DataFrame Operations

Background on the weather data

- 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

```
import numpy as np
import pandas as pd

weather = pd.read_csv('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

```
# index_col='date' and parse_dates=True is vital for this section
fb = pd.read_csv('fb_2018.csv', index_col='date', parse_dates=True)
fb.head()
```

date	open	high	low	close	volume
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

z score formula - (x - mean) / standard deviation

```
# using .assign() would configure all the columns
# in this case, we implement the formula of z score and included .abs() for absolute value

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') # showcases only z score above 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:`

```
fb.assign(
  volume_pct_change=fb.volume.pct_change(), # get pct_change of the volume
  pct_change_rank=lambda x: x.volume_pct_change.abs().rank( # using rank(), rank the pct_change
  ascending=False # ascending = False while using nsmallest would yield the highest to lowest
  )
).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']
```

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

```
(fb > 215).any()
```

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

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

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

Binning and thresholds

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

```
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:

```
#.cut() is frequently used when binning, label them into 3
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
) # sort_values() for sorting the high values, use sort_values()
```

	open	high	low	close	volume
date					
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']
```

	open	high	low	close	volume
date					
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:

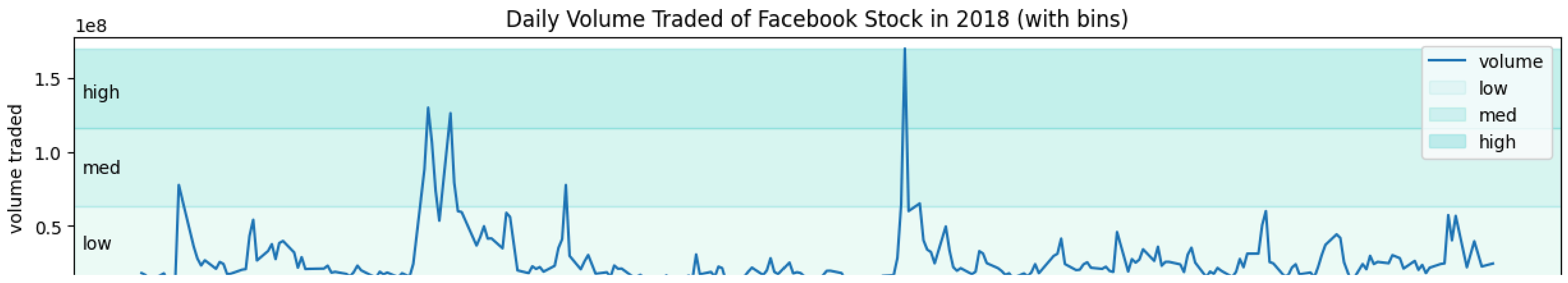
```
fb['2018-03-16':'2018-03-20']
```

	open	high	low	close	volume
date					
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

```
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()
```

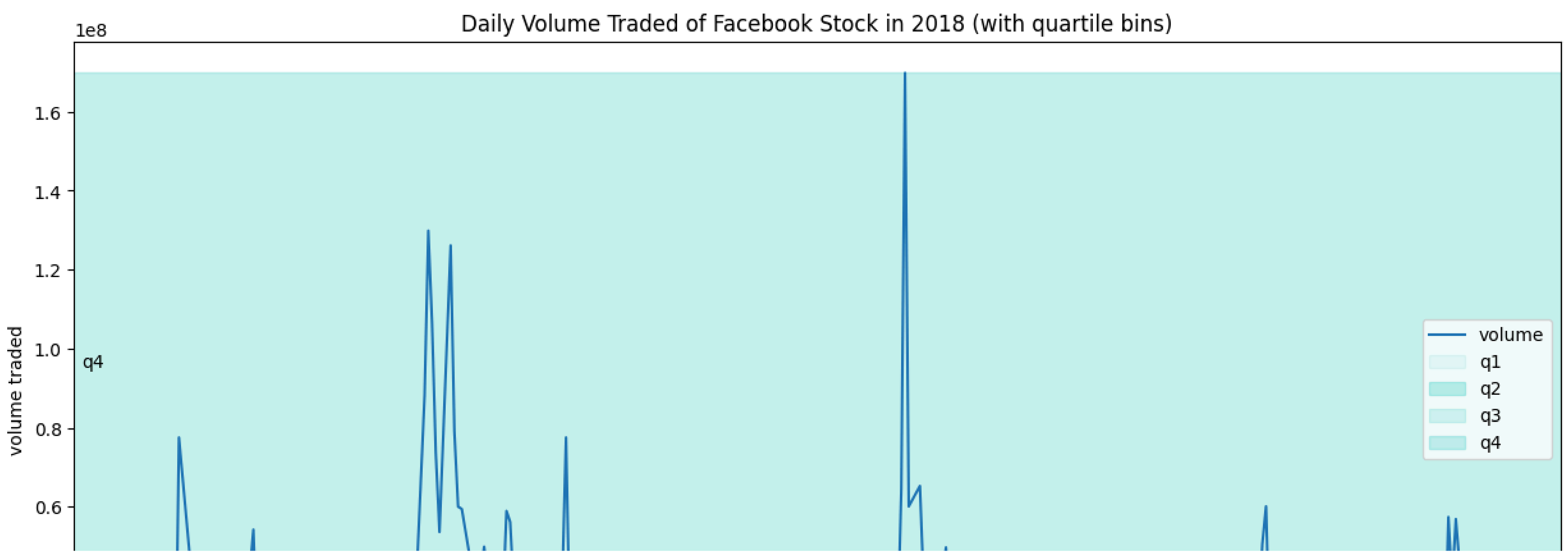



```
# qcut() brings out quantiles, in this case, we use quartiles
volume_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
volume_qbinned.value_counts()
```

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

```
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()
```




```
central_park_weather = weather.query(
  'station == "GHCND:USW00094728"'
).pivot(index='date', columns='datatype', values='value')
#.pivot() for setting the index, columns, and values in which are not specified so it showed all the data
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

```
central_park_weather.SNOW.clip(0, 1).value_counts()
#.clip(0,1).value_counts() shows teh number of days it snowed
```

```
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
```

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:

```
oct_weather_z_scores.query('PRCP > 3')
```

datatype / date	TMIN	TMAX	PRCP
2018-10-27	-0.740976	-1.170397	3.983866

Indeed, this day was much higher than the rest:

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

```
count    30.000000
mean      2.676667
std       7.435826
min       0.000000
25%       0.000000
50%       0.000000
75%       0.950000
max      32.300000
Name: PRCP, dtype: float64
```

- 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

```
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
```

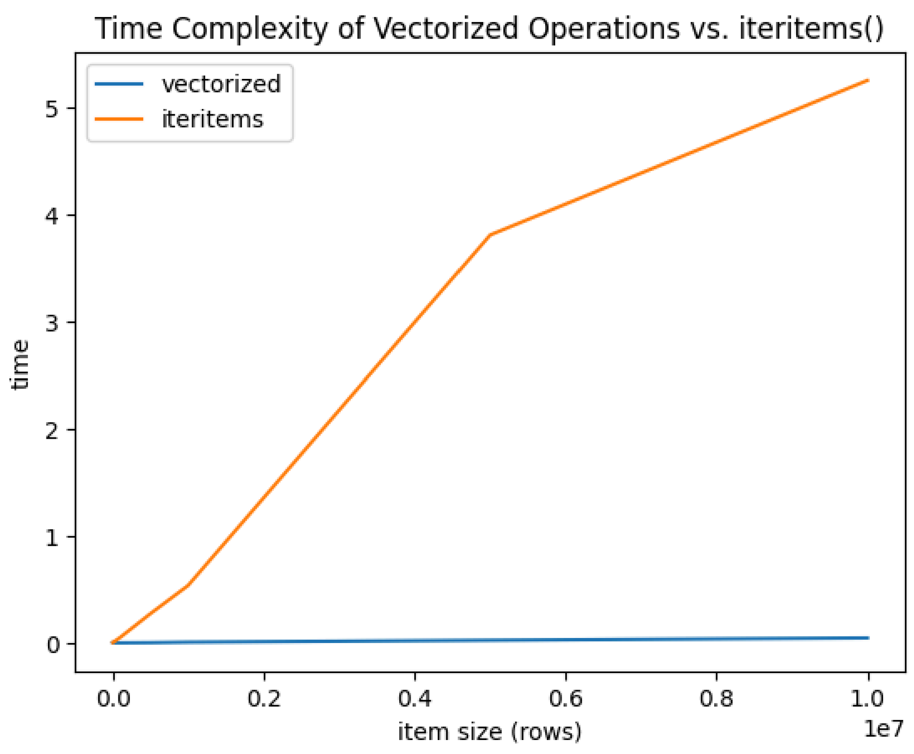
A simple operation of addition to each element in a series grows linearly in time complexity when using iteritems() , but stays near 0 when using vectorized operations.
iteritems() and related methods should only be used if there is no vectorized solution

```
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-67-025648b545d9>:18: FutureWarning: iteritems is deprecated and will be removed in a future version. Use .items instead.
  for i, v in test.iteritems():
```



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( # use assign() for window calculations
  rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum() # set window size to 3 days (3D) then get the sumd
)[['PRCP', 'rolling_PRCP']].head(7).T
```

```
<ipython-input-82-04280828d53d>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like `frame[string]`, is deprecated and will be removed in a future version. Use `frame.loc[string]` instead.
  central_park_weather['2018-10'].assign(
```

date / datatype	2018-10-01	2018-10-02	2018-10-03	2018-10-04	2018-10-05	2018-10-06	2018-10-07
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] #gets the mean while using .rolling()
```

```
<ipython-input-15-2abb37634d3b>:1: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like `frame[string]`, is deprecated and will be removed in a future version. Use `frame.loc[string]` instead.
  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) # sort columns so rolling calcs are next to originals
```

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
```

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( # the expanding aggregations are separated and is joined with the original
  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

```
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-74-195e192b92c3>:3: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like `frame[string]`, is deprecated and will be removed in a future version. Use `frame.loc[string]` instead.
  fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
<ipython-input-74-195e192b92c3>:4: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like `frame[string]`, is deprecated and will be removed in a future version. Use `frame.loc[string]` instead.
  == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
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:

```
fb.pipe(pd.DataFrame.rolling, '20D').mean().equals(fb.rolling('20D').mean()) #.pipe is a flexible version of .rolling()
# equality with rolling is checked
```

```
True
```

```
pd.DataFrame.rolling(fb, '20D').mean().equals(fb.rolling('20D').mean())
# equality with rolling is checked
```

```
True
```

```
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)
```

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

```
window_calc(fb, pd.DataFrame.expanding, np.median).head()
# window_calc function is used to check the expanding median for facebook data
```

	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()
# in this case, rolling calculations are done to get the max, min, mean, and sum of certain columns for 3D
```

```
<ipython-input-27-f68a24f53b38>:2: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the rows, like `frame[string]`, is deprecated and will be removed in a future version. Use `frame.loc[string]` instead.
  central_park_weather['2018-10'],
```

datatype	TMAX	TMIN	AWND	PRCP
date				
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