no1flhy76

April 2, 2024

[ ]:
```python
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()
```

[ ]:

	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

1 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:

[ ]:
```python
fb['2018-10-11':'2018-10-15'] #fething data from October 11 to October 15
```

[ ]:

	open	high	low	close	volume	trading_volume
date						
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

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

```
<ipython-input-3-f01e3c270a70>: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.
  fb['2018-q1'].equals(fb['2018-01':'2018-03'])
```

[ ]: 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

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

```
[ ]:               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
```

The last() method will take from the end

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

```
[ ]:               open    high     low   close    volume trading_volume
date
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

```
[ ]: 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()
```

```
[ ]:                          open      high       low     close    volume
date
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

```
[ ]: stock_data_per_minute.groupby(pd.Grouper(freq='1D')).agg({ #putting a number at␣
 ↪the frequency is like the multiplier for that
'open': 'first',
'high': 'max',
'low': 'min',
'close': 'last',
'volume': 'sum'
```

```
})
```

[ ]:

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

[ ]:
```
stock_data_per_minute.groupby(pd.Grouper(freq='2D')).agg({ #we can try at 2D␣
 ↪which means every 2 Days
'open': 'first',
'high': 'max',
'low': 'min',
'close': 'last',
'volume': 'sum'
})
```

[ ]:

date	open	high	low	close	volume
2019-05-20	181.62	185.5800	181.6200	184.82	17243243.0
2019-05-22	184.81	186.5603	179.7559	180.87	20891604.0
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 (930 AM)

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

[ ]:

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

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

[ ]:

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

[ ]:
```
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
```

[ ]:
```
18592.967741935485
```

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

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

[ ]:
```
               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

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

[ ]:
```
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]
```

2 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)

[ ]:
```
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')
```

[ ]:
```
              open    high     low   close     volume trading_volume  \
date
2018-07-26  174.89  180.13  173.75  176.26  169803668           high
2018-04-26  173.22  176.27  170.80  174.16   77556934            med
2018-01-12  178.06  181.48  177.40  179.37   77551299            med
2018-10-31  155.00  156.40  148.96  151.79   60101251            low
2018-03-19  177.01  177.17  170.06  172.56   88140060            med

            prior_close  after_hours_change_in_price  abs_change
date
2018-07-26       217.50                       -42.61       42.61
2018-04-26       159.69                        13.53       13.53
2018-01-12       187.77                        -9.71        9.71
2018-10-31       146.22                         8.78        8.78
2018-03-19       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

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

[ ]:
```
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

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

```
<ipython-input-21-d8ca41528993>: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.
  fb['2018-09'].first_valid_index()
```

[ ]:
```
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

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

```
<ipython-input-22-ef6e024573c9>: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.
  fb['2018-09'].last_valid_index()
```

[ ]:
```
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

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

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

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

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

[ ]:
```
open                  168.33
high                  168.79
low                   162.56
close                 164.46
volume              34265638
trading_volume           low
Name: 2018-09-30 00:00:00, dtype: object
```

3 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()

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

[ ]:
```
True
```

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

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

[ ]:
```
            open  high     low  close     volume
date
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

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

[ ]:
```
            open  high     low  close     volume
date
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
```

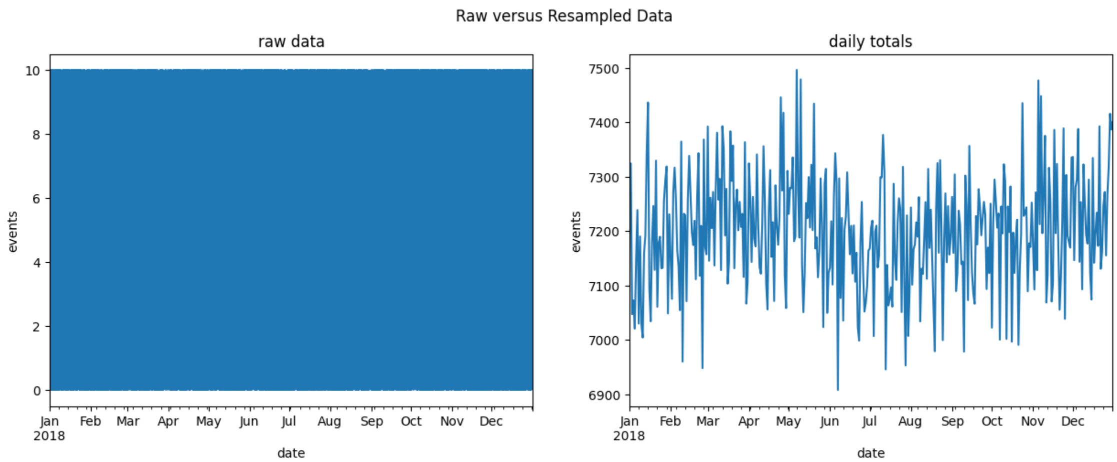
4 Resampling

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.

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

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))
```

```python
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

[ ]:
```python
stock_data_per_minute.head()
```

[ ]:

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:

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

[ ]:

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

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

```
<ipython-input-39-f6fd3d834d43>:1: FutureWarning: The default value of
numeric_only in DataFrameGroupBy.mean is deprecated. In a future version,
numeric_only will default to False. Either specify numeric_only or select only
columns which should be valid for the function.
  fb.resample('Q').mean()
```

[ ]:

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	180.704688	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

[ ]:
```
fb2 = pd.DataFrame(fb.drop(columns='trading_volume').resample('Q').apply(
lambda x: x.last('1D').values - x.first('1D').values
))
fb2
```

[ ]:

date	0
2018-03-31	[[-22.53, -20.160000000000025, -23.41000000000…
2018-06-30	[[39.50999999999999, 38.399700000000024, 39.84…
2018-09-30	[[-25.039999999999992, -28.659999999999997, -2…
2018-12-31	[[-28.580000000000013, -31.24000000000001, -31…

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

[ ]:
```
melted_stock_data = pd.read_csv('data/melted_stock_data.csv', index_col='date',␣
  ↪parse_dates=True)
melted_stock_data.head()
```

[ ]:

```
                     price
date
```

```
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

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

[ ]:
```
              open      high       low   close
date
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:

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

[ ]:
```
                       open    high     low   close      volume trading_volume
date
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()

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

```
<ipython-input-51-39179f05e435>:1: FutureWarning: pad is deprecated and will be
removed in a future version. Use ffill instead.
  fb.resample('6H').pad().head()
```

[ ]:
```
                       open    high     low   close    volume trading_volume
date
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()

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

[ ]:
```
                       open    high     low   close    volume trading_volume
date
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

[ ]:
```
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()
```

[ ]:
```
                       open    high     low   close      volume trading_volume
date
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
```

5 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

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

[ ]:
```
fb_prices.head()
```

[ ]:
```
                                FB
date
```

```
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
```

[ ]:
```
aapl_prices.head()
```

[ ]:
```
                         AAPL
date
2019-05-20 09:30:00  183.5200
2019-05-20 09:31:52  182.8710
2019-05-20 09:32:36  182.5000
2019-05-20 09:33:34  182.1067
2019-05-20 09:34:55  181.5000
```

The Facebook prices are at the minute granularity

[ ]:
```
fb_prices.index.second.unique()
```

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

However, the Apple prices have information for the second

[ ]:
```
aapl_prices.index.second.unique()
```

[ ]:
```
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 93152 will go with 932 and 93707 will go with 937. Since the times are on the index, we pass left_index and right_index , as we did with merges earlier this chapter

[ ]:
```
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()
```

[ ]:
```
                           FB      AAPL
date
```

```
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

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

[ ]:
```
                           FB     AAPL
date
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

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

[ ]:
```
                           FB     AAPL
date
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
```