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]:
```
%matplotlib inline

import warnings
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import pandas_datareader.data as web
from pyfinance.ols import PandasRollingOLS
```

[2]:
```
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
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:

[3]:
```
DATA_STORE = '../../data/assets.h5'
```

[4]:
```
with pd.HDFStore(DATA_STORE) as store:
    prices = store['quandl/wiki/prices'].loc[idx['2000':'2018', :],␣
↪'adj_close'].unstack('ticker')
    stocks = store['us_equities/stocks'].loc[:, ['marketcap', 'ipoyear',␣
↪'sector']]
```

1.2.1 Keep data with stock info

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

[5]:
```
stocks = stocks[~stocks.index.duplicated()]
stocks.index.name = 'ticker'
```

Get tickers with both price information and metdata

[6]:
```
shared = prices.columns.intersection(stocks.index)
```

[7]:
```
stocks = stocks.loc[shared, :]
stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2289 entries, A to ZUMZ
Data columns (total 3 columns):
marketcap    2287 non-null object
ipoyear      1002 non-null float64
sector       2248 non-null object
dtypes: float64(1), object(2)
memory usage: 71.5+ KB
```

[8]:
```
prices = prices.loc[:, shared]
prices.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4706 entries, 2000-01-03 to 2018-03-27
Columns: 2289 entries, A to ZUMZ
dtypes: float64(2289)
memory usage: 82.2 MB
```

[9]:
```
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:

[10]:
```
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:

[11]:
```
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: 381505 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 6 columns):
return_1m     381505 non-null float64
return_2m     381505 non-null float64
return_3m     381505 non-null float64
return_6m     381505 non-null float64
return_9m     381505 non-null float64
return_12m    381505 non-null float64
dtypes: float64(6)
memory usage: 18.9+ MB
```

1.4 Drop stocks with less than 10 yrs of returns

[12]:
```
min_obs = 120
nobs = data.groupby(level='ticker').size()
keep = nobs[nobs>min_obs].index
```

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

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 6 columns):
return_1m     345502 non-null float64
return_2m     345502 non-null float64
return_3m     345502 non-null float64
return_6m     345502 non-null float64
return_9m     345502 non-null float64
return_12m    345502 non-null float64
dtypes: float64(6)
memory usage: 17.2+ MB
```

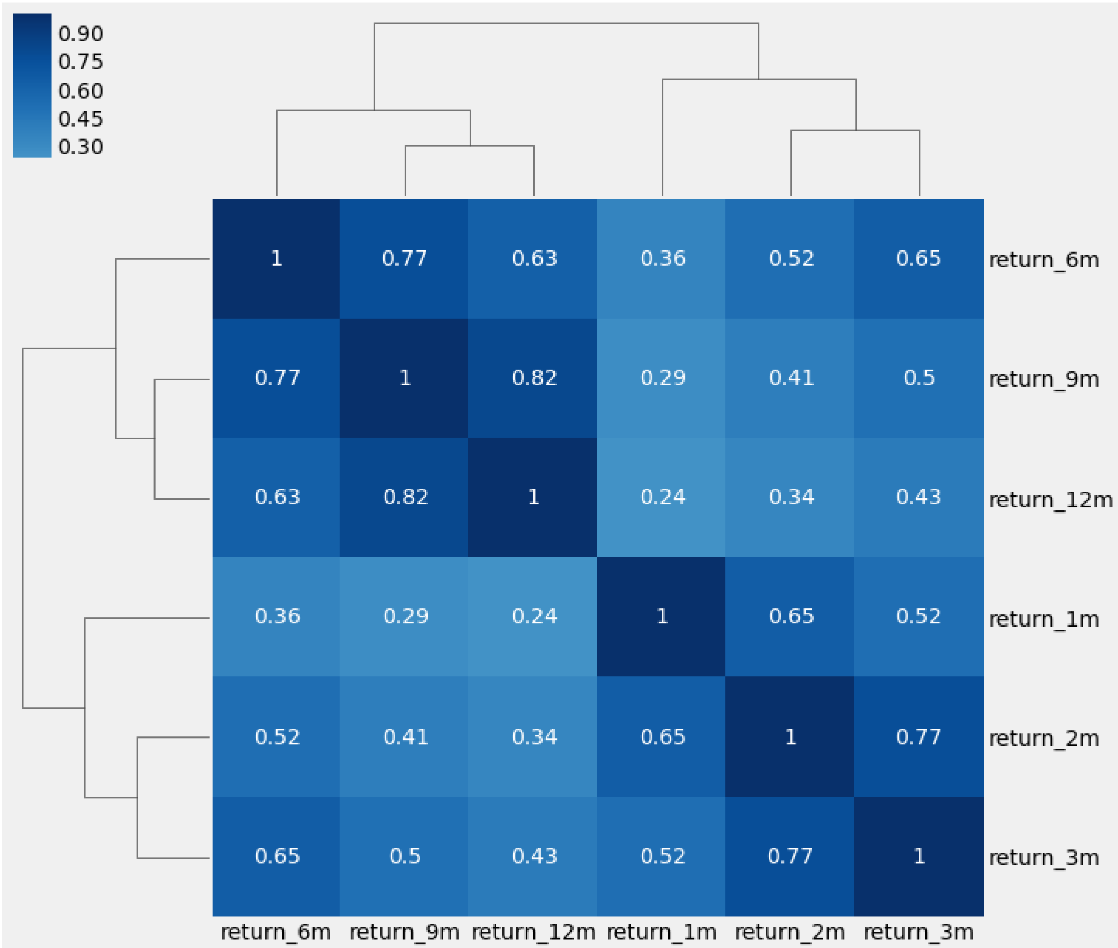
[13]:
```python
data.describe()
```

[13]:

	return_1m	return_2m	return_3m	return_6m
count	345502.000000	345502.000000	345502.000000	345502.000000
mean	0.012353	0.009353	0.008338	0.007200
std	0.113467	0.080550	0.066075	0.048059
min	-0.327398	-0.253506	-0.212981	-0.160337
25%	-0.046028	-0.030347	-0.023647	-0.014607
50%	0.009524	0.009820	0.009832	0.009467
75%	0.065875	0.049190	0.042032	0.031989
max	0.428725	0.279875	0.220522	0.153314

	return_9m	return_12m
count	345502.000000	345502.000000
mean	0.006731	0.006475
std	0.039555	0.034491
min	-0.130775	-0.112947
25%	-0.010836	-0.008764
50%	0.009105	0.008852
75%	0.027203	0.024636
max	0.123776	0.105675

[14]:
```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 1,775 tickers.

[15]:
```
data.index.get_level_values('ticker').nunique()
```

[15]: 1756

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 8, 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 `PandasRollingOLS` rolling linear regression functionality in the `pyfinance` 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.

[16]:
```
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: 230 entries, 2000-01-31 to 2019-02-28
Freq: M
Data columns (total 5 columns):
Mkt-RF    230 non-null float64
SMB       230 non-null float64
HML       230 non-null float64
RMW       230 non-null float64
CMA       230 non-null float64
dtypes: float64(5)
memory usage: 10.8 KB
```

[17]:
```
factor_data = factor_data.join(data['return_1m']).sort_index()
factor_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 6 columns):
Mkt-RF       345502 non-null float64
SMB          345502 non-null float64
HML          345502 non-null float64
RMW          345502 non-null float64
CMA          345502 non-null float64
return_1m    345502 non-null float64
dtypes: float64(6)
memory usage: 17.2+ MB
```

[18]:
```
T = 24
betas = (factor_data
         .groupby(level='ticker', group_keys=False)
         .apply(lambda x: PandasRollingOLS(window=min(T, x.shape[0]-1), y=x.
 ↪return_1m, x=x.drop('return_1m', axis=1)).beta))
```

[19]:
```
betas.describe().join(betas.sum(1).describe().to_frame('total'))
```

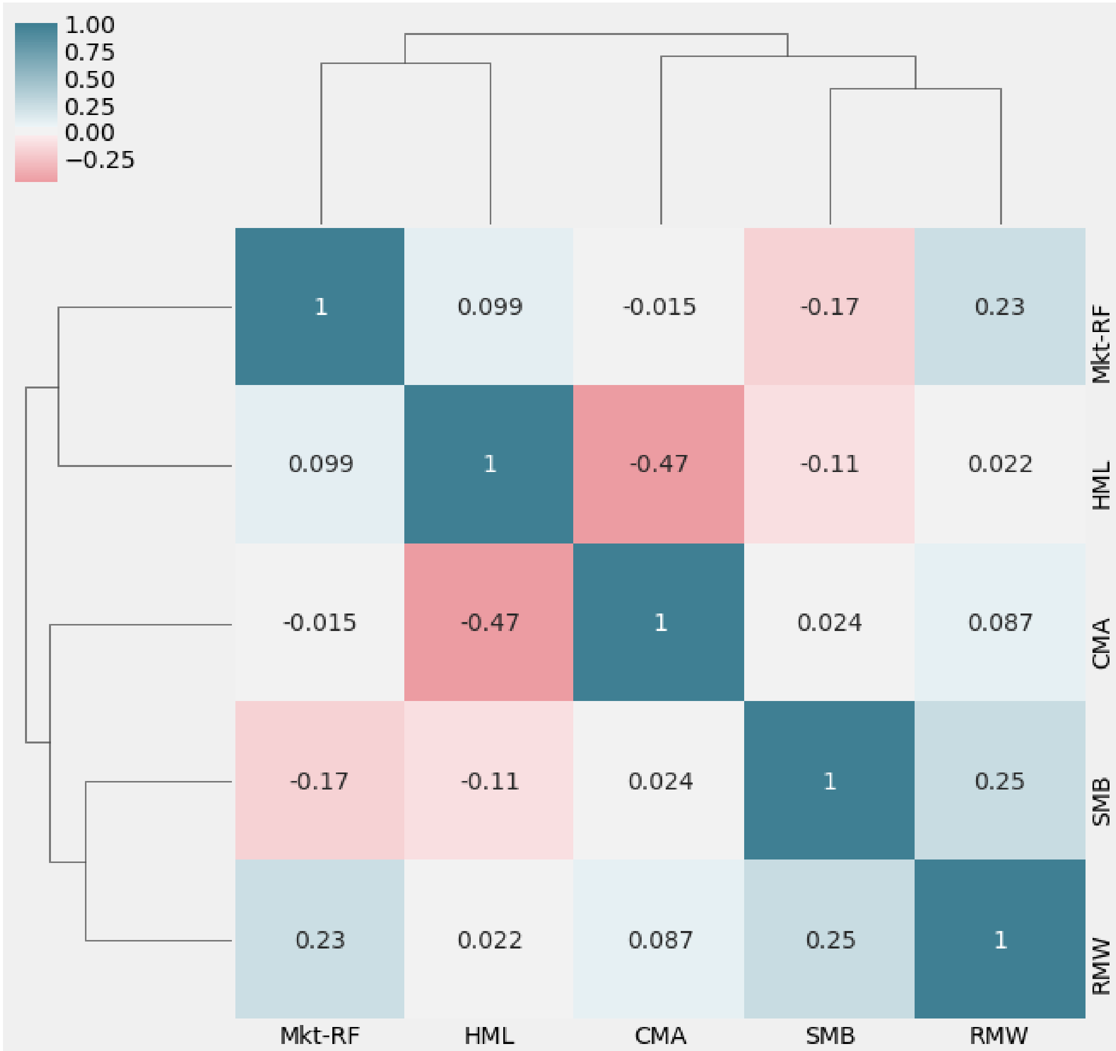
[19]:

```
              Mkt-RF            SMB            HML            RMW  \
count  305114.000000  305114.000000  305114.000000  305114.000000
mean        0.979211       0.624869       0.128957      -0.061538
std         0.911302       1.250830       1.569375       1.995244
min        -9.250214     -10.248056     -15.383714     -26.090632
25%         0.461364      -0.117809      -0.691242      -0.998343
50%         0.929989       0.542886       0.103899       0.047608
75%         1.446082       1.301350       0.930312       0.986083
max        10.428027      10.351943      13.129851      18.378405

                 CMA          total
count  305114.000000  305114.000000
mean        0.017315       1.688816
std         2.182142       3.591829
min       -18.445731     -37.529387
25%        -1.086057      -0.141855
50%         0.043913       1.637183
75%         1.144610       3.517309
max        16.423135      35.902406
```

[20]:

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



[21]:
```python
data = (data
        .join(betas
              .groupby(level='ticker')
              .shift()))
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 11 columns):
return_1m      345502 non-null float64
return_2m      345502 non-null float64
return_3m      345502 non-null float64
return_6m      345502 non-null float64
return_9m      345502 non-null float64
```

```
return_12m    345502 non-null float64
Mkt-RF        303358 non-null float64
SMB           303358 non-null float64
HML           303358 non-null float64
RMW           303358 non-null float64
CMA           303358 non-null float64
dtypes: float64(11)
memory usage: 40.3+ MB
```

1.5.1 Impute mean for missing factor betas

[22]:
```
data.loc[:, factors] = data.groupby('ticker')[factors].apply(lambda x: x.
↪fillna(x.mean()))
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 11 columns):
return_1m     345502 non-null float64
return_2m     345502 non-null float64
return_3m     345502 non-null float64
return_6m     345502 non-null float64
return_9m     345502 non-null float64
return_12m    345502 non-null float64
Mkt-RF        345502 non-null float64
SMB           345502 non-null float64
HML           345502 non-null float64
RMW           345502 non-null float64
CMA           345502 non-null float64
dtypes: float64(11)
memory usage: 40.3+ 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:

[23]:
```
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

[24]:
```
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:

[25]:
```
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: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 25 columns):
return_1m        345502 non-null float64
return_2m        345502 non-null float64
return_3m        345502 non-null float64
return_6m        345502 non-null float64
return_9m        345502 non-null float64
return_12m       345502 non-null float64
Mkt-RF           345502 non-null float64
SMB              345502 non-null float64
HML              345502 non-null float64
RMW              345502 non-null float64
CMA              345502 non-null float64
momentum_2       345502 non-null float64
momentum_3       345502 non-null float64
momentum_6       345502 non-null float64
momentum_9       345502 non-null float64
momentum_12      345502 non-null float64
momentum_3_12    345502 non-null float64
year             345502 non-null int64
month            345502 non-null int64
return_1m_t-1    343746 non-null float64
return_1m_t-2    341990 non-null float64
return_1m_t-3    340234 non-null float64
return_1m_t-4    338478 non-null float64
return_1m_t-5    336722 non-null float64
return_1m_t-6    334966 non-null float64
dtypes: float64(23), int64(2)
memory usage: 77.2+ 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

[26]:
```
for t in [1,2,3,6,12]:
    data[f'target_{t}m'] = data.groupby(level='ticker')[f'return_{t}m'].
 ↪shift(-t)
```

[27]:
```
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)
```

[27]:

ticker	date	target_1m	target_2m	target_3m	return_1m	return_2m
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

ticker	date	return_3m	return_1m_t-1	return_1m_t-2	return_1m_t-3
A	2001-04-30	-0.105747	-0.146389	-0.327398	-0.003653
	2001-05-31	-0.023317	0.269444	-0.146389	-0.327398
	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

[28]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 30 columns):
return_1m        345502 non-null float64
return_2m        345502 non-null float64
return_3m        345502 non-null float64
return_6m        345502 non-null float64
return_9m        345502 non-null float64
return_12m       345502 non-null float64
Mkt-RF           345502 non-null float64
SMB              345502 non-null float64
HML              345502 non-null float64
RMW              345502 non-null float64
CMA              345502 non-null float64
momentum_2       345502 non-null float64
momentum_3       345502 non-null float64
momentum_6       345502 non-null float64
momentum_9       345502 non-null float64
momentum_12      345502 non-null float64
momentum_3_12    345502 non-null float64
year             345502 non-null int64
month            345502 non-null int64
return_1m_t-1    343746 non-null float64
return_1m_t-2    341990 non-null float64
return_1m_t-3    340234 non-null float64
return_1m_t-4    338478 non-null float64
return_1m_t-5    336722 non-null float64
return_1m_t-6    334966 non-null float64
target_1m        343746 non-null float64
target_2m        341990 non-null float64
target_3m        340234 non-null float64
target_6m        334966 non-null float64
target_12m       324430 non-null float64
dtypes: float64(28), int64(2)
memory usage: 90.5+ MB
```

1.10 Create age proxy

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

[29]:
```python
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.

[30]:
```
stocks.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2289 entries, A to ZUMZ
Data columns (total 3 columns):
marketcap    2287 non-null object
ipoyear      1002 non-null float64
sector       2248 non-null object
dtypes: float64(1), object(2)
memory usage: 151.5+ 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:

[37]:
```
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
Freq: -1M
Columns: 1756 entries, A to UFS
dtypes: float64(1756)
memory usage: 2.8 MB
```

[38]:
```
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:

[39]:
```
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

[40]:
```
data = data.join(stocks[['sector']])
data.sector = data.sector.fillna('Unknown')
```

[41]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 33 columns):
return_1m         345502 non-null float64
return_2m         345502 non-null float64
return_3m         345502 non-null float64
return_6m         345502 non-null float64
return_9m         345502 non-null float64
return_12m        345502 non-null float64
Mkt-RF            345502 non-null float64
SMB               345502 non-null float64
HML               345502 non-null float64
RMW               345502 non-null float64
CMA               345502 non-null float64
momentum_2        345502 non-null float64
momentum_3        345502 non-null float64
momentum_6        345502 non-null float64
momentum_9        345502 non-null float64
momentum_12       345502 non-null float64
momentum_3_12     345502 non-null float64
year              345502 non-null int64
month             345502 non-null int64
return_1m_t-1     343746 non-null float64
return_1m_t-2     341990 non-null float64
return_1m_t-3     340234 non-null float64
return_1m_t-4     338478 non-null float64
return_1m_t-5     336722 non-null float64
return_1m_t-6     334966 non-null float64
target_1m         343746 non-null float64
target_2m         341990 non-null float64
target_3m         340234 non-null float64
target_6m         334966 non-null float64
target_12m        324430 non-null float64
age               345502 non-null int64
msize             345502 non-null float64
sector            345502 non-null object
dtypes: float64(29), int64(3), object(1)
memory usage: 98.4+ MB
```

1.13 Store data

We will use the data again in several later chapters, starting in Chapter 6 on Linear Models.

[42]:
```
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->[343746,33])
/fred/assets                        frame          (shape->[4826,5])
/quandl/wiki/prices                 frame          (shape->[15389314,12])
/quandl/wiki/stocks                 frame          (shape->[1,2])
/sp500/prices                       frame          (shape->[37721,5])
/sp500/stocks                       frame          (shape->[1,7])
/us_equities/stocks                 frame          (shape->[1,6])
```

1.14 Create Dummy variables

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

[43]:
```
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: 345502 entries, (A, 2001-01-31 00:00:00) to (ZUMZ, 2018-03-31
00:00:00)
Data columns (total 88 columns):
return_1m                 345502 non-null float64
return_2m                 345502 non-null float64
return_3m                 345502 non-null float64
return_6m                 345502 non-null float64
return_9m                 345502 non-null float64
return_12m                345502 non-null float64
Mkt-RF                    345502 non-null float64
SMB                       345502 non-null float64
HML                       345502 non-null float64
RMW                       345502 non-null float64
CMA                       345502 non-null float64
momentum_2                345502 non-null float64
momentum_3                345502 non-null float64
momentum_6                345502 non-null float64
```

```
momentum_9              345502 non-null float64
momentum_12             345502 non-null float64
momentum_3_12           345502 non-null float64
return_1m_t-1           343746 non-null float64
return_1m_t-2           341990 non-null float64
return_1m_t-3           340234 non-null float64
return_1m_t-4           338478 non-null float64
return_1m_t-5           336722 non-null float64
return_1m_t-6           334966 non-null float64
target_1m               343746 non-null float64
target_2m               341990 non-null float64
target_3m               340234 non-null float64
target_6m               334966 non-null float64
target_12m              324430 non-null float64
year_2001               345502 non-null uint8
year_2002               345502 non-null uint8
year_2003               345502 non-null uint8
year_2004               345502 non-null uint8
year_2005               345502 non-null uint8
year_2006               345502 non-null uint8
year_2007               345502 non-null uint8
year_2008               345502 non-null uint8
year_2009               345502 non-null uint8
year_2010               345502 non-null uint8
year_2011               345502 non-null uint8
year_2012               345502 non-null uint8
year_2013               345502 non-null uint8
year_2014               345502 non-null uint8
year_2015               345502 non-null uint8
year_2016               345502 non-null uint8
year_2017               345502 non-null uint8
year_2018               345502 non-null uint8
month_1                 345502 non-null uint8
month_2                 345502 non-null uint8
month_3                 345502 non-null uint8
month_4                 345502 non-null uint8
month_5                 345502 non-null uint8
month_6                 345502 non-null uint8
month_7                 345502 non-null uint8
month_8                 345502 non-null uint8
month_9                 345502 non-null uint8
month_10                345502 non-null uint8
month_11                345502 non-null uint8
month_12                345502 non-null uint8
msize_-1                345502 non-null uint8
msize_1                 345502 non-null uint8
msize_2                 345502 non-null uint8
msize_3                 345502 non-null uint8
```

```
msize_4                  345502 non-null uint8
msize_5                  345502 non-null uint8
msize_6                  345502 non-null uint8
msize_7                  345502 non-null uint8
msize_8                  345502 non-null uint8
msize_9                  345502 non-null uint8
msize_10                 345502 non-null uint8
age_0                    345502 non-null uint8
age_1                    345502 non-null uint8
age_2                    345502 non-null uint8
age_3                    345502 non-null uint8
age_4                    345502 non-null uint8
age_5                    345502 non-null uint8
Basic Industries         345502 non-null uint8
Capital Goods            345502 non-null uint8
Consumer Durables        345502 non-null uint8
Consumer Non-Durables    345502 non-null uint8
Consumer Services        345502 non-null uint8
Energy                   345502 non-null uint8
Finance                  345502 non-null uint8
Health Care              345502 non-null uint8
Miscellaneous            345502 non-null uint8
Public Utilities         345502 non-null uint8
Technology               345502 non-null uint8
Transportation           345502 non-null uint8
Unknown                  345502 non-null uint8
dtypes: float64(28), uint8(60)
memory usage: 94.9+ MB
```