8.3 Dataframe Operations

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Section: CPE22S3

Course: Computational Thinking with Python

Course Code: CPE311

```
import numpy as np
import pandas as pd
weather = pd.read_csv('data/nyc_weather_2018.csv', parse_dates=['date'])
weather.head()
```

	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

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

	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

Finding thr Z-scores for the volume traded and looking at the days where this was more than 3 standard deviations from the mean

```
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')
```

	open	high	low	close	volume	abs_z_score_volume
date						
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

```
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')
```

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

```
fb['2018-01-11':'2018-01-12'] #checking the OHLC and volume tranded of fb stocks at January 11 and January 12
```

date	open	high	low	close	volume
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

```
(fb > 215).any() #checking if there are stock price below 215
```

```
open       True
high       True
low       False
close      True
volume     True
dtype: bool
```

```
(fb > 200).any() #trying other stock prices
```

```
open      True
high      True
low       True
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

```
(fb > 215).all()
```

```
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

pandas.Series.value_counts

`Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)` [source]

Return a Series containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

```
(fb.volume.value_counts() > 1).sum()

#using value_counts(), we can identify if all our dataframes have unique values
```

```
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

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

```
low     240
med       8
high      3
Name: volume, dtype: int64
```

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

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

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

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

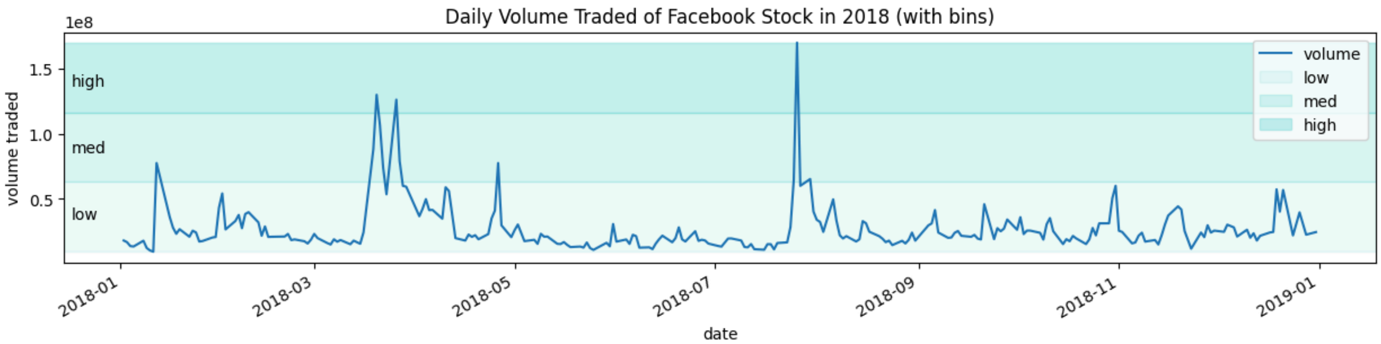
Cambridge Analytica scandal broke on Saturday March 17th, so we look to the Monday for the numbers

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

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

```
import matplotlib.pyplot as plt
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()
```

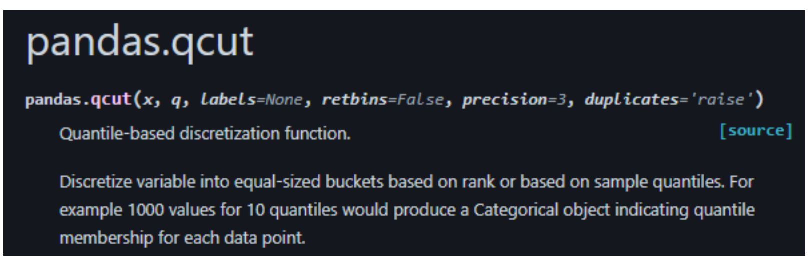


If we split using quantiles, the bins will have roughly the same number of observations. For this, we use qcut() . We will make 4 quartiles

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

```
q1    63
q2    63
q4    63
q3    62
Name: volume, dtype: int64
```

Trying OHLC 4 quartiles using qcut



pandas.qcut

pandas.qcut(x, q, labels=None, retbins=False, precision=3, duplicates='raise')

Quantile-based discretization function. [source]

Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

```
open_qbinned = pd.qcut(fb.open, q=4, labels=['q1', 'q2', 'q3', 'q4'])
open_qbinned.value_counts()
```

```
q1    63
q2    63
q4    63
q3    62
Name: open, dtype: int64
```

```
high_qbinned = pd.qcut(fb.high, q=4, labels=['q1', 'q2', 'q3', 'q4'])
high_qbinned.value_counts()
```

```
q1    63
q2    63
q4    63
q3    62
Name: high, dtype: int64
```

```
low_qbinned = pd.qcut(fb.low, q=4, labels=['q1', 'q2', 'q3', 'q4'])
low_qbinned.value_counts()
```

```
q1    63
q2    63
q4    63
q3    62
Name: low, dtype: int64
```

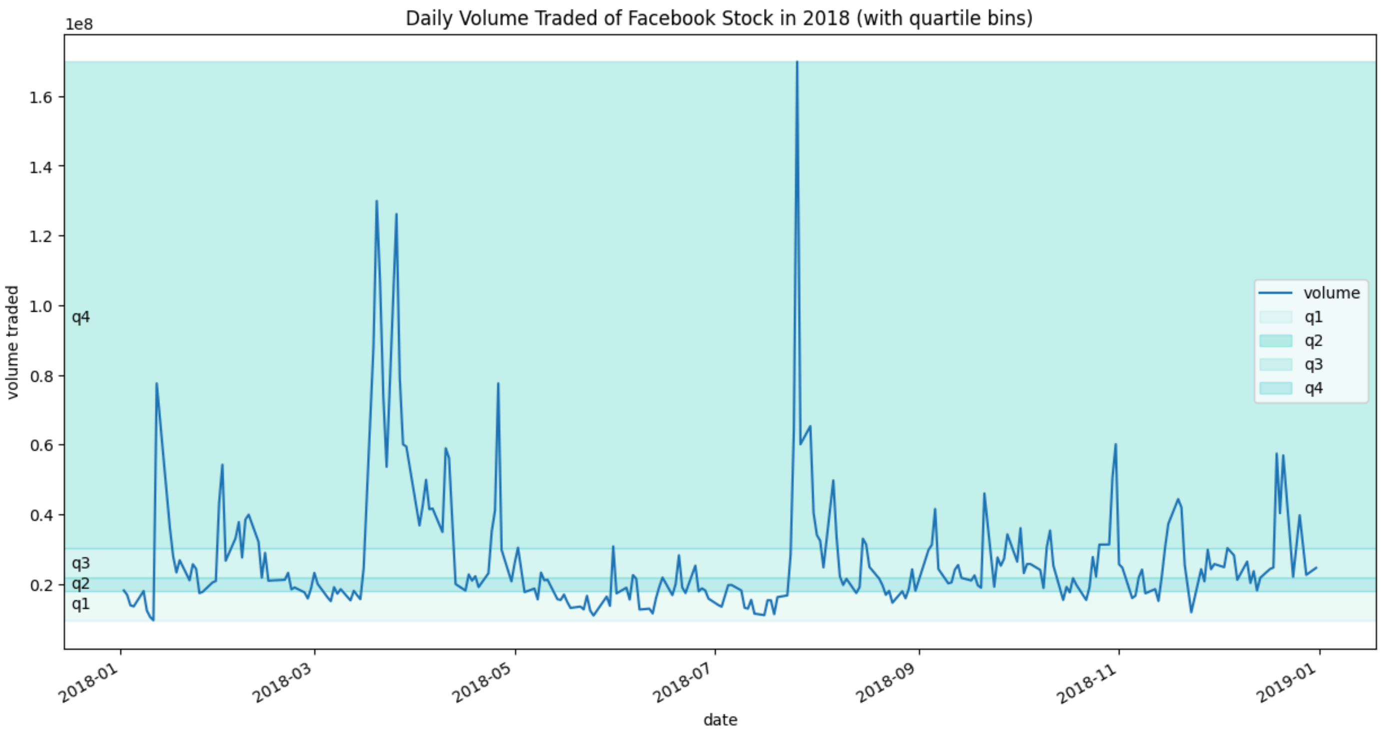
```
close_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
close_qbinned.value_counts()
```

```
q1    63
q2    63
q4    63
q3    62
Name: volume, dtype: int64
```

OHLC and Volume almost have the same value

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

```
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

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

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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2018-12-27	NaN	0.0	0.0	0.0	6.7	2.8	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-12-28	NaN	29.2	0.0	0.0	15.6	6.1	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN
2018-12-29	NaN	0.0	0.0	0.0	13.9	3.9	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-12-30	NaN	0.0	0.0	0.0	4.4	0.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2018-12-31	NaN	25.9	0.0	0.0	8.9	2.2	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN

365 rows × 15 columns

Next steps: View recommended plots

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

```
central_park_weather.SNOW.clip(0, 1).value_counts()
```

```
0.0    354
1.0     11
Name: SNOW, dtype: int64
```

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

```
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
```

	count	mean	std	min	25%	50%	75%	max
datatype								
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

```
oct_weather_z_scores.query('PRCP > 3') #locating the day where the PRCP is greater than 3
                                       # we can use .loc(). However, using .query() is much simplier
```

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

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

```
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:

```
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))))
)
```

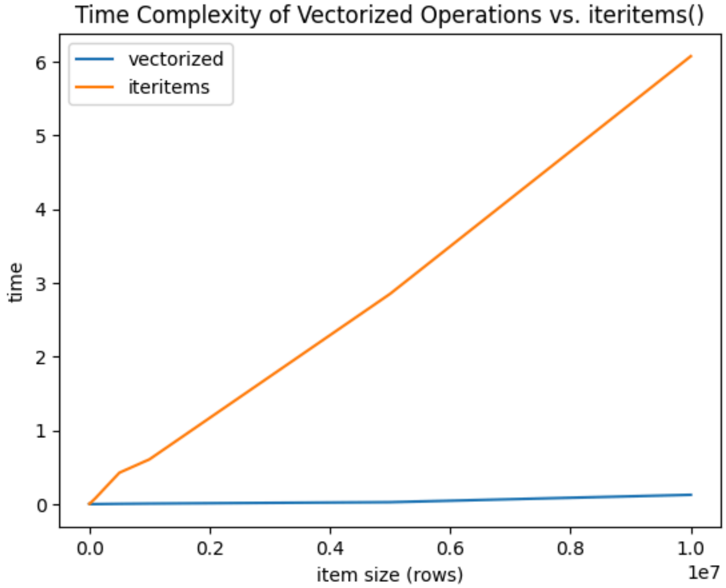
```
True
```

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:

```
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()
```

```
<ipython-input-39-f7b8724eefa5>:16: FutureWarning: iteritems is deprecated and will be removed in a future version. Use .items instead.
  for i, v in test.iteritems():
```



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)

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

```
<ipython-input-40-289d253875a5>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  central_park_weather['2018-10'].assign(
```

date	2018-10-01	2018-10-02	2018-10-03	2018-10-04	2018-10-05	2018-10-06	2018-10-07
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

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

```
<ipython-input-41-2abb37634d3b>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  central_park_weather['2018-10'].rolling('3D').mean().head(7).iloc[:,:6]
```

datatype	AWND	PRCP	SNOW	SNWD	TMAX	TMIN
date						
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

```
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)
```

datatype	AWND	AWND_rolling	PRCP	PRCP_rolling	TMAX	TMAX_rolling	TMIN	TMIN_rolling
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	0.800000	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)

```
central_park_weather.PRCP.expanding().sum().equals(central_park_weather.PRCP.cumsum())
```

```
False
```

```
central_park_weather.PRCP.expanding().sum() #checking the values if its the same
```

```
date
2018-01-01       0.0
2018-01-02       0.0
2018-01-03       0.0
2018-01-04      19.3
2018-01-05      19.3
               ...
2018-12-27    1610.2
2018-12-28    1639.4
2018-12-29    1639.4
2018-12-30    1639.4
2018-12-31    1665.3
Name: PRCP, Length: 365, dtype: float64
```

```
central_park_weather.PRCP.cumsum()
```

```
date
2018-01-01       0.0
2018-01-02       0.0
2018-01-03       0.0
2018-01-04      19.3
2018-01-05      19.3
               ...
2018-12-27    1610.2
2018-12-28    1639.4
2018-12-29    1639.4
2018-12-30    1639.4
2018-12-31    1665.3
Name: PRCP, Length: 365, dtype: float64
```

As you can see, I have the same values for the head() and the tail() of the dataframe. THe following days might not be the same and that could be the reason why it returned False

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

```
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)
```

datatype	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:

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

	close	close_ewma
date		
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

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

```
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()))
```

```
<ipython-input-51-762522dabad3>:4: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  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())
True
```

Passing pd.DataFrame.rolling to pipe() is equivalent to calling rolling() directly on the dataframe, except we have more flexiblity to change this

```
fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean())
```

    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:

```
pd.DataFrame.rolling(fb, '20D').mean().equals(fb.rolling('20D').mean())
```

    True

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

```
def window_calc(df, func, agg_dict, *args, **kwargs):
  return df.pipe(func, *args, **kwargs).agg(agg_dict)
```

```
window_calc(fb, pd.DataFrame.expanding, np.median).head()
```

	open	high	low	close	volume
date					
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

```
window_calc(fb, pd.DataFrame.ewm, 'mean', span=3).head()
```

	open	high	low	close	volume
date					
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

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

```
<ipython-input-61-31ab72cfb87f>:2: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows
  central_park_weather['2018-10'],
```

datatype	TMAX	TMIN	AWND	PRCP
date				
2018-10-01	24.4	17.2	0.900000	0.0