Financial Data Analysis with Python

Instructor: Luping Yu

Apr 19, 2022

Lecture 07. Time Series

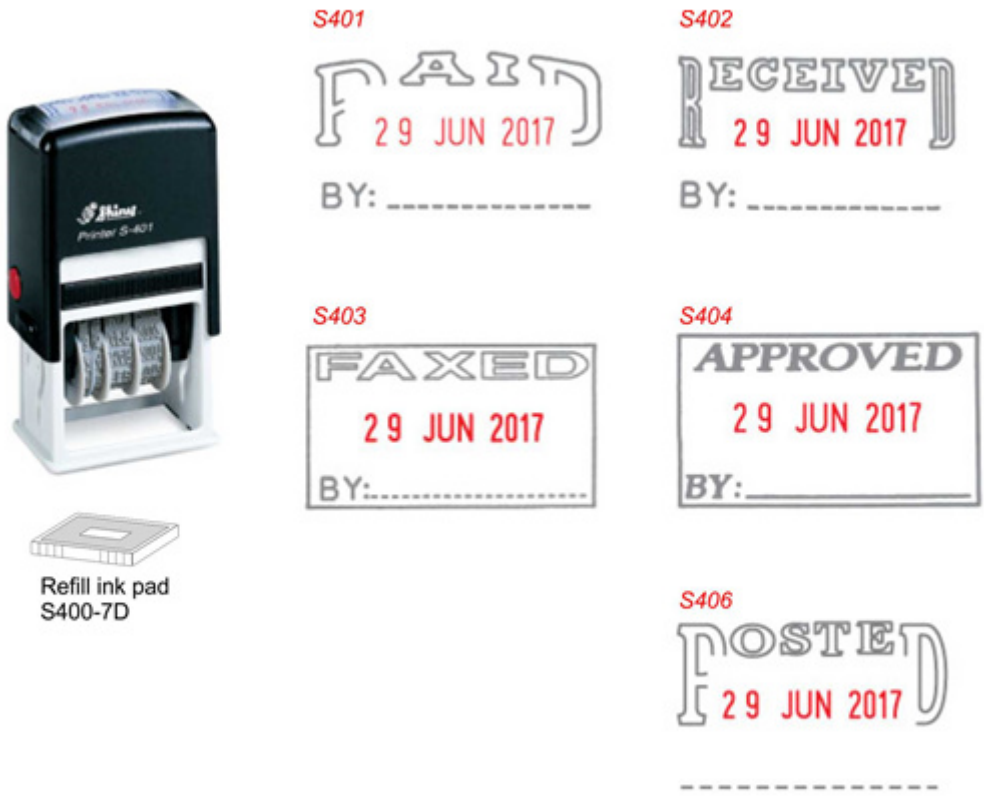
Time series data is an important form of structured data in many different fields, such as finance, economics, ecology, neuroscience, and physics. Anything that is observed or measured at many points in time forms a time series.

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.

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)

The simplest and most widely used kind of time series are those indexed by **timestamp**.



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 [162…
```
from datetime import datetime

now = datetime.now()

now
```

Out[162]:
```
datetime.datetime(2022, 4, 19, 13, 41, 57, 354961)
```

In [161…
```
now.year, now.month, now.day
```

Out[161]:
```
(2022, 4, 19)
```

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

In [163…
```
delta = datetime(2011, 1, 7) - datetime(2008, 6, 24, 8, 15)

delta
```

Out[163]:
```
datetime.timedelta(days=926, seconds=56700)
```

In [165…
```
delta.days
```

Out[165]:
```
926
```

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

In [171…
```
from datetime import timedelta

start = datetime(2011, 1, 7)

start - timedelta(2)
```

Out[171]:
```
datetime.datetime(2011, 1, 5, 0, 0)
```

In [170…
```
start + 2 * timedelta(weeks=2)
```

Out[170]:
```
datetime.datetime(2011, 2, 4, 0, 0)
```

The following table 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.

- 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 twodatetimevalues (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 as strings using str or the strftime method, passing a format specification:

In [177…
```
stamp = datetime(2011, 1, 3)

str(stamp)
```

Out[177]:
```
'2011-01-03 00:00:00'
```

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

In [179…
```
value = '2011-01-03'
```

```
datetime.strptime(value, '%Y-%m-%d')
```

Out[179]:
```
datetime.datetime(2011, 1, 3, 0, 0)
```

See the following table for a complete list of the format codes.

- 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]
%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+HHMMor-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)

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 [13]:
```
from dateutil.parser import parse

parse('2011-01-03')
```

Out[13]:
```
datetime.datetime(2011, 1, 3, 0, 0)
```

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

In [14]:
```
parse('Jan 31, 1997 10:45 PM')
```

Out[14]:
```
datetime.datetime(1997, 1, 31, 22, 45)
```

dateutil.parser is a useful but **imperfect** tool. Notably, it will recognize some strings as dates that you might prefer that it didn't.

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

In [15]:
```
parse('6/12/2011', dayfirst=True)
```

Out[15]:
```
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:

In [180…
```
import pandas as pd

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

pd.to_datetime(datestrs)
```

Out[180]:
```
DatetimeIndex(['2011-07-06 12:00:00', '2011-08-06 00:00:00'], dtype='dateti
me64[ns]', freq=None)
```

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 [181…
```
import numpy as np
from datetime import datetime

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)]

ts = pd.Series(np.random.randn(6), index=dates)

ts
```

Out[181]:
```
2011-01-02   -1.111609
2011-01-05    0.730356
2011-01-07    1.137256
2011-01-08   -0.546944
2011-01-10    1.739067
2011-01-12   -0.037028
dtype: float64
```

These *datetime* objects have been put in a **DatetimeIndex**:

In [182…
```
ts.index
```

Out[182]:
```
DatetimeIndex(['2011-01-02', '2011-01-05', '2011-01-07', '2011-01-08',
               '2011-01-10', '2011-01-12'],
              dtype='datetime64[ns]', freq=None)
```

Scalar values from a DatetimeIndex are pandas **Timestamp** objects. A Timestamp can be substituted anywhere you would use a datetime object.

In [23]:
```
stamp = ts.index[0]

stamp
```

Out[23]:
```
Timestamp('2011-01-02 00:00:00')
```

Indexing, Selection, Subsetting

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

In [24]:
```
ts
```

Out[24]:
```
2011-01-02   -0.911718
2011-01-05    2.197026
2011-01-07   -0.689209
2011-01-08    0.274974
2011-01-10    0.824664
2011-01-12    1.499308
dtype: float64
```

In [188…
```
stamp = ts.index[2]

stamp
```

Out[188]:
```
Timestamp('2011-01-07 00:00:00')
```

In [189…
```
ts[stamp]
```

Out[189]:
```
1.1372558017988617
```

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

In [197…
```
ts['1/07/2011']
```

Out[197]:
```
1.1372558017988617
```

In [198…
```
ts['20110107']
```

Out[198]:
```
1.1372558017988617
```

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

In [199…
```
longer_ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000',

longer_ts
```

Out[199]:
```
2000-01-01   -0.435354
2000-01-02   -0.386446
2000-01-03   -1.957366
2000-01-04   -0.183992
2000-01-05   -1.863349
                ...
2002-09-22   -0.432783
2002-09-23   -0.592788
2002-09-24   -0.968569
2002-09-25    1.069541
2002-09-26    0.269476
Freq: D, Length: 1000, dtype: float64
```

In [200…
```
longer_ts['2001']
```

Out[200]:
```
2001-01-01   -0.087670
2001-01-02    1.777985
2001-01-03   -1.202116
2001-01-04    1.012693
2001-01-05   -1.014581
                ...
2001-12-27    0.467473
2001-12-28    1.535767
2001-12-29   -0.368054
2001-12-30   -0.786765
2001-12-31    0.793735
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 [201…
```
longer_ts['2001-05']
```

Out[201]:
```
2001-05-01    0.829231
2001-05-02    1.000593
2001-05-03    0.147581
2001-05-04   -0.191247
2001-05-05    1.831707
2001-05-06    0.039325
2001-05-07   -1.623693
2001-05-08   -0.559242
2001-05-09    0.882382
2001-05-10   -0.437419
2001-05-11   -2.055227
2001-05-12   -0.331504
2001-05-13    1.119251
2001-05-14   -0.331821
2001-05-15    0.164686
2001-05-16   -0.469816
2001-05-17    0.460466
2001-05-18    1.081028
2001-05-19    0.495317
2001-05-20   -0.572936
2001-05-21    0.761781
2001-05-22   -0.398715
2001-05-23   -0.342683
2001-05-24    0.775179
2001-05-25    0.753699
2001-05-26   -0.788235
2001-05-27   -2.093216
2001-05-28    1.718284
2001-05-29   -1.005148
2001-05-30   -1.138641
2001-05-31   -0.091314
Freq: D, dtype: float64
```

Slicing with datetime objects works as well:

In [202…
```
ts
```

Out[202]:
```
2011-01-02   -1.111609
2011-01-05    0.730356
2011-01-07    1.137256
2011-01-08   -0.546944
2011-01-10    1.739067
2011-01-12   -0.037028
dtype: float64
```

In [203…
```
ts['1/7/2011':]
```

Out[203]:
```
2011-01-07    1.137256
2011-01-08   -0.546944
2011-01-10    1.739067
2011-01-12   -0.037028
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 [204…
```
ts['1/6/2011':'1/11/2011']
```

Out[204]:
```
2011-01-07    1.137256
2011-01-08   -0.546944
2011-01-10    1.739067
dtype: float64
```

As before, you can pass **either** a string date, datetime, or timestamp.

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

In [205…
```
dates = pd.date_range('1/1/2000', periods=100, freq='W-WED')

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

long_df
```

Out[205]:

	Colorado	Texas	New York	Ohio
2000-01-05	0.799164	0.051463	0.445165	0.224321
2000-01-12	1.752338	-0.751045	-0.626184	0.118493
2000-01-19	-0.158154	-0.277779	0.663892	1.333085
2000-01-26	0.782488	-0.220731	2.284401	-0.954393
2000-02-02	0.554732	0.877276	0.835223	-0.029460
…	…	…	…	…
2001-10-31	-0.307398	-0.424102	0.307677	-0.011703
2001-11-07	-0.837008	0.254166	1.554311	0.805128
2001-11-14	-1.740764	0.955150	-2.065485	0.461094
2001-11-21	1.495330	1.507724	-1.651472	-1.271039
2001-11-28	-1.099605	-0.144070	-0.067349	-0.469499

100 rows × 4 columns

In [206…
```
long_df.loc['5-2001']
```

Out[206]:

	Colorado	Texas	New York	Ohio
2001-05-02	-0.002584	0.846190	-1.300307	0.196798
2001-05-09	1.360740	1.498257	0.437565	-1.545533
2001-05-16	0.737758	-1.650453	-0.369436	0.133414
2001-05-23	-1.025775	-0.195434	-1.510350	-1.242903
2001-05-30	-0.546969	0.171810	0.136771	-0.776349

Date Ranges, Frequencies, and Shifting

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.

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

In [207…
```
index = pd.date_range('2012-04-01', '2012-06-01')

index
```

Out[207]:
```
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 [208…
```
pd.date_range(start='2012-04-01', periods=20)
```

```
Out[208]: 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 [209…
pd.date_range(end='2012-06-01', periods=20)
```

```
Out[209]: 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 the following table) and only dates falling on or inside the date interval will be included:

```
In [210…
pd.date_range('2000-01-01', '2000-12-01', freq='BM')
```

```
Out[210]: 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')
```

- 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-3FRIfor the third Friday of each month)

Alias	Offset type	Description
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

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. Putting an integer before the base frequency creates a multiple:

In [61]:
```
pd.date_range('2000-01-01', '2000-01-03 23:59', freq='4H')
```

Out[61]:
```
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')
```

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 whether the month ends on a weekend or not. We refer to these as **anchored offsets**.

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 [211…
```
third_friday = pd.date_range('2012-01-01', '2012-09-01', freq='WOM-3FRI')

third_friday
```

Out[211]:
```
DatetimeIndex(['2012-01-20', '2012-02-17', '2012-03-16', '2012-04-20',
               '2012-05-18', '2012-06-15', '2012-07-20', '2012-08-17'],
              dtype='datetime64[ns]', freq='WOM-3FRI')
```

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 [212…
```
ts = pd.Series(np.random.randn(4),
               index=pd.date_range('1/1/2000', periods=4, freq='M'))

ts
```

Out[212]:
```
2000-01-31   -0.725961
2000-02-29   -0.172155
2000-03-31   -1.366800
2000-04-30    0.026437
Freq: M, dtype: float64
```

In [213…
```
ts.shift(2)
```

Out[213]:
```
2000-01-31         NaN
2000-02-29         NaN
2000-03-31   -0.725961
2000-04-30   -0.172155
Freq: M, dtype: float64
```

In [214…
```
ts.shift(-2)
```

Out[214]:
```
2000-01-31   -1.366800
2000-02-29    0.026437
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:

In [215…
```
ts
```

Out[215]:
```
2000-01-31   -0.725961
2000-02-29   -0.172155
2000-03-31   -1.366800
2000-04-30    0.026437
Freq: M, dtype: float64
```

In [216…
```
 ts / ts.shift(1) - 1
```

Out[216]:
```
2000-01-31         NaN
2000-02-29   -0.762859
2000-03-31    6.939357
2000-04-30   -1.019342
Freq: M, dtype: float64
```

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 [74]:
```
ts
```

Out[74]:
```
2000-01-31    1.626873
2000-02-29   -0.726341
2000-03-31   -0.360541
2000-04-30   -0.234084
Freq: M, dtype: float64
```

In [75]:
```
ts.shift(2, freq='M')
```

Out[75]:
```
2000-03-31    1.626873
2000-04-30   -0.726341
2000-05-31   -0.360541
2000-06-30   -0.234084
Freq: M, dtype: float64
```

In [73]:
```
ts.shift(3, freq='D')
```

Out[73]:
```
2000-02-03    1.626873
2000-03-03   -0.726341
2000-04-03   -0.360541
2000-05-03   -0.234084
dtype: float64
```

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. The time in China follows a single standard time offset of UTC+08:00 (eight hours ahead of UTC), even though China spans almost five geographical time zones.

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

In [217…
```
rng = pd.date_range('3/9/2012 9:30', periods=6, freq='D')

ts = pd.Series(np.random.randn(len(rng)), index=rng)

ts
```

Out[217]:
```
2012-03-09 09:30:00    1.103999
2012-03-10 09:30:00    1.880919
2012-03-11 09:30:00    2.458479
2012-03-12 09:30:00    0.318431
2012-03-13 09:30:00   -0.179107
2012-03-14 09:30:00   -0.820670
Freq: D, dtype: float64
```

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

In [218…
```
ts_utc = ts.tz_localize('UTC')

ts_utc
```

Out[218]:
```
2012-03-09 09:30:00+00:00    1.103999
2012-03-10 09:30:00+00:00    1.880919
2012-03-11 09:30:00+00:00    2.458479
2012-03-12 09:30:00+00:00    0.318431
2012-03-13 09:30:00+00:00   -0.179107
2012-03-14 09:30:00+00:00   -0.820670
Freq: D, dtype: float64
```

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

List of all time zones

In [219…
```
ts_utc.tz_convert('America/New_York')
```

Out[219]:
```
2012-03-09 04:30:00-05:00    1.103999
2012-03-10 04:30:00-05:00    1.880919
2012-03-11 05:30:00-04:00    2.458479
2012-03-12 05:30:00-04:00    0.318431
2012-03-13 05:30:00-04:00   -0.179107
2012-03-14 05:30:00-04:00   -0.820670
Freq: D, dtype: float64
```

In [220…
```
ts_utc.tz_convert('Asia/Shanghai')
```

Out[220]:
```
2012-03-09 17:30:00+08:00    1.103999
2012-03-10 17:30:00+08:00    1.880919
2012-03-11 17:30:00+08:00    2.458479
2012-03-12 17:30:00+08:00    0.318431
2012-03-13 17:30:00+08:00   -0.179107
2012-03-14 17:30:00+08:00   -0.820670
Freq: D, dtype: float64
```

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.

In [221…
```
p = pd.Period(2007, freq='A-DEC')

p
```

Out[221]:
```
Period('2007', 'A-DEC')
```

In this case, the Period object represents the full timespan from January 1, 2007, to December 31, 2007, inclusive.

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:

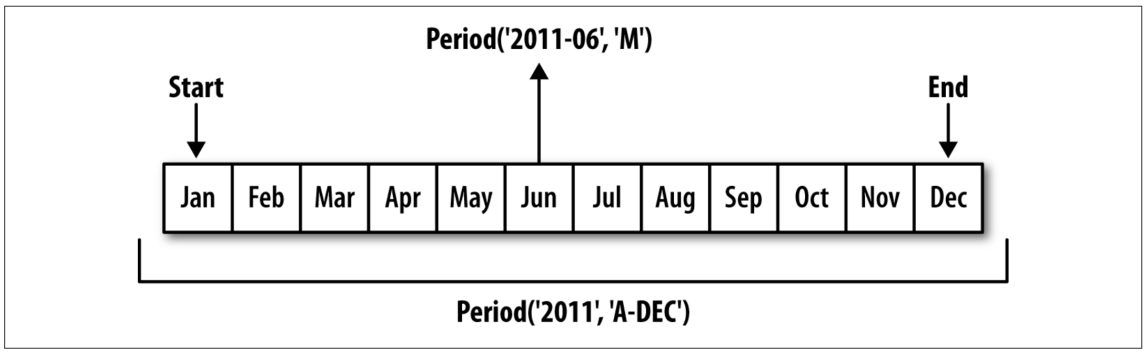
In [222…
```
p.asfreq('M', how='start')
```

```
Out[222]: Period('2007-01', 'M')
```

```
In [107…
p.asfreq('M', how='end')
```

```
Out[107]: Period('2007-12', 'M')
```

- Period frequency conversion illustration



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.

pandas supports all 12 possible quarterly frequencies as Q-JAN through Q-DEC:

```
In [223…
p = pd.Period('2012Q4', freq='Q-JAN')

p
```

```
Out[223]: 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:

```
In [224…
p.asfreq('D', 'start')
```

```
Out[224]: Period('2011-11-01', 'D')
```

```
In [225…
p.asfreq('D', 'end')
```

```
Out[225]: Period('2012-01-31', 'D')
```

- Different quarterly frequency conventions

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**.

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 [115…
```
rng = pd.date_range('2000-01-01', periods=100, freq='D')

ts = pd.Series(np.random.randn(len(rng)), index=rng)

ts
```

Out[115]:
```
2000-01-01   -0.827863
2000-01-02   -0.633088
2000-01-03   -0.722080
2000-01-04   -1.602322
2000-01-05    0.212868
                ...
2000-04-05   -0.505932
2000-04-06    0.547278
2000-04-07   -0.057368
2000-04-08   -0.800720
2000-04-09   -0.321209
Freq: D, Length: 100, dtype: float64
```

In [116…
```
ts.resample('M').mean()
```

Out[116]:
```
2000-01-31   -0.357645
2000-02-29   -0.035910
2000-03-31   -0.178485
2000-04-30    0.056938
Freq: M, dtype: float64
```

In [117…
```
ts.resample('M', kind='period').mean()
```

Out[117]:
```
2000-01   -0.357645
2000-02   -0.035910
2000-03   -0.178485
2000-04    0.056938
Freq: M, dtype: float64
```

resample is a flexible and high-performance method that can be used to process very large time series. The following table summarizes some of its options.

- 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 labeled9:30or9:35)
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 convert

Downsampling

Aggregating data to a regular, lower frequency is a pretty normal time series task.

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.

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

In [226…
```
rng = pd.date_range('2000-01-01', periods=12, freq='T')

ts = pd.Series(np.arange(12), index=rng)

ts
```

Out[226]:
```
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 [227…
```
ts.resample('5min').sum()
```

Out[227]:
```
2000-01-01 00:00:00    10
2000-01-01 00:05:00    35
2000-01-01 00:10:00    21
Freq: 5T, dtype: int64
```

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 [228…
```
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'])

frame
```

Out[228]:

	Colorado	Texas	New York	Ohio
2000-01-05	1.542921	-0.685958	0.354229	-0.635666
2000-01-12	2.799644	0.783979	-0.939225	-0.771202

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 [229…
```
df_daily = frame.resample('D').asfreq()

df_daily
```

Out[229]:

	Colorado	Texas	New York	Ohio
2000-01-05	1.542921	-0.685958	0.354229	-0.635666
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	2.799644	0.783979	-0.939225	-0.771202

Suppose you wanted to fill forward each weekly value on the non-Wednesdays:

In [230…
```
frame.resample('D').ffill()
```

Out[230]:

	Colorado	Texas	New York	Ohio
2000-01-05	1.542921	-0.685958	0.354229	-0.635666
2000-01-06	1.542921	-0.685958	0.354229	-0.635666
2000-01-07	1.542921	-0.685958	0.354229	-0.635666
2000-01-08	1.542921	-0.685958	0.354229	-0.635666
2000-01-09	1.542921	-0.685958	0.354229	-0.635666
2000-01-10	1.542921	-0.685958	0.354229	-0.635666
2000-01-11	1.542921	-0.685958	0.354229	-0.635666
2000-01-12	2.799644	0.783979	-0.939225	-0.771202

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

In [231…

```
frame.resample('D').ffill(limit=2)
```

Out[231]:

	Colorado	Texas	New York	Ohio
2000-01-05	1.542921	-0.685958	0.354229	-0.635666
2000-01-06	1.542921	-0.685958	0.354229	-0.635666
2000-01-07	1.542921	-0.685958	0.354229	-0.635666
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	2.799644	0.783979	-0.939225	-0.771202

Moving Window Functions

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

In [234…

```
close_px_all = pd.read_csv('examples/stock_px_2.csv',
                           parse_dates=True, index_col=0)

close_px_all
```

Out[234]:

	AAPL	MSFT	XOM	SPX
2003-01-02	7.40	21.11	29.22	909.03
2003-01-03	7.45	21.14	29.24	908.59
2003-01-06	7.45	21.52	29.96	929.01
2003-01-07	7.43	21.93	28.95	922.93
2003-01-08	7.28	21.31	28.83	909.93
...	...	...	...	...
2011-10-10	388.81	26.94	76.28	1194.89
2011-10-11	400.29	27.00	76.27	1195.54
2011-10-12	402.19	26.96	77.16	1207.25
2011-10-13	408.43	27.18	76.37	1203.66
2011-10-14	422.00	27.27	78.11	1224.58

2214 rows × 4 columns

In [237…

```
close_px = close_px_all.resample('B').ffill()

close_px
```

Out[237]:

	AAPL	MSFT	XOM	SPX
2003-01-02	7.40	21.11	29.22	909.03
2003-01-03	7.45	21.14	29.24	908.59
2003-01-06	7.45	21.52	29.96	929.01
2003-01-07	7.43	21.93	28.95	922.93
2003-01-08	7.28	21.31	28.83	909.93
...	...	...	...	...
2011-10-10	388.81	26.94	76.28	1194.89
2011-10-11	400.29	27.00	76.27	1195.54
2011-10-12	402.19	26.96	77.16	1207.25
2011-10-13	408.43	27.18	76.37	1203.66
2011-10-14	422.00	27.27	78.11	1224.58

2292 rows × 4 columns

We 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:

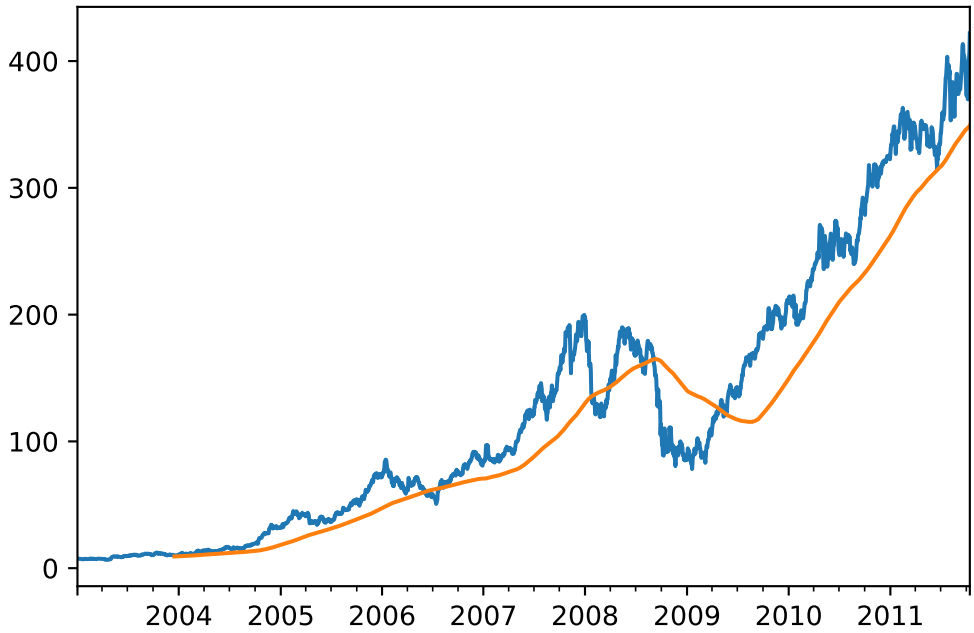
In [238…

```
%matplotlib inline
%config InlineBackend.figure_format = 'svg'

close_px['AAPL'].plot()
close_px['AAPL'].rolling(250).mean().plot()
```

Out[238]:

```
<AxesSubplot:>
```



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 [239…
```
returns = close_px / close_px.shift(1) - 1

returns
```

Out[239]:

	AAPL	MSFT	XOM	SPX
2003-01-02	NaN	NaN	NaN	NaN
2003-01-03	0.006757	0.001421	0.000684	-0.000484
2003-01-06	0.000000	0.017975	0.024624	0.022474
2003-01-07	-0.002685	0.019052	-0.033712	-0.006545
2003-01-08	-0.020188	-0.028272	-0.004145	-0.014086
…	…	…	…	…
2011-10-10	0.051406	0.026286	0.036977	0.034125
2011-10-11	0.029526	0.002227	-0.000131	0.000544
2011-10-12	0.004747	-0.001481	0.011669	0.009795
2011-10-13	0.015515	0.008160	-0.010238	-0.002974
2011-10-14	0.033225	0.003311	0.022784	0.017380

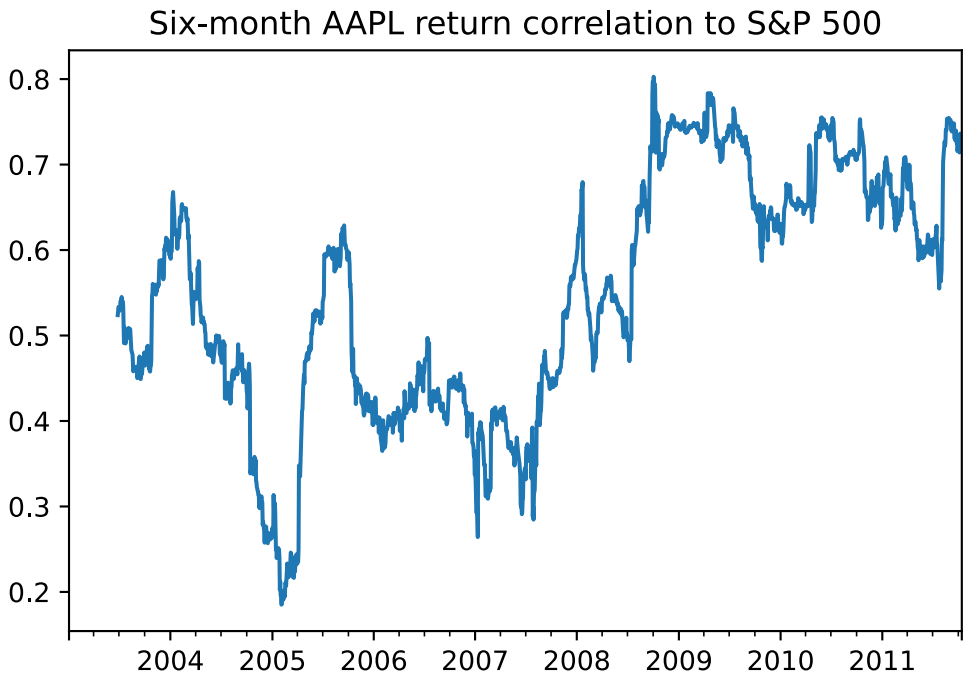
2292 rows × 4 columns

The **corr** aggregation function after we call rolling can then compute the rolling correlation with S&P Index:

In [240…
```
corr = returns['AAPL'].rolling(125).corr(returns['SPX'])
```

```
corr.plot(title="Six-month AAPL return correlation to S&P 500")
```

Out[240]:
```
<AxesSubplot:title={'center':'Six-month AAPL return correlation to S&P 50
0'}>
```



In [241…
```
corr = returns.rolling(125).corr(returns['SPX'])

corr.plot(title="Six-month return correlations to S&P 500")
```

Out[241]:
```
<AxesSubplot:title={'center':'Six-month return correlations to S&P 500'}>
```