Setup

John Rome A. Belocora

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

```
import numpy as np
import pandas as pd
# The 'parse_dates' parameter is used to specify the column(s) that contain date information
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

Next steps: View recommended plots

```
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

Next steps: View recommended plots

```
# The lambda function calculates the absolute Z-score for the 'volume' column
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

```
# The rank is calculated based on the absolute value of 'volume_pct_change', ordered in descending order
# The lambda function computes the absolute percentage change, ranks it, and assigns it to the 'pct_change_rank' column
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

```
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

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:

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

```
0
```

```
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

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

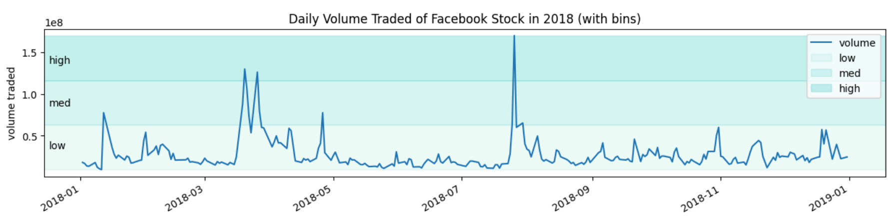
date	open	high	low	close	volume
2018-07-25	215.715	218.62	214.27	217.50	64592585
2018-07-26	174.890	180.13	173.75	176.26	169803668

```
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

```
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()
```

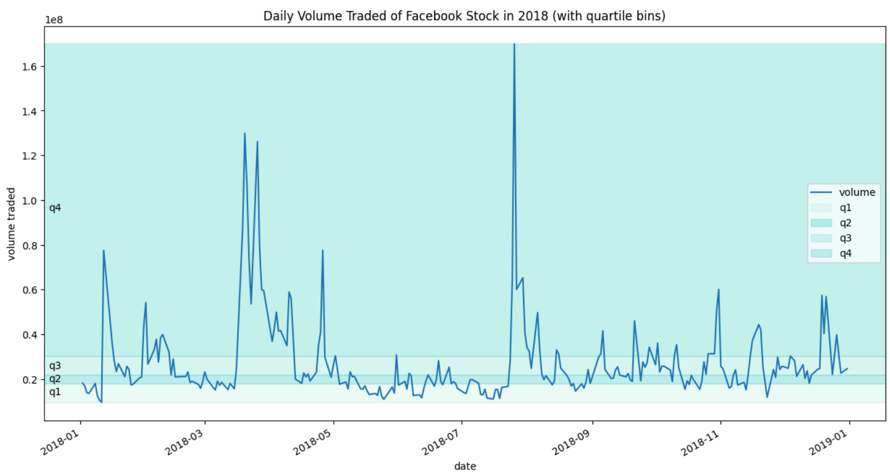



```
volume_qbinned = pd.qcut(fb.volume, q=4, labels=['q1', 'q2', 'q3', 'q4'])
```

```
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')
```

```
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

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

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

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

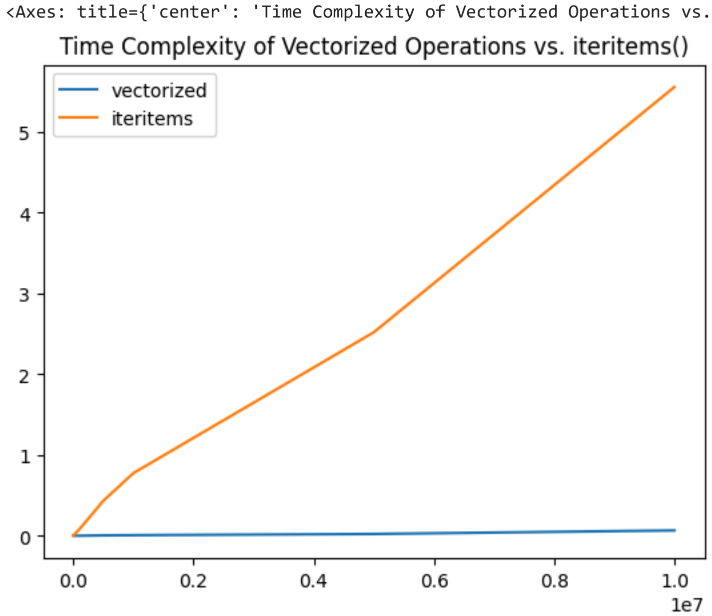
```
count    31.000000
mean      2.941935
std       7.458542
min       0.000000
25%       0.000000
50%       0.000000
75%       1.150000
max      32.300000
Name: PRCP, dtype: float64
```

```
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
```

```
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-28-3c22fcab22ab>:21: FutureWarning: iteritems is deprecated and will be
  for i, v in test.iteritems():
<Axes: title={'center': 'Time Complexity of Vectorized Operations vs. 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-29-bb4c4ebde8ce>:1: FutureWarning: Indexing a DataFrame with a datetimel
  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

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

```
<ipython-input-30-2abb37634d3b>:1: FutureWarning: Indexing a DataFrame with a datetimel
  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

```
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-								

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

```
False
```

```
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_ε
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	0.825000	1.0	18.5	24.4	25.0	16.1	
2018-10-								

```
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-36-e5fa6db8109a>:3: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()).pipe(get_info)\
<ipython-input-36-e5fa6db8109a>:4: FutureWarning: Indexing a DataFrame with a datetimelike index using a single string to slice the row
  == get_info(fb['2018-Q1'].apply(lambda x: (x - x.mean())/x.std()))
True
```

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

```
True
```

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

```
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
```

```
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

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

date	open	high	low	close	volume