Time Series

About the Data

In this notebook, we will be working with 5 data sets:

- (CSV) Facebook's stock price daily throughout 2018 (obtained using the `stock_analysis` package).
- (CSV) Facebook's OHLC stock data from May 20, 2019 - May 24, 2019 per minute from Nasdaq.com.
- (CSV) melted stock data for Facebook from May 20, 2019 - May 24, 2019 per minute from Nasdaq.com.
- (DB) stock opening prices by the minute for Apple from May 20, 2019 - May 24, 2019 altered to have seconds in the time from Nasdaq.com.
- (DB) stock opening prices by the minute for Facebook from May 20, 2019 - May 24, 2019 from Nasdaq.com.

Setup

In [1]:
```
import numpy as np
import pandas as pd

fb = pd.read_csv('data/fb_2018.csv', index_col='date', parse_dates=True).assign(
    trading_volume=lambda x: pd.cut(x.volume, bins=3, labels=['low', 'med', 'high'])
)
fb.head()
```

Out[1]:

	open	high	low	close	volume	trading_volume
date						
2018-01-02	177.68	181.58	177.5500	181.42	18151903	low
2018-01-03	181.88	184.78	181.3300	184.67	16886563	low
2018-01-04	184.90	186.21	184.0996	184.33	13880896	low
2018-01-05	185.59	186.90	184.9300	186.85	13574535	low
2018-01-08	187.20	188.90	186.3300	188.28	17994726	low

Time-based selection and filtering

Remember, when we have a `DatetimeIndex`, we can use datetime slicing. We can provide a range of dates. We only get three days back because the stock market is closed on the weekends:

In [2]:
```
fb['2018-10-11':'2018-10-15']
```

Out[2]:

date	open	high	low	close	volume	trading_volume
2018-10-11	150.13	154.81	149.1600	153.35	35338901	low
2018-10-12	156.73	156.89	151.2998	153.74	25293492	low
2018-10-15	153.32	155.57	152.5500	153.52	15433521	low

We can select ranges of months and quarters:

In [3]:
```
fb['2018-q1'].equals(fb['2018-01':'2018-03'])
```

Out[3]:
```
True
```

The `first()` method will give us a specified length of time from the beginning of the time series. Here, we ask for a week. January 1, 2018 was a holiday—meaning the market was closed. It was also a Monday, so the week here is only four days:

In [4]:
```
fb.first('1W')
```

Out[4]:

date	open	high	low	close	volume	trading_volume
2018-01-02	177.68	181.58	177.5500	181.42	18151903	low
2018-01-03	181.88	184.78	181.3300	184.67	16886563	low
2018-01-04	184.90	186.21	184.0996	184.33	13880896	low
2018-01-05	185.59	186.90	184.9300	186.85	13574535	low

The `last()` method will take from the end:

In [5]:
```
fb.last('1W')
```

Out[5]:

date	open	high	low	close	volume	trading_volume
2018-12-31	134.45	134.64	129.95	131.09	24625308	low

For the next few examples, we need datetimes, so we will read in the stock data per minute file:

In [6]:
```
stock_data_per_minute = pd.read_csv(
    'data/fb_week_of_may_20_per_minute.csv', index_col='date', parse_dates=True,
    date_parser=lambda x: pd.to_datetime(x, format='%Y-%m-%d %H-%M')
)

stock_data_per_minute.head()
```

Out[6]:

date	open	high	low	close	volume
2019-05-20 09:30:00	181.6200	181.6200	181.6200	181.6200	159049.0
2019-05-20 09:31:00	182.6100	182.6100	182.6100	182.6100	468017.0
2019-05-20 09:32:00	182.7458	182.7458	182.7458	182.7458	97258.0
2019-05-20 09:33:00	182.9500	182.9500	182.9500	182.9500	43961.0
2019-05-20 09:34:00	183.0600	183.0600	183.0600	183.0600	79562.0

We can use the `Grouper` to roll up our data to the daily level along with `first` and `last`:

In [7]:
```
stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
})
```

Out[7]:

date	open	high	low	close	volume
2019-05-20	181.62	184.1800	181.6200	182.72	10044838.0
2019-05-21	184.53	185.5800	183.9700	184.82	7198405.0
2019-05-22	184.81	186.5603	184.0120	185.32	8412433.0
2019-05-23	182.50	183.7300	179.7559	180.87	12479171.0
2019-05-24	182.33	183.5227	181.0400	181.06	7686030.0

The `at_time()` method allows us to pull out all datetimes that match a certain time. Here, we can grab all the rows from the time the stock market opens (9:30 AM):

In [8]:
```
stock_data_per_minute.at_time('9:30')
```

Out[8]:

date	open	high	low	close	volume
2019-05-20 09:30:00	181.62	181.62	181.62	181.62	159049.0
2019-05-21 09:30:00	184.53	184.53	184.53	184.53	58171.0
2019-05-22 09:30:00	184.81	184.81	184.81	184.81	41585.0
2019-05-23 09:30:00	182.50	182.50	182.50	182.50	121930.0
2019-05-24 09:30:00	182.33	182.33	182.33	182.33	52681.0

We can use `between_time()` to grab data for the last two minutes of trading daily:

In [9]:
```
stock_data_per_minute.between_time('15:59', '16:00')
```

Out[9]:

date	open	high	low	close	volume
2019-05-20 15:59:00	182.915	182.915	182.915	182.915	134569.0
2019-05-20 16:00:00	182.720	182.720	182.720	182.720	1113672.0
2019-05-21 15:59:00	184.840	184.840	184.840	184.840	61606.0
2019-05-21 16:00:00	184.820	184.820	184.820	184.820	801080.0
2019-05-22 15:59:00	185.290	185.290	185.290	185.290	96099.0
2019-05-22 16:00:00	185.320	185.320	185.320	185.320	1220993.0
2019-05-23 15:59:00	180.720	180.720	180.720	180.720	109648.0
2019-05-23 16:00:00	180.870	180.870	180.870	180.870	1329217.0
2019-05-24 15:59:00	181.070	181.070	181.070	181.070	52994.0
2019-05-24 16:00:00	181.060	181.060	181.060	181.060	764906.0

On average, are more shares traded within the first 30 minutes of trading or in the last 30 minutes? We can combine `between_time()` with `Groupers` and `filter()` from the **aggregation.ipynb notebook** to answer this question. For the week in question, more are traded on average around opening time than closing time:

In [10]:

```
shares_traded_in_first_30_min = stock_data_per_minute\
    .between_time('9:30', '10:00')\
    .groupby(pd.Grouper(freq='1D'))\
    .filter(lambda x: (x.volume > 0).all())\
    .volume.mean()

shares_traded_in_last_30_min = stock_data_per_minute\
    .between_time('15:30', '16:00')\
    .groupby(pd.Grouper(freq='1D'))\
    .filter(lambda x: (x.volume > 0).all())\
    .volume.mean()

shares_traded_in_first_30_min - shares_traded_in_last_30_min
```

Out[10]:

```
18592.967741935485
```

In cases where time doesn't matter, we can normalize the times to midnight:

In [11]:
```
pd.DataFrame(
    dict(before=stock_data_per_minute.index, after=stock_data_per_minute.index.normalize())
).head()
```

Out[11]:

	before	after
0	2019-05-20 09:30:00	2019-05-20
1	2019-05-20 09:31:00	2019-05-20
2	2019-05-20 09:32:00	2019-05-20
3	2019-05-20 09:33:00	2019-05-20
4	2019-05-20 09:34:00	2019-05-20

Note that we can also use `normalize()` on a `Series` object after accessing the `dt` attribute:

In [12]:
```
stock_data_per_minute.index.to_series().dt.normalize().head()
```

Out[12]:
```
date
2019-05-20 09:30:00   2019-05-20
2019-05-20 09:31:00   2019-05-20
2019-05-20 09:32:00   2019-05-20
2019-05-20 09:33:00   2019-05-20
2019-05-20 09:34:00   2019-05-20
Name: date, dtype: datetime64[ns]
```

Shifting for lagged data

We can use `shift()` to create some lagged data. By default, the shift will be one period. For example, we can use `shift()` to create a new column that indicates the previous day's closing price. From this new column, we can calculate the price change due to after hours trading (after the close one day right up to the open the following day):

In [13]:
```
fb.assign(
    prior_close=lambda x: x.close.shift(),
    after_hours_change_in_price=lambda x: x.open - x.prior_close,
    abs_change=lambda x: x.after_hours_change_in_price.abs()
).nlargest(5, 'abs_change')
```

Out[13]:

date	open	high	low	close	volume	trading_volume	prior_close	after_hours_change_in_price	abs_change
2018-07-26	174.89	180.13	173.75	176.26	169803668	high	217.50	-42.61	42.61
2018-04-26	173.22	176.27	170.80	174.16	77556934	med	159.69	13.53	13.53
2018-01-12	178.06	181.48	177.40	179.37	77551299	med	187.77	-9.71	9.71
2018-10-31	155.00	156.40	148.96	151.79	60101251	low	146.22	8.78	8.78
2018-03-19	177.01	177.17	170.06	172.56	88140060	med	185.09	-8.08	8.08

The `tshift()` method will shift the `DatetimeIndex` rather than the data. However, if the goal is to to add/subtract time we can use `pd.Timedelta`:

In [14]:
```
pd.date_range('2018-01-01', freq='D', periods=5) + pd.Timedelta('9 hours 30 minutes')
```

Out[14]:
```
DatetimeIndex(['2018-01-01 09:30:00', '2018-01-02 09:30:00',
               '2018-01-03 09:30:00', '2018-01-04 09:30:00',
               '2018-01-05 09:30:00'],
              dtype='datetime64[ns]', freq='D')
```

When working with stock data, we only have data for the dates the market was open. We can use `first_valid_index()` to give us the index of the first non-null entry in our data. For September 2018, this is September 4th:

In [15]:
```
fb['2018-09'].first_valid_index()
```

Out[15]:
```
Timestamp('2018-09-04 00:00:00')
```

Conversely, we can use `last_valid_index()` to get the last entry of non-null data. For September 2018, this is September 28th:

In [16]:
```
fb['2018-09'].last_valid_index()
```

Out[16]:
```
Timestamp('2018-09-28 00:00:00')
```

We can use `asof()` to find the last non-null data before the point we are looking for, if it isn't in the index. From the previous result, we know that the market was not open on September 30th. It also isn't in the index:

In [17]:
```
fb.index.contains('2018-09-30')
```

Out[17]:
```
False
```

If we ask for it, we will get the data from the index we got from `fb['2018-09'].last_valid_index()`, which was September 28th:

In [18]:
```
fb.asof('2018-09-30')
```

Out[18]:
```
open                    168.33
high                    168.79
low                     162.56
close                   164.46
volume             3.42656e+07
trading_volume             low
Name: 2018-09-30 00:00:00, dtype: object
```

Differenced data

Using the `diff()` method is a quick way to calculate the difference between the data and a lagged version of it. By default, it will yield the result of `data - data.shift()`:

In [19]:
```
(
    fb.drop(columns='trading_volume')
    - fb.drop(columns='trading_volume').shift()
).equals(
    fb.drop(columns='trading_volume').diff()
)
```

Out[19]:
```
True
```

We can use this to see how Facebook stock changed day-over-day:

In [20]:
```
fb.drop(columns='trading_volume').diff().head()
```

Out[20]:

date	open	high	low	close	volume
2018-01-02	NaN	NaN	NaN	NaN	NaN
2018-01-03	4.20	3.20	3.7800	3.25	-1265340.0
2018-01-04	3.02	1.43	2.7696	-0.34	-3005667.0
2018-01-05	0.69	0.69	0.8304	2.52	-306361.0
2018-01-08	1.61	2.00	1.4000	1.43	4420191.0

We can specify the number of periods, can be any positive or negative integer:

In [21]:
```
fb.drop(columns='trading_volume').diff(-3).head()
```

Out[21]:

date	open	high	low	close	volume
2018-01-02	-7.91	-5.32	-7.3800	-5.43	4577368.0
2018-01-03	-5.32	-4.12	-5.0000	-3.61	-1108163.0
2018-01-04	-3.80	-2.59	-3.0004	-3.54	1487839.0
2018-01-05	-1.35	-0.99	-0.7000	-0.99	3044641.0
2018-01-08	-1.20	0.50	-1.0500	0.51	8406139.0

Resampling

Sometimes the data is at a granularity that isn't conducive to our analysis. Consider the case where we have data per minute for the full year of 2018. Let's see what happens if we try to plot this.

Plotting will be covered in the next module, so don't worry too much about the code.

First, we import `matplotlib` for plotting:

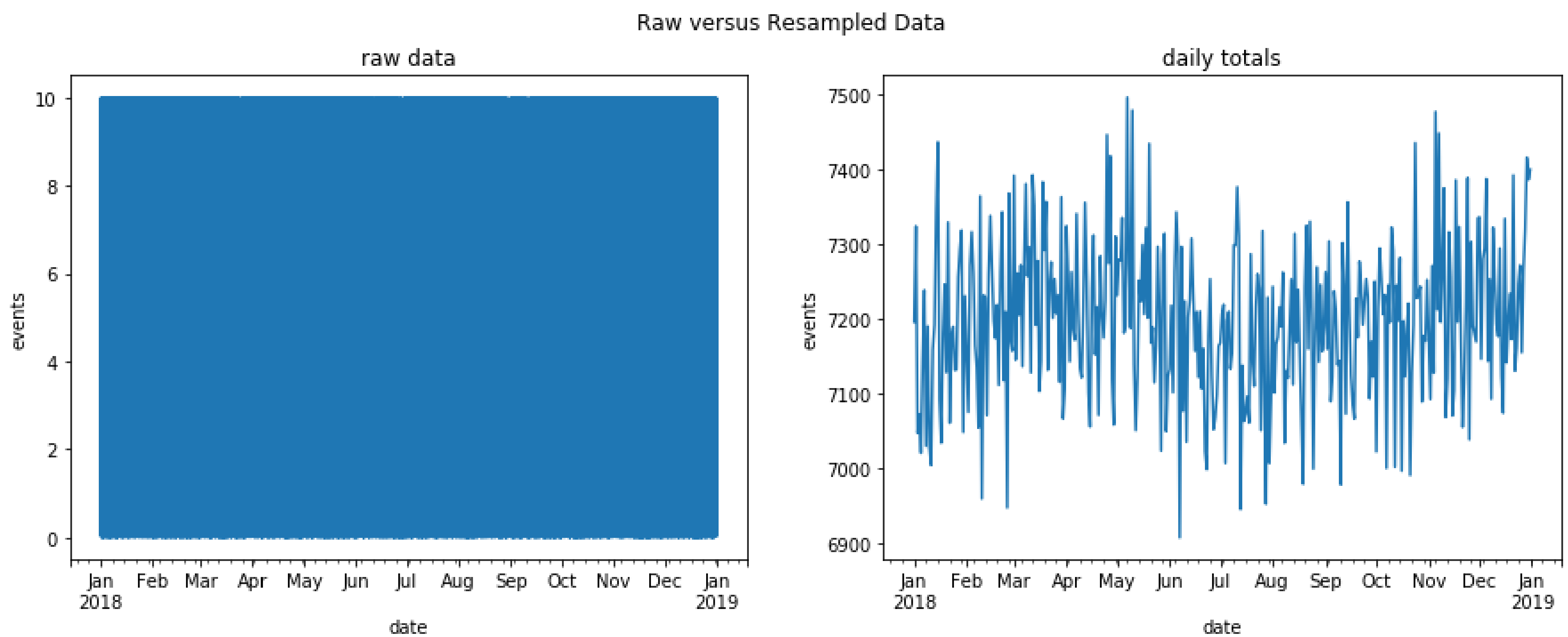
In [22]:
```
import matplotlib.pyplot as plt
```

Then we will look at the plot at the minute level and at the daily aggregated level (summed):

In [23]:
```python
np.random.seed(0)
index = pd.date_range('2018-01-01', freq='T', periods=365*24*60)
raw = pd.DataFrame(
    np.random.uniform(0, 10, size=index.shape[0]), index=index
)

fig, axes = plt.subplots(1, 2, figsize=(15, 5))
raw.plot(legend=False, ax=axes[0], title='raw data')
raw.resample('1D').sum().plot(legend=False, ax=axes[1], title='daily totals')
for ax in axes:
    ax.set_xlabel('date')
    ax.set_ylabel('events')

plt.suptitle('Raw versus Resampled Data')
plt.show()
```



The plot on the left has so much data we can't see anything. However, when we aggregate to the daily totals, we see the data. We can alter the granularity of the data we are working with using resampling. Recall our minute-by-minute stock data:

In [24]:
```
stock_data_per_minute.head()
```

Out[24]:

date	open	high	low	close	volume
2019-05-20 09:30:00	181.6200	181.6200	181.6200	181.6200	159049.0
2019-05-20 09:31:00	182.6100	182.6100	182.6100	182.6100	468017.0
2019-05-20 09:32:00	182.7458	182.7458	182.7458	182.7458	97258.0
2019-05-20 09:33:00	182.9500	182.9500	182.9500	182.9500	43961.0
2019-05-20 09:34:00	183.0600	183.0600	183.0600	183.0600	79562.0

We can resample this to get to a daily frequency:

In [25]:
```
stock_data_per_minute.resample('1D').agg({
    'open': 'first',
    'high': 'max',
    'low': 'min',
    'close': 'last',
    'volume': 'sum'
})
```

Out[25]:

date	open	high	low	close	volume
2019-05-20	181.62	184.1800	181.6200	182.72	10044838.0
2019-05-21	184.53	185.5800	183.9700	184.82	7198405.0
2019-05-22	184.81	186.5603	184.0120	185.32	8412433.0
2019-05-23	182.50	183.7300	179.7559	180.87	12479171.0
2019-05-24	182.33	183.5227	181.0400	181.06	7686030.0

We can downsample to quarterly data:

In [26]:
```
fb.resample('Q').mean()
```

Out[26]:

date	open	high	low	close	volume
2018-03-31	179.472295	181.794659	177.040428	179.551148	3.292640e+07
2018-06-30	180.373770	182.277689	178.595964	180.704687	2.405532e+07
2018-09-30	180.812130	182.890886	178.955229	181.028492	2.701982e+07
2018-12-31	145.272460	147.620121	142.718943	144.868730	2.697433e+07

We can also use `apply()`. Here, we show the quarterly change from start to end:

In [27]:

```
fb.drop(columns='trading_volume').resample('Q').apply(
    lambda x: x.last('1D').values - x.first('1D').values
)
```

Out[27]:

date	open	high	low	close	volume
2018-03-31	-22.53	-20.1600	-23.410	-21.63	41282390
2018-06-30	39.51	38.3997	39.844	38.93	-20984389
2018-09-30	-25.04	-28.6600	-29.660	-32.90	20304060
2018-12-31	-28.58	-31.2400	-31.310	-31.35	-1782369

Consider the following melted stock data by the minute. We don't see the OHLC data directly:

In [28]:

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

Out[28]:

date	price
2019-05-20 09:30:00	181.6200
2019-05-20 09:31:00	182.6100
2019-05-20 09:32:00	182.7458
2019-05-20 09:33:00	182.9500
2019-05-20 09:34:00	183.0600

We can use the `ohlc()` method after resampling to recover the OHLC columns:

In [29]:
```
melted_stock_data.resample('1D').ohlc()['price']
```

Out[29]:

date	open	high	low	close
2019-05-20	181.62	184.1800	181.6200	182.72
2019-05-21	184.53	185.5800	183.9700	184.82
2019-05-22	184.81	186.5603	184.0120	185.32
2019-05-23	182.50	183.7300	179.7559	180.87
2019-05-24	182.33	183.5227	181.0400	181.06

Alternatively, we can upsample to increase the granularity. Note this will introduce `NaN` values:

In [30]:
```
fb.resample('6H').asfreq().head()
```

Out[30]:

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.0	low
2018-01-02 06:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-02 12:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-02 18:00:00	NaN	NaN	NaN	NaN	NaN	NaN
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.0	low

There are many ways to handle these `NaN` values. We can forward-fill with `pad()`:

In [31]:
```
fb.resample('6H').pad().head()
```

Out[31]:

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 06:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 12:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 18:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563	low

We can specify a specific value or a method with `fillna()`:

In [32]:
```
fb.resample('6H').fillna('nearest').head()
```

Out[32]:

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 06:00:00	177.68	181.58	177.55	181.42	18151903	low
2018-01-02 12:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-02 18:00:00	181.88	184.78	181.33	184.67	16886563	low
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563	low

We can use `asfreq()` and `assign()` to specify the action per column:

In [33]:

```
fb.resample('6H').asfreq().assign(
    volume=lambda x: x.volume.fillna(0), # put 0 when market is closed
    close=lambda x: x.close.fillna(method='ffill'), # carry forward
    # take the closing price if these aren't available
    open=lambda x: np.where(x.open.isnull(), x.close, x.open),
    high=lambda x: np.where(x.high.isnull(), x.close, x.high),
    low=lambda x: np.where(x.low.isnull(), x.close, x.low)
).head()
```

Out[33]:

date	open	high	low	close	volume	trading_volume
2018-01-02 00:00:00	177.68	181.58	177.55	181.42	18151903.0	low
2018-01-02 06:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-02 12:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-02 18:00:00	181.42	181.42	181.42	181.42	0.0	NaN
2018-01-03 00:00:00	181.88	184.78	181.33	184.67	16886563.0	low

Merging

We saw merging examples the **querying_and_merging notebook**. However, they all matched based on keys. With time series, it is possible that they are so granular that we never have the same time for multiple entries. Let's work with some stock data at different granularities:

In [34]:
```python
import sqlite3

with sqlite3.connect('data/stocks.db') as connection:
    fb_prices = pd.read_sql(
        'SELECT * FROM fb_prices', connection,
        index_col='date', parse_dates=['date']
    )
    aapl_prices = pd.read_sql(
        'SELECT * FROM aapl_prices', connection,
        index_col='date', parse_dates=['date']
    )
```

The Facebook prices are at the minute granularity:

In [35]:
```python
fb_prices.index.second.unique()
```

Out[35]:
```
Int64Index([0], dtype='int64', name='date')
```

However, the Apple prices have information for the second:

In [36]:
```python
aapl_prices.index.second.unique()
```

Out[36]:
```
Int64Index([ 0, 52, 36, 34, 55, 35,  7, 12, 59, 17,  5, 20, 26, 23, 54, 49, 19,
            53, 11, 22, 13, 21, 10, 46, 42, 38, 33, 18, 16,  9, 56, 39,  2, 50,
            31, 58, 48, 24, 29,  6, 47, 51, 40,  3, 15, 14, 25,  4, 43,  8, 32,
            27, 30, 45,  1, 44, 57, 41, 37, 28],
           dtype='int64', name='date')
```

We can perform an `asof` merge to try to line these up the best we can. We specify how to handle the mismatch with the `direction` and `tolerance` parameters. We will fill in with the `direction` of `nearest` and a `tolerance` of 30 seconds. This will place the Apple data with the minute that it is closest to, so 9:31:52 will go with 9:32 and 9:37:07 will go with 9:37. Since the times are on the index, we pass `left_index` and `right_index`, as we did with merges earlier this chapter:

In [37]:
```python
pd.merge_asof(
    fb_prices, aapl_prices,
    left_index=True, right_index=True, # datetimes are in the index
    # merge with nearest minute
    direction='nearest', tolerance=pd.Timedelta(30, unit='s')
).head()
```

Out[37]:

date	FB	AAPL
2019-05-20 09:30:00	181.6200	183.5200
2019-05-20 09:31:00	182.6100	NaN
2019-05-20 09:32:00	182.7458	182.8710
2019-05-20 09:33:00	182.9500	182.5000
2019-05-20 09:34:00	183.0600	182.1067

If we don't want to lose the seconds information with the Apple data, we can use `pd.merge_ordered()` instead, which will interleave the two. Note this is an outer join by default (`how` parameter). The only catch here is that we need to reset the index in order to join on it:

In [38]:
```
pd.merge_ordered(
    fb_prices.reset_index(), aapl_prices.reset_index()
).set_index('date').head()
```

Out[38]:

date	FB	AAPL
2019-05-20 09:30:00	181.6200	183.520
2019-05-20 09:31:00	182.6100	NaN
2019-05-20 09:31:52	NaN	182.871
2019-05-20 09:32:00	182.7458	NaN
2019-05-20 09:32:36	NaN	182.500

We can pass a `fill_method` to handle `NaN` values:

In [39]:
```
pd.merge_ordered(
    fb_prices.reset_index(), aapl_prices.reset_index(),
    fill_method='ffill'
).set_index('date').head()
```

Out[39]:

date	FB	AAPL
2019-05-20 09:30:00	181.6200	183.520
2019-05-20 09:31:00	182.6100	183.520
2019-05-20 09:31:52	182.6100	182.871
2019-05-20 09:32:00	182.7458	182.871
2019-05-20 09:32:36	182.7458	182.500

Alternatively, we can use `fillna()`.