tg9nzsgpb

April 2, 2024

[ ]:
```
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()
```

[ ]:

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

1 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')
```

[ ]:

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(),
pct_change_rank=lambda x: x.volume_pct_change.abs().rank(
ascending=False
)
).nsmallest(5, 'pct_change_rank')
```

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

            pct_change_rank
date
2018-01-12              1.0
2018-03-19              2.0
2018-07-26              3.0
2018-09-21              4.0
2018-03-26              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
```

[ ]:
```
              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

[ ]:
```
(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
```

[ ]:
```
(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)
```

[ ]:
```
              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
```

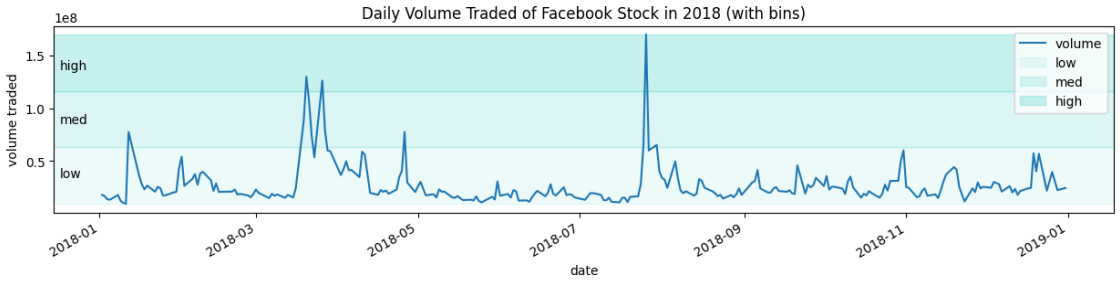
Cambridge Analytica scandal broke on Saturday March 17th, so we look to the Monday for the numbers

[ ]:
```
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
```

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
```

[ ]:
```
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()
```

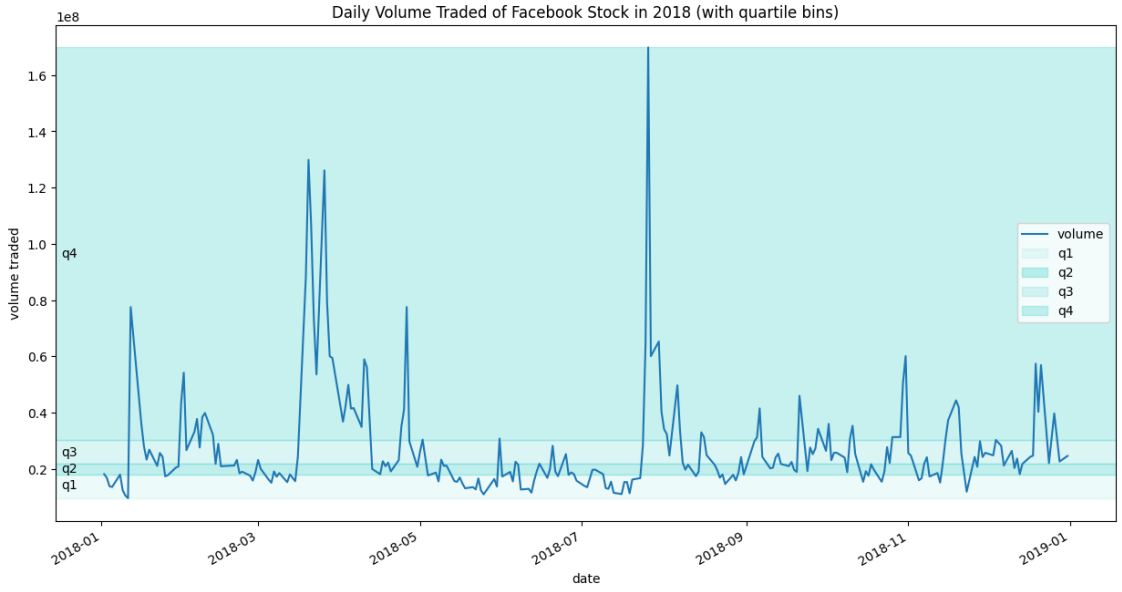
[ ]:
```
q1    63
q2    63
q4    63
```

```
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
```

[ ]:
```
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')
central_park_weather
```

[ ]:
```
datatype    AWND  PRCP   SNOW   SNWD  TMAX  TMIN   WDF2   WDF5  WSF2  WSF5  \
date
2018-01-01   3.5   0.0    0.0    0.0  -7.1 -13.8  300.0  300.0   6.7  11.2
2018-01-02   3.6   0.0    0.0    0.0  -3.2 -10.5  260.0  250.0   7.2  12.5
2018-01-03   1.4   0.0    0.0    0.0  -1.0  -8.8  260.0  270.0   6.3   9.8
2018-01-04   5.6  19.3  249.0   30.0  -1.6  -7.1  310.0  310.0  10.7  19.2
2018-01-05   5.8   0.0    0.0  180.0  -7.1 -12.7  280.0  280.0   9.4  15.7
…            …    …      …      …    …     …      …      …     …     …
2018-12-27   NaN   0.0    0.0    0.0   6.7   2.8    NaN    NaN   NaN   NaN
2018-12-28   NaN  29.2    0.0    0.0  15.6   6.1    NaN    NaN   NaN   NaN
2018-12-29   NaN   0.0    0.0    0.0  13.9   3.9    NaN    NaN   NaN   NaN
2018-12-30   NaN   0.0    0.0    0.0   4.4   0.6    NaN    NaN   NaN   NaN
2018-12-31   NaN  25.9    0.0    0.0   8.9   2.2    NaN    NaN   NaN   NaN

datatype    WT01  WT02  WT03  WT06  WT08
date
2018-01-01   NaN   NaN   NaN   NaN   NaN
2018-01-02   NaN   NaN   NaN   NaN   NaN
2018-01-03   NaN   NaN   NaN   NaN   NaN
2018-01-04   1.0   1.0   NaN   NaN   1.0
2018-01-05   NaN   NaN   NaN   NaN   NaN
…            …     …     …     …     …
2018-12-27   NaN   NaN   NaN   NaN   NaN
2018-12-28   1.0   NaN   NaN   NaN   NaN
2018-12-29   NaN   NaN   NaN   NaN   NaN
2018-12-30   NaN   NaN   NaN   NaN   NaN
2018-12-31   1.0   NaN   NaN   NaN   NaN

[365 rows x 15 columns]
```

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

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

2 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%  \
     datatype
     TMIN        31.0 -1.790682e-16  1.0 -1.339112 -0.751019 -0.474269  1.065152
     TMAX        31.0  1.951844e-16  1.0 -1.305582 -0.870013 -0.138258  1.011643
     PRCP        31.0  4.655774e-17  1.0 -0.394438 -0.394438 -0.394438 -0.240253

                    max
     datatype
     TMIN      1.843511
     TMAX      1.604016
     PRCP      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))))
)
```

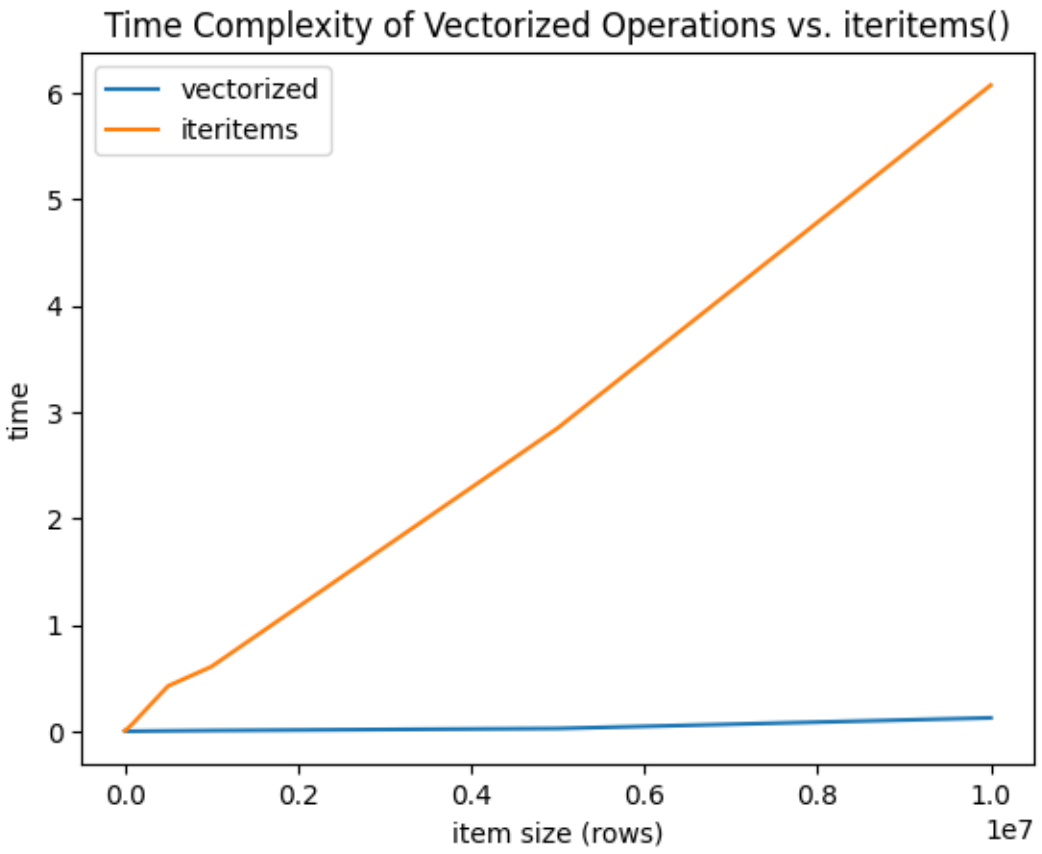
[ ]:
```
True
```

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():
```



3 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, 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          2018-10-01  2018-10-02  2018-10-03  2018-10-04  2018-10-05  \
datatype
PRCP                 0.0        17.5         0.0         1.0         0.0
rolling_PRCP         0.0        17.5        17.5        18.5         1.0

date          2018-10-06  2018-10-07
datatype
PRCP                 0.0         0.0
rolling_PRCP         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, 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)
```

[ ]:
```
datatype    AWND  AWND_rolling  PRCP  PRCP_rolling  TMAX  TMAX_rolling  TMIN  \
date
2018-10-01   0.9      0.900000   0.0           0.0  24.4          24.4  17.2
2018-10-02   0.9      0.900000  17.5          17.5  25.0          25.0  18.3
2018-10-03   1.1      0.966667   0.0          17.5  23.3          25.0  17.2
2018-10-04   0.4      0.800000   1.0          18.5  24.4          25.0  16.1
2018-10-05   1.6      1.033333   0.0           1.0  21.7          24.4  15.6
```

```
2018-10-06   0.5      0.833333   0.0          1.0  20.0          24.4  17.2
2018-10-07   1.1      1.066667   0.0          0.0  26.1          26.1  19.4
```

```
datatype    TMIN_rolling
date
2018-10-01          17.2
2018-10-02          17.2
2018-10-03          17.2
2018-10-04          16.1
2018-10-05          15.6
2018-10-06          15.6
2018-10-07          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
```

[ ]:
```
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  \
date
2018-10-01   0.9        0.900000   0.0             0.0  24.4            24.4
2018-10-02   0.9        0.900000  17.5            17.5  25.0            25.0
2018-10-03   1.1        0.966667   0.0            17.5  23.3            25.0
2018-10-04   0.4        0.825000   1.0            18.5  24.4            25.0
2018-10-05   1.6        0.980000   0.0            18.5  21.7            25.0
2018-10-06   0.5        0.900000   0.0            18.5  20.0            25.0
2018-10-07   1.1        0.928571   0.0            18.5  26.1            26.1

datatype    TMIN  TMIN_expanding
date
2018-10-01  17.2            17.2
2018-10-02  18.3            17.2
2018-10-03  17.2            17.2
2018-10-04  16.1            16.1
2018-10-05  15.6            15.6
2018-10-06  17.2            15.6
2018-10-07  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
```

4 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, 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) ==
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()
```

[ ]:

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

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

[ ]:

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

[ ]:
```
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, like
`frame[string]`, is deprecated and will be removed in a future version. Use
`frame.loc[string]` instead.
  central_park_weather['2018-10'],
```

[ ]:

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