DataFrame Operations

About the Data

In this notebook, we will be working with 2 data sets:

- Facebook's stock price throughout 2018 (obtained using the `stock_analysis` package).
- daily weather data for NYC from the National Centers for Environmental Information (NCEI) API.

Note: The NCEI is part of the National Oceanic and Atmospheric Administration (NOAA) and, as you can see from the URL for the API, this resource was created when the NCEI was called the NCDC. Should the URL for this resource change in the future, you can search for the NCEI weather API to find the updated one.

Background on the weather data

Data meanings:

- `AWND` : average wind speed
- `PRCP` : precipitation in millimeters
- `SNOW` : snowfall in millimeters
- `SNWD` : snow depth in millimeters
- `TMAX` : maximum daily temperature in Celsius
- `TMIN` : minimum daily temperature in Celsius

Setup

In [1]:
```
import numpy as np
import pandas as pd

weather = pd.read_csv('data/nyc_weather_2018.csv', parse_dates=['date'])
weather.head()
```

Out[1]:

	attributes	datatype	date	station	value
0	,,N,	PRCP	2018-01-01	GHCND:US1CTFR0039	0.0
1	,,N,	PRCP	2018-01-01	GHCND:US1NJBG0015	0.0
2	,,N,	SNOW	2018-01-01	GHCND:US1NJBG0015	0.0
3	,,N,	PRCP	2018-01-01	GHCND:US1NJBG0017	0.0
4	,,N,	SNOW	2018-01-01	GHCND:US1NJBG0017	0.0

In [2]:

```
fb = pd.read_csv('data/fb_2018.csv', index_col='date', parse_dates=True)
fb.head()
```

Out[2]:

	open	high	low	close	volume
date					
2018-01-02	177.68	181.58	177.5500	181.42	18151903
2018-01-03	181.88	184.78	181.3300	184.67	16886563
2018-01-04	184.90	186.21	184.0996	184.33	13880896
2018-01-05	185.59	186.90	184.9300	186.85	13574535
2018-01-08	187.20	188.90	186.3300	188.28	17994726

Arithmetic and statistics

We already saw that we can use mathematical operators like `+` and `/` with dataframes directly. However, we can also use methods, which allow us to specify the axis to perform the calculation over. By default this is per column. Let's find the z-scores for the volume traded and look at the days where this was more than 3 standard deviations from the mean:

In [3]:

```
fb.assign(
    abs_z_score_volume=lambda x: x.volume.sub(x.volume.mean()).div(x.volume.std()).abs()
).query('abs_z_score_volume > 3')
```

Out[3]:

date	open	high	low	close	volume	abs_z_score_volume
2018-03-19	177.01	177.17	170.06	172.56	88140060	3.145078
2018-03-20	167.47	170.20	161.95	168.15	129851768	5.315169
2018-03-21	164.80	173.40	163.30	169.39	106598834	4.105413
2018-03-26	160.82	161.10	149.02	160.06	126116634	5.120845
2018-07-26	174.89	180.13	173.75	176.26	169803668	7.393705

We can use `rank()` and `pct_change()` to see which days had the largest change in volume traded from the day before:

In [4]:
```
fb.assign(
    volume_pct_change=fb.volume.pct_change(),
    pct_change_rank=lambda x: x.volume_pct_change.abs().rank(
        ascending=False
    )
).nsmallest(5, 'pct_change_rank')
```

Out[4]:

date	open	high	low	close	volume	volume_pct_change	pct_change_rank
2018-01-12	178.06	181.48	177.40	179.37	77551299	7.087876	1.0
2018-03-19	177.01	177.17	170.06	172.56	88140060	2.611789	2.0
2018-07-26	174.89	180.13	173.75	176.26	169803668	1.628841	3.0
2018-09-21	166.64	167.25	162.81	162.93	45994800	1.428956	4.0
2018-03-26	160.82	161.10	149.02	160.06	126116634	1.352496	5.0

January 12th was when the news that Facebook changed its news feed product to focus more on content from a users' friends over the brands they follow. Given that Facebook's advertising is a key component of its business (nearly 89% in 2017), many shares were sold and the price dropped in panic:

In [5]:
```
fb['2018-01-11':'2018-01-12']
```

Out[5]:

	open	high	low	close	volume
date					
2018-01-11	188.40	188.40	187.38	187.77	9588587
2018-01-12	178.06	181.48	177.40	179.37	77551299

Throughout 2018, Facebook's stock price never had a low above $215:

In [6]:
```
(fb > 215).any()
```

Out[6]:
```
open       True
high       True
low       False
close      True
volume     True
dtype: bool
```

Facebook's OHLC (open, high, low, and close) prices all had at least one day they were at $215 or less:

In [7]:
```
(fb > 215).all()
```

Out[7]:
```
open      False
high      False
low       False
close     False
volume     True
dtype: bool
```

Binning and thresholds

When working with the volume traded, we may be interested in ranges of volume rather than the exact values. No two days have the same volume traded:

In [8]:
```
(fb.volume.value_counts() > 1).sum()
```

Out[8]:
```
0
```

We can use `pd.cut()` to create 3 bins of even an even range in volume traded and name them. Then we can work with low, medium, and high volume traded categories:

In [9]:
```
volume_binned = pd.cut(fb.volume, bins=3, labels=['low', 'med', 'high'])
volume_binned.value_counts()
```

Out[9]:
```
low     240
med       8
high      3
Name: volume, dtype: int64
```

In [10]:
```
fb[volume_binned == 'high'].sort_values(
    'volume', ascending=False
)
```

Out[10]:

date	open	high	low	close	volume
2018-07-26	174.89	180.13	173.75	176.26	169803668
2018-03-20	167.47	170.20	161.95	168.15	129851768
2018-03-26	160.82	161.10	149.02	160.06	126116634

July 25th Facebook announced disappointing user growth and the stock tanked in the after hours:

In [11]:
```
fb['2018-07-25':'2018-07-26']
```

Out[11]:

date	open	high	low	close	volume
2018-07-25	215.715	218.62	214.27	217.50	64592585
2018-07-26	174.890	180.13	173.75	176.26	169803668

Cambridge Analytica scandal broke on Saturday March 17th, so we look to the Monday for the numbers:

In [12]:
```
fb['2018-03-16':'2018-03-20']
```

Out[12]:

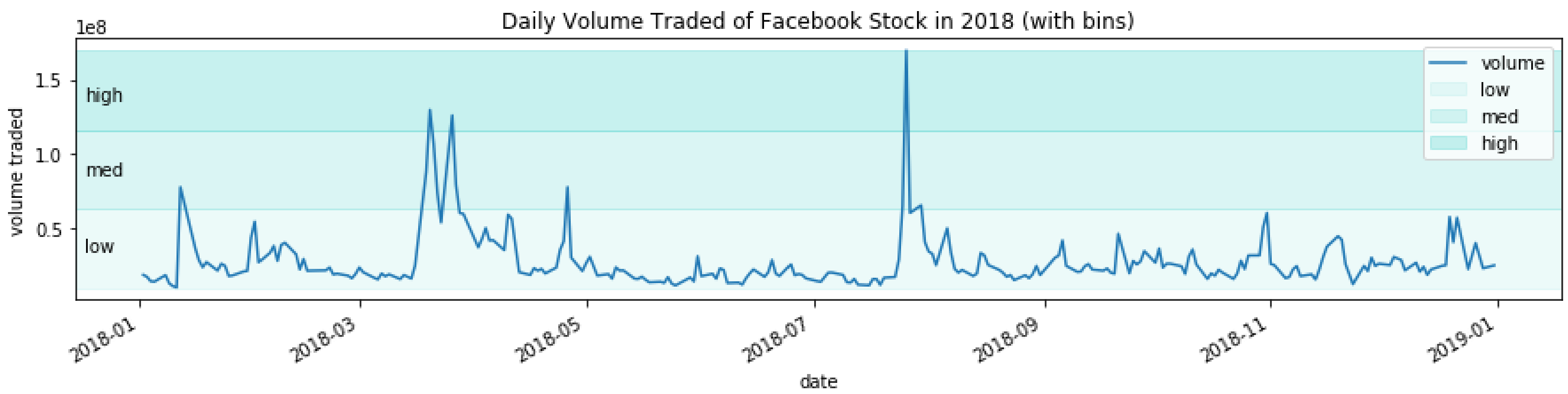
date	open	high	low	close	volume
2018-03-16	184.49	185.33	183.41	185.09	24403438
2018-03-19	177.01	177.17	170.06	172.56	88140060
2018-03-20	167.47	170.20	161.95	168.15	129851768

Since most days have similar volume, but a few are very large, we have very wide bins. Most of the data is in the low bin.

Note: visualizations will be covered in chapters 5 and 6.

In [13]:
```
import matplotlib.pyplot as plt
```

In [14]:
```
fb.plot(y='volume', figsize=(15, 3), title='Daily Volume Traded of Facebook Stock in 2018 (with bins)')

for bin_name, alpha, bounds in zip(
    ['low', 'med', 'high'], [0.1, 0.2, 0.3], pd.cut(fb.volume, bins=3).unique().categories.values
):
    plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumturquoise')
    plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

plt.ylabel('volume traded')
plt.legend()
plt.show()
```



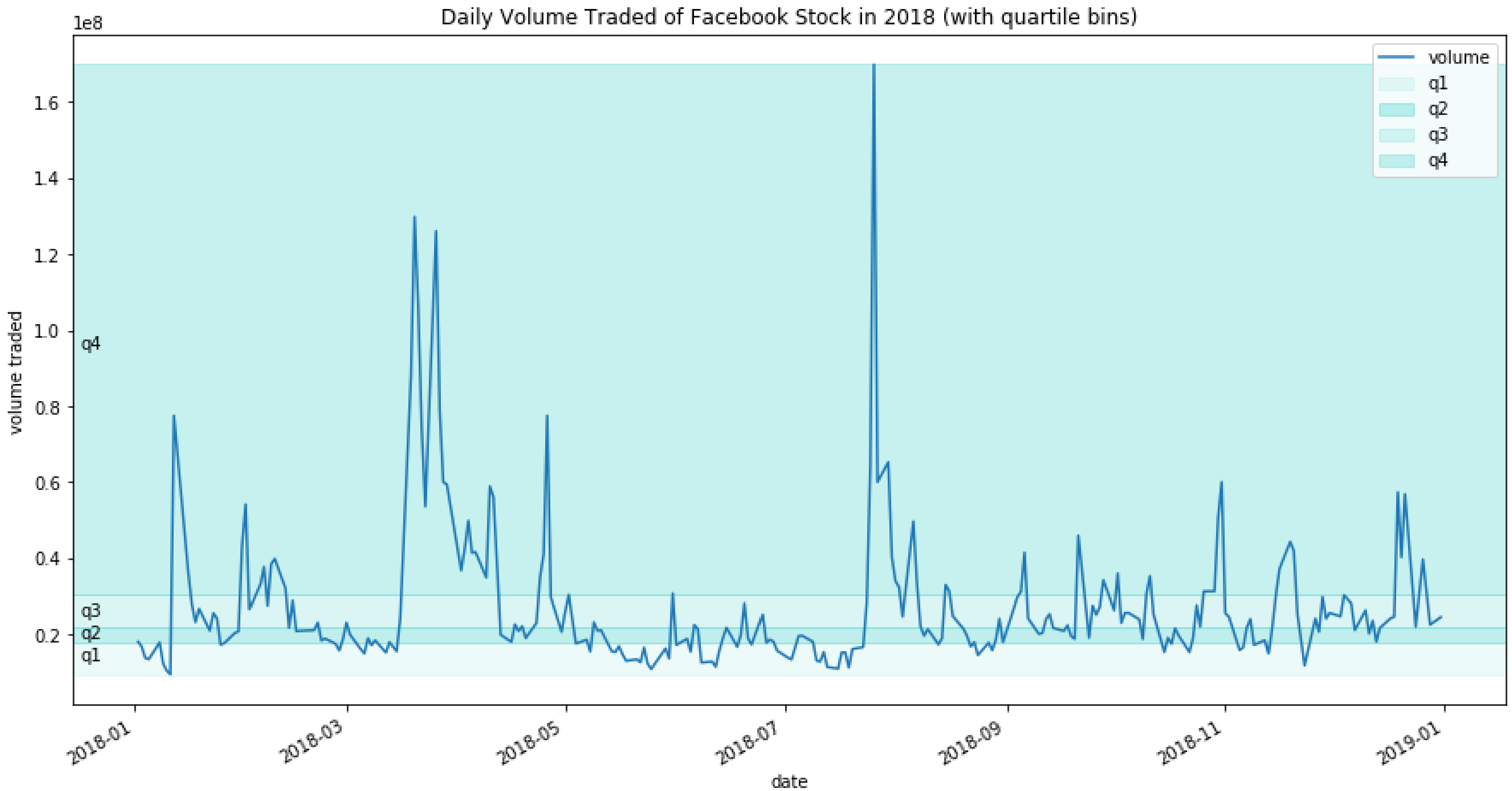
If we split using quantiles, the bins will have roughly the same number of observations. For this, we use `qcut()`. We will make 4 quartiles:

In [15]:
```
volume_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
volume_qbinned.value_counts()
```

Out[15]:
```
q4    63
q2    63
q1    63
q3    62
Name: volume, dtype: int64
```

Notice the bins don't cover ranges of the same size anymore:

In [16]:
```
fb.plot(y='volume', figsize=(15, 8), title='Daily Volume Traded of Facebook Stock in 2018 (with quartile bins)')

for bin_name, alpha, bounds in zip(
    ['q1', 'q2', 'q3', 'q4'], [0.1, 0.35, 0.2, 0.3], pd.qcut(fb.volume, q=4).unique().categories.values
):
    plt.axhspan(bounds.left, bounds.right, alpha=alpha, label=bin_name, color='mediumturquoise')
    plt.annotate(bin_name, xy=('2017-12-17', (bounds.left + bounds.right)/2.1))

plt.ylabel('volume traded')
plt.legend()
plt.show()
```



Sometimes we don't want to make bins, but rather cap values at a threshold. Before we look at an example, let's pivot our weather data for the Central Park station:

In [17]:
```
central_park_weather = weather.query(
    'station == "GHCND:USW00094728"'
).pivot(index='date', columns='datatype', values='value')
```

Out[17]:

datatype	AWND	PRCP	SNOW	SNWD	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5	WT01	WT02	WT03	WT06	WT08
date															
2018-01-01	3.5	0.0	0.0	0.0	-7.1	-13.8	300.0	300.0	6.7	11.2	NaN	NaN	NaN	NaN	NaN
2018-01-02	3.6	0.0	0.0	0.0	-3.2	-10.5	260.0	250.0	7.2	12.5	NaN	NaN	NaN	NaN	NaN
2018-01-03	1.4	0.0	0.0	0.0	-1.0	-8.8	260.0	270.0	6.3	9.8	NaN	NaN	NaN	NaN	NaN
2018-01-04	5.6	19.3	249.0	30.0	-1.6	-7.1	310.0	310.0	10.7	19.2	1.0	1.0	NaN	NaN	1.0
2018-01-05	5.8	0.0	0.0	180.0	-7.1	-12.7	280.0	280.0	9.4	15.7	NaN	NaN	NaN	NaN	NaN

Say we don't care how much snow their was, just that it snowed in Central Park. However, we don't want to make a Boolean column since we need to preserve the data type of float. We can use `clip()` to replace values above a upper threshold with the threshold and replace values below a lower threshold with the lower threshold. This means we can use `clip(0, 1)` to change all the snow values of one or more to 1, which easily shows us the days snow was recorded in Central Park. Preserving the data type will save some work later on if we are building a model:

In [18]:
```
central_park_weather.SNOW.clip(0, 1).value_counts()
```

Out[18]:
```
0.0    354
1.0     11
Name: SNOW, dtype: int64
```

Note: the `clip()` method can also be called on the dataframe itself.

Applying Functions

We can use the `apply()` method to run the same operation on all columns (or rows) of the dataframe. Let's calculate the z-scores of the TMIN, TMAX, and PRCP observations in Central Park in October 2018:

In [19]:
```
oct_weather_z_scores = central_park_weather.loc[
    '2018-10', ['TMIN', 'TMAX', 'PRCP']
```

```
].apply(lambda x: x.sub(x.mean()).div(x.std()))
oct_weather_z_scores.describe().T
```

Out[19]:

datatype	count	mean	std	min	25%	50%	75%	max
TMIN	31.0	-1.790682e-16	1.0	-1.339112	-0.751019	-0.474269	1.065152	1.843511
TMAX	31.0	1.951844e-16	1.0	-1.305582	-0.870013	-0.138258	1.011643	1.604016
PRCP	31.0	4.655774e-17	1.0	-0.394438	-0.394438	-0.394438	-0.240253	3.936167

October 27th rained much more than the rest of the days:

In [20]:
```
oct_weather_z_scores.query('PRCP > 3')
```

Out[20]:

datatype date	TMIN	TMAX	PRCP
2018-10-27	-0.751019	-1.201045	3.936167

Indeed, this day was much higher than the rest:

In [21]:
```
central_park_weather.loc['2018-10', 'PRCP'].describe()
```

Out[21]:
```
count    31.000000
mean      2.941935
std       7.458542
min       0.000000
25%       0.000000
50%       0.000000
75%       1.150000
max      32.300000
Name: PRCP, dtype: float64
```

When the function we want to apply isn't vectorized, we can:

- use `np.vectorize()` to vectorize it (similar to how `map()` works) and then use it with `apply()`
- use `applymap()` and pass it the non-vectorized function directly

Say we wanted to count the digits of the whole numbers for the Facebook data. `len()` is not vectorized:

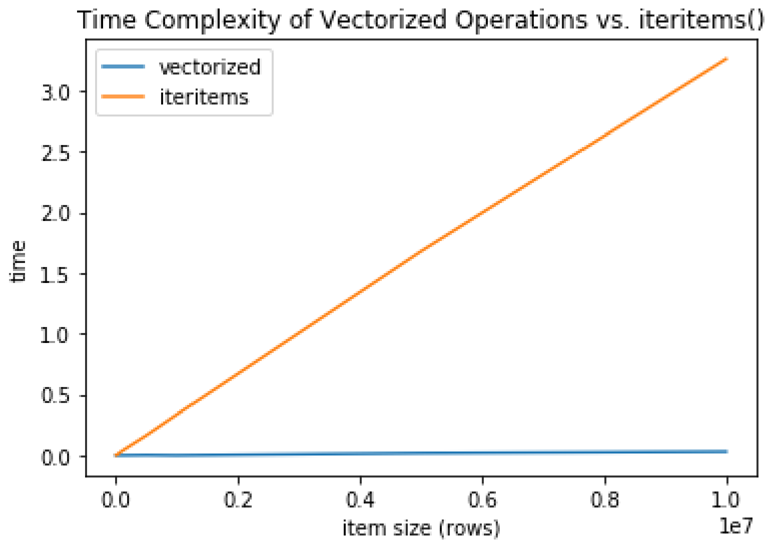
In [22]:
```python
import numpy as np

fb.apply(
    lambda x: np.vectorize(lambda y: len(str(np.ceil(y))))(x)
).astype('int64').equals(
    fb.applymap(lambda x: len(str(np.ceil(x))))
)
```

Out[22]:
```
True
```

A simple operation of addition to each element in a series grows linearly in time complexity when using `iteritems()`, but stays near 0 when using vectorized operations. `iteritems()` and related methods should only be used if there is no vectorized solution:

In [23]:
```python
import time

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

np.random.seed(0)

vectorized_results = {}
iteritems_results = {}

for size in [10, 100, 1000, 10000, 100000, 500000, 1000000, 5000000, 10000000]:
    test = pd.Series(np.random.uniform(size=size))

    start = time.time()
    x = test + 10
    end = time.time()
    vectorized_results[size] = end - start

    start = time.time()
    x = []
    for i, v in test.iteritems():
        x.append(v + 10)
    x = pd.Series(x)
    end = time.time()
    iteritems_results[size] = end - start

pd.DataFrame(
    [pd.Series(vectorized_results, name='vectorized'), pd.Series(iteritems_results, name='iteritems')]
).T.plot(title='Time Complexity of Vectorized Operations vs. iteritems()')
```

```
plt.xlabel('item size (rows)')
plt.ylabel('time')
plt.show()
```



Window Calculations

*Consult the **understanding windows calculation notebook** for interactive visualizations to help understand window calculations.*

The `rolling()` method allows us to perform rolling window calculations. We simply specify the window size (3 days here) and follow it with a call to an aggregation function (sum here):

In [24]:
```
central_park_weather['2018-10'].assign(
    rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum()
)[['PRCP', 'rolling_PRCP']].head(7).T
```

Out[24]:

date	2018-10-01 00:00:00	2018-10-02 00:00:00	2018-10-03 00:00:00	2018-10-04 00:00:00	2018-10-05 00:00:00	2018-10-06 00:00:00	2018-10-07 00:00:00
datatype							
PRCP	0.0	17.5	0.0	1.0	0.0	0.0	0.0
rolling_PRCP	0.0	17.5	17.5	18.5	1.0	1.0	0.0

We can also perform the rolling calculations on the entire dataframe at once. This will apply the same aggregation function to each column:

```
In [25]: central_park_weather['2018-10'].rolling('3D').mean().head(7).iloc[:,:6]
```

Out[25]:

datatype date	AWND	PRCP	SNOW	SNWD	TMAX	TMIN
2018-10-01	0.900000	0.000000	0.0	0.0	24.400000	17.200000
2018-10-02	0.900000	8.750000	0.0	0.0	24.700000	17.750000
2018-10-03	0.966667	5.833333	0.0	0.0	24.233333	17.566667
2018-10-04	0.800000	6.166667	0.0	0.0	24.233333	17.200000
2018-10-05	1.033333	0.333333	0.0	0.0	23.133333	16.300000
2018-10-06	0.833333	0.333333	0.0	0.0	22.033333	16.300000
2018-10-07	1.066667	0.000000	0.0	0.0	22.600000	17.400000

We can use different aggregation functions per column if we use `agg()` instead. We pass in a dictionary mapping the column to the aggregation to perform on it:

```
In [26]: central_park_weather['2018-10-01':'2018-10-07'].rolling('3D').agg(
             {'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'}
         ).join( # join with original data for comparison
             central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
             lsuffix='_rolling'
         ).sort_index(axis=1) # sort columns so rolling calcs are next to originals
```

Out[26]:

date	AWND	AWND_rolling	PRCP	PRCP_rolling	TMAX	TMAX_rolling	TMIN	TMIN_rolling
2018-10-01	0.9	0.900000	0.0	0.0	24.4	24.4	17.2	17.2
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	18.3	17.2
2018-10-03	1.1	0.966667	0.0	17.5	23.3	25.0	17.2	17.2
2018-10-04	0.4	0.800000	1.0	18.5	24.4	25.0	16.1	16.1
2018-10-05	1.6	1.033333	0.0	1.0	21.7	24.4	15.6	15.6
2018-10-06	0.5	0.833333	0.0	1.0	20.0	24.4	17.2	15.6
2018-10-07	1.1	1.066667	0.0	0.0	26.1	26.1	19.4	15.6

Rolling calculations (`rolling()`) use a sliding window. Expanding calculations (`expanding()`) however grow in size. These are equivalent to cumulative aggregations like `cumsum()` ; however, we can specify the minimum number of periods required to start calculating (default is 1):

In [27]:
```
central_park_weather.PRCP.expanding().sum().equals(central_park_weather.PRCP.cumsum())
```

Out[27]:
```
True
```

Separate expanding aggregations per column. Note that `agg()` will accept numpy functions too:

In [28]:
```
central_park_weather['2018-10-01':'2018-10-07'].expanding().agg(
    {'TMAX': np.max, 'TMIN': np.min, 'AWND': np.mean, 'PRCP': np.sum}
).join(
    central_park_weather[['TMAX', 'TMIN', 'AWND', 'PRCP']],
    lsuffix='_expanding'
).sort_index(axis=1)
```

Out[28]:

	AWND	AWND_expanding	PRCP	PRCP_expanding	TMAX	TMAX_expanding	TMIN	TMIN_expanding
date								
2018-10-01	0.9	0.900000	0.0	0.0	24.4	24.4	17.2	17.2
2018-10-02	0.9	0.900000	17.5	17.5	25.0	25.0	18.3	17.2
2018-10-03	1.1	0.966667	0.0	17.5	23.3	25.0	17.2	17.2
2018-10-04	0.4	0.825000	1.0	18.5	24.4	25.0	16.1	16.1
2018-10-05	1.6	0.980000	0.0	18.5	21.7	25.0	15.6	15.6
2018-10-06	0.5	0.900000	0.0	18.5	20.0	25.0	17.2	15.6
2018-10-07	1.1	0.928571	0.0	18.5	26.1	26.1	19.4	15.6

We can calculate the exponentially weighted moving average as follows. Note that `span` here is the periods to use:

In [29]:
```
fb.assign(
    close_ewma=lambda x: x.close.ewm(span=5).mean()
).tail(10)[['close', 'close_ewma']]
```

Out[29]:

date	close	close_ewma
2018-12-17	140.19	142.235433
2018-12-18	143.66	142.710289
2018-12-19	133.24	139.553526
2018-12-20	133.40	137.502350
2018-12-21	124.95	133.318234
2018-12-24	124.06	130.232156
2018-12-26	134.18	131.548104
2018-12-27	134.52	132.538736
2018-12-28	133.20	132.759157
2018-12-31	131.09	132.202772

*Consult the **understanding_window_calculations.ipynb** notebook for interactive visualizations to help understand window calculations.*

Pipes

Pipes all use to apply any function that accepts our data as the first argument and pass in any additional arguments. This makes it easy to chain steps together regardless of if they are methods or functions:

We can pass any function that will accept the caller of `pipe()` as the first argument:

In [30]:
```
def get_info(df):
    return '%d rows and %d columns and max closing z-score was %d' % (*df.shape, df.close.max())

fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
    == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
```

Out[30]:
```
True
```

For example, passing `pd.DataFrame.rolling` to `pipe()` is equivalent to calling `rolling()` directly on the dataframe, except we have more flexiblity to change this:

In [31]:
```python
fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean())
```

Out[31]:
```
True
```

The pipe takes the function passed in and calls it with the object that called `pipe()` as the first argument. Positional and keyword arguments are passed down:

In [32]:
```python
pd.DataFrame.rolling(fb, '20D').mean().equals(fb.rolling('20D').mean())
```

Out[32]:
```
True
```

We can use a pipe to make a function that we can use for all our window calculation needs:

In [33]:
```python
from window_calc import window_calc
window_calc??
```

```
Signature: window_calc(df, func, agg_dict, *args, **kwargs)
Source:
def window_calc(df, func, agg_dict, *args, **kwargs):
    """
    Run a window calculation of your choice on a DataFrame.

    Parameters:
        - df: The DataFrame to run the calculation on.
        - func: The window calculation method that takes df
              as the first argument.
        - agg_dict: Information to pass to `agg()`, could be a
                    dictionary mapping the columns to the aggregation
                    function to use, a string name for the function,
                    or the function itself.
        - args: Positional arguments to pass to `func`.
        - kwargs: Keyword arguments to pass to `func`.

    Returns:
        - A new DataFrame object.
    """
    return df.pipe(func, *args, **kwargs).agg(agg_dict)
File:      c:\users\molinstefanie\packt\hands-on-data-analysis-with-pandas\ch_04\window_calc.py
Type:      function
```

We can use the same interface to calculate various window calculations now. Let's find the expanding median for the Facebook data:

In [34]:
```python
window_calc(fb, pd.DataFrame.expanding, np.median).head()
```

Out[34]:

date	open	high	low	close	volume
2018-01-02	177.68	181.580	177.5500	181.420	18151903.0
2018-01-03	179.78	183.180	179.4400	183.045	17519233.0
2018-01-04	181.88	184.780	181.3300	184.330	16886563.0
2018-01-05	183.39	185.495	182.7148	184.500	15383729.5
2018-01-08	184.90	186.210	184.0996	184.670	16886563.0

Using the exponentially weighted moving average requires we pass in a keyword argument:

In [35]:
```
window_calc(fb, pd.DataFrame.ewm, 'mean', span=3).head()
```

Out[35]:

date	open	high	low	close	volume
2018-01-02	177.680000	181.580000	177.550000	181.420000	1.815190e+07
2018-01-03	180.480000	183.713333	180.070000	183.586667	1.730834e+07
2018-01-04	183.005714	185.140000	182.372629	184.011429	1.534980e+07
2018-01-05	184.384000	186.078667	183.736560	185.525333	1.440299e+07
2018-01-08	185.837419	187.534839	185.075110	186.947097	1.625679e+07

With rolling calculations, we can pass in a positional argument for the window size:

In [36]:
```
window_calc(
    central_park_weather['2018-10'],
    pd.DataFrame.rolling,
    {'TMAX': 'max', 'TMIN': 'min', 'AWND': 'mean', 'PRCP': 'sum'},
    '3D'
).head()
```

Out[36]:

date	TMAX	TMIN	AWND	PRCP
2018-10-01	24.4	17.2	0.900000	0.0
2018-10-02	25.0	17.2	0.900000	17.5
2018-10-03	25.0	17.2	0.966667	17.5
2018-10-04	25.0	16.1	0.800000	18.5
2018-10-05	24.4	15.6	1.033333	1.0