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.

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

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

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```
fb = pd.read_csv('/content/fb_2018 8.3.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

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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:

```
fb.assign(abs_z_score_vloume=lambda x: x.volume.sub(x.volume.mean()).div(x.volume.std()).abs
```

date	open	high	low	close	volume	abs_z_score_vloume
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)).nsmalle
```

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

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()
```

	0
open	True
high	True
low	False
close	True
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()
```

```
np.int64(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()
```

volume	count
low	240
med	8
high	3

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

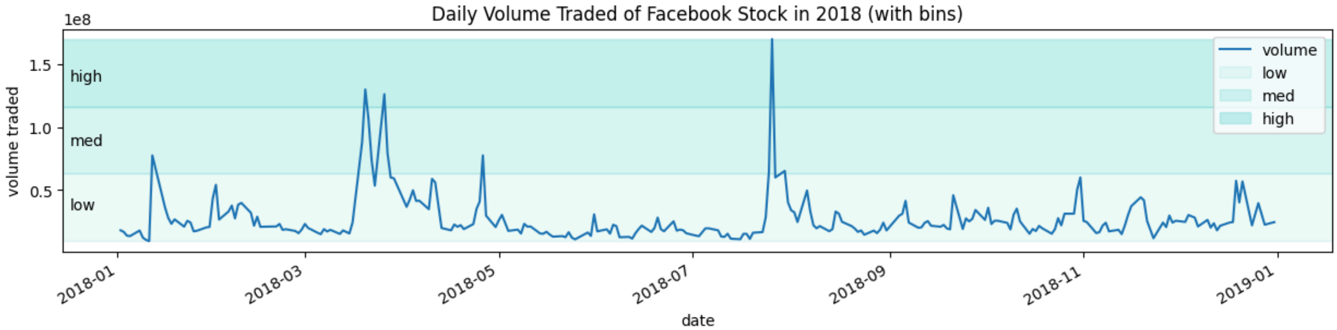
Since most days have similar volume, but a few are very large, we have very wide bins. Most of the data is in the low bin. Note: visualizations will be covered in chapters 5 and 6.

```
import matplotlib.pyplot as plt

fb.plot(y='volume', figsize=(15, 3), title='Daily Volume Traded of Facebook Stock in 2018 (w

for bin_name, alpha, bounds in zip(
    ['low', 'med', 'high'], [0.1, 0.2, 0.3], pd.cut(fb.volume, bins=3).unique().categories.v
  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()
```

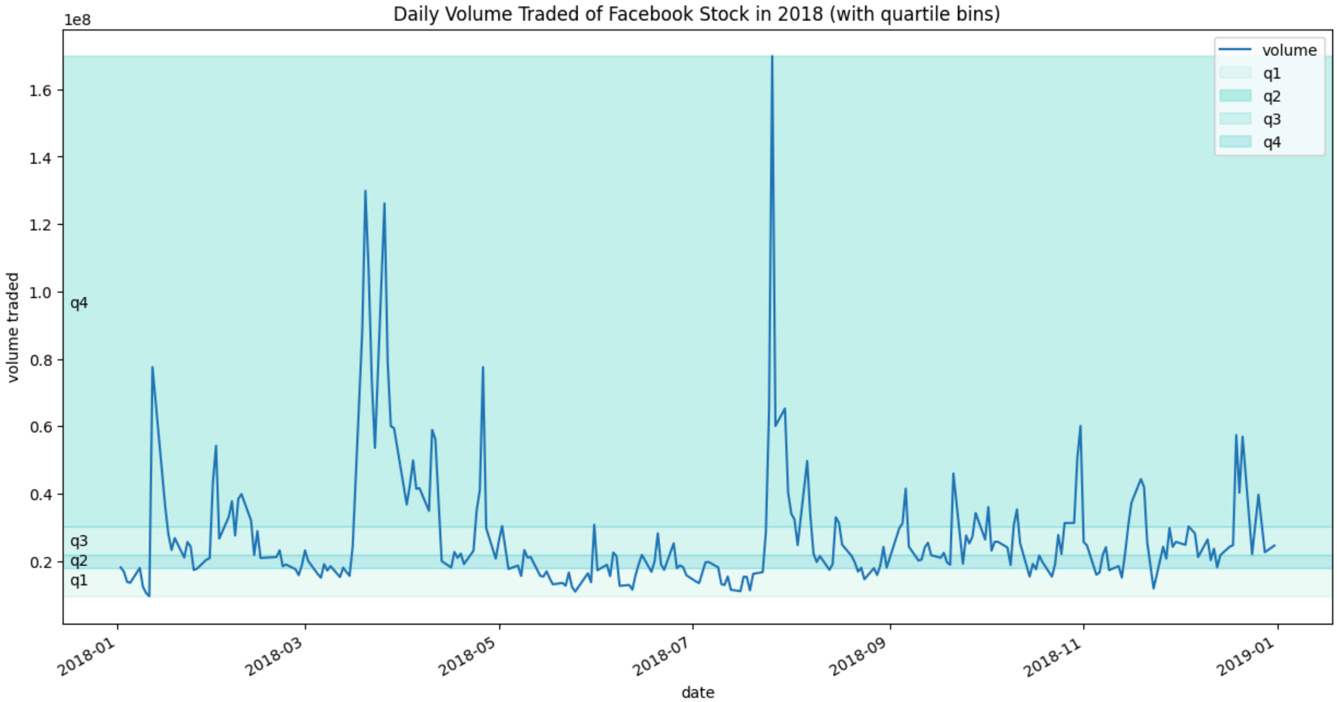
volume	count
q1	63
q2	63
q4	63
q3	62

dtype: int64

```
fb.plot(y='volume', figsize=(15, 8), title='Daily Volume Traded of Facebook Stock in 2018 (w

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().catego
  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.head()
```

datatype	AWND	PRCP	SNOW	SNWD	TMAX	TMIN	WDF2	WDF5	WSF2	WSF5	WT01	WT02	WT03
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
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
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

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

	count
SNOW	
0.0	354
1.0	11

dtype: int64

```
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()
```

	PRCP
count	31.000000
mean	2.941935
std	7.458542
min	0.000000
25%	0.000000
50%	0.000000
75%	1.150000
max	32.300000

dtype: float64

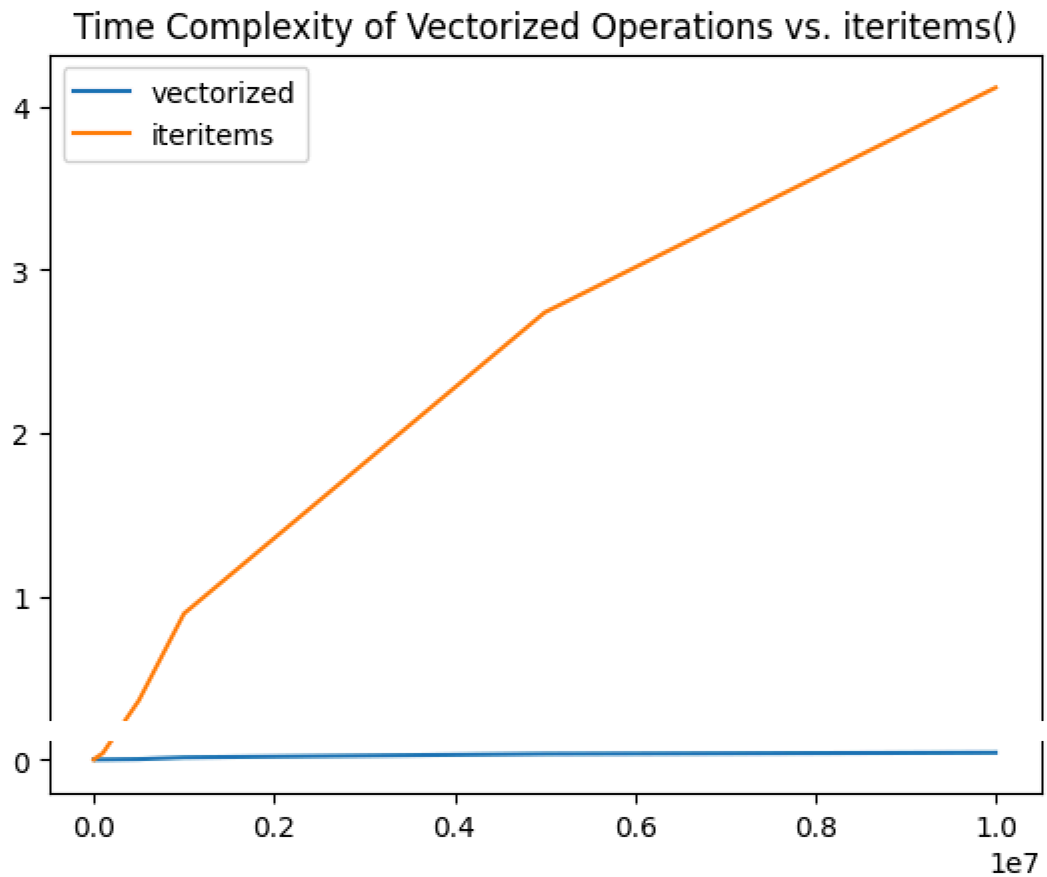
```
import numpy as np

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

```
<ipython-input-21-f374e8e36619>:3: FutureWarning: DataFrame.applymap has been deprecatec
  fb.apply(lambda x: np.vectorize(lambda y: len(str(np.ceil(y))))(x)).astype('int64').ec
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.items():
    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,
            ).T.plot(title='Time Complexity of Vectorized Operations vs. 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.loc['2018-10'].assign(rolling_PRCP=lambda x: x.PRCP.rolling('3D').sum()
```

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.loc['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(
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-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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

datatype	AWND	AWND_expanding	PRCP	PRCP_expanding	TMAX	TMAX_expanding	TMIN	TMIN_e
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.ma

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

```
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):
```

```
window_calc(fb, pd.DataFrame.expanding, "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	183.30	185.495	182.7148	184.500	15383729.5