  float64
 20  return_1m_t-2   357076 non-null  float64
 21  return_1m_t-3   355238 non-null  float64
 22  return_1m_t-4   353400 non-null  float64
 23  return_1m_t-5   351562 non-null  float64
 24  return_1m_t-6   349724 non-null  float64
 25  target_1m       358914 non-null  float64
 26  target_2m       357076 non-null  float64
```

```
 27   target_3m      355238 non-null   float64
 28   target_6m      349724 non-null   float64
 29   target_12m     338696 non-null   float64
 30   age            360752 non-null   int64
 31   msize          360752 non-null   float64
 32   sector         360752 non-null   object
dtypes: float64(29), int64(3), object(1)
memory usage: 100.4+ MB
```

1.13 Store data

We will use the data again in several later chapters, starting in Chapter 7 on Linear Models.

[41]:
```
with pd.HDFStore(DATA_STORE) as store:
    store.put('engineered_features', data.sort_index().loc[idx[:, :
↪datetime(2018, 3, 1)], :])
    print(store.info())
```

```
<class 'pandas.io.pytables.HDFStore'>
File path: ../data/assets.h5
/engineered_features                            frame        (shape->[358914,33])
/quandl/wiki/prices                             frame        (shape->[15389314,12])
/quandl/wiki/stocks                             frame        (shape->[1,2])
/sp500/fred                                     frame        (shape->[2609,1])
/sp500/sp500_stooq                              frame        (shape->[17700,5])
/sp500/stocks                                   frame        (shape->[1,7])
/sp500/stooq                                    frame        (shape->[17700,5])
/stooq/jp/tse/stocks/prices                     frame_table  (typ->appendable_multi,
nrows->10283141,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/jp/tse/stocks/tickers                    frame_table
(typ->appendable,nrows->3732,ncols->2,indexers->[index],dc->[])
/stooq/us/nasdaq/etfs/prices                    frame_table  (typ->appendable_multi,
nrows->359912,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/us/nasdaq/etfs/tickers                   frame_table
(typ->appendable,nrows->171,ncols->2,indexers->[index],dc->[])
/stooq/us/nasdaq/stocks/prices                  frame_table  (typ->appendable_multi,
nrows->6415760,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/us/nasdaq/stocks/tickers                 frame_table
(typ->appendable,nrows->3570,ncols->2,indexers->[index],dc->[])
/stooq/us/nyse/etfs/prices                      frame_table  (typ->appendable_multi,
nrows->2435526,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/us/nyse/etfs/tickers                     frame_table
(typ->appendable,nrows->1023,ncols->2,indexers->[index],dc->[])
/stooq/us/nyse/stocks/prices                    frame_table  (typ->appendable_multi,
nrows->7983429,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/us/nyse/stocks/tickers                   frame_table
(typ->appendable,nrows->3969,ncols->2,indexers->[index],dc->[])
/stooq/us/nysemkt/stocks/prices                 frame_table  (typ->appendable_multi,
```

```
nrows->744452,ncols->7,indexers->[index],dc->[date,ticker])
/stooq/us/nysemkt/stocks/tickers            frame_table
(typ->appendable,nrows->298,ncols->2,indexers->[index],dc->[])
/us_equities/stocks                         frame        (shape->[6834,6])
```

1.14 Create Dummy variables

For most models, we need to encode categorical variables as 'dummies' (one-hot encoding):

[42]:
```python
dummy_data = pd.get_dummies(data,
                            columns=['year','month', 'msize', 'age',  'sector'],
                            prefix=['year','month', 'msize', 'age', ''],
                            prefix_sep=['_', '_', '_', '_', ''])
dummy_data = dummy_data.rename(columns={c:c.replace('.0', '') for c in␣
 ↪dummy_data.columns})
dummy_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 360752 entries, ('A', Timestamp('2001-01-31 00:00:00', freq='M')) to
('ZUMZ', Timestamp('2018-03-31 00:00:00', freq='M'))
Data columns (total 88 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   return_1m              360752 non-null  float64
 1   return_2m              360752 non-null  float64
 2   return_3m              360752 non-null  float64
 3   return_6m              360752 non-null  float64
 4   return_9m              360752 non-null  float64
 5   return_12m             360752 non-null  float64
 6   Mkt-RF                 360752 non-null  float64
 7   SMB                    360752 non-null  float64
 8   HML                    360752 non-null  float64
 9   RMW                    360752 non-null  float64
 10  CMA                    360752 non-null  float64
 11  momentum_2             360752 non-null  float64
 12  momentum_3             360752 non-null  float64
 13  momentum_6             360752 non-null  float64
 14  momentum_9             360752 non-null  float64
 15  momentum_12            360752 non-null  float64
 16  momentum_3_12          360752 non-null  float64
 17  return_1m_t-1          358914 non-null  float64
 18  return_1m_t-2          357076 non-null  float64
 19  return_1m_t-3          355238 non-null  float64
 20  return_1m_t-4          353400 non-null  float64
 21  return_1m_t-5          351562 non-null  float64
 22  return_1m_t-6          349724 non-null  float64
 23  target_1m              358914 non-null  float64
 24  target_2m              357076 non-null  float64
```

```
25  target_3m               355238 non-null  float64
26  target_6m               349724 non-null  float64
27  target_12m              338696 non-null  float64
28  year_2001               360752 non-null  uint8
29  year_2002               360752 non-null  uint8
30  year_2003               360752 non-null  uint8
31  year_2004               360752 non-null  uint8
32  year_2005               360752 non-null  uint8
33  year_2006               360752 non-null  uint8
34  year_2007               360752 non-null  uint8
35  year_2008               360752 non-null  uint8
36  year_2009               360752 non-null  uint8
37  year_2010               360752 non-null  uint8
38  year_2011               360752 non-null  uint8
39  year_2012               360752 non-null  uint8
40  year_2013               360752 non-null  uint8
41  year_2014               360752 non-null  uint8
42  year_2015               360752 non-null  uint8
43  year_2016               360752 non-null  uint8
44  year_2017               360752 non-null  uint8
45  year_2018               360752 non-null  uint8
46  month_1                 360752 non-null  uint8
47  month_2                 360752 non-null  uint8
48  month_3                 360752 non-null  uint8
49  month_4                 360752 non-null  uint8
50  month_5                 360752 non-null  uint8
51  month_6                 360752 non-null  uint8
52  month_7                 360752 non-null  uint8
53  month_8                 360752 non-null  uint8
54  month_9                 360752 non-null  uint8
55  month_10                360752 non-null  uint8
56  month_11                360752 non-null  uint8
57  month_12                360752 non-null  uint8
58  msize_-1                360752 non-null  uint8
59  msize_1                 360752 non-null  uint8
60  msize_2                 360752 non-null  uint8
61  msize_3                 360752 non-null  uint8
62  msize_4                 360752 non-null  uint8
63  msize_5                 360752 non-null  uint8
64  msize_6                 360752 non-null  uint8
65  msize_7                 360752 non-null  uint8
66  msize_8                 360752 non-null  uint8
67  msize_9                 360752 non-null  uint8
68  msize_10                360752 non-null  uint8
69  age_0                   360752 non-null  uint8
70  age_1                   360752 non-null  uint8
71  age_2                   360752 non-null  uint8
72  age_3                   360752 non-null  uint8
```

```
 73  age_4                   360752 non-null  uint8
 74  age_5                   360752 non-null  uint8
 75  Basic Industries        360752 non-null  uint8
 76  Capital Goods           360752 non-null  uint8
 77  Consumer Durables       360752 non-null  uint8
 78  Consumer Non-Durables   360752 non-null  uint8
 79  Consumer Services       360752 non-null  uint8
 80  Energy                  360752 non-null  uint8
 81  Finance                 360752 non-null  uint8
 82  Health Care             360752 non-null  uint8
 83  Miscellaneous           360752 non-null  uint8
 84  Public Utilities        360752 non-null  uint8
 85  Technology              360752 non-null  uint8
 86  Transportation          360752 non-null  uint8
 87  Unknown                 360752 non-null  uint8
dtypes: float64(28), uint8(60)
memory usage: 107.2+ MB
```