CHAPTER 11

Time Series

Time series data is an important form of structured data in many different fields, such as finance, economics, ecology, neuroscience, and physics. Anything that is observed or measured at many points in time forms a time series. Many time series are *fixed frequency*, which is to say that data points occur at regular intervals according to some rule, such as every 15 seconds, every 5 minutes, or once per month. Time series can also be *irregular* without a fixed unit of time or offset between units. How you mark and refer to time series data depends on the application, and you may have one of the following:

- *Timestamps*, specific instants in time
- Fixed *periods*, such as the month January 2007 or the full year 2010
- *Intervals* of time, indicated by a start and end timestamp. Periods can be thought of as special cases of intervals
- Experiment or elapsed time; each timestamp is a measure of time relative to a particular start time (e.g., the diameter of a cookie baking each second since being placed in the oven)

In this chapter, I am mainly concerned with time series in the first three categories, though many of the techniques can be applied to experimental time series where the index may be an integer or floating-point number indicating elapsed time from the start of the experiment. The simplest and most widely used kind of time series are those indexed by timestamp.

pandas also supports indexes based on timedeltas, which can be a useful way of representing experiment or elapsed time. We do not explore timedelta indexes in this book, but you can learn more in the pandas documentation.

pandas provides many built-in time series tools and data algorithms. You can efficiently work with very large time series and easily slice and dice, aggregate, and resample irregular- and fixed-frequency time series. Some of these tools are especially useful for financial and economics applications, but you could certainly use them to analyze server log data, too.

11.1 Date and Time Data Types and Tools

The Python standard library includes data types for date and time data, as well as calendar-related functionality. The `datetime`, `time`, and `calendar` modules are the main places to start. The `datetime.datetime` type, or simply `datetime`, is widely used:

```
In [10]: from datetime import datetime

In [11]: now = datetime.now()

In [12]: now
Out[12]: datetime.datetime(2017, 9, 25, 14, 5, 52, 72973)

In [13]: now.year, now.month, now.day
Out[13]: (2017, 9, 25)
```

`datetime` stores both the date and time down to the microsecond. `timedelta` represents the temporal difference between two `datetime` objects:

```
In [14]: delta = datetime(2011, 1, 7) - datetime(2008, 6, 24, 8, 15)

In [15]: delta
Out[15]: datetime.timedelta(926, 56700)

In [16]: delta.days
Out[16]: 926

In [17]: delta.seconds
Out[17]: 56700
```

You can add (or subtract) a `timedelta` or multiple thereof to a `datetime` object to yield a new shifted object:

```
In [18]: from datetime import timedelta

In [19]: start = datetime(2011, 1, 7)
```

```
In [20]: start + timedelta(12)
Out[20]: datetime.datetime(2011, 1, 19, 0, 0)

In [21]: start - 2 * timedelta(12)
Out[21]: datetime.datetime(2010, 12, 14, 0, 0)
```

Table 11-1 summarizes the data types in the `datetime` module. While this chapter is mainly concerned with the data types in pandas and higher-level time series manipulation, you may encounter the `datetime`-based types in many other places in Python in the wild.

Table 11-1. Types in datetime module

Type	Description
`date`	Store calendar date (year, month, day) using the Gregorian calendar
`time`	Store time of day as hours, minutes, seconds, and microseconds
`datetime`	Stores both date and time
`timedelta`	Represents the difference between two `datetime` values (as days, seconds, and microseconds)
`tzinfo`	Base type for storing time zone information

Converting Between String and Datetime

You can format `datetime` objects and pandas `Timestamp` objects, which I'll introduce later, as strings using `str` or the `strftime` method, passing a format specification:

```
In [22]: stamp = datetime(2011, 1, 3)

In [23]: str(stamp)
Out[23]: '2011-01-03 00:00:00'

In [24]: stamp.strftime('%Y-%m-%d')
Out[24]: '2011-01-03'
```

See Table 11-2 for a complete list of the format codes (reproduced from Chapter 2).

Table 11-2. Datetime format specification (ISO C89 compatible)

Type	Description
`%Y`	Four-digit year
`%y`	Two-digit year
`%m`	Two-digit month [01, 12]
`%d`	Two-digit day [01, 31]
`%H`	Hour (24-hour clock) [00, 23]
`%I`	Hour (12-hour clock) [01, 12]
`%M`	Two-digit minute [00, 59]
`%S`	Second [00, 61] (seconds 60, 61 account for leap seconds)
`%w`	Weekday as integer [0 (Sunday), 6]

Type	Description
%U	Week number of the year [00, 53]; Sunday is considered the first day of the week, and days before the first Sunday of the year are "week 0"
%W	Week number of the year [00, 53]; Monday is considered the first day of the week, and days before the first Monday of the year are "week 0"
%z	UTC time zone offset as +HHMM or -HHMM; empty if time zone naive
%F	Shortcut for %Y-%m-%d (e.g., 2012-4-18)
%D	Shortcut for %m/%d/%y (e.g., 04/18/12)

You can use these same format codes to convert strings to dates using `datetime.strptime`:

```
In [25]: value = '2011-01-03'

In [26]: datetime.strptime(value, '%Y-%m-%d')
Out[26]: datetime.datetime(2011, 1, 3, 0, 0)

In [27]: datestrs = ['7/6/2011', '8/6/2011']

In [28]: [datetime.strptime(x, '%m/%d/%Y') for x in datestrs]
Out[28]:
[datetime.datetime(2011, 7, 6, 0, 0),
 datetime.datetime(2011, 8, 6, 0, 0)]
```

`datetime.strptime` is a good way to parse a date with a known format. However, it can be a bit annoying to have to write a format spec each time, especially for common date formats. In this case, you can use the `parser.parse` method in the third-party `dateutil` package (this is installed automatically when you install pandas):

```
In [29]: from dateutil.parser import parse

In [30]: parse('2011-01-03')
Out[30]: datetime.datetime(2011, 1, 3, 0, 0)
```

`dateutil` is capable of parsing most human-intelligible date representations:

```
In [31]: parse('Jan 31, 1997 10:45 PM')
Out[31]: datetime.datetime(1997, 1, 31, 22, 45)
```

In international locales, day appearing before month is very common, so you can pass `dayfirst=True` to indicate this:

```
In [32]: parse('6/12/2011', dayfirst=True)
Out[32]: datetime.datetime(2011, 12, 6, 0, 0)
```

pandas is generally oriented toward working with arrays of dates, whether used as an axis index or a column in a DataFrame. The `to_datetime` method parses many different kinds of date representations. Standard date formats like ISO 8601 can be parsed very quickly:

```
In [33]: datestrs = ['2011-07-06 12:00:00', '2011-08-06 00:00:00']

In [34]: pd.to_datetime(datestrs)
Out[34]: DatetimeIndex(['2011-07-06 12:00:00', '2011-08-06 00:00:00'], dtype='dat
etime64[ns]', freq=None)
```

It also handles values that should be considered missing (`None`, empty string, etc.):

```
In [35]: idx = pd.to_datetime(datestrs + [None])

In [36]: idx
Out[36]: DatetimeIndex(['2011-07-06 12:00:00', '2011-08-06 00:00:00', 'NaT'], dty
pe='datetime64[ns]', freq=None)

In [37]: idx[2]
Out[37]: NaT

In [38]: pd.isnull(idx)
Out[38]: array([False, False,  True], dtype=bool)
```

`NaT` (Not a Time) is pandas's null value for timestamp data.

> `dateutil.parser` is a useful but imperfect tool. Notably, it will recognize some strings as dates that you might prefer that it didn't—for example, `'42'` will be parsed as the year `2042` with today's calendar date.

`datetime` objects also have a number of locale-specific formatting options for systems in other countries or languages. For example, the abbreviated month names will be different on German or French systems compared with English systems. See Table 11-3 for a listing.

Table 11-3. Locale-specific date formatting

Type	Description
%a	Abbreviated weekday name
%A	Full weekday name
%b	Abbreviated month name
%B	Full month name
%c	Full date and time (e.g., 'Tue 01 May 2012 04:20:57 PM')
%p	Locale equivalent of AM or PM
%x	Locale-appropriate formatted date (e.g., in the United States, May 1, 2012 yields '05/01/2012')
%X	Locale-appropriate time (e.g., '04:24:12 PM')

11.2 Time Series Basics

A basic kind of time series object in pandas is a Series indexed by timestamps, which is often represented external to pandas as Python strings or `datetime` objects:

```
In [39]: from datetime import datetime

In [40]: dates = [datetime(2011, 1, 2), datetime(2011, 1, 5),
   ....:          datetime(2011, 1, 7), datetime(2011, 1, 8),
   ....:          datetime(2011, 1, 10), datetime(2011, 1, 12)]

In [41]: ts = pd.Series(np.random.randn(6), index=dates)

In [42]: ts
Out[42]: 
2011-01-02   -0.204708
2011-01-05    0.478943
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
2011-01-12    1.393406
dtype: float64
```

Under the hood, these `datetime` objects have been put in a `DatetimeIndex`:

```
In [43]: ts.index
Out[43]: 
DatetimeIndex(['2011-01-02', '2011-01-05', '2011-01-07', '2011-01-08',
               '2011-01-10', '2011-01-12'],
              dtype='datetime64[ns]', freq=None)
```

Like other Series, arithmetic operations between differently indexed time series automatically align on the dates:

```
In [44]: ts + ts[::2]
Out[44]: 
2011-01-02   -0.409415
2011-01-05         NaN
2011-01-07   -1.038877
2011-01-08         NaN
2011-01-10    3.931561
2011-01-12         NaN
dtype: float64
```

Recall that `ts[::2]` selects every second element in `ts`.

pandas stores timestamps using NumPy's `datetime64` data type at the nanosecond resolution:

```
In [45]: ts.index.dtype
Out[45]: dtype('<M8[ns]')
```

Scalar values from a `DatetimeIndex` are pandas `Timestamp` objects:

```
In [46]: stamp = ts.index[0]

In [47]: stamp
Out[47]: Timestamp('2011-01-02 00:00:00')
```

A `Timestamp` can be substituted anywhere you would use a `datetime` object. Additionally, it can store frequency information (if any) and understands how to do time zone conversions and other kinds of manipulations. More on both of these things later.

Indexing, Selection, Subsetting

Time series behaves like any other `pandas.Series` when you are indexing and selecting data based on label:

```
In [48]: stamp = ts.index[2]

In [49]: ts[stamp]
Out[49]: -0.51943871505673811
```

As a convenience, you can also pass a string that is interpretable as a date:

```
In [50]: ts['1/10/2011']
Out[50]: 1.9657805725027142

In [51]: ts['20110110']
Out[51]: 1.9657805725027142
```

For longer time series, a year or only a year and month can be passed to easily select slices of data:

```
In [52]: longer_ts = pd.Series(np.random.randn(1000),
   ....:                       index=pd.date_range('1/1/2000', periods=1000))

In [53]: longer_ts
Out[53]:
2000-01-01    0.092908
2000-01-02    0.281746
2000-01-03    0.769023
2000-01-04    1.246435
2000-01-05    1.007189
2000-01-06   -1.296221
2000-01-07    0.274992
2000-01-08    0.228913
2000-01-09    1.352917
2000-01-10    0.886429
                 ...
2002-09-17   -0.139298
2002-09-18   -1.159926
2002-09-19    0.618965
2002-09-20    1.373890
2002-09-21   -0.983505
```

```
2002-09-22    0.930944
2002-09-23   -0.811676
2002-09-24   -1.830156
2002-09-25   -0.138730
2002-09-26    0.334088
Freq: D, Length: 1000, dtype: float64

In [54]: longer_ts['2001']
Out[54]:
2001-01-01    1.599534
2001-01-02    0.474071
2001-01-03    0.151326
2001-01-04   -0.542173
2001-01-05   -0.475496
2001-01-06    0.106403
2001-01-07   -1.308228
2001-01-08    2.173185
2001-01-09    0.564561
2001-01-10   -0.190481
                 ...
2001-12-22    0.000369
2001-12-23    0.900885
2001-12-24   -0.454869
2001-12-25   -0.864547
2001-12-26    1.129120
2001-12-27    0.057874
2001-12-28   -0.433739
2001-12-29    0.092698
2001-12-30   -1.397820
2001-12-31    1.457823
Freq: D, Length: 365, dtype: float64
```

Here, the string `'2001'` is interpreted as a year and selects that time period. This also works if you specify the month:

```
In [55]: longer_ts['2001-05']
Out[55]:
2001-05-01   -0.622547
2001-05-02    0.936289
2001-05-03    0.750018
2001-05-04   -0.056715
2001-05-05    2.300675
2001-05-06    0.569497
2001-05-07    1.489410
2001-05-08    1.264250
2001-05-09   -0.761837
2001-05-10   -0.331617
                 ...
2001-05-22    0.503699
2001-05-23   -1.387874
2001-05-24    0.204851
2001-05-25    0.603705
2001-05-26    0.545680
```

```
2001-05-27    0.235477
2001-05-28    0.111835
2001-05-29   -1.251504
2001-05-30   -2.949343
2001-05-31    0.634634
Freq: D, Length: 31, dtype: float64
```

Slicing with `datetime` objects works as well:

```
In [56]: ts[datetime(2011, 1, 7):]
Out[56]:
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
2011-01-12    1.393406
dtype: float64
```

Because most time series data is ordered chronologically, you can slice with timestamps not contained in a time series to perform a range query:

```
In [57]: ts
Out[57]:
2011-01-02   -0.204708
2011-01-05    0.478943
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
2011-01-12    1.393406
dtype: float64

In [58]: ts['1/6/2011':'1/11/2011']
Out[58]:
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
dtype: float64
```

As before, you can pass either a string date, `datetime`, or timestamp. Remember that slicing in this manner produces views on the source time series like slicing NumPy arrays. This means that no data is copied and modifications on the slice will be reflected in the original data.

There is an equivalent instance method, `truncate`, that slices a Series between two dates:

```
In [59]: ts.truncate(after='1/9/2011')
Out[59]:
2011-01-02   -0.204708
2011-01-05    0.478943
2011-01-07   -0.519439
2011-01-08   -0.555730
dtype: float64
```

All of this holds true for DataFrame as well, indexing on its rows:

```
In [60]: dates = pd.date_range('1/1/2000', periods=100, freq='W-WED')

In [61]: long_df = pd.DataFrame(np.random.randn(100, 4),
   ....:                        index=dates,
   ....:                        columns=['Colorado', 'Texas',
   ....:                                 'New York', 'Ohio'])

In [62]: long_df.loc['5-2001']
Out[62]:
            Colorado     Texas  New York      Ohio
2001-05-02 -0.006045  0.490094 -0.277186 -0.707213
2001-05-09 -0.560107  2.735527  0.927335  1.513906
2001-05-16  0.538600  1.273768  0.667876 -0.969206
2001-05-23  1.676091 -0.817649  0.050188  1.951312
2001-05-30  3.260383  0.963301  1.201206 -1.852001
```

Time Series with Duplicate Indices

In some applications, there may be multiple data observations falling on a particular timestamp. Here is an example:

```
In [63]: dates = pd.DatetimeIndex(['1/1/2000', '1/2/2000', '1/2/2000',
   ....:                           '1/2/2000', '1/3/2000'])

In [64]: dup_ts = pd.Series(np.arange(5), index=dates)

In [65]: dup_ts
Out[65]:
2000-01-01    0
2000-01-02    1
2000-01-02    2
2000-01-02    3
2000-01-03    4
dtype: int64
```

We can tell that the index is not unique by checking its `is_unique` property:

```
In [66]: dup_ts.index.is_unique
Out[66]: False
```

Indexing into this time series will now either produce scalar values or slices depending on whether a timestamp is duplicated:

```
In [67]: dup_ts['1/3/2000']  # not duplicated
Out[67]: 4

In [68]: dup_ts['1/2/2000']  # duplicated
Out[68]:
2000-01-02    1
2000-01-02    2
```

```
2000-01-02    3
dtype: int64
```

Suppose you wanted to aggregate the data having non-unique timestamps. One way to do this is to use `groupby` and pass `level=0`:

```
In [69]: grouped = dup_ts.groupby(level=0)

In [70]: grouped.mean()
Out[70]:
2000-01-01    0
2000-01-02    2
2000-01-03    4
dtype: int64

In [71]: grouped.count()
Out[71]:
2000-01-01    1
2000-01-02    3
2000-01-03    1
dtype: int64
```

11.3 Date Ranges, Frequencies, and Shifting

Generic time series in pandas are assumed to be irregular; that is, they have no fixed frequency. For many applications this is sufficient. However, it's often desirable to work relative to a fixed frequency, such as daily, monthly, or every 15 minutes, even if that means introducing missing values into a time series. Fortunately pandas has a full suite of standard time series frequencies and tools for resampling, inferring frequencies, and generating fixed-frequency date ranges. For example, you can convert the sample time series to be fixed daily frequency by calling `resample`:

```
In [72]: ts
Out[72]:
2011-01-02   -0.204708
2011-01-05    0.478943
2011-01-07   -0.519439
2011-01-08   -0.555730
2011-01-10    1.965781
2011-01-12    1.393406
dtype: float64

In [73]: resampler = ts.resample('D')
```

The string `'D'` is interpreted as daily frequency.

Conversion between frequencies or *resampling* is a big enough topic to have its own section later (Section 11.6, "Resampling and Frequency Conversion," on page 348). Here I'll show you how to use the base frequencies and multiples thereof.

Generating Date Ranges

While I used it previously without explanation, `pandas.date_range` is responsible for generating a `DatetimeIndex` with an indicated length according to a particular frequency:

```
In [74]: index = pd.date_range('2012-04-01', '2012-06-01')

In [75]: index
Out[75]:
DatetimeIndex(['2012-04-01', '2012-04-02', '2012-04-03', '2012-04-04',
               '2012-04-05', '2012-04-06', '2012-04-07', '2012-04-08',
               '2012-04-09', '2012-04-10', '2012-04-11', '2012-04-12',
               '2012-04-13', '2012-04-14', '2012-04-15', '2012-04-16',
               '2012-04-17', '2012-04-18', '2012-04-19', '2012-04-20',
               '2012-04-21', '2012-04-22', '2012-04-23', '2012-04-24',
               '2012-04-25', '2012-04-26', '2012-04-27', '2012-04-28',
               '2012-04-29', '2012-04-30', '2012-05-01', '2012-05-02',
               '2012-05-03', '2012-05-04', '2012-05-05', '2012-05-06',
               '2012-05-07', '2012-05-08', '2012-05-09', '2012-05-10',
               '2012-05-11', '2012-05-12', '2012-05-13', '2012-05-14',
               '2012-05-15', '2012-05-16', '2012-05-17', '2012-05-18',
               '2012-05-19', '2012-05-20', '2012-05-21', '2012-05-22',
               '2012-05-23', '2012-05-24', '2012-05-25', '2012-05-26',
               '2012-05-27', '2012-05-28', '2012-05-29', '2012-05-30',
               '2012-05-31', '2012-06-01'],
              dtype='datetime64[ns]', freq='D')
```

By default, `date_range` generates daily timestamps. If you pass only a start or end date, you must pass a number of periods to generate:

```
In [76]: pd.date_range(start='2012-04-01', periods=20)
Out[76]:
DatetimeIndex(['2012-04-01', '2012-04-02', '2012-04-03', '2012-04-04',
               '2012-04-05', '2012-04-06', '2012-04-07', '2012-04-08',
               '2012-04-09', '2012-04-10', '2012-04-11', '2012-04-12',
               '2012-04-13', '2012-04-14', '2012-04-15', '2012-04-16',
               '2012-04-17', '2012-04-18', '2012-04-19', '2012-04-20'],
              dtype='datetime64[ns]', freq='D')

In [77]: pd.date_range(end='2012-06-01', periods=20)
Out[77]:
DatetimeIndex(['2012-05-13', '2012-05-14', '2012-05-15', '2012-05-16',
               '2012-05-17', '2012-05-18', '2012-05-19', '2012-05-20',
               '2012-05-21', '2012-05-22', '2012-05-23', '2012-05-24',
               '2012-05-25', '2012-05-26', '2012-05-27', '2012-05-28',
               '2012-05-29', '2012-05-30', '2012-05-31', '2012-06-01'],
              dtype='datetime64[ns]', freq='D')
```

The start and end dates define strict boundaries for the generated date index. For example, if you wanted a date index containing the last business day of each month, you would pass the `'BM'` frequency (business end of month; see more complete listing of frequencies in Table 11-4) and only dates falling on or inside the date interval will be included:

```
In [78]: pd.date_range('2000-01-01', '2000-12-01', freq='BM')
Out[78]:
DatetimeIndex(['2000-01-31', '2000-02-29', '2000-03-31', '2000-04-28',
               '2000-05-31', '2000-06-30', '2000-07-31', '2000-08-31',
               '2000-09-29', '2000-10-31', '2000-11-30'],
              dtype='datetime64[ns]', freq='BM')
```

Table 11-4. Base time series frequencies (not comprehensive)

Alias	Offset type	Description
`D`	`Day`	Calendar daily
`B`	`BusinessDay`	Business daily
`H`	`Hour`	Hourly
`T` or `min`	`Minute`	Minutely
`S`	`Second`	Secondly
`L` or `ms`	`Milli`	Millisecond (1/1,000 of 1 second)
`U`	`Micro`	Microsecond (1/1,000,000 of 1 second)
`M`	`MonthEnd`	Last calendar day of month
`BM`	`BusinessMonthEnd`	Last business day (weekday) of month
`MS`	`MonthBegin`	First calendar day of month
`BMS`	`BusinessMonthBegin`	First weekday of month
`W-MON, W-TUE, ...`	`Week`	Weekly on given day of week (MON, TUE, WED, THU, FRI, SAT, or SUN)
`WOM-1MON, WOM-2MON, ...`	`WeekOfMonth`	Generate weekly dates in the first, second, third, or fourth week of the month (e.g., `WOM-3FRI` for the third Friday of each month)
`Q-JAN, Q-FEB, ...`	`QuarterEnd`	Quarterly dates anchored on last calendar day of each month, for year ending in indicated month (JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, or DEC)
`BQ-JAN, BQ-FEB, ...`	`BusinessQuarterEnd`	Quarterly dates anchored on last weekday day of each month, for year ending in indicated month
`QS-JAN, QS-FEB, ...`	`QuarterBegin`	Quarterly dates anchored on first calendar day of each month, for year ending in indicated month
`BQS-JAN, BQS-FEB, ...`	`BusinessQuarterBegin`	Quarterly dates anchored on first weekday day of each month, for year ending in indicated month
`A-JAN, A-FEB, ...`	`YearEnd`	Annual dates anchored on last calendar day of given month (JAN, FEB, MAR, APR, MAY, JUN, JUL, AUG, SEP, OCT, NOV, or DEC)
`BA-JAN, BA-FEB, ...`	`BusinessYearEnd`	Annual dates anchored on last weekday of given month
`AS-JAN, AS-FEB, ...`	`YearBegin`	Annual dates anchored on first day of given month
`BAS-JAN, BAS-FEB, ...`	`BusinessYearBegin`	Annual dates anchored on first weekday of given month

`date_range` by default preserves the time (if any) of the start or end timestamp:

```
In [79]: pd.date_range('2012-05-02 12:56:31', periods=5)
Out[79]:
DatetimeIndex(['2012-05-02 12:56:31', '2012-05-03 12:56:31',
               '2012-05-04 12:56:31', '2012-05-05 12:56:31',
               '2012-05-06 12:56:31'],
              dtype='datetime64[ns]', freq='D')
```

Sometimes you will have start or end dates with time information but want to generate a set of timestamps *normalized* to midnight as a convention. To do this, there is a `normalize` option:

```
In [80]: pd.date_range('2012-05-02 12:56:31', periods=5, normalize=True)
Out[80]:
DatetimeIndex(['2012-05-02', '2012-05-03', '2012-05-04', '2012-05-05',
               '2012-05-06'],
              dtype='datetime64[ns]', freq='D')
```

Frequencies and Date Offsets

Frequencies in pandas are composed of a *base frequency* and a multiplier. Base frequencies are typically referred to by a string alias, like `'M'` for monthly or `'H'` for hourly. For each base frequency, there is an object defined generally referred to as a *date offset*. For example, hourly frequency can be represented with the `Hour` class:

```
In [81]: from pandas.tseries.offsets import Hour, Minute

In [82]: hour = Hour()

In [83]: hour
Out[83]: <Hour>
```

You can define a multiple of an offset by passing an integer:

```
In [84]: four_hours = Hour(4)

In [85]: four_hours
Out[85]: <4 * Hours>
```

In most applications, you would never need to explicitly create one of these objects, instead using a string alias like `'H'` or `'4H'`. Putting an integer before the base frequency creates a multiple:

```
In [86]: pd.date_range('2000-01-01', '2000-01-03 23:59', freq='4h')
Out[86]:
DatetimeIndex(['2000-01-01 00:00:00', '2000-01-01 04:00:00',
               '2000-01-01 08:00:00', '2000-01-01 12:00:00',
               '2000-01-01 16:00:00', '2000-01-01 20:00:00',
               '2000-01-02 00:00:00', '2000-01-02 04:00:00',
               '2000-01-02 08:00:00', '2000-01-02 12:00:00',
               '2000-01-02 16:00:00', '2000-01-02 20:00:00',
```

```
                '2000-01-03 00:00:00', '2000-01-03 04:00:00',
                '2000-01-03 08:00:00', '2000-01-03 12:00:00',
                '2000-01-03 16:00:00', '2000-01-03 20:00:00'],
               dtype='datetime64[ns]', freq='4H')
```

Many offsets can be combined together by addition:

```
In [87]: Hour(2) + Minute(30)
Out[87]: <150 * Minutes>
```

Similarly, you can pass frequency strings, like `'1h30min'`, that will effectively be parsed to the same expression:

```
In [88]: pd.date_range('2000-01-01', periods=10, freq='1h30min')
Out[88]:
DatetimeIndex(['2000-01-01 00:00:00', '2000-01-01 01:30:00',
               '2000-01-01 03:00:00', '2000-01-01 04:30:00',
               '2000-01-01 06:00:00', '2000-01-01 07:30:00',
               '2000-01-01 09:00:00', '2000-01-01 10:30:00',
               '2000-01-01 12:00:00', '2000-01-01 13:30:00'],
              dtype='datetime64[ns]', freq='90T')
```

Some frequencies describe points in time that are not evenly spaced. For example, `'M'` (calendar month end) and `'BM'` (last business/weekday of month) depend on the number of days in a month and, in the latter case, whether the month ends on a weekend or not. We refer to these as *anchored* offsets.

Refer back to Table 11-4 for a listing of frequency codes and date offset classes available in pandas.

> Users can define their own custom frequency classes to provide date logic not available in pandas, though the full details of that are outside the scope of this book.

Week of month dates

One useful frequency class is "week of month," starting with `WOM`. This enables you to get dates like the third Friday of each month:

```
In [89]: rng = pd.date_range('2012-01-01', '2012-09-01', freq='WOM-3FRI')

In [90]: list(rng)
Out[90]:
[Timestamp('2012-01-20 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-02-17 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-03-16 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-04-20 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-05-18 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-06-15 00:00:00', freq='WOM-3FRI'),
```

```
 Timestamp('2012-07-20 00:00:00', freq='WOM-3FRI'),
 Timestamp('2012-08-17 00:00:00', freq='WOM-3FRI')]
```

Shifting (Leading and Lagging) Data

"Shifting" refers to moving data backward and forward through time. Both Series and DataFrame have a `shift` method for doing naive shifts forward or backward, leaving the index unmodified:

```
In [91]: ts = pd.Series(np.random.randn(4),
   ....:                index=pd.date_range('1/1/2000', periods=4, freq='M'))

In [92]: ts
Out[92]:
2000-01-31   -0.066748
2000-02-29    0.838639
2000-03-31   -0.117388
2000-04-30   -0.517795
Freq: M, dtype: float64

In [93]: ts.shift(2)
Out[93]:
2000-01-31         NaN
2000-02-29         NaN
2000-03-31   -0.066748
2000-04-30    0.838639
Freq: M, dtype: float64

In [94]: ts.shift(-2)
Out[94]:
2000-01-31   -0.117388
2000-02-29   -0.517795
2000-03-31         NaN
2000-04-30         NaN
Freq: M, dtype: float64
```

When we shift like this, missing data is introduced either at the start or the end of the time series.

A common use of `shift` is computing percent changes in a time series or multiple time series as DataFrame columns. This is expressed as:

```
ts / ts.shift(1) - 1
```

Because naive shifts leave the index unmodified, some data is discarded. Thus if the frequency is known, it can be passed to `shift` to advance the timestamps instead of simply the data:

```
In [95]: ts.shift(2, freq='M')
Out[95]:
2000-03-31   -0.066748
2000-04-30    0.838639
```

```
2000-05-31   -0.117388
2000-06-30   -0.517795
Freq: M, dtype: float64
```

Other frequencies can be passed, too, giving you some flexibility in how to lead and lag the data:

```
In [96]: ts.shift(3, freq='D')
Out[96]:
2000-02-03   -0.066748
2000-03-03    0.838639
2000-04-03   -0.117388
2000-05-03   -0.517795
dtype: float64

In [97]: ts.shift(1, freq='90T')
Out[97]:
2000-01-31 01:30:00   -0.066748
2000-02-29 01:30:00    0.838639
2000-03-31 01:30:00   -0.117388
2000-04-30 01:30:00   -0.517795
Freq: M, dtype: float64
```

The `T` here stands for minutes.

Shifting dates with offsets

The pandas date offsets can also be used with `datetime` or `Timestamp` objects:

```
In [98]: from pandas.tseries.offsets import Day, MonthEnd

In [99]: now = datetime(2011, 11, 17)

In [100]: now + 3 * Day()
Out[100]: Timestamp('2011-11-20 00:00:00')
```

If you add an anchored offset like `MonthEnd`, the first increment will "roll forward" a date to the next date according to the frequency rule:

```
In [101]: now + MonthEnd()
Out[101]: Timestamp('2011-11-30 00:00:00')

In [102]: now + MonthEnd(2)
Out[102]: Timestamp('2011-12-31 00:00:00')
```

Anchored offsets can explicitly "roll" dates forward or backward by simply using their `rollforward` and `rollback` methods, respectively:

```
In [103]: offset = MonthEnd()

In [104]: offset.rollforward(now)
Out[104]: Timestamp('2011-11-30 00:00:00')
```

```
In [105]: offset.rollback(now)
Out[105]: Timestamp('2011-10-31 00:00:00')
```

A creative use of date offsets is to use these methods with `groupby`:

```
In [106]: ts = pd.Series(np.random.randn(20),
   .....:                index=pd.date_range('1/15/2000', periods=20, freq='4d'))

In [107]: ts
Out[107]:
2000-01-15   -0.116696
2000-01-19    2.389645
2000-01-23   -0.932454
2000-01-27   -0.229331
2000-01-31   -1.140330
2000-02-04    0.439920
2000-02-08   -0.823758
2000-02-12   -0.520930
2000-02-16    0.350282
2000-02-20    0.204395
2000-02-24    0.133445
2000-02-28    0.327905
2000-03-03    0.072153
2000-03-07    0.131678
2000-03-11   -1.297459
2000-03-15    0.997747
2000-03-19    0.870955
2000-03-23   -0.991253
2000-03-27    0.151699
2000-03-31    1.266151
Freq: 4D, dtype: float64

In [108]: ts.groupby(offset.rollforward).mean()
Out[108]:
2000-01-31   -0.005833
2000-02-29    0.015894
2000-03-31    0.150209
dtype: float64
```

Of course, an easier and faster way to do this is using `resample` (we'll discuss this in much more depth in Section 11.6, "Resampling and Frequency Conversion," on page 348):

```
In [109]: ts.resample('M').mean()
Out[109]:
2000-01-31   -0.005833
2000-02-29    0.015894
2000-03-31    0.150209
Freq: M, dtype: float64
```

11.4 Time Zone Handling

Working with time zones is generally considered one of the most unpleasant parts of time series manipulation. As a result, many time series users choose to work with time series in *coordinated universal time* or *UTC*, which is the successor to Greenwich Mean Time and is the current international standard. Time zones are expressed as offsets from UTC; for example, New York is four hours behind UTC during daylight saving time and five hours behind the rest of the year.

In Python, time zone information comes from the third-party `pytz` library (installable with pip or conda), which exposes the *Olson database*, a compilation of world time zone information. This is especially important for historical data because the daylight saving time (DST) transition dates (and even UTC offsets) have been changed numerous times depending on the whims of local governments. In the United States, the DST transition times have been changed many times since 1900!

For detailed information about the `pytz` library, you'll need to look at that library's documentation. As far as this book is concerned, pandas wraps `pytz`'s functionality so you can ignore its API outside of the time zone names. Time zone names can be found interactively and in the docs:

```
In [110]: import pytz

In [111]: pytz.common_timezones[-5:]
Out[111]: ['US/Eastern', 'US/Hawaii', 'US/Mountain', 'US/Pacific', 'UTC']
```

To get a time zone object from `pytz`, use `pytz.timezone`:

```
In [112]: tz = pytz.timezone('America/New_York')

In [113]: tz
Out[113]: <DstTzInfo 'America/New_York' LMT-1 day, 19:04:00 STD>
```

Methods in pandas will accept either time zone names or these objects.

Time Zone Localization and Conversion

By default, time series in pandas are *time zone naive*. For example, consider the following time series:

```
In [114]: rng = pd.date_range('3/9/2012 9:30', periods=6, freq='D')

In [115]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [116]: ts
Out[116]:
2012-03-09 09:30:00   -0.202469
2012-03-10 09:30:00    0.050718
2012-03-11 09:30:00    0.639869
2012-03-12 09:30:00    0.597594
```

```
2012-03-13 09:30:00   -0.797246
2012-03-14 09:30:00    0.472879
Freq: D, dtype: float64
```

The index's `tz` field is `None`:

```
In [117]: print(ts.index.tz)
None
```

Date ranges can be generated with a time zone set:

```
In [118]: pd.date_range('3/9/2012 9:30', periods=10, freq='D', tz='UTC')
Out[118]:
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10 09:30:00+00:00',
               '2012-03-11 09:30:00+00:00', '2012-03-12 09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14 09:30:00+00:00',
               '2012-03-15 09:30:00+00:00', '2012-03-16 09:30:00+00:00',
               '2012-03-17 09:30:00+00:00', '2012-03-18 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

Conversion from naive to *localized* is handled by the `tz_localize` method:

```
In [119]: ts
Out[119]:
2012-03-09 09:30:00   -0.202469
2012-03-10 09:30:00    0.050718
2012-03-11 09:30:00    0.639869
2012-03-12 09:30:00    0.597594
2012-03-13 09:30:00   -0.797246
2012-03-14 09:30:00    0.472879
Freq: D, dtype: float64

In [120]: ts_utc = ts.tz_localize('UTC')

In [121]: ts_utc
Out[121]:
2012-03-09 09:30:00+00:00   -0.202469
2012-03-10 09:30:00+00:00    0.050718
2012-03-11 09:30:00+00:00    0.639869
2012-03-12 09:30:00+00:00    0.597594
2012-03-13 09:30:00+00:00   -0.797246
2012-03-14 09:30:00+00:00    0.472879
Freq: D, dtype: float64

In [122]: ts_utc.index
Out[122]:
DatetimeIndex(['2012-03-09 09:30:00+00:00', '2012-03-10 09:30:00+00:00',
               '2012-03-11 09:30:00+00:00', '2012-03-12 09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='D')
```

Once a time series has been localized to a particular time zone, it can be converted to another time zone with `tz_convert`:

```
In [123]: ts_utc.tz_convert('America/New_York')
Out[123]:
2012-03-09 04:30:00-05:00   -0.202469
2012-03-10 04:30:00-05:00    0.050718
2012-03-11 05:30:00-04:00    0.639869
2012-03-12 05:30:00-04:00    0.597594
2012-03-13 05:30:00-04:00   -0.797246
2012-03-14 05:30:00-04:00    0.472879
Freq: D, dtype: float64
```

In the case of the preceding time series, which straddles a DST transition in the America/New_York time zone, we could localize to EST and convert to, say, UTC or Berlin time:

```
In [124]: ts_eastern = ts.tz_localize('America/New_York')

In [125]: ts_eastern.tz_convert('UTC')
Out[125]:
2012-03-09 14:30:00+00:00   -0.202469
2012-03-10 14:30:00+00:00    0.050718
2012-03-11 13:30:00+00:00    0.639869
2012-03-12 13:30:00+00:00    0.597594
2012-03-13 13:30:00+00:00   -0.797246
2012-03-14 13:30:00+00:00    0.472879
Freq: D, dtype: float64

In [126]: ts_eastern.tz_convert('Europe/Berlin')
Out[126]:
2012-03-09 15:30:00+01:00   -0.202469
2012-03-10 15:30:00+01:00    0.050718
2012-03-11 14:30:00+01:00    0.639869
2012-03-12 14:30:00+01:00    0.597594
2012-03-13 14:30:00+01:00   -0.797246
2012-03-14 14:30:00+01:00    0.472879
Freq: D, dtype: float64
```

`tz_localize` and `tz_convert` are also instance methods on `DatetimeIndex`:

```
In [127]: ts.index.tz_localize('Asia/Shanghai')
Out[127]:
DatetimeIndex(['2012-03-09 09:30:00+08:00', '2012-03-10 09:30:00+08:00',
               '2012-03-11 09:30:00+08:00', '2012-03-12 09:30:00+08:00',
               '2012-03-13 09:30:00+08:00', '2012-03-14 09:30:00+08:00'],
              dtype='datetime64[ns, Asia/Shanghai]', freq='D')
```

Localizing naive timestamps also checks for ambiguous or non-existent times around daylight saving time transitions.

Operations with Time Zone–Aware Timestamp Objects

Similar to time series and date ranges, individual `Timestamp` objects similarly can be localized from naive to time zone–aware and converted from one time zone to another:

```
In [128]: stamp = pd.Timestamp('2011-03-12 04:00')

In [129]: stamp_utc = stamp.tz_localize('utc')

In [130]: stamp_utc.tz_convert('America/New_York')
Out[130]: Timestamp('2011-03-11 23:00:00-0500', tz='America/New_York')
```

You can also pass a time zone when creating the `Timestamp`:

```
In [131]: stamp_moscow = pd.Timestamp('2011-03-12 04:00', tz='Europe/Moscow')

In [132]: stamp_moscow
Out[132]: Timestamp('2011-03-12 04:00:00+0300', tz='Europe/Moscow')
```

Time zone–aware `Timestamp` objects internally store a UTC timestamp value as nanoseconds since the Unix epoch (January 1, 1970); this UTC value is invariant between time zone conversions:

```
In [133]: stamp_utc.value
Out[133]: 1299902400000000000

In [134]: stamp_utc.tz_convert('America/New_York').value
Out[134]: 1299902400000000000
```

When performing time arithmetic using pandas's `DateOffset` objects, pandas respects daylight saving time transitions where possible. Here we construct timestamps that occur right before DST transitions (forward and backward). First, 30 minutes before transitioning to DST:

```
In [135]: from pandas.tseries.offsets import Hour

In [136]: stamp = pd.Timestamp('2012-03-12 01:30', tz='US/Eastern')

In [137]: stamp
Out[137]: Timestamp('2012-03-12 01:30:00-0400', tz='US/Eastern')

In [138]: stamp + Hour()
Out[138]: Timestamp('2012-03-12 02:30:00-0400', tz='US/Eastern')
```

Then, 90 minutes before transitioning out of DST:

```
In [139]: stamp = pd.Timestamp('2012-11-04 00:30', tz='US/Eastern')

In [140]: stamp
Out[140]: Timestamp('2012-11-04 00:30:00-0400', tz='US/Eastern')
```

```
In [141]: stamp + 2 * Hour()
Out[141]: Timestamp('2012-11-04 01:30:00-0500', tz='US/Eastern')
```

Operations Between Different Time Zones

If two time series with different time zones are combined, the result will be UTC. Since the timestamps are stored under the hood in UTC, this is a straightforward operation and requires no conversion to happen:

```
In [142]: rng = pd.date_range('3/7/2012 9:30', periods=10, freq='B')

In [143]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [144]: ts
Out[144]:
2012-03-07 09:30:00    0.522356
2012-03-08 09:30:00   -0.546348
2012-03-09 09:30:00   -0.733537
2012-03-12 09:30:00    1.302736
2012-03-13 09:30:00    0.022199
2012-03-14 09:30:00    0.364287
2012-03-15 09:30:00   -0.922839
2012-03-16 09:30:00    0.312656
2012-03-19 09:30:00   -1.128497
2012-03-20 09:30:00   -0.333488
Freq: B, dtype: float64

In [145]: ts1 = ts[:7].tz_localize('Europe/London')

In [146]: ts2 = ts1[2:].tz_convert('Europe/Moscow')

In [147]: result = ts1 + ts2

In [148]: result.index
Out[148]:
DatetimeIndex(['2012-03-07 09:30:00+00:00', '2012-03-08 09:30:00+00:00',
               '2012-03-09 09:30:00+00:00', '2012-03-12 09:30:00+00:00',
               '2012-03-13 09:30:00+00:00', '2012-03-14 09:30:00+00:00',
               '2012-03-15 09:30:00+00:00'],
              dtype='datetime64[ns, UTC]', freq='B')
```

11.5 Periods and Period Arithmetic

Periods represent timespans, like days, months, quarters, or years. The `Period` class represents this data type, requiring a string or integer and a frequency from Table 11-4:

```
In [149]: p = pd.Period(2007, freq='A-DEC')

In [150]: p
Out[150]: Period('2007', 'A-DEC')
```

In this case, the `Period` object represents the full timespan from January 1, 2007, to December 31, 2007, inclusive. Conveniently, adding and subtracting integers from periods has the effect of shifting by their frequency:

```
In [151]: p + 5
Out[151]: Period('2012', 'A-DEC')

In [152]: p - 2
Out[152]: Period('2005', 'A-DEC')
```

If two periods have the same frequency, their difference is the number of units between them:

```
In [153]: pd.Period('2014', freq='A-DEC') - p
Out[153]: 7
```

Regular ranges of periods can be constructed with the `period_range` function:

```
In [154]: rng = pd.period_range('2000-01-01', '2000-06-30', freq='M')

In [155]: rng
Out[155]: PeriodIndex(['2000-01', '2000-02', '2000-03', '2000-04', '2000-05', '20
00-06'], dtype='period[M]', freq='M')
```

The `PeriodIndex` class stores a sequence of periods and can serve as an axis index in any pandas data structure:

```
In [156]: pd.Series(np.random.randn(6), index=rng)
Out[156]:
2000-01   -0.514551
2000-02   -0.559782
2000-03   -0.783408
2000-04   -1.797685
2000-05   -0.172670
2000-06    0.680215
Freq: M, dtype: float64
```

If you have an array of strings, you can also use the `PeriodIndex` class:

```
In [157]: values = ['2001Q3', '2002Q2', '2003Q1']

In [158]: index = pd.PeriodIndex(values, freq='Q-DEC')

In [159]: index
Out[159]: PeriodIndex(['2001Q3', '2002Q2', '2003Q1'], dtype='period[Q-DEC]', freq
='Q-DEC')
```

Period Frequency Conversion

Periods and `PeriodIndex` objects can be converted to another frequency with their `asfreq` method. As an example, suppose we had an annual period and wanted to convert it into a monthly period either at the start or end of the year. This is fairly straightforward:

```
In [160]: p = pd.Period('2007', freq='A-DEC')

In [161]: p
Out[161]: Period('2007', 'A-DEC')

In [162]: p.asfreq('M', how='start')
Out[162]: Period('2007-01', 'M')

In [163]: p.asfreq('M', how='end')
Out[163]: Period('2007-12', 'M')
```

You can think of `Period('2007', 'A-DEC')` as being a sort of cursor pointing to a span of time, subdivided by monthly periods. See Figure 11-1 for an illustration of this. For a *fiscal year* ending on a month other than December, the corresponding monthly subperiods are different:

```
In [164]: p = pd.Period('2007', freq='A-JUN')

In [165]: p
Out[165]: Period('2007', 'A-JUN')

In [166]: p.asfreq('M', 'start')
Out[166]: Period('2006-07', 'M')

In [167]: p.asfreq('M', 'end')
Out[167]: Period('2007-06', 'M')
```

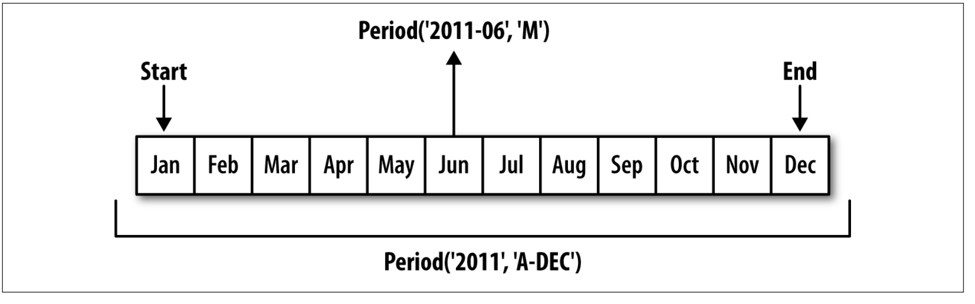

Figure 11-1. Period frequency conversion illustration

When you are converting from high to low frequency, pandas determines the superperiod depending on where the subperiod "belongs." For example, in `A-JUN` frequency, the month `Aug-2007` is actually part of the `2008` period:

```
In [168]: p = pd.Period('Aug-2007', 'M')

In [169]: p.asfreq('A-JUN')
Out[169]: Period('2008', 'A-JUN')
```

Whole `PeriodIndex` objects or time series can be similarly converted with the same semantics:

```
In [170]: rng = pd.period_range('2006', '2009', freq='A-DEC')

In [171]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [172]: ts
Out[172]:
2006    1.607578
2007    0.200381
2008   -0.834068
2009   -0.302988
Freq: A-DEC, dtype: float64

In [173]: ts.asfreq('M', how='start')
Out[173]:
2006-01    1.607578
2007-01    0.200381
2008-01   -0.834068
2009-01   -0.302988
Freq: M, dtype: float64
```

Here, the annual periods are replaced with monthly periods corresponding to the first month falling within each annual period. If we instead wanted the last business day of each year, we can use the `'B'` frequency and indicate that we want the end of the period:

```
In [174]: ts.asfreq('B', how='end')
Out[174]:
2006-12-29    1.607578
2007-12-31    0.200381
2008-12-31   -0.834068
2009-12-31   -0.302988
Freq: B, dtype: float64
```

Quarterly Period Frequencies

Quarterly data is standard in accounting, finance, and other fields. Much quarterly data is reported relative to a *fiscal year end*, typically the last calendar or business day of one of the 12 months of the year. Thus, the period `2012Q4` has a different meaning depending on fiscal year end. pandas supports all 12 possible quarterly frequencies as `Q-JAN` through `Q-DEC`:

```
In [175]: p = pd.Period('2012Q4', freq='Q-JAN')

In [176]: p
Out[176]: Period('2012Q4', 'Q-JAN')
```

In the case of fiscal year ending in January, `2012Q4` runs from November through January, which you can check by converting to daily frequency. See Figure 11-2 for an illustration.

Figure 11-2. Different quarterly frequency conventions

```
In [177]: p.asfreq('D', 'start')
Out[177]: Period('2011-11-01', 'D')

In [178]: p.asfreq('D', 'end')
Out[178]: Period('2012-01-31', 'D')
```

Thus, it's possible to do easy period arithmetic; for example, to get the timestamp at 4 PM on the second-to-last business day of the quarter, you could do:

```
In [179]: p4pm = (p.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [180]: p4pm
Out[180]: Period('2012-01-30 16:00', 'T')

In [181]: p4pm.to_timestamp()
Out[181]: Timestamp('2012-01-30 16:00:00')
```

You can generate quarterly ranges using `period_range`. Arithmetic is identical, too:

```
In [182]: rng = pd.period_range('2011Q3', '2012Q4', freq='Q-JAN')

In [183]: ts = pd.Series(np.arange(len(rng)), index=rng)

In [184]: ts
Out[184]:
2011Q3    0
2011Q4    1
2012Q1    2
2012Q2    3
2012Q3    4
2012Q4    5
Freq: Q-JAN, dtype: int64

In [185]: new_rng = (rng.asfreq('B', 'e') - 1).asfreq('T', 's') + 16 * 60

In [186]: ts.index = new_rng.to_timestamp()
```

```
In [187]: ts
Out[187]:
2010-10-28 16:00:00    0
2011-01-28 16:00:00    1
2011-04-28 16:00:00    2
2011-07-28 16:00:00    3
2011-10-28 16:00:00    4
2012-01-30 16:00:00    5
dtype: int64
```

Converting Timestamps to Periods (and Back)

Series and DataFrame objects indexed by timestamps can be converted to periods with the `to_period` method:

```
In [188]: rng = pd.date_range('2000-01-01', periods=3, freq='M')

In [189]: ts = pd.Series(np.random.randn(3), index=rng)

In [190]: ts
Out[190]:
2000-01-31    1.663261
2000-02-29   -0.996206
2000-03-31    1.521760
Freq: M, dtype: float64

In [191]: pts = ts.to_period()

In [192]: pts
Out[192]:
2000-01    1.663261
2000-02   -0.996206
2000-03    1.521760
Freq: M, dtype: float64
```

Since periods refer to non-overlapping timespans, a timestamp can only belong to a single period for a given frequency. While the frequency of the new `PeriodIndex` is inferred from the timestamps by default, you can specify any frequency you want. There is also no problem with having duplicate periods in the result:

```
In [193]: rng = pd.date_range('1/29/2000', periods=6, freq='D')

In [194]: ts2 = pd.Series(np.random.randn(6), index=rng)

In [195]: ts2
Out[195]:
2000-01-29    0.244175
2000-01-30    0.423331
2000-01-31   -0.654040
2000-02-01    2.089154
2000-02-02   -0.060220
```

```
2000-02-03   -0.167933
Freq: D, dtype: float64

In [196]: ts2.to_period('M')
Out[196]:
2000-01    0.244175
2000-01    0.423331
2000-01   -0.654040
2000-02    2.089154
2000-02   -0.060220
2000-02   -0.167933
Freq: M, dtype: float64
```

To convert back to timestamps, use `to_timestamp`:

```
In [197]: pts = ts2.to_period()

In [198]: pts
Out[198]:
2000-01-29    0.244175
2000-01-30    0.423331
2000-01-31   -0.654040
2000-02-01    2.089154
2000-02-02   -0.060220
2000-02-03   -0.167933
Freq: D, dtype: float64

In [199]: pts.to_timestamp(how='end')
Out[199]:
2000-01-29    0.244175
2000-01-30    0.423331
2000-01-31   -0.654040
2000-02-01    2.089154
2000-02-02   -0.060220
2000-02-03   -0.167933
Freq: D, dtype: float64
```

Creating a PeriodIndex from Arrays

Fixed frequency datasets are sometimes stored with timespan information spread across multiple columns. For example, in this macroeconomic dataset, the year and quarter are in different columns:

```
In [200]: data = pd.read_csv('examples/macrodata.csv')

In [201]: data.head(5)
Out[201]:
     year  quarter   realgdp  realcons  realinv  realgovt  realdpi    cpi  \
0  1959.0      1.0  2710.349    1707.4  286.898   470.045   1886.9  28.98
1  1959.0      2.0  2778.801    1733.7  310.859   481.301   1919.7  29.15
2  1959.0      3.0  2775.488    1751.8  289.226   491.260   1916.4  29.35
3  1959.0      4.0  2785.204    1753.7  299.356   484.052   1931.3  29.37
```

```
4  1960.0      1.0  2847.699    1770.5  331.722   462.199   1955.5  29.54
      m1  tbilrate  unemp      pop  infl  realint
0  139.7      2.82    5.8  177.146  0.00     0.00
1  141.7      3.08    5.1  177.830  2.34     0.74
2  140.5      3.82    5.3  178.657  2.74     1.09
3  140.0      4.33    5.6  179.386  0.27     4.06
4  139.6      3.50    5.2  180.007  2.31     1.19

In [202]: data.year
Out[202]:
0      1959.0
1      1959.0
2      1959.0
3      1959.0
4      1960.0
5      1960.0
6      1960.0
7      1960.0
8      1961.0
9      1961.0
        ...
193    2007.0
194    2007.0
195    2007.0
196    2008.0
197    2008.0
198    2008.0
199    2008.0
200    2009.0
201    2009.0
202    2009.0
Name: year, Length: 203, dtype: float64

In [203]: data.quarter
Out[203]:
0      1.0
1      2.0
2      3.0
3      4.0
4      1.0
5      2.0
6      3.0
7      4.0
8      1.0
9      2.0
      ...
193    2.0
194    3.0
195    4.0
196    1.0
197    2.0
198    3.0
```

```
199    4.0
200    1.0
201    2.0
202    3.0
Name: quarter, Length: 203, dtype: float64
```

By passing these arrays to `PeriodIndex` with a frequency, you can combine them to form an index for the DataFrame:

```
In [204]: index = pd.PeriodIndex(year=data.year, quarter=data.quarter,
   .....:                        freq='Q-DEC')

In [205]: index
Out[205]:
PeriodIndex(['1959Q1', '1959Q2', '1959Q3', '1959Q4', '1960Q1', '1960Q2',
             '1960Q3', '1960Q4', '1961Q1', '1961Q2',
             ...
             '2007Q2', '2007Q3', '2007Q4', '2008Q1', '2008Q2', '2008Q3',
             '2008Q4', '2009Q1', '2009Q2', '2009Q3'],
            dtype='period[Q-DEC]', length=203, freq='Q-DEC')

In [206]: data.index = index

In [207]: data.infl
Out[207]:
1959Q1    0.00
1959Q2    2.34
1959Q3    2.74
1959Q4    0.27
1960Q1    2.31
1960Q2    0.14
1960Q3    2.70
1960Q4    1.21
1961Q1   -0.40
1961Q2    1.47
          ...
2007Q2    2.75
2007Q3    3.45
2007Q4    6.38
2008Q1    2.82
2008Q2    8.53
2008Q3   -3.16
2008Q4   -8.79
2009Q1    0.94
2009Q2    3.37
2009Q3    3.56
Freq: Q-DEC, Name: infl, Length: 203, dtype: float64
```

11.6 Resampling and Frequency Conversion

Resampling refers to the process of converting a time series from one frequency to another. Aggregating higher frequency data to lower frequency is called *downsampling*, while converting lower frequency to higher frequency is called *upsampling*. Not all resampling falls into either of these categories; for example, converting `W-WED` (weekly on Wednesday) to `W-FRI` is neither upsampling nor downsampling.

pandas objects are equipped with a `resample` method, which is the workhorse function for all frequency conversion. `resample` has a similar API to `groupby`; you call `resample` to group the data, then call an aggregation function:

```
In [208]: rng = pd.date_range('2000-01-01', periods=100, freq='D')

In [209]: ts = pd.Series(np.random.randn(len(rng)), index=rng)

In [210]: ts
Out[210]:
2000-01-01    0.631634
2000-01-02   -1.594313
2000-01-03   -1.519937
2000-01-04    1.108752
2000-01-05    1.255853
2000-01-06   -0.024330
2000-01-07   -2.047939
2000-01-08   -0.272657
2000-01-09   -1.692615
2000-01-10    1.423830
                ...
2000-03-31   -0.007852
2000-04-01   -1.638806
2000-04-02    1.401227
2000-04-03    1.758539
2000-04-04    0.628932
2000-04-05   -0.423776
2000-04-06    0.789740
2000-04-07    0.937568
2000-04-08   -2.253294
2000-04-09   -1.772919
Freq: D, Length: 100, dtype: float64

In [211]: ts.resample('M').mean()
Out[211]:
2000-01-31   -0.165893
2000-02-29    0.078606
2000-03-31    0.223811
2000-04-30   -0.063643
Freq: M, dtype: float64

In [212]: ts.resample('M', kind='period').mean()
Out[212]:
```

```
2000-01   -0.165893
2000-02    0.078606
2000-03    0.223811
2000-04   -0.063643
Freq: M, dtype: float64
```

resample is a flexible and high-performance method that can be used to process very large time series. The examples in the following sections illustrate its semantics and use. Table 11-5 summarizes some of its options.

Table 11-5. Resample method arguments

Argument	Description
freq	String or DateOffset indicating desired resampled frequency (e.g., 'M', '5min', or Second(15))
axis	Axis to resample on; default axis=0
fill_method	How to interpolate when upsampling, as in 'ffill' or 'bfill'; by default does no interpolation
closed	In downsampling, which end of each interval is closed (inclusive), 'right' or 'left'
label	In downsampling, how to label the aggregated result, with the 'right' or 'left' bin edge (e.g., the 9:30 to 9:35 five-minute interval could be labeled 9:30 or 9:35)
loffset	Time adjustment to the bin labels, such as '-1s' / Second(-1) to shift the aggregate labels one second earlier
limit	When forward or backward filling, the maximum number of periods to fill
kind	Aggregate to periods ('period') or timestamps ('timestamp'); defaults to the type of index the time series has
convention	When resampling periods, the convention ('start' or 'end') for converting the low-frequency period to high frequency; defaults to 'end'

Downsampling

Aggregating data to a regular, lower frequency is a pretty normal time series task. The data you're aggregating doesn't need to be fixed frequently; the desired frequency defines *bin edges* that are used to slice the time series into pieces to aggregate. For example, to convert to monthly, 'M' or 'BM', you need to chop up the data into one-month intervals. Each interval is said to be *half-open*; a data point can only belong to one interval, and the union of the intervals must make up the whole time frame. There are a couple things to think about when using resample to downsample data:

- Which side of each interval is *closed*
- How to label each aggregated bin, either with the start of the interval or the end

To illustrate, let's look at some one-minute data:

```
In [213]: rng = pd.date_range('2000-01-01', periods=12, freq='T')

In [214]: ts = pd.Series(np.arange(12), index=rng)
```

```
In [215]: ts
Out[215]:
2000-01-01 00:00:00     0
2000-01-01 00:01:00     1
2000-01-01 00:02:00     2
2000-01-01 00:03:00     3
2000-01-01 00:04:00     4
2000-01-01 00:05:00     5
2000-01-01 00:06:00     6
2000-01-01 00:07:00     7
2000-01-01 00:08:00     8
2000-01-01 00:09:00     9
2000-01-01 00:10:00    10
2000-01-01 00:11:00    11
Freq: T, dtype: int64
```

Suppose you wanted to aggregate this data into five-minute chunks or *bars* by taking the sum of each group:

```
In [216]: ts.resample('5min', closed='right').sum()
Out[216]:
1999-12-31 23:55:00     0
2000-01-01 00:00:00    15
2000-01-01 00:05:00    40
2000-01-01 00:10:00    11
Freq: 5T, dtype: int64
```

The frequency you pass defines bin edges in five-minute increments. By default, the *left* bin edge is inclusive, so the `00:00` value is included in the `00:00` to `00:05` interval.[1] Passing `closed='right'` changes the interval to be closed on the right:

```
In [217]: ts.resample('5min', closed='right').sum()
Out[217]:
1999-12-31 23:55:00     0
2000-01-01 00:00:00    15
2000-01-01 00:05:00    40
2000-01-01 00:10:00    11
Freq: 5T, dtype: int64
```

The resulting time series is labeled by the timestamps from the left side of each bin. By passing `label='right'` you can label them with the right bin edge:

```
In [218]: ts.resample('5min', closed='right', label='right').sum()
Out[218]:
2000-01-01 00:00:00     0
2000-01-01 00:05:00    15
```

1 The choice of the default values for `closed` and `label` might seem a bit odd to some users. In practice the choice is somewhat arbitrary; for some target frequencies, `closed='left'` is preferable, while for others `closed='right'` makes more sense. The important thing is that you keep in mind exactly how you are segmenting the data.

```
2000-01-01 00:10:00    40
2000-01-01 00:15:00    11
Freq: 5T, dtype: int64
```

See Figure 11-3 for an illustration of minute frequency data being resampled to five-minute frequency.

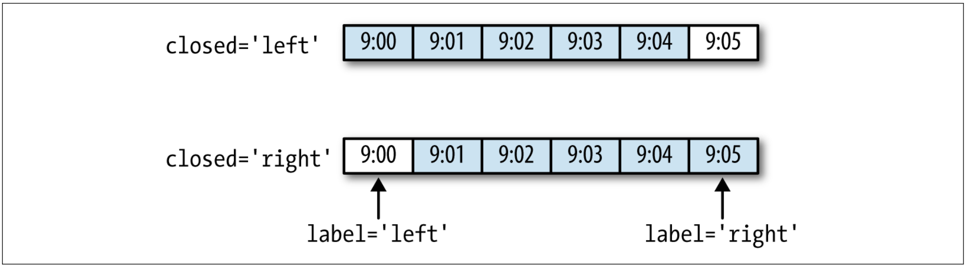

Figure 11-3. Five-minute resampling illustration of closed, label conventions

Lastly, you might want to shift the result index by some amount, say subtracting one second from the right edge to make it more clear which interval the timestamp refers to. To do this, pass a string or date offset to `loffset`:

```
In [219]: ts.resample('5min', closed='right',
   .....:                label='right', loffset='-1s').sum()
Out[219]:
1999-12-31 23:59:59     0
2000-01-01 00:04:59    15
2000-01-01 00:09:59    40
2000-01-01 00:14:59    11
Freq: 5T, dtype: int64
```

You also could have accomplished the effect of `loffset` by calling the `shift` method on the result without the `loffset`.

Open-High-Low-Close (OHLC) resampling

In finance, a popular way to aggregate a time series is to compute four values for each bucket: the first (open), last (close), maximum (high), and minimal (low) values. By using the `ohlc` aggregate function you will obtain a DataFrame having columns containing these four aggregates, which are efficiently computed in a single sweep of the data:

```
In [220]: ts.resample('5min').ohlc()
Out[220]:
                     open  high  low  close
2000-01-01 00:00:00     0     4    0      4
2000-01-01 00:05:00     5     9    5      9
2000-01-01 00:10:00    10    11   10     11
```

Upsampling and Interpolation

When converting from a low frequency to a higher frequency, no aggregation is needed. Let's consider a DataFrame with some weekly data:

```
In [221]: frame = pd.DataFrame(np.random.randn(2, 4),
   .....:                      index=pd.date_range('1/1/2000', periods=2,
   .....:                                          freq='W-WED'),
   .....:                      columns=['Colorado', 'Texas', 'New York', 'Ohio'])

In [222]: frame
Out[222]:
            Colorado     Texas  New York      Ohio
2000-01-05 -0.896431  0.677263  0.036503  0.087102
2000-01-12 -0.046662  0.927238  0.482284 -0.867130
```

When you are using an aggregation function with this data, there is only one value per group, and missing values result in the gaps. We use the `asfreq` method to convert to the higher frequency without any aggregation:

```
In [223]: df_daily = frame.resample('D').asfreq()

In [224]: df_daily
Out[224]:
            Colorado     Texas  New York      Ohio
2000-01-05 -0.896431  0.677263  0.036503  0.087102
2000-01-06       NaN       NaN       NaN       NaN
2000-01-07       NaN       NaN       NaN       NaN
2000-01-08       NaN       NaN       NaN       NaN
2000-01-09       NaN       NaN       NaN       NaN
2000-01-10       NaN       NaN       NaN       NaN
2000-01-11       NaN       NaN       NaN       NaN
2000-01-12 -0.046662  0.927238  0.482284 -0.867130
```

Suppose you wanted to fill forward each weekly value on the non-Wednesdays. The same filling or interpolation methods available in the `fillna` and `reindex` methods are available for resampling:

```
In [225]: frame.resample('D').ffill()
Out[225]:
            Colorado     Texas  New York      Ohio
2000-01-05 -0.896431  0.677263  0.036503  0.087102
2000-01-06 -0.896431  0.677263  0.036503  0.087102
2000-01-07 -0.896431  0.677263  0.036503  0.087102
2000-01-08 -0.896431  0.677263  0.036503  0.087102
2000-01-09 -0.896431  0.677263  0.036503  0.087102
2000-01-10 -0.896431  0.677263  0.036503  0.087102
2000-01-11 -0.896431  0.677263  0.036503  0.087102
2000-01-12 -0.046662  0.927238  0.482284 -0.867130
```

You can similarly choose to only fill a certain number of periods forward to limit how far to continue using an observed value:

```
In [226]: frame.resample('D').ffill(limit=2)
Out[226]:
            Colorado     Texas  New York      Ohio
2000-01-05 -0.896431  0.677263  0.036503  0.087102
2000-01-06 -0.896431  0.677263  0.036503  0.087102
2000-01-07 -0.896431  0.677263  0.036503  0.087102
2000-01-08       NaN       NaN       NaN       NaN
2000-01-09       NaN       NaN       NaN       NaN
2000-01-10       NaN       NaN       NaN       NaN
2000-01-11       NaN       NaN       NaN       NaN
2000-01-12 -0.046662  0.927238  0.482284 -0.867130
```

Notably, the new date index need not overlap with the old one at all:

```
In [227]: frame.resample('W-THU').ffill()
Out[227]:
            Colorado     Texas  New York      Ohio
2000-01-06 -0.896431  0.677263  0.036503  0.087102
2000-01-13 -0.046662  0.927238  0.482284 -0.867130
```

Resampling with Periods

Resampling data indexed by periods is similar to timestamps:

```
In [228]: frame = pd.DataFrame(np.random.randn(24, 4),
   .....:                      index=pd.period_range('1-2000', '12-2001',
   .....:                                            freq='M'),
   .....:                      columns=['Colorado', 'Texas', 'New York', 'Ohio'])

In [229]: frame[:5]
Out[229]:
         Colorado     Texas  New York      Ohio
2000-01  0.493841 -0.155434  1.397286  1.507055
2000-02 -1.179442  0.443171  1.395676 -0.529658
2000-03  0.787358  0.248845  0.743239  1.267746
2000-04  1.302395 -0.272154 -0.051532 -0.467740
2000-05 -1.040816  0.426419  0.312945 -1.115689

In [230]: annual_frame = frame.resample('A-DEC').mean()

In [231]: annual_frame
Out[231]:
      Colorado     Texas  New York      Ohio
2000  0.556703  0.016631  0.111873 -0.027445
2001  0.046303  0.163344  0.251503 -0.157276
```

Upsampling is more nuanced, as you must make a decision about which end of the timespan in the new frequency to place the values before resampling, just like the `asfreq` method. The `convention` argument defaults to `'start'` but can also be `'end'`:

```
# Q-DEC: Quarterly, year ending in December
In [232]: annual_frame.resample('Q-DEC').ffill()
Out[232]:
```

```
          Colorado     Texas  New York      Ohio
2000Q1  0.556703  0.016631  0.111873 -0.027445
2000Q2  0.556703  0.016631  0.111873 -0.027445
2000Q3  0.556703  0.016631  0.111873 -0.027445
2000Q4  0.556703  0.016631  0.111873 -0.027445
2001Q1  0.046303  0.163344  0.251503 -0.157276
2001Q2  0.046303  0.163344  0.251503 -0.157276
2001Q3  0.046303  0.163344  0.251503 -0.157276
2001Q4  0.046303  0.163344  0.251503 -0.157276

In [233]: annual_frame.resample('Q-DEC', convention='end').ffill()
Out[233]:
          Colorado     Texas  New York      Ohio
2000Q4  0.556703  0.016631  0.111873 -0.027445
2001Q1  0.556703  0.016631  0.111873 -0.027445
2001Q2  0.556703  0.016631  0.111873 -0.027445
2001Q3  0.556703  0.016631  0.111873 -0.027445
2001Q4  0.046303  0.163344  0.251503 -0.157276
```

Since periods refer to timespans, the rules about upsampling and downsampling are more rigid:

- In downsampling, the target frequency must be a *subperiod* of the source frequency.
- In upsampling, the target frequency must be a *superperiod* of the source frequency.

If these rules are not satisfied, an exception will be raised. This mainly affects the quarterly, annual, and weekly frequencies; for example, the timespans defined by `Q-MAR` only line up with `A-MAR`, `A-JUN`, `A-SEP`, and `A-DEC`:

```
In [234]: annual_frame.resample('Q-MAR').ffill()
Out[234]:
          Colorado     Texas  New York      Ohio
2000Q4  0.556703  0.016631  0.111873 -0.027445
2001Q1  0.556703  0.016631  0.111873 -0.027445
2001Q2  0.556703  0.016631  0.111873 -0.027445
2001Q3  0.556703  0.016631  0.111873 -0.027445
2001Q4  0.046303  0.163344  0.251503 -0.157276
2002Q1  0.046303  0.163344  0.251503 -0.157276
2002Q2  0.046303  0.163344  0.251503 -0.157276
2002Q3  0.046303  0.163344  0.251503 -0.157276
```

11.7 Moving Window Functions

An important class of array transformations used for time series operations are statistics and other functions evaluated over a sliding window or with exponentially decaying weights. This can be useful for smoothing noisy or gappy data. I call these *moving window functions*, even though it includes functions without a fixed-length window like exponentially weighted moving average. Like other statistical functions, these also automatically exclude missing data.

Before digging in, we can load up some time series data and resample it to business day frequency:

```
In [235]: close_px_all = pd.read_csv('examples/stock_px_2.csv',
   .....:                            parse_dates=True, index_col=0)

In [236]: close_px = close_px_all[['AAPL', 'MSFT', 'XOM']]

In [237]: close_px = close_px.resample('B').ffill()
```

I now introduce the `rolling` operator, which behaves similarly to `resample` and `groupby`. It can be called on a Series or DataFrame along with a `window` (expressed as a number of periods; see Figure 11-4 for the plot created):

```
In [238]: close_px.AAPL.plot()
Out[238]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2f2570cf98>

In [239]: close_px.AAPL.rolling(250).mean().plot()
```

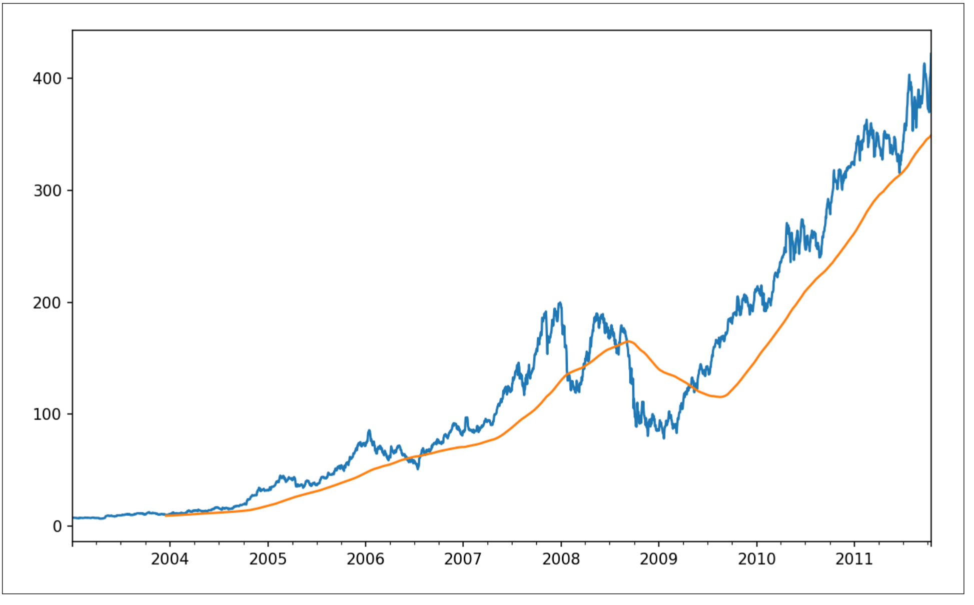

Figure 11-4. Apple Price with 250-day MA

The expression `rolling(250)` is similar in behavior to `groupby`, but instead of grouping it creates an object that enables grouping over a 250-day sliding window. So here we have the 250-day moving window average of Apple's stock price.

By default rolling functions require all of the values in the window to be non-NA. This behavior can be changed to account for missing data and, in particular, the fact that you will have fewer than `window` periods of data at the beginning of the time series (see Figure 11-5):

```
In [241]: appl_std250 = close_px.AAPL.rolling(250, min_periods=10).std()

In [242]: appl_std250[5:12]
Out[242]:
2003-01-09         NaN
2003-01-10         NaN
2003-01-13         NaN
2003-01-14         NaN
2003-01-15    0.077496
2003-01-16    0.074760
2003-01-17    0.112368
Freq: B, Name: AAPL, dtype: float64

In [243]: appl_std250.plot()
```

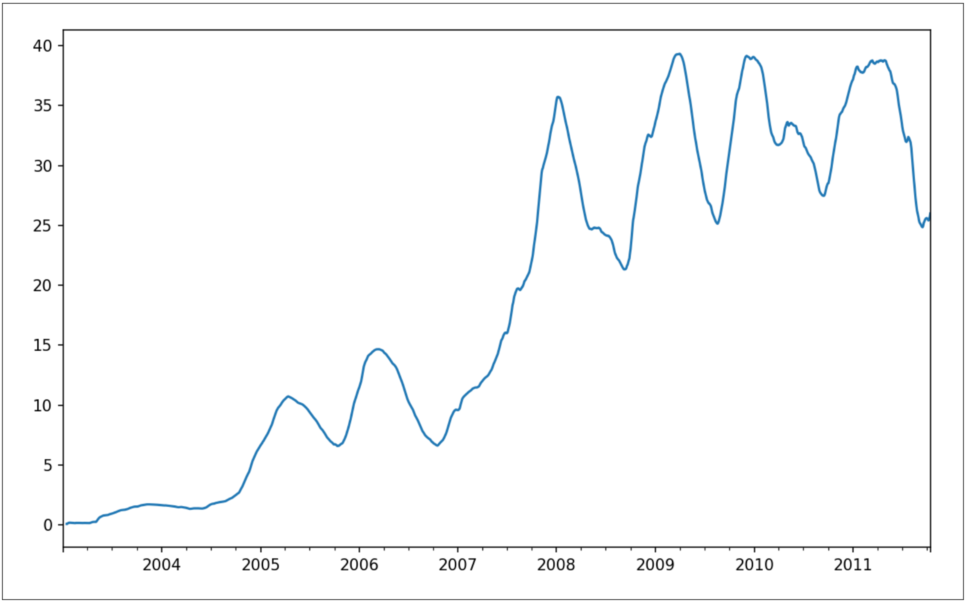

Figure 11-5. Apple 250-day daily return standard deviation

In order to compute an *expanding window mean*, use the `expanding` operator instead of `rolling`. The expanding mean starts the time window from the beginning of the time series and increases the size of the window until it encompasses the whole series. An expanding window mean on the `apple_std250` time series looks like this:

```
In [244]: expanding_mean = appl_std250.expanding().mean()
```

Calling a moving window function on a DataFrame applies the transformation to each column (see Figure 11-6):

```
In [246]: close_px.rolling(60).mean().plot(logy=True)
```

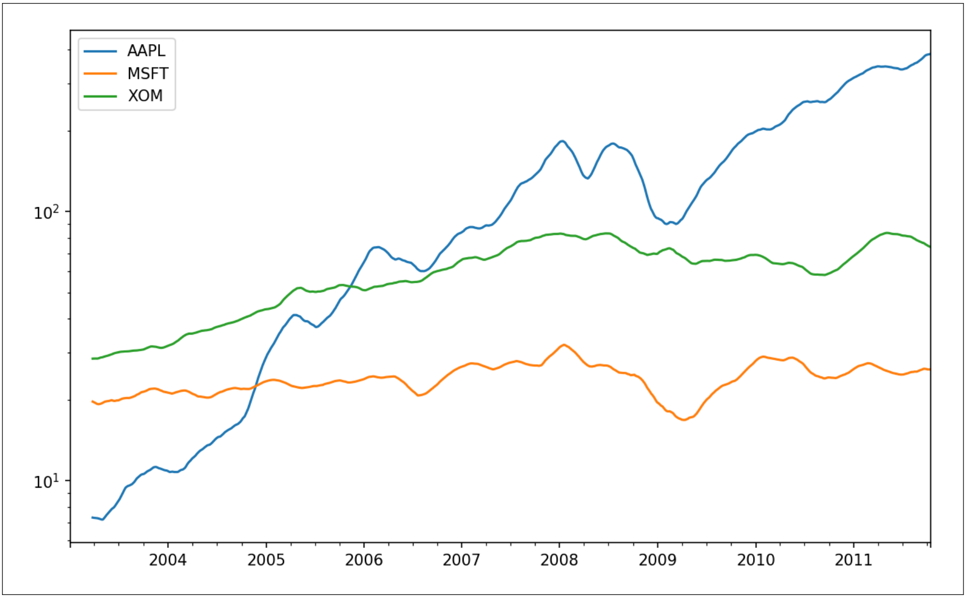

Figure 11-6. Stocks prices 60-day MA (log Y-axis)

The `rolling` function also accepts a string indicating a fixed-size time offset rather than a set number of periods. Using this notation can be useful for irregular time series. These are the same strings that you can pass to `resample`. For example, we could compute a 20-day rolling mean like so:

```
In [247]: close_px.rolling('20D').mean()
Out[247]:
                  AAPL       MSFT        XOM
2003-01-02    7.400000  21.110000  29.220000
2003-01-03    7.425000  21.125000  29.230000
2003-01-06    7.433333  21.256667  29.473333
2003-01-07    7.432500  21.425000  29.342500
2003-01-08    7.402000  21.402000  29.240000
2003-01-09    7.391667  21.490000  29.273333
2003-01-10    7.387143  21.558571  29.238571
2003-01-13    7.378750  21.633750  29.197500
2003-01-14    7.370000  21.717778  29.194444
2003-01-15    7.355000  21.757000  29.152000
...                ...        ...        ...
2011-10-03  398.002143  25.890714  72.413571
2011-10-04  396.802143  25.807857  72.427143
2011-10-05  395.751429  25.729286  72.422857
```

```
2011-10-06  394.099286  25.673571  72.375714
2011-10-07  392.479333  25.712000  72.454667
2011-10-10  389.351429  25.602143  72.527857
2011-10-11  388.505000  25.674286  72.835000
2011-10-12  388.531429  25.810000  73.400714
2011-10-13  388.826429  25.961429  73.905000
2011-10-14  391.038000  26.048667  74.185333
[2292 rows x 3 columns]
```

Exponentially Weighted Functions

An alternative to using a static window size with equally weighted observations is to specify a constant *decay factor* to give more weight to more recent observations. There are a couple of ways to specify the decay factor. A popular one is using a *span*, which makes the result comparable to a simple moving window function with window size equal to the span.

Since an exponentially weighted statistic places more weight on more recent observations, it "adapts" faster to changes compared with the equal-weighted version.

pandas has the `ewm` operator to go along with `rolling` and `expanding`. Here's an example comparing a 60-day moving average of Apple's stock price with an EW moving average with `span=60` (see Figure 11-7):

```
In [249]: aapl_px = close_px.AAPL['2006':'2007']

In [250]: ma60 = aapl_px.rolling(30, min_periods=20).mean()

In [251]: ewma60 = aapl_px.ewm(span=30).mean()

In [252]: ma60.plot(style='k--', label='Simple MA')
Out[252]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2f252161d0>

In [253]: ewma60.plot(style='k-', label='EW MA')
Out[253]: <matplotlib.axes._subplots.AxesSubplot at 0x7f2f252161d0>

In [254]: plt.legend()
```

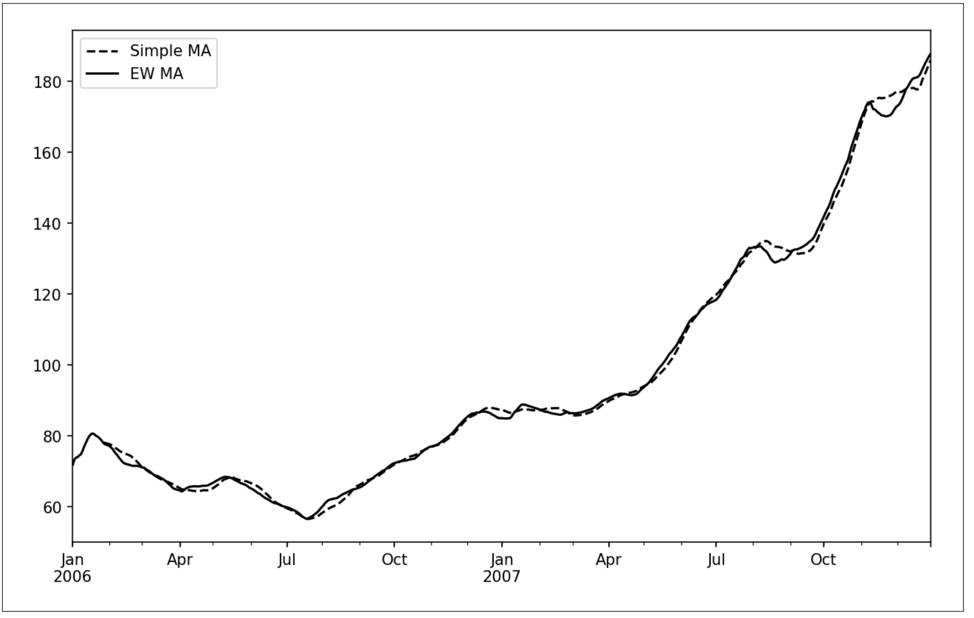

Figure 11-7. Simple moving average versus exponentially weighted

Binary Moving Window Functions

Some statistical operators, like correlation and covariance, need to operate on two time series. As an example, financial analysts are often interested in a stock's correlation to a benchmark index like the S&P 500. To have a look at this, we first compute the percent change for all of our time series of interest:

```
In [256]: spx_px = close_px_all['SPX']

In [257]: spx_rets = spx_px.pct_change()

In [258]: returns = close_px.pct_change()
```

The `corr` aggregation function after we call `rolling` can then compute the rolling correlation with `spx_rets` (see Figure 11-8 for the resulting plot):

```
In [259]: corr = returns.AAPL.rolling(125, min_periods=100).corr(spx_rets)

In [260]: corr.plot()
```

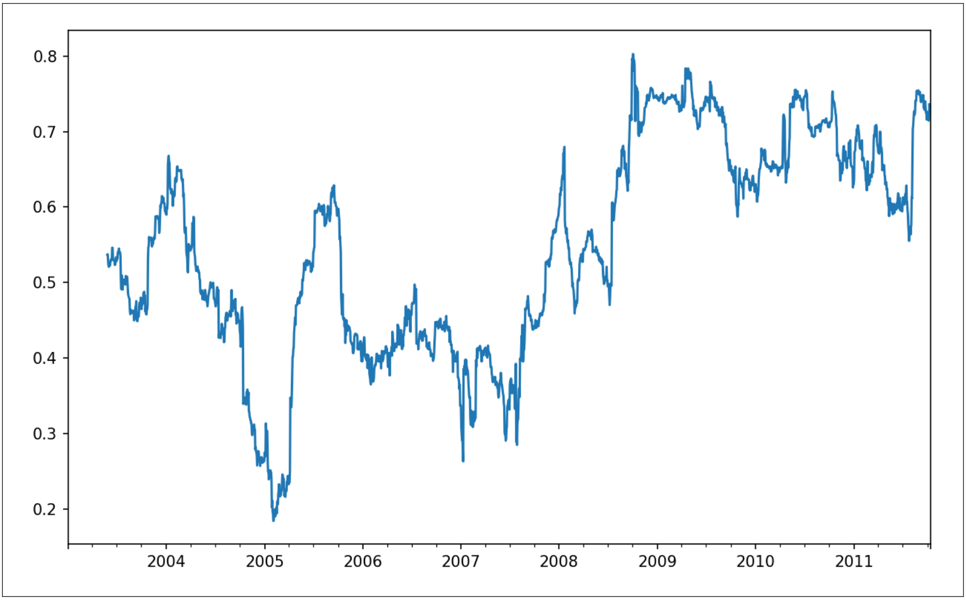

Figure 11-8. Six-month AAPL return correlation to S&P 500

Suppose you wanted to compute the correlation of the S&P 500 index with many stocks at once. Writing a loop and creating a new DataFrame would be easy but might get repetitive, so if you pass a Series and a DataFrame, a function like `rolling_corr` will compute the correlation of the Series (`spx_rets`, in this case) with each column in the DataFrame (see Figure 11-9 for the plot of the result):

```
In [262]: corr = returns.rolling(125, min_periods=100).corr(spx_rets)

In [263]: corr.plot()
```

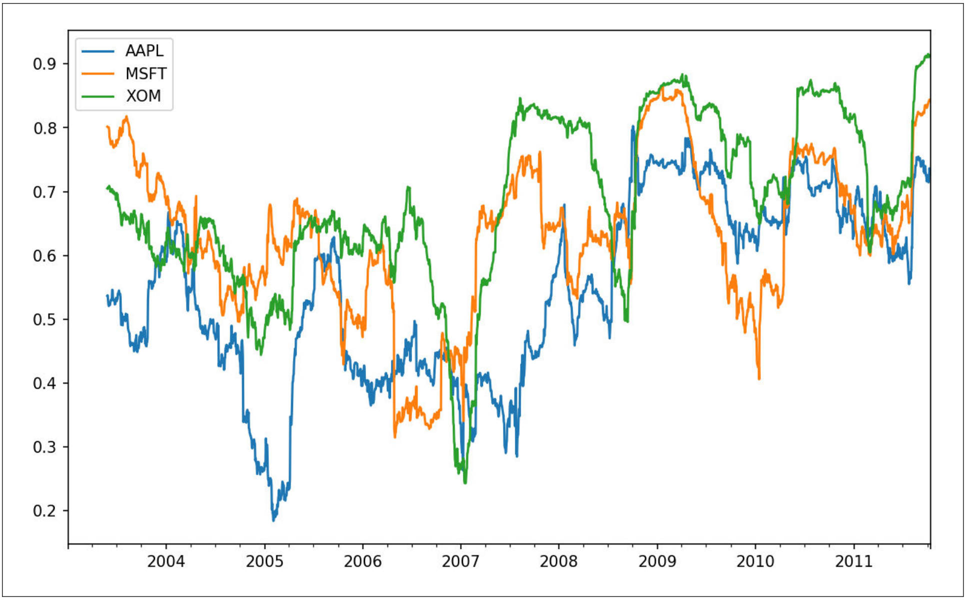

Figure 11-9. Six-month return correlations to S&P 500

User-Defined Moving Window Functions

The `apply` method on `rolling` and related methods provides a means to apply an array function of your own devising over a moving window. The only requirement is that the function produce a single value (a reduction) from each piece of the array. For example, while we can compute sample quantiles using `rolling(...).quantile(q)`, we might be interested in the percentile rank of a particular value over the sample. The `scipy.stats.percentileofscore` function does just this (see Figure 11-10 for the resulting plot):

```
In [265]: from scipy.stats import percentileofscore

In [266]: score_at_2percent = lambda x: percentileofscore(x, 0.02)

In [267]: result = returns.AAPL.rolling(250).apply(score_at_2percent)

In [268]: result.plot()
```

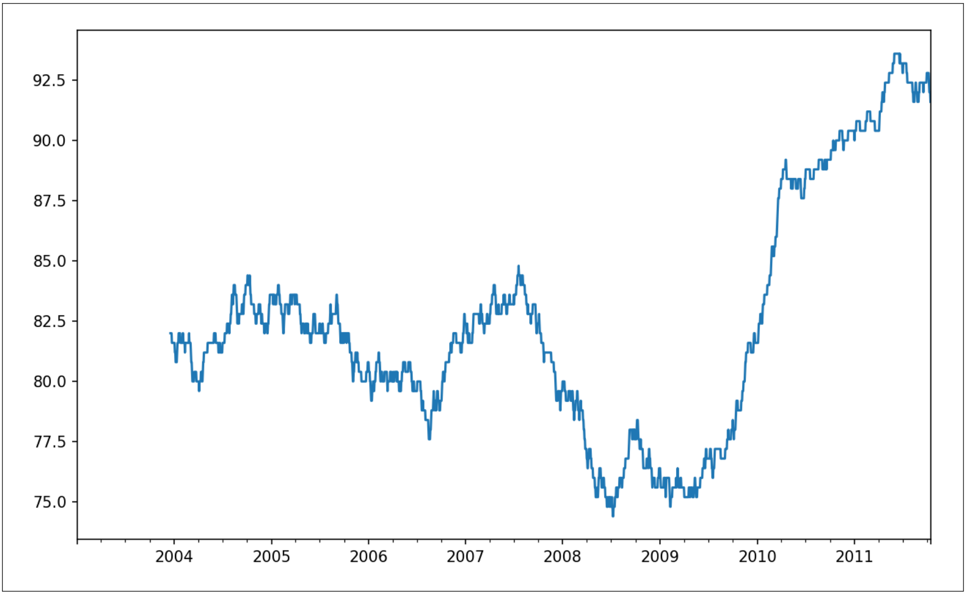

Figure 11-10. Percentile rank of 2% AAPL return over one-year window

If you don't have SciPy installed already, you can install it with conda or pip.

11.8 Conclusion

Time series data calls for different types of analysis and data transformation tools than the other types of data we have explored in previous chapters.

In the following chapters, we will move on to some advanced pandas methods and show how to start using modeling libraries like statsmodels and scikit-learn.