Plotting

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
```

The plots in this document are made using matplotlib's `ggplot` style (new in version 1.4):

```
import matplotlib
matplotlib.style.use('ggplot')
```

If your version of matplotlib is 1.3 or lower, you can set `display.mpl_style` to `'default'` with `pd.options.display.mpl_style = 'default'` to produce more appealing plots. When set, matplotlib's `rcParams` are changed (globally!) to nicer-looking settings.

We provide the basics in pandas to easily create decent looking plots. See the *ecosystem* section for visualization libraries that go beyond the basics documented here.

Note: All calls to `np.random` are seeded with 123456.

Basic Plotting: `plot`

See the *cookbook* for some advanced strategies

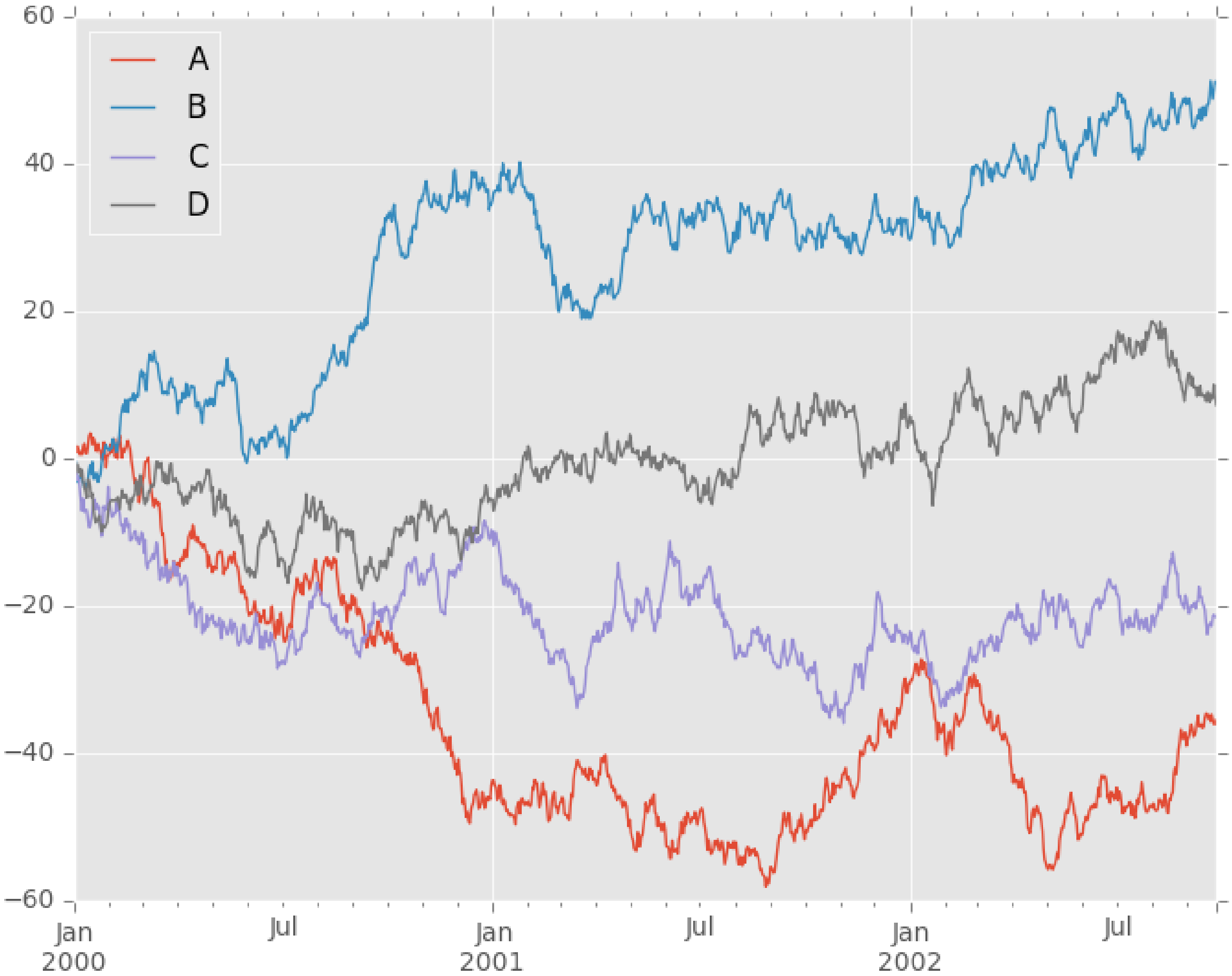
The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [2]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [3]: ts = ts.cumsum()

In [4]: ts.plot()
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x9e433bec>
```

If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

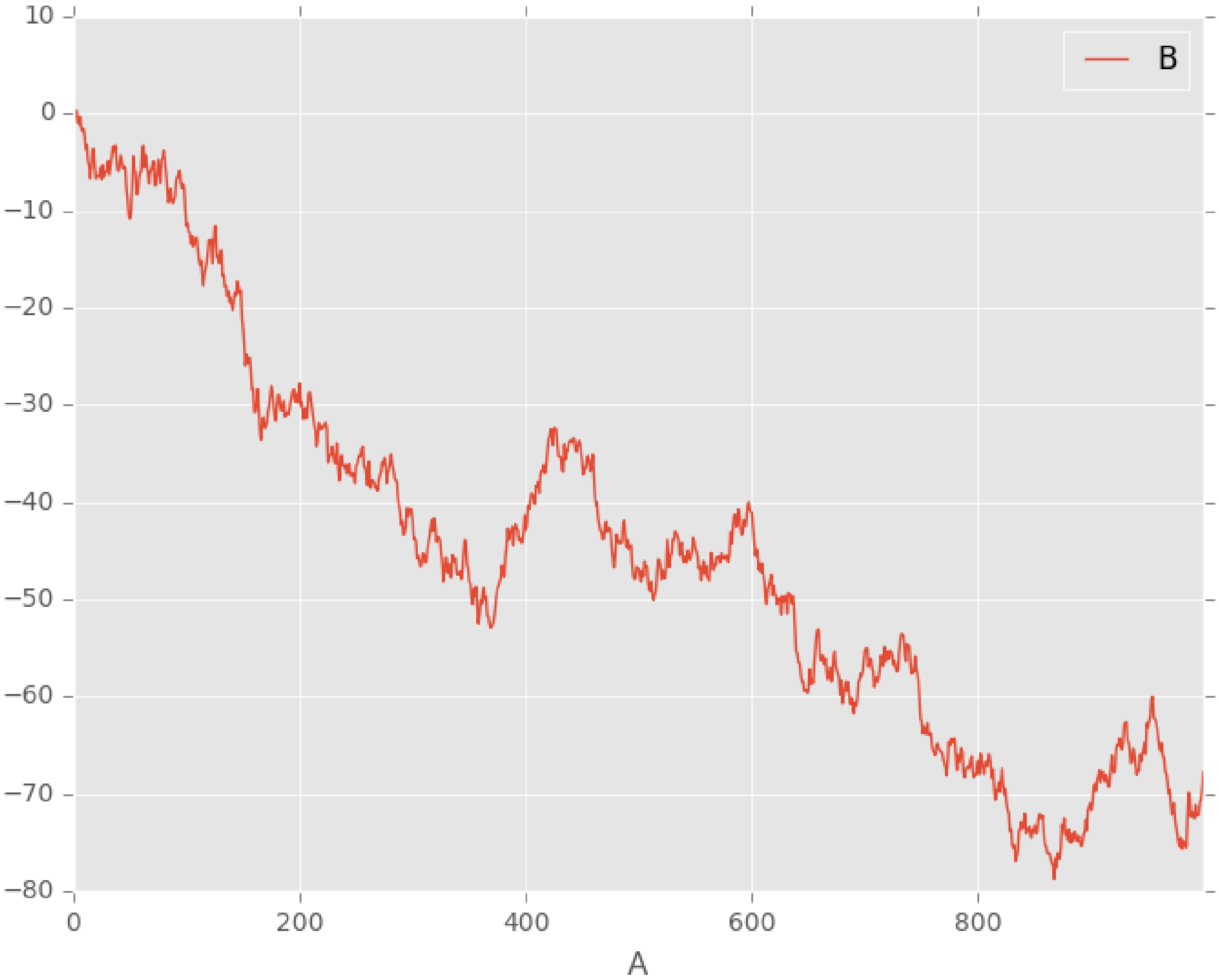
On DataFrame, `plot()` is a convenience to plot all of the columns with labels:

```
In [5]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [6]: df = df.cumsum()

In [7]: plt.figure(); df.plot();
```



You can plot one column versus another using the *x* and *y* keywords in `plot()`:

```
In [8]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()

In [9]: df3['A'] = pd.Series(list(range(len(df))))

In [10]: df3.plot(x='A', y='B')
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x9e1aeb6c>
```



Note: For more formatting and sytling options, see *below*.

Other Plots

Plotting methods allow for a handful of plot styles other than the default Line plot. These methods can be provided as the `kind` keyword argument to `plot()`. These include:

- *'bar'* or *'barh'* for bar plots
- *'hist'* for histogram
- *'box'* for boxplot
- *'kde'* or `'density'` for density plots
- *'area'* for area plots
- *'scatter'* for scatter plots
- *'hexbin'* for hexagonal bin plots
- *'pie'* for pie plots

New in version 0.17.

You can also create these other plots using the methods `DataFrame.plot.<kind>` instead of providing the `kind` keyword argument. This makes it easier to discover plot methods and the specific arguments they use:

```
In [11]: df = pd.DataFrame()

In [12]: df.plot.<TAB>
df.plot.area      df.plot.barh      df.plot.density   df.plot.hist      df.plot.line      df.plot.s
df.plot.bar       df.plot.box       df.plot.hexbin    df.plot.kde       df.plot.pie
```

In addition to these `kind` s, there are the *DataFrame.hist()*, and *DataFrame.boxplot()* methods, which use a separate interface.

Finally, there are several *plotting functions* in `pandas.tools.plotting` that take a `Series` or `DataFrame` as an argument. These include

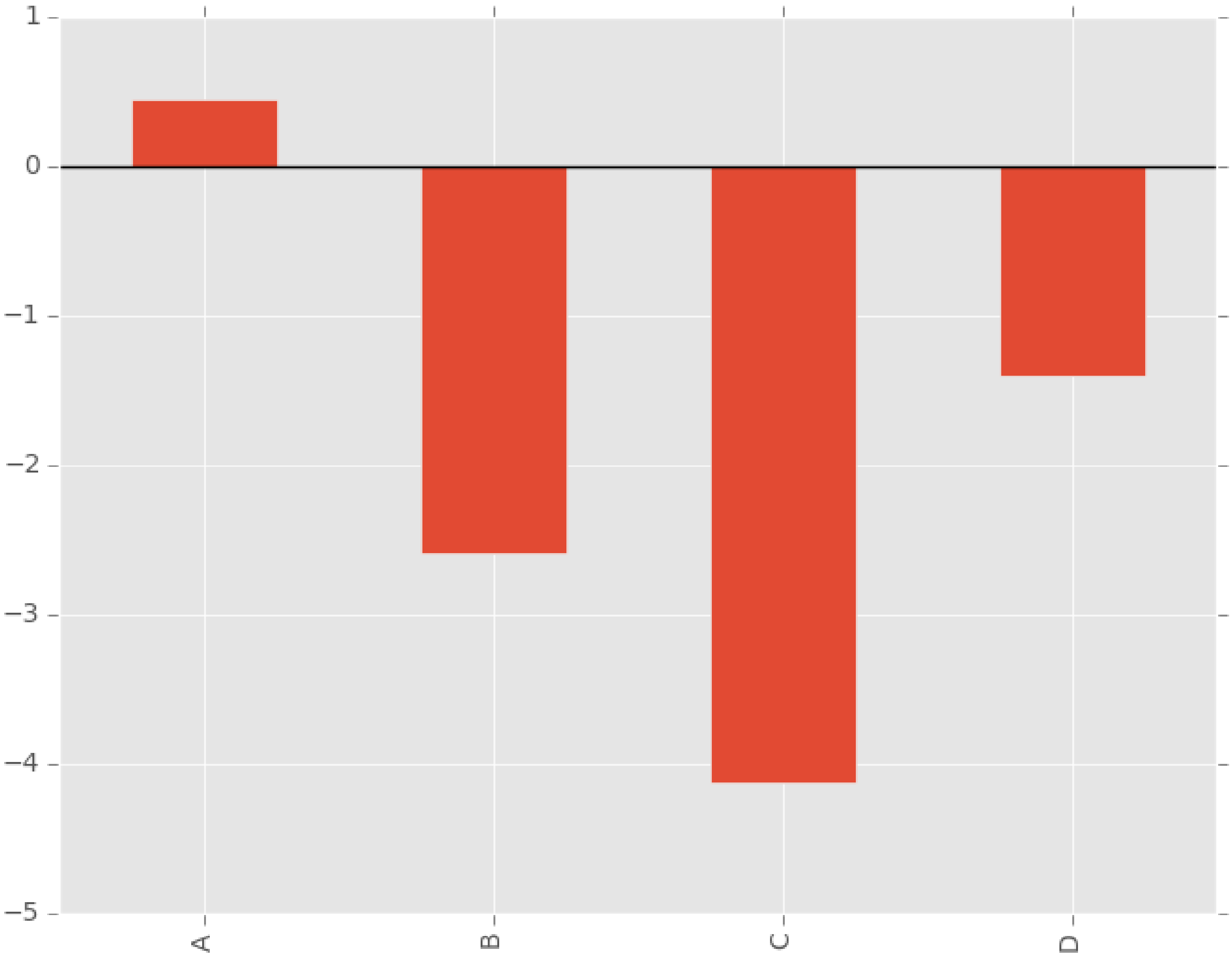
- *Scatter Matrix*
- *Andrews Curves*
- *Parallel Coordinates*
- *Lag Plot*
- *Autocorrelation Plot*
- *Bootstrap Plot*
- *RadViz*

Plots may also be adorned with *errorbars* or *tables*.

Bar plots

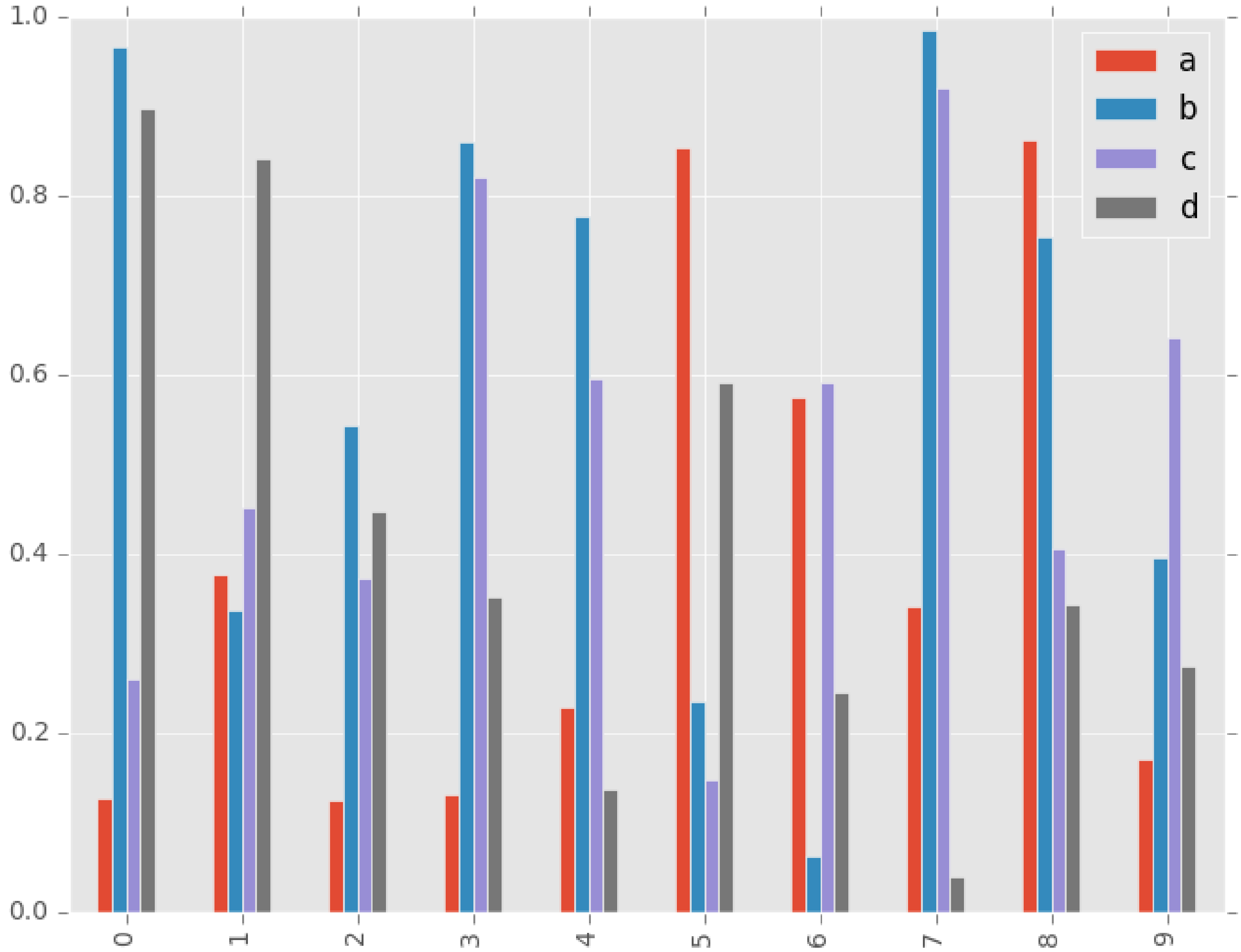
For labeled, non-time series data, you may wish to produce a bar plot:

```
In [13]: plt.figure();

In [14]: df.ix[5].plot(kind='bar'); plt.axhline(0, color='k')
Out[14]: <matplotlib.lines.Line2D at 0x9ed176ec>
```



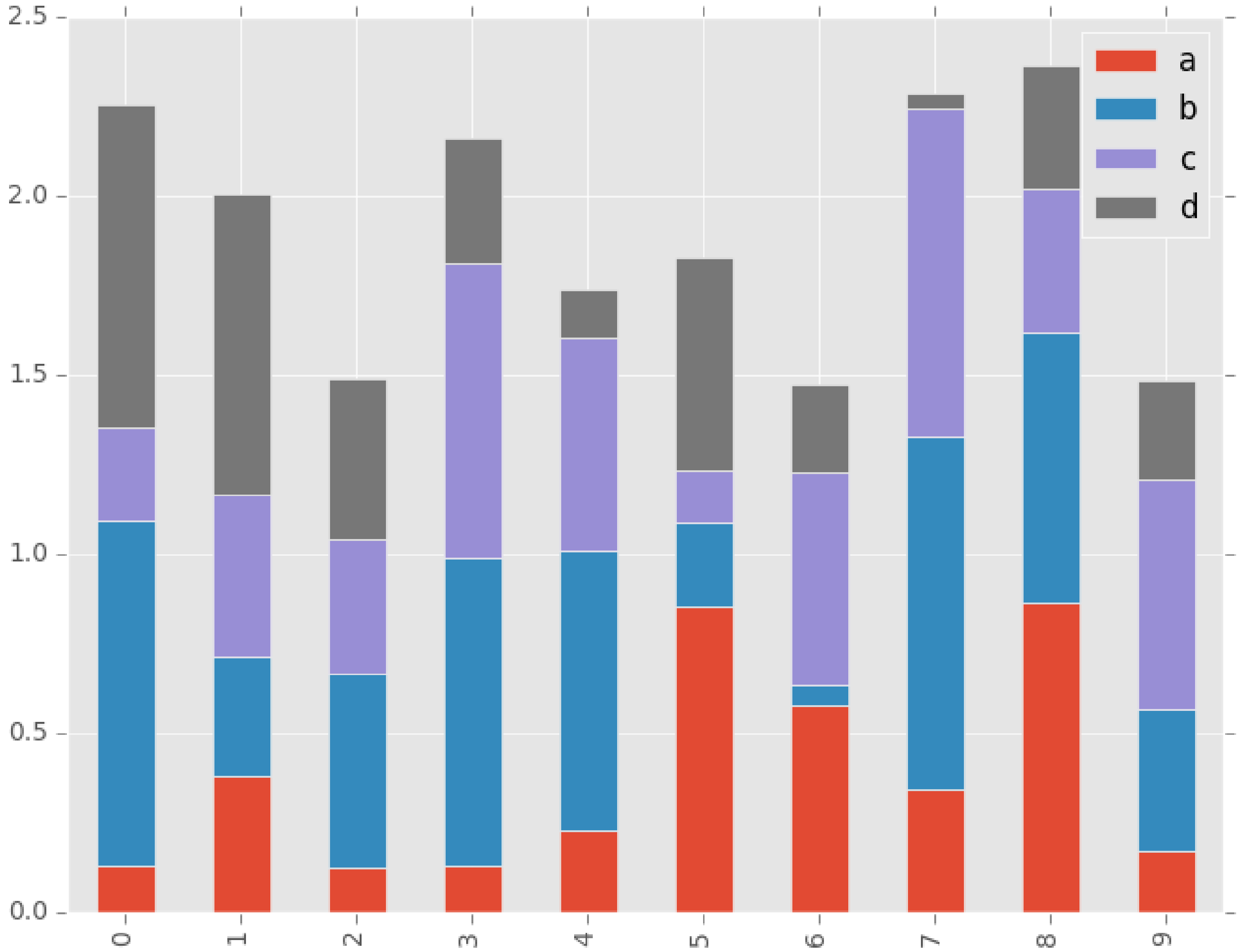
Calling a DataFrame's `plot()` method with `kind='bar'` produces a multiple bar plot:

```
In [15]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

In [16]: df2.plot(kind='bar');
```



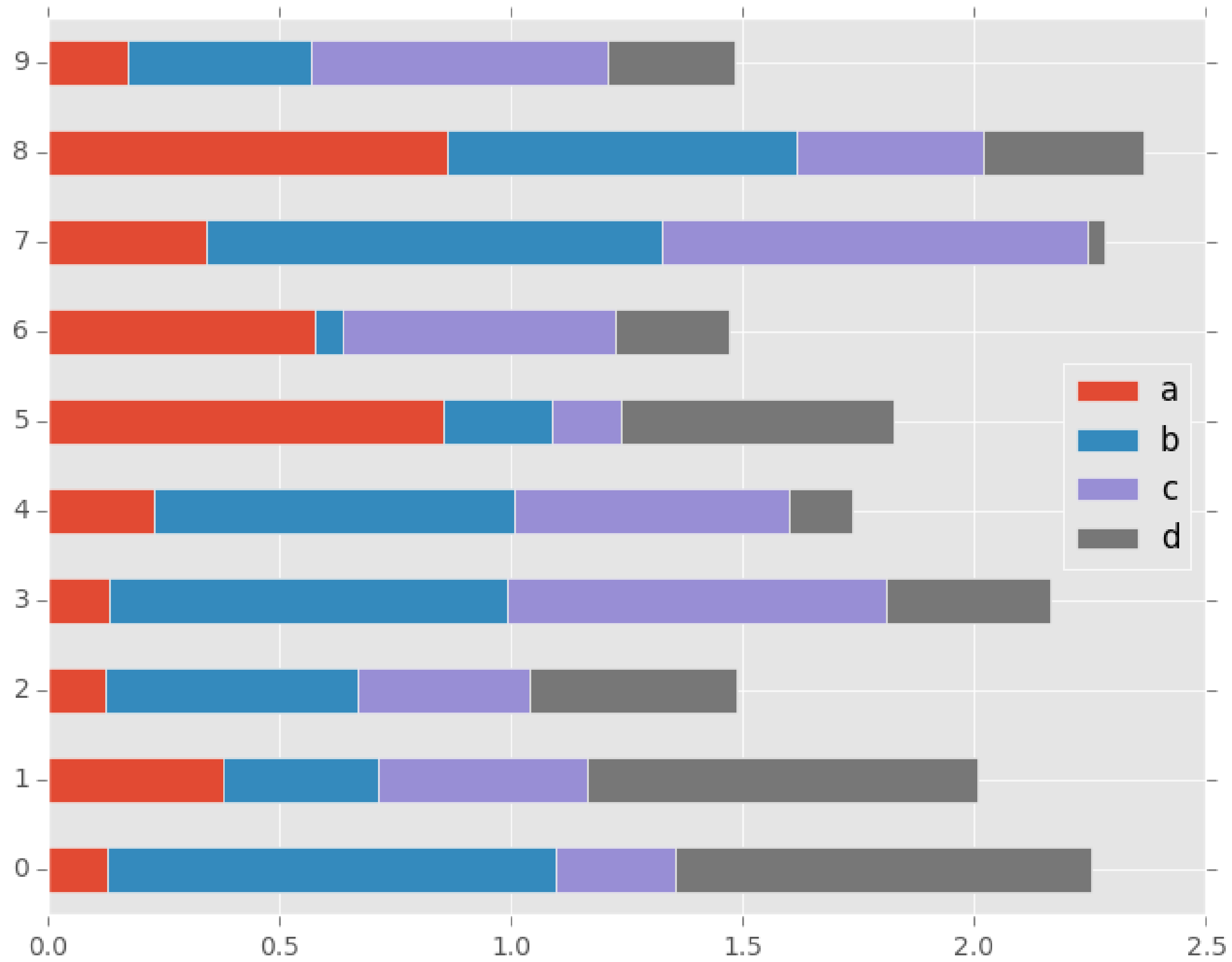
To produce a stacked bar plot, pass `stacked=True`:

```
In [17]: df2.plot(kind='bar', stacked=True);
```



To get horizontal bar plots, pass `kind='barh'`:

```
In [18]: df2.plot(kind='barh', stacked=True);
```

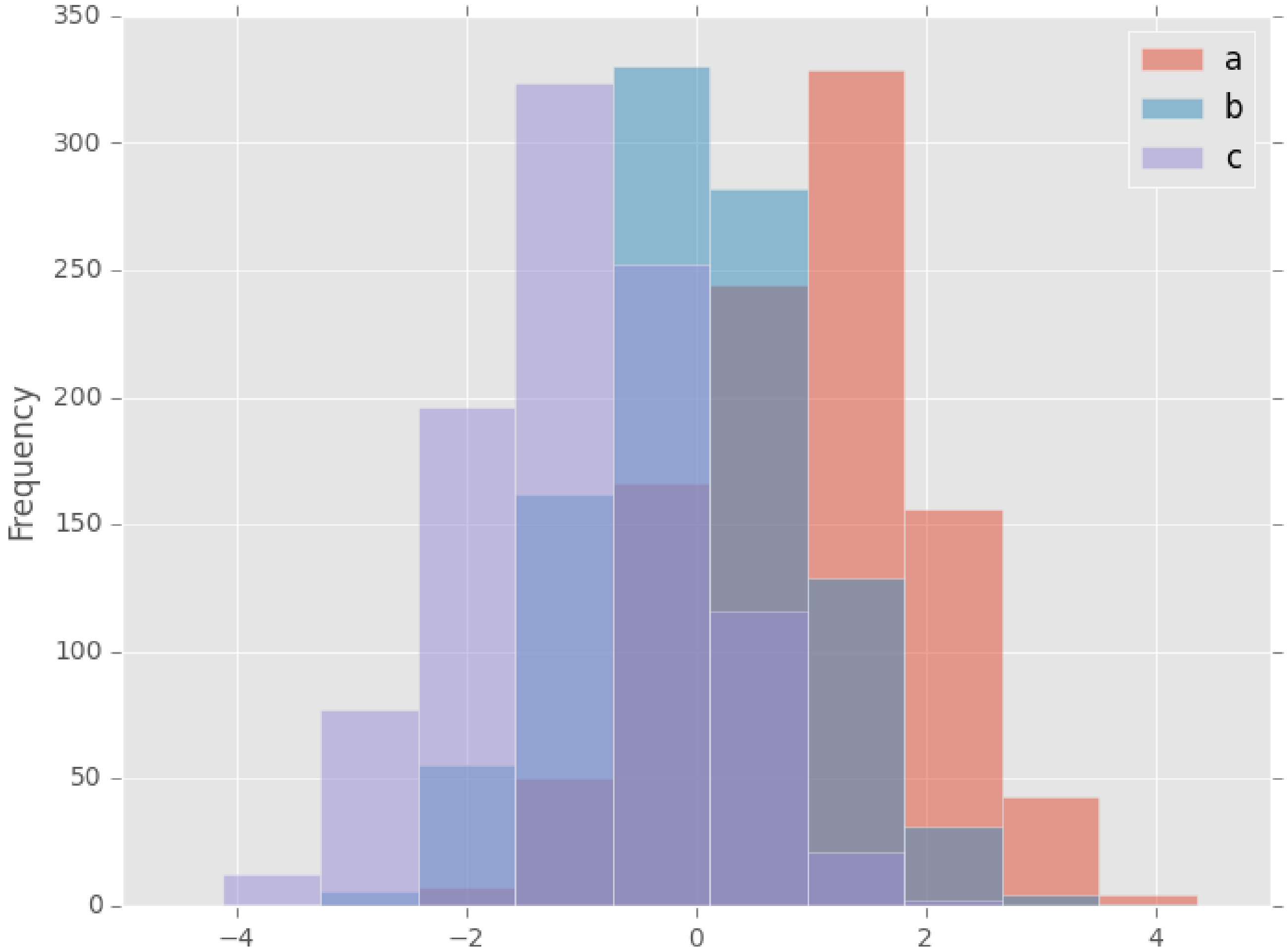


Histograms

New in version 0.15.0.

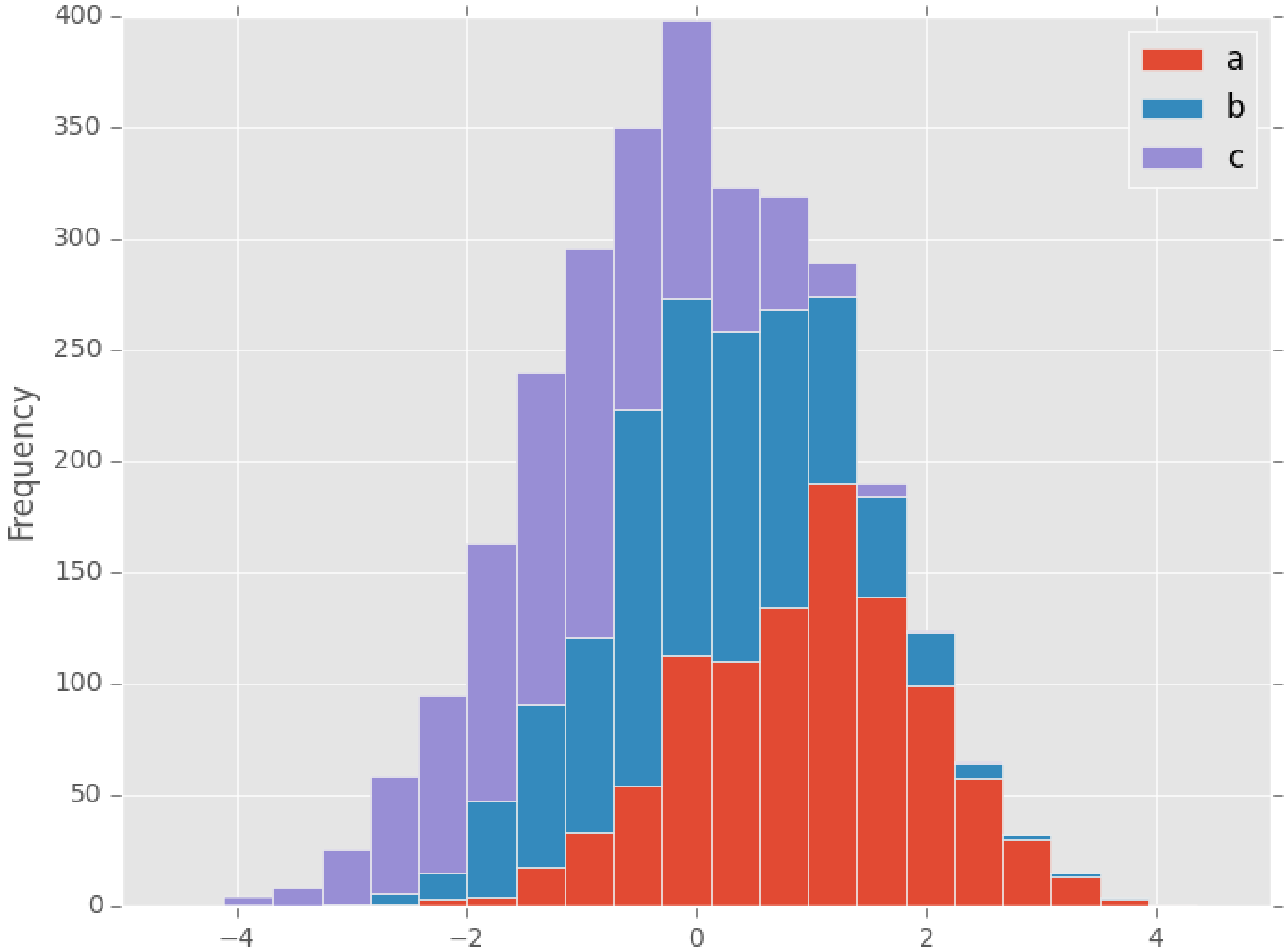
Histogram can be drawn specifying `kind='hist'`.

```
In [19]: df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.randn(1000),
   ....:                     'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])
   ....:

In [20]: plt.figure();

In [21]: df4.plot(kind='hist', alpha=0.5)
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x9f0ec46c>
```



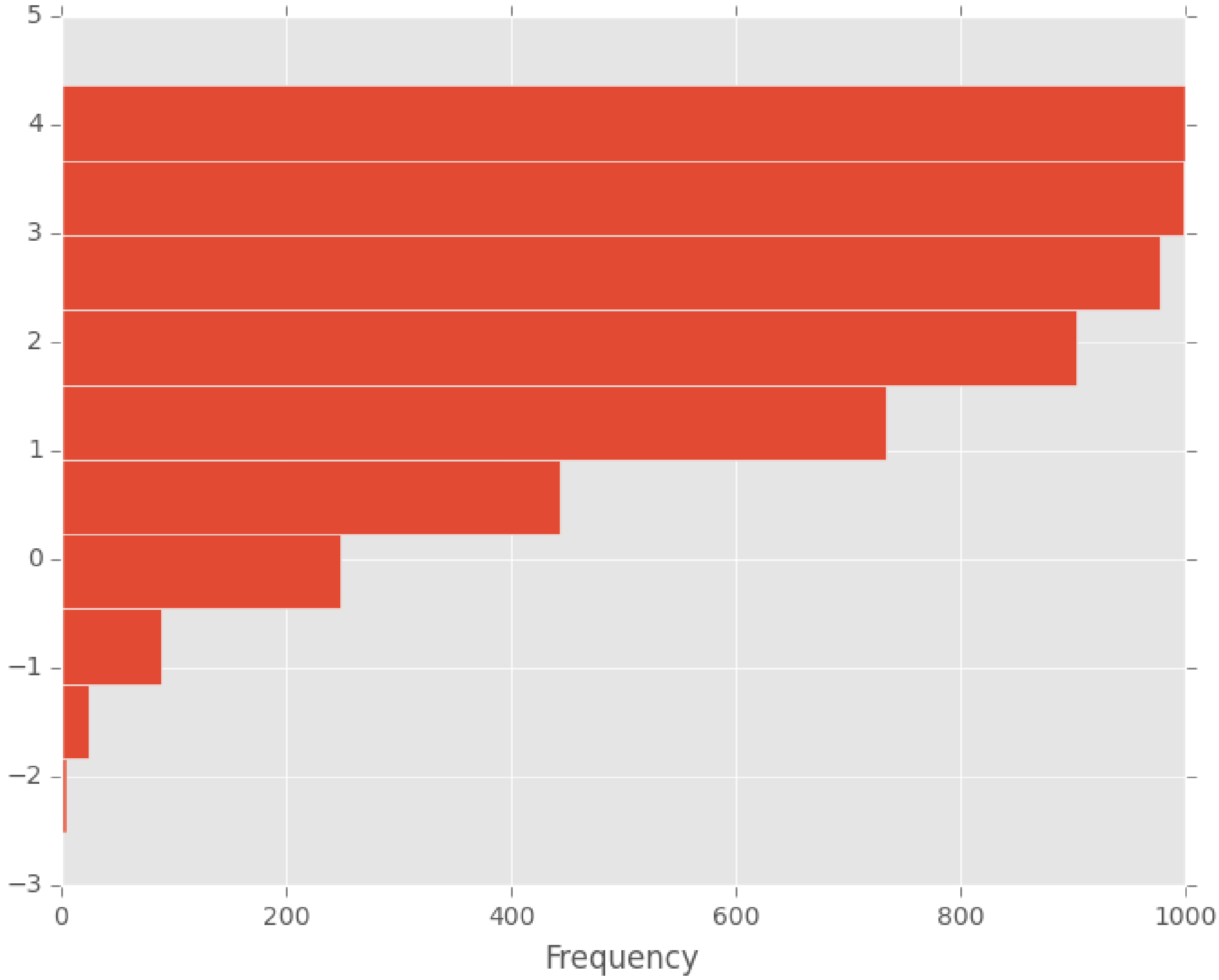
Histogram can be stacked by `stacked=True`. Bin size can be changed by `bins` keyword.

```
In [22]: plt.figure();

In [23]: df4.plot(kind='hist', stacked=True, bins=20)
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x9f3132cc>
```



You can pass other keywords supported by matplotlib `hist`. For example, horizontal and cumulative histgram can be drawn by `orientation='horizontal'` and `cumulative='True'`.

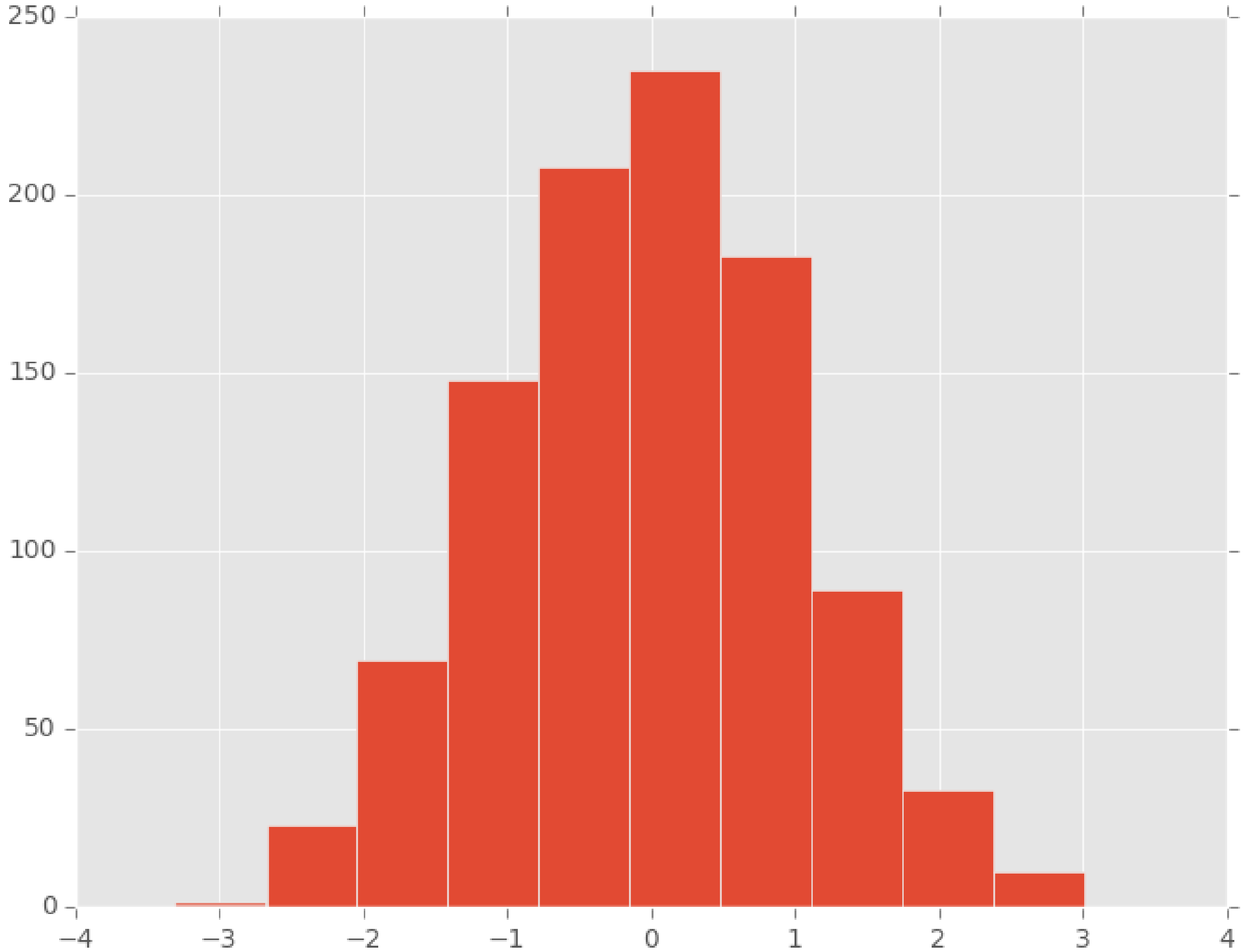
```
In [24]: plt.figure();

In [25]: df4['a'].plot(kind='hist', orientation='horizontal', cumulative=True)
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xa45ed04c>
```



See the `hist` method and the matplotlib hist documentation for more.

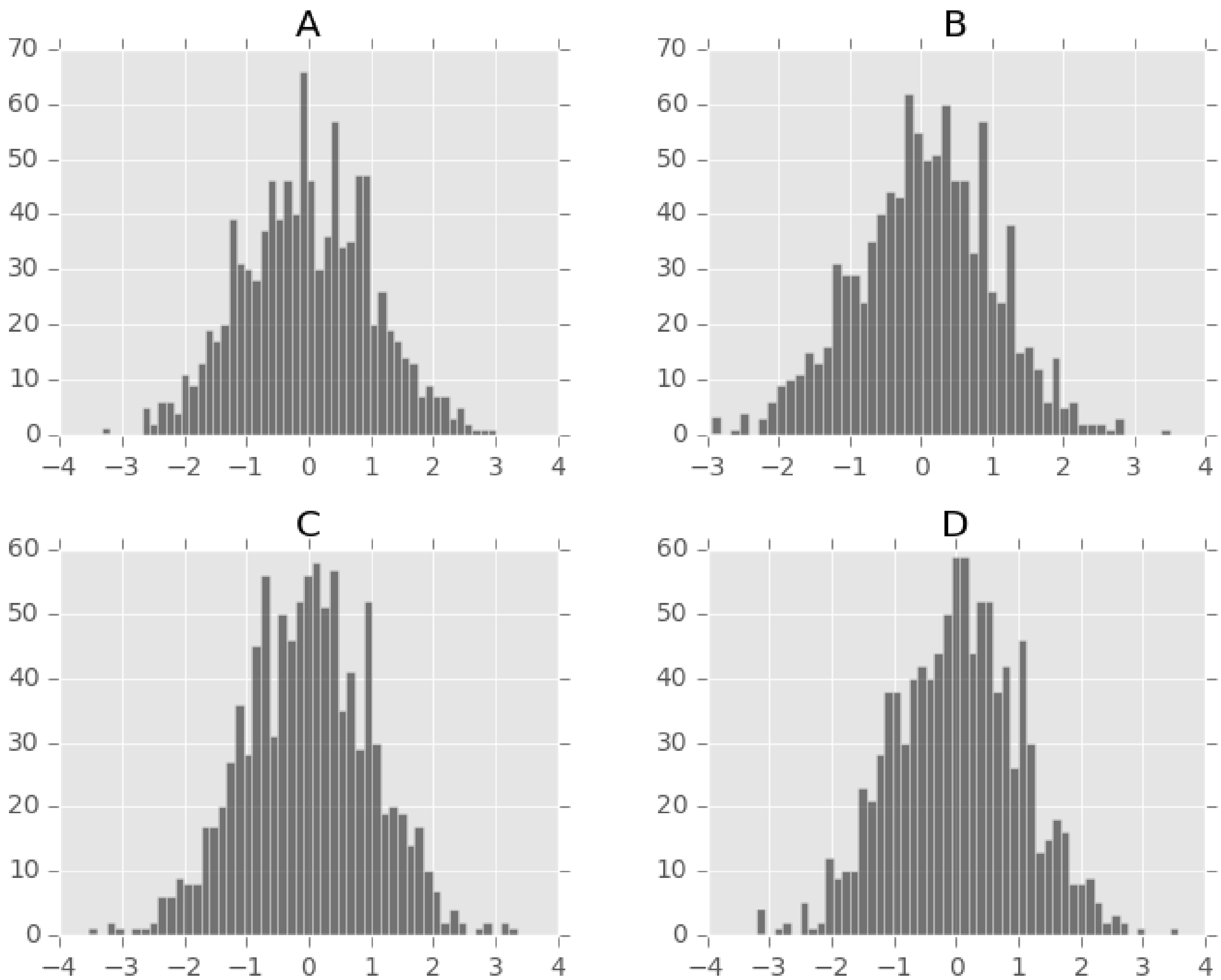
The existing interface `DataFrame.hist` to plot histogram still can be used.

```
In [26]: plt.figure();

In [27]: df['A'].diff().hist()
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x9ee5856c>
```



`DataFrame.hist()` plots the histograms of the columns on multiple subplots:

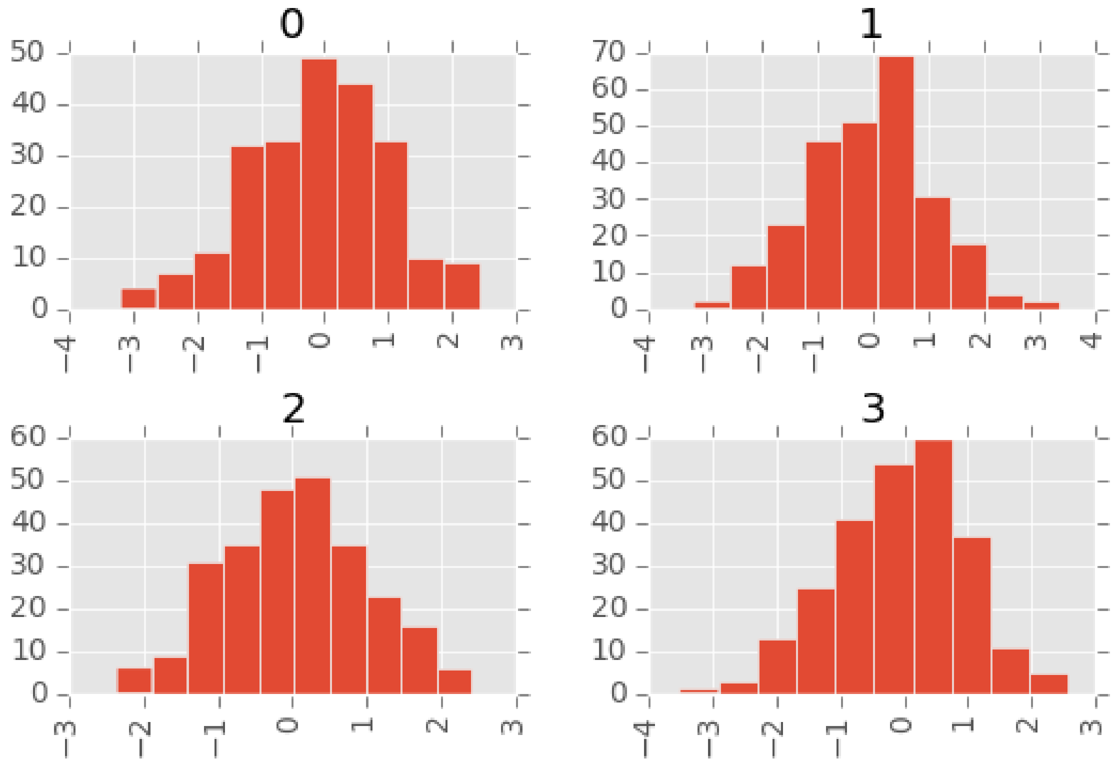
```
In [28]: plt.figure()
Out[28]: <matplotlib.figure.Figure at 0xb0706f2c>

In [29]: df.diff().hist(color='k', alpha=0.5, bins=50)
Out[29]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9f2071cc>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9dba50ec>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9ee34b4c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9e8c922c>]], dtype=object)
```



New in version 0.10.0.

The `by` keyword can be specified to plot grouped histograms:

```
In [30]: data = pd.Series(np.random.randn(1000))

In [31]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
Out[31]:
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9db440ec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9de009ac>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9e450b4c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9e4e684c>]], dtype=object)
```



Box Plots

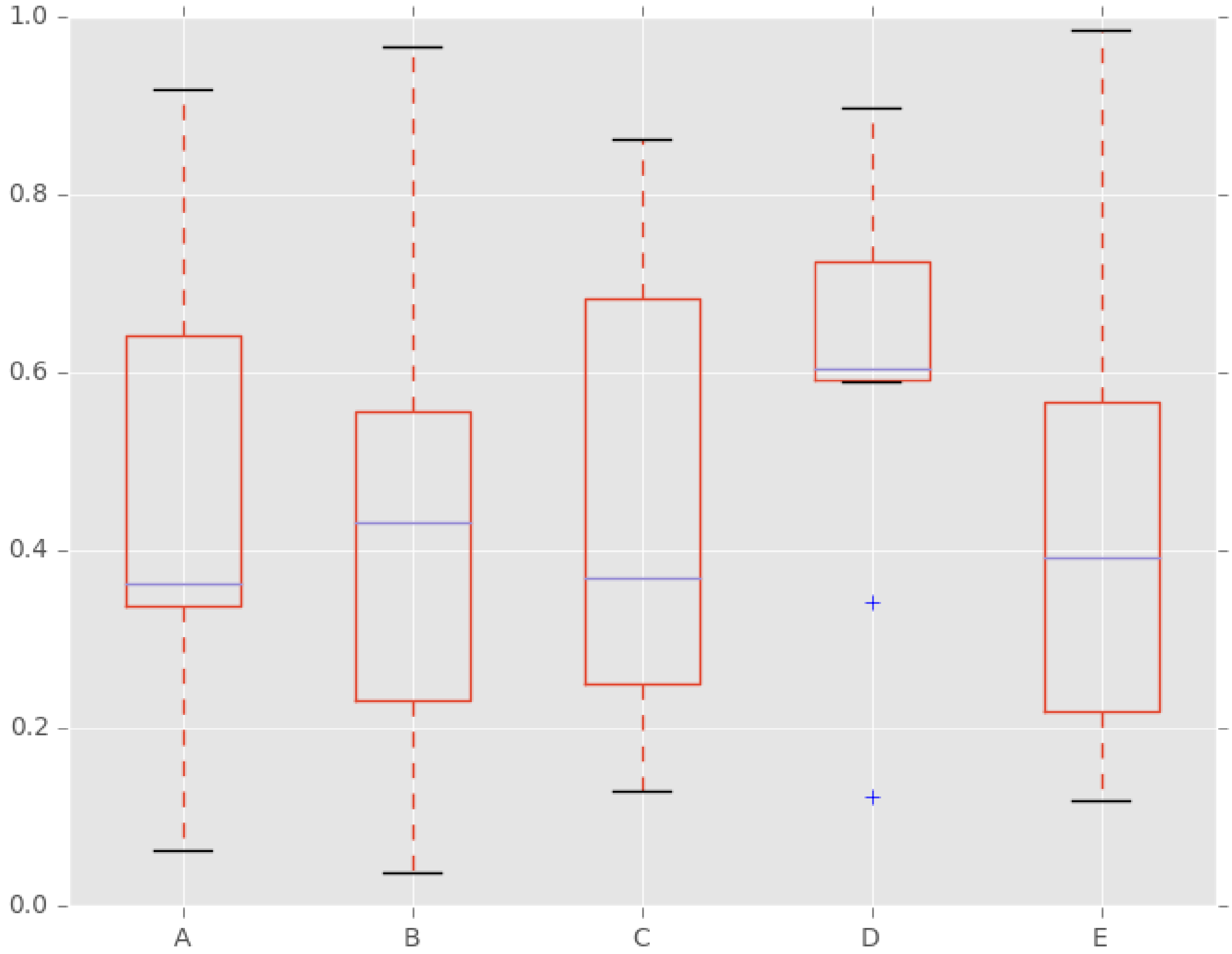
Boxplot can be drawn calling a `Series` and `DataFrame.plot` with `kind='box'`, or `DataFrame.boxplot` to visualize the distribution of values within each column.

New in version 0.15.0.

`plot` method now supports `kind='box'` to draw boxplot.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on [0,1).

```
In [32]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])

In [33]: df.plot(kind='box')
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x9dd0802c>
```

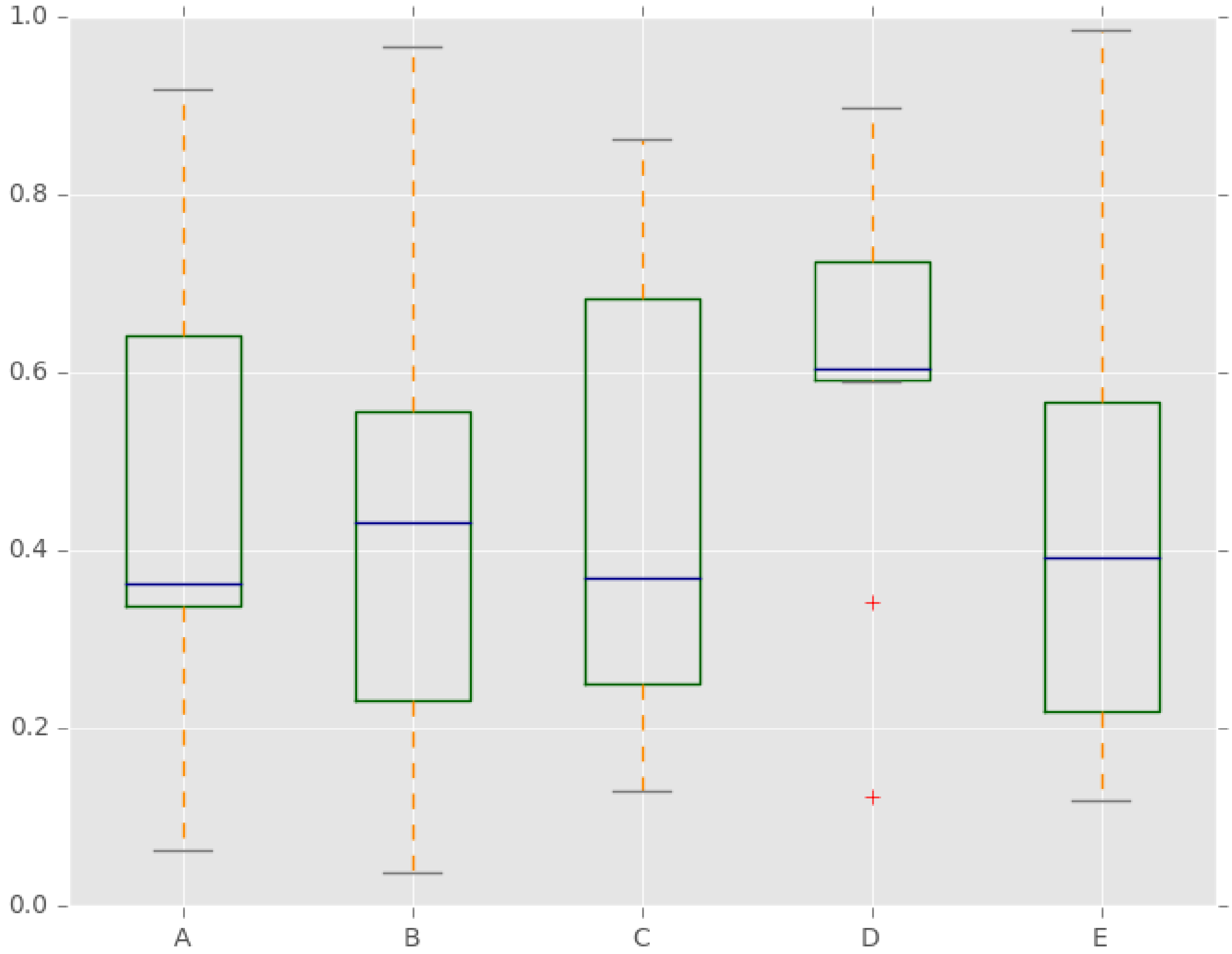


Boxplot can be colorized by passing `color` keyword. You can pass a `dict` whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the `dict`, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

When you pass other type of arguments via `color` keyword, it will be directly passed to matplotlib for all the `boxes`, `whiskers`, `medians` and `caps` colorization.

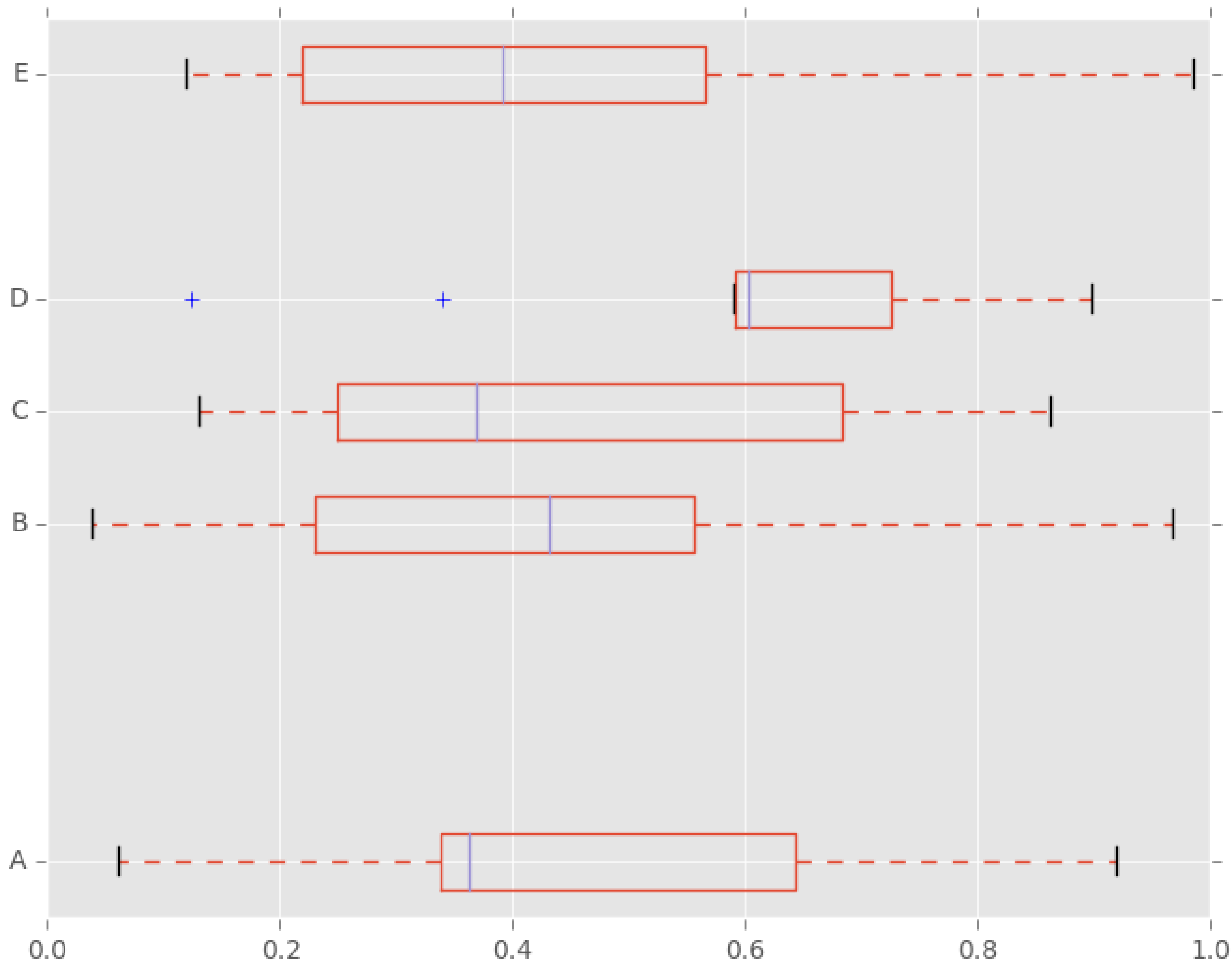
The colors are applied to every boxes to be drawn. If you want more complicated colorization, you can get each drawn artists by passing *return_type*.

```
In [34]: color = dict(boxes='DarkGreen', whiskers='DarkOrange',
   ....:               medians='DarkBlue', caps='Gray')
   ....:

In [35]: df.plot(kind='box', color=color, sym='r+')
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x9dfad5cc>
```



Also, you can pass other keywords supported by matplotlib `boxplot`. For example, horizontal and custom-positioned boxplot can be drawn by `vert=False` and `positions` keywords.

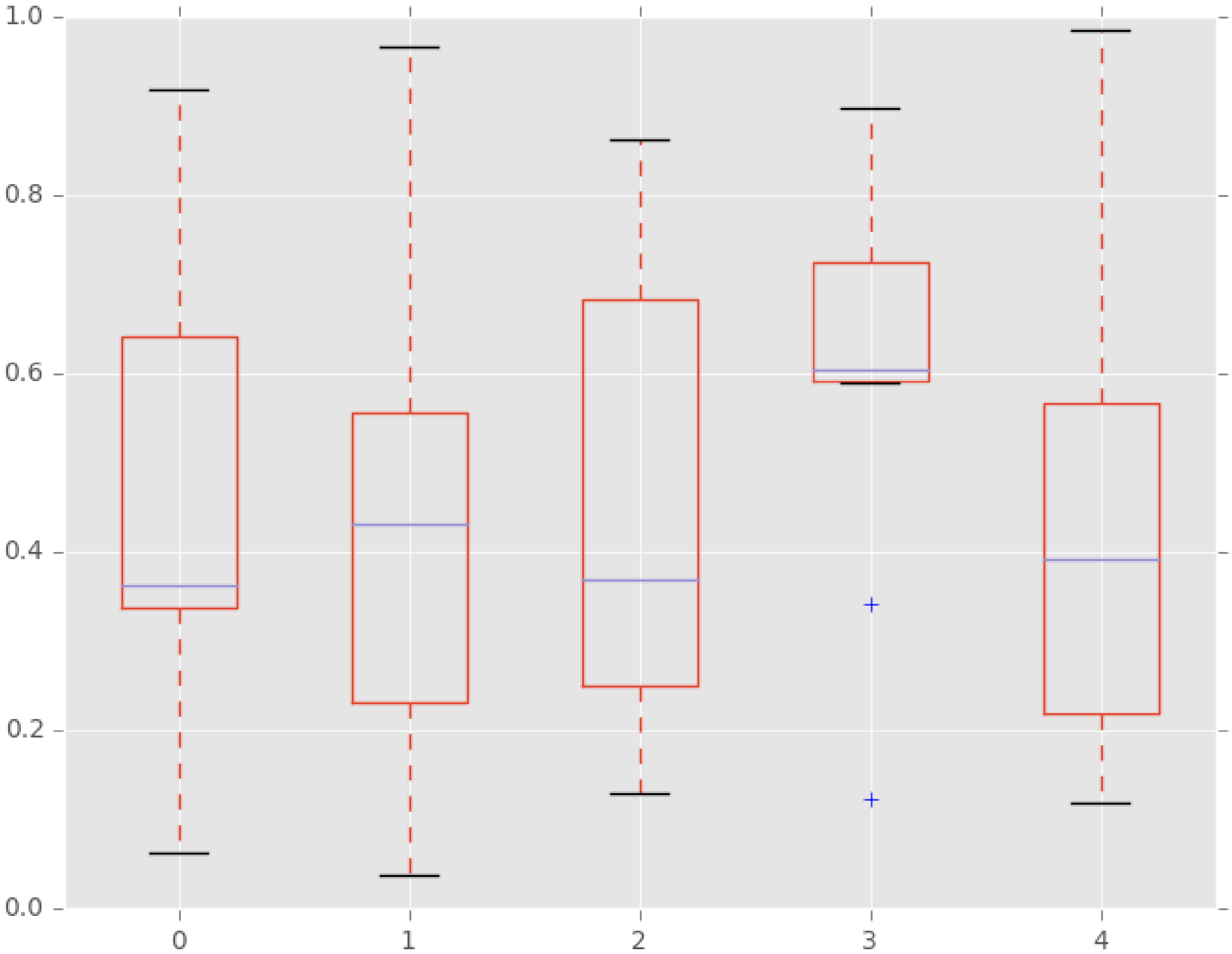
```
In [36]: df.plot(kind='box', vert=False, positions=[1, 4, 5, 6, 8])
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x9d742c4c>
```



See the `boxplot` method and the matplotlib boxplot documentation for more.

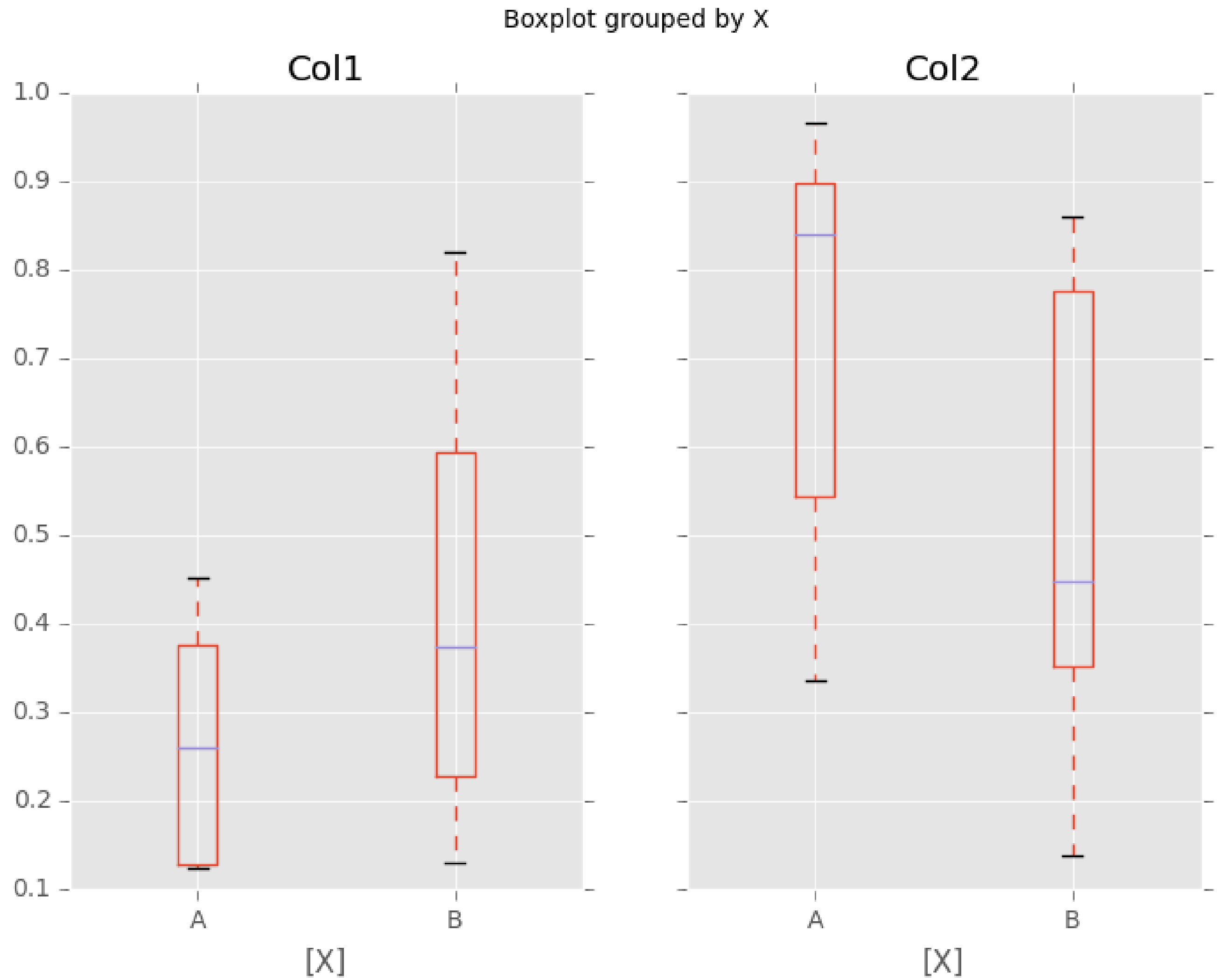
The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```
In [37]: df = pd.DataFrame(np.random.rand(10,5))

In [38]: plt.figure();

In [39]: bp = df.boxplot()
```



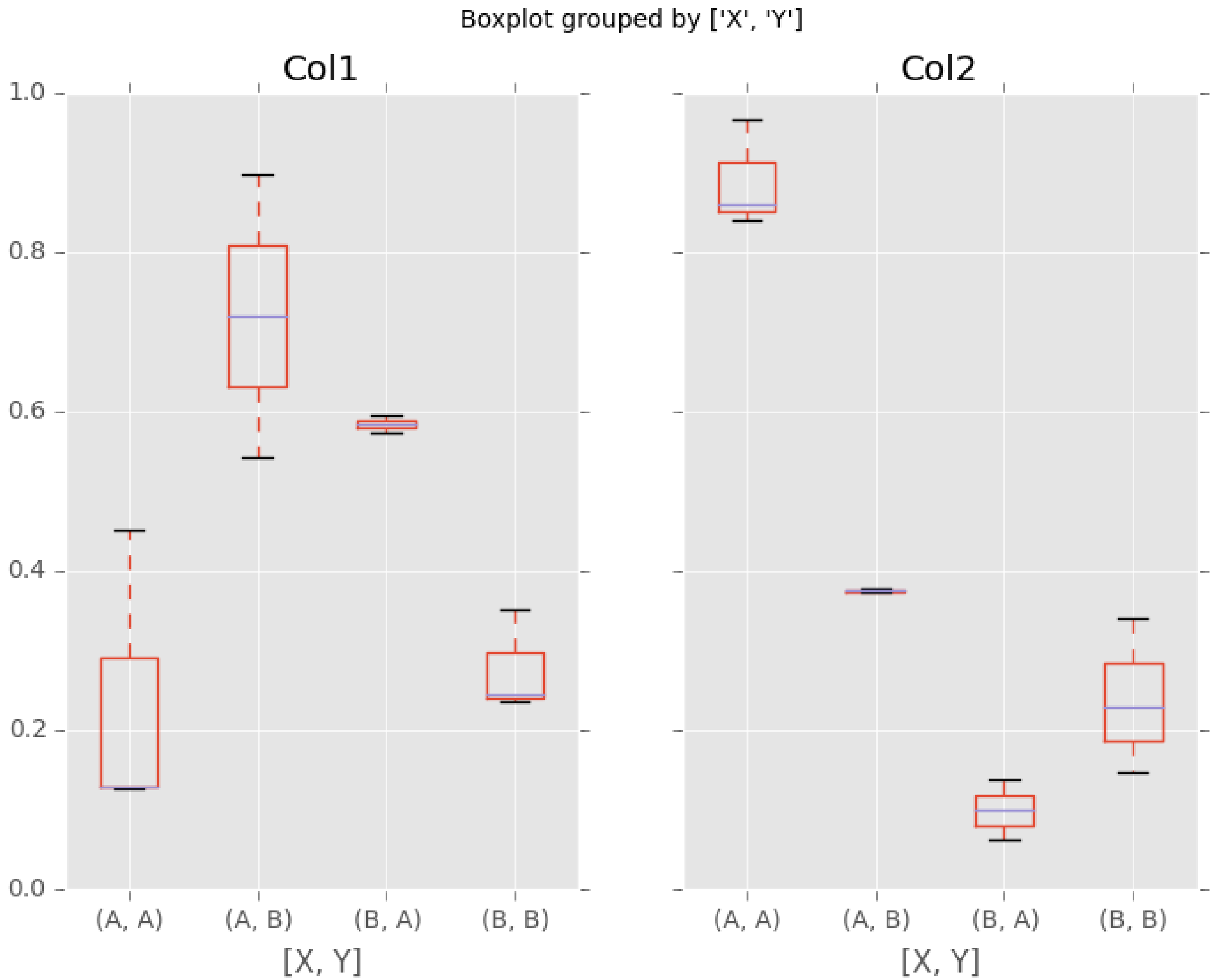
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [40]: df = pd.DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'] )

In [41]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])

In [42]: plt.figure();

In [43]: bp = df.boxplot(by='X')
```



You can also pass a subset of columns to plot, as well as group by multiple columns:

```
In [44]: df = pd.DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])

In [45]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])

In [46]: df['Y'] = pd.Series(['A','B','A','B','A','B','A','B','A','B'])

In [47]: plt.figure();

In [48]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```



Basically, plot functions return `matplotlib Axes` as a return value. In `boxplot`, the return type can be changed by argument `return_type`, and whether the subplots is enabled (`subplots=True` in `plot` or `by` is specified in `boxplot`).

When `subplots=False` / `by` is `None`:

- if `return_type` is `'dict'`, a dictionary containing the `matplotlib Lines` is returned. The keys are "boxes", "caps", "fliers", "medians", and "whiskers".

    This is the default of `boxplot` in historical reason. Note that `plot(kind='box')` returns `Axes` as default as the same as other plots.

- if `return_type` is `'axes'`, a `matplotlib Axes` containing the boxplot is returned.

- if `return_type` is `'both'` a namedtuple containging the `matplotlib Axes`

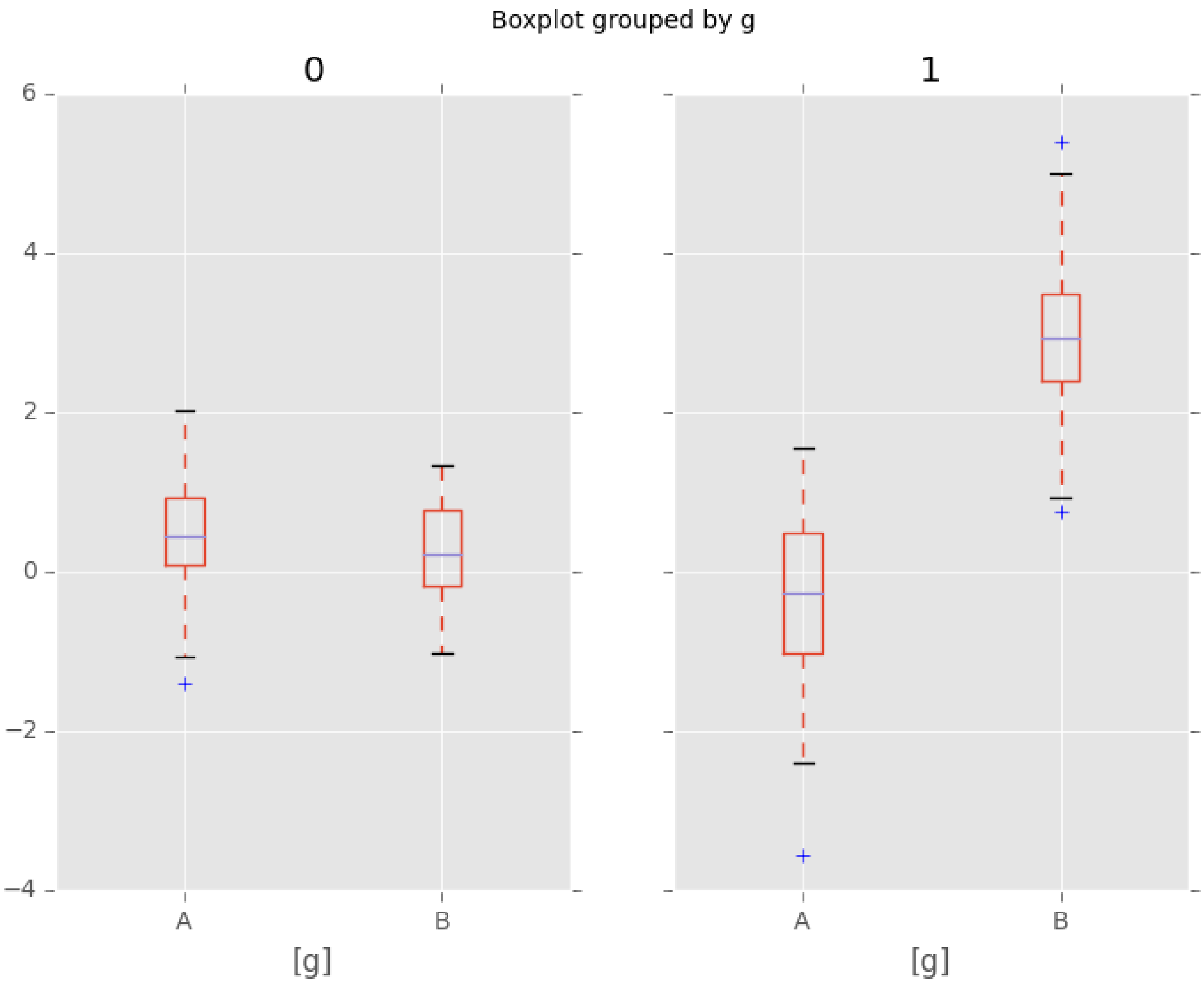
    and `matplotlib Lines` is returned

When `subplots=True` / `by` is some column of the DataFrame:

- A dict of `return_type` is returned, where the keys are the columns of the DataFrame. The plot has a facet for each column of the DataFrame, with a separate box for each value of `by`.

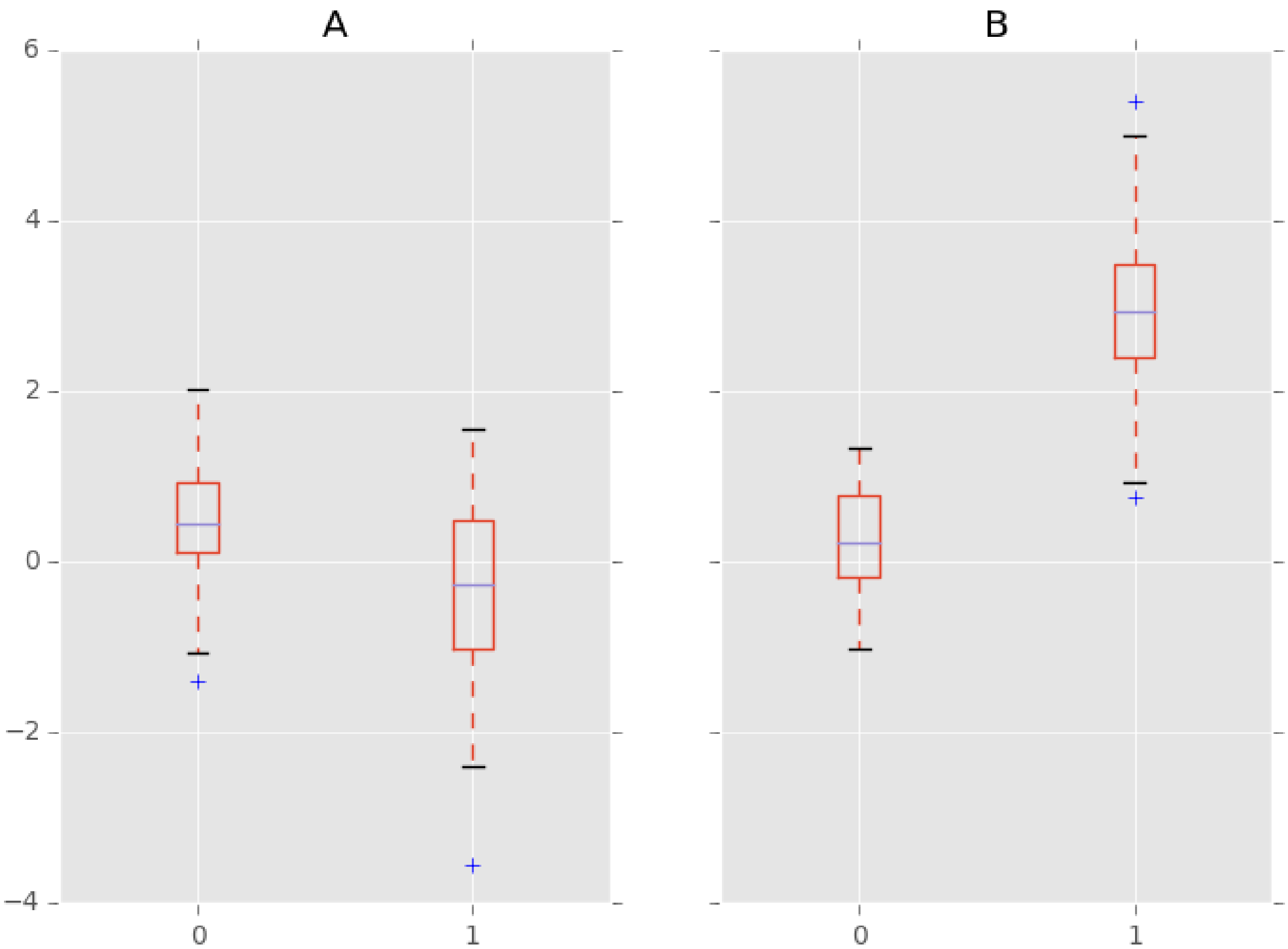
Finally, when calling boxplot on a `Groupby` object, a dict of `return_type` is returned, where the keys are the same as the Groupby object. The plot has a facet for each key, with each facet containing a box for each column of the DataFrame.

```
In [49]: np.random.seed(1234)

In [50]: df_box = pd.DataFrame(np.random.randn(50, 2))

In [51]: df_box['g'] = np.random.choice(['A', 'B'], size=50)

In [52]: df_box.loc[df_box['g'] == 'B', 1] += 3

In [53]: bp = df_box.boxplot(by='g')
```



Compare to:

```
In [54]: bp = df_box.groupby('g').boxplot()
```



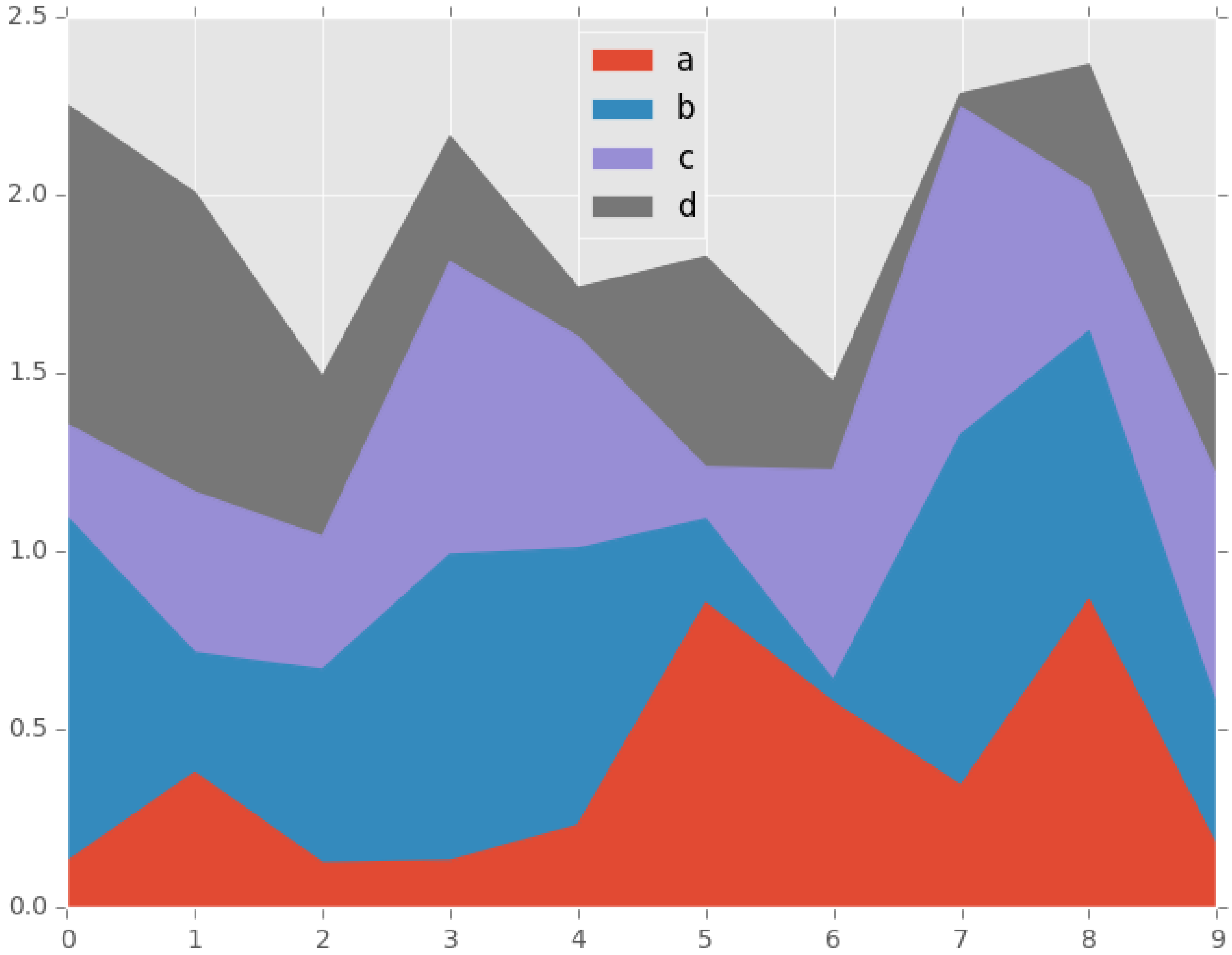
Area Plot

New in version 0.14.

You can create area plots with `Series.plot` and `DataFrame.plot` by passing `kind='area'`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

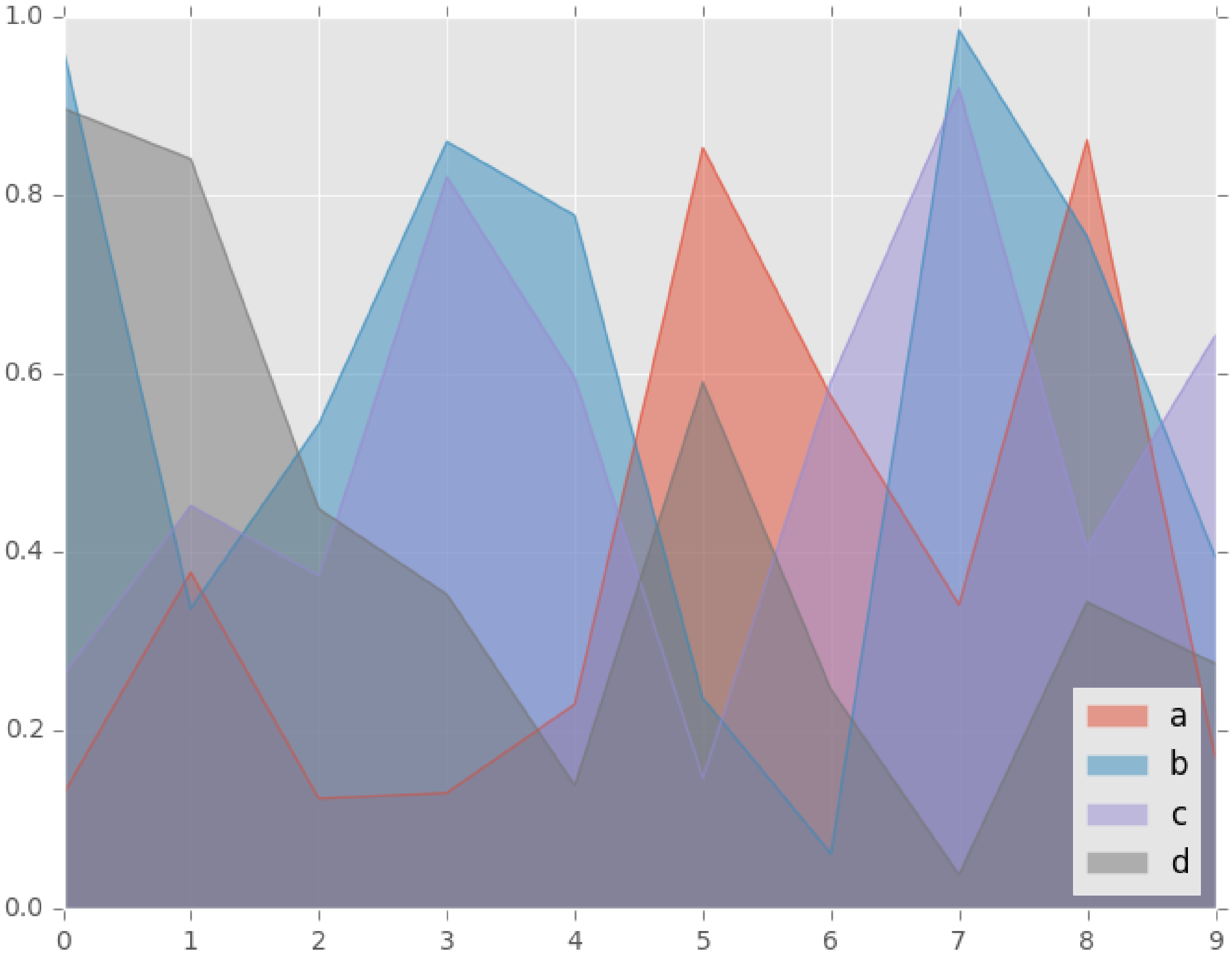
When input data contains *NaN*, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling *plot*.

```
In [55]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])

In [56]: df.plot(kind='area');
```



To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [57]: df.plot(kind='area', stacked=False);
```

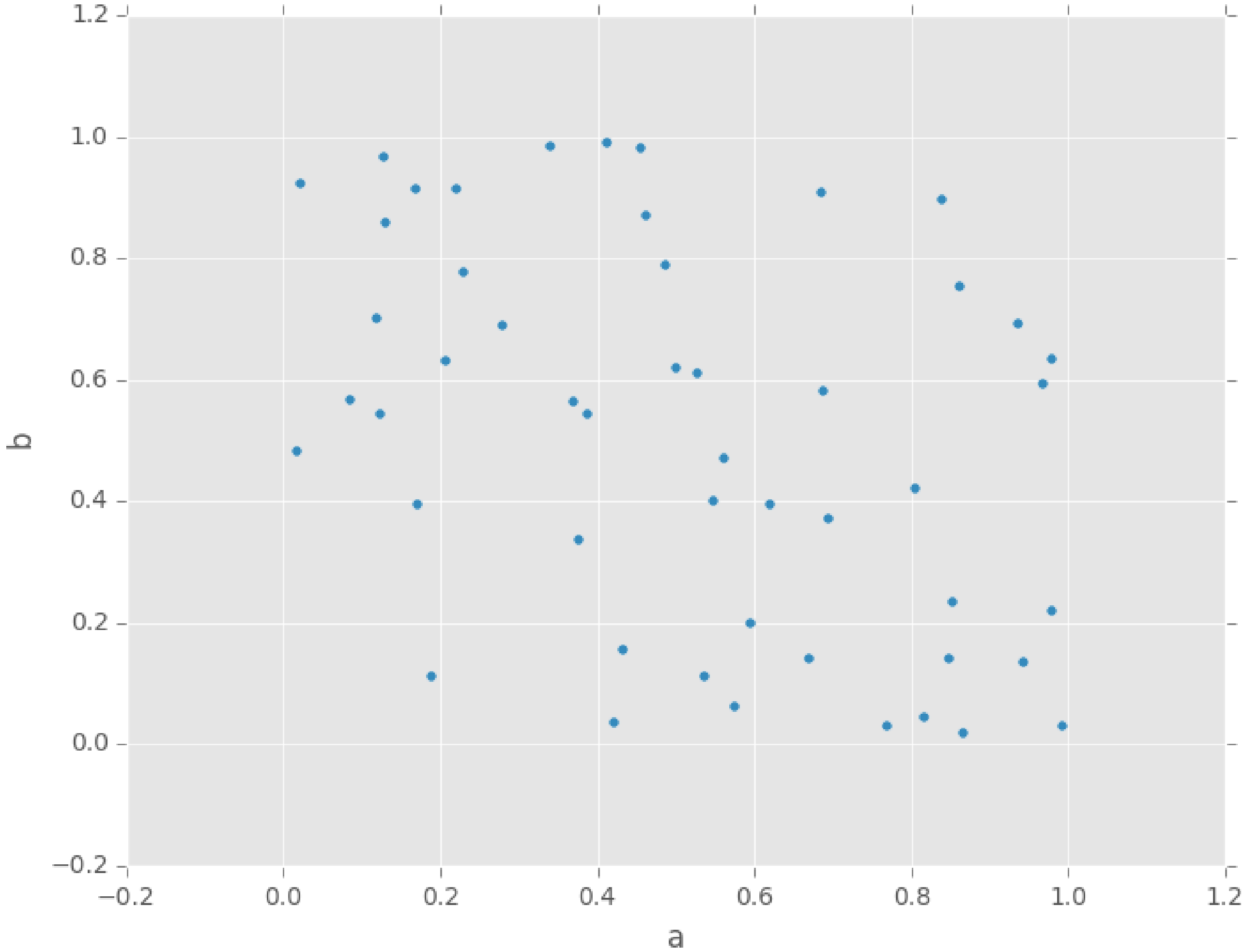


Scatter Plot

New in version 0.13.

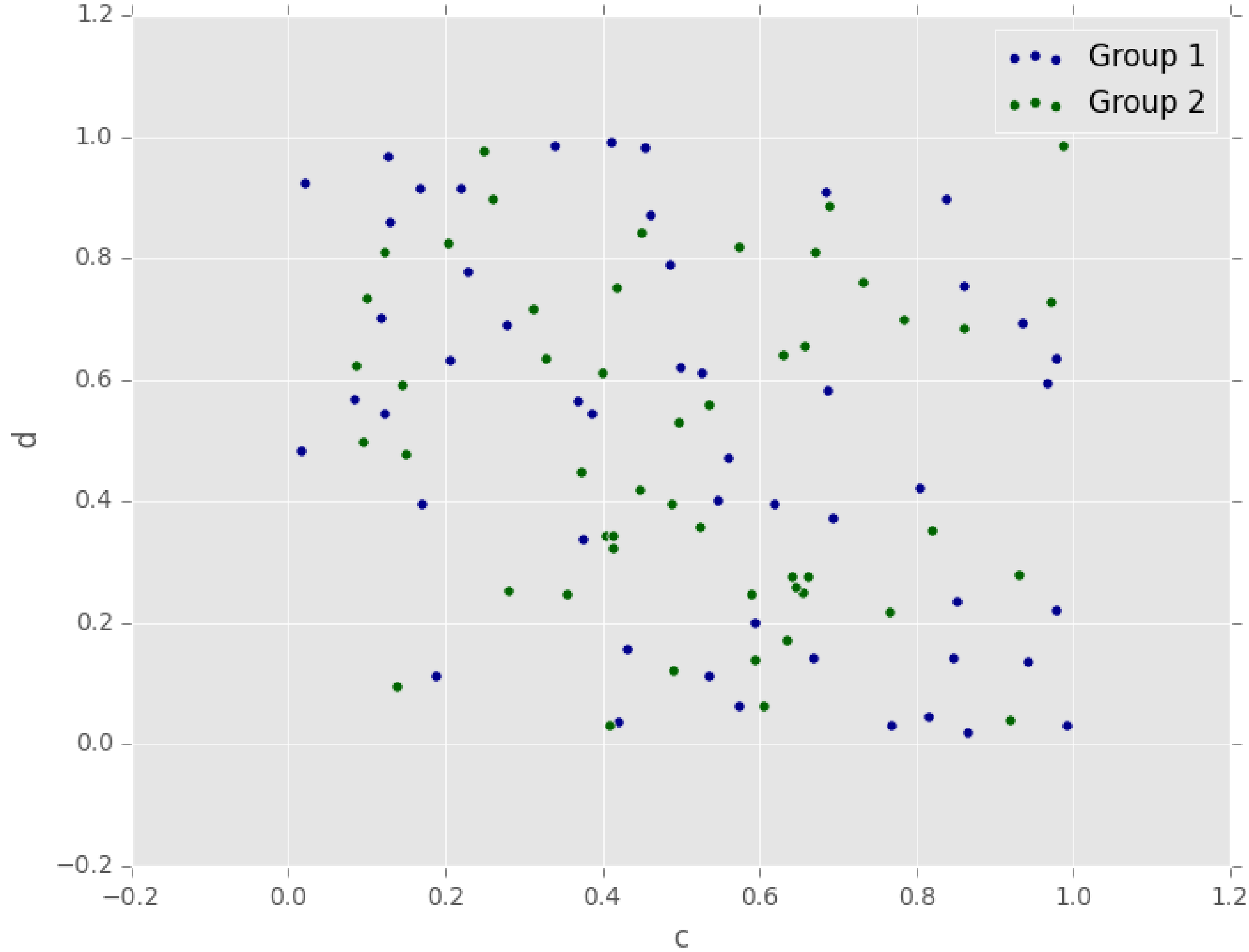
You can create scatter plots with `DataFrame.plot` by passing `kind='scatter'`. Scatter plot requires numeric columns for x and y axis. These can be specified by `x` and `y` keywords each.

```
In [58]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])

In [59]: df.plot(kind='scatter', x='a', y='b');
```



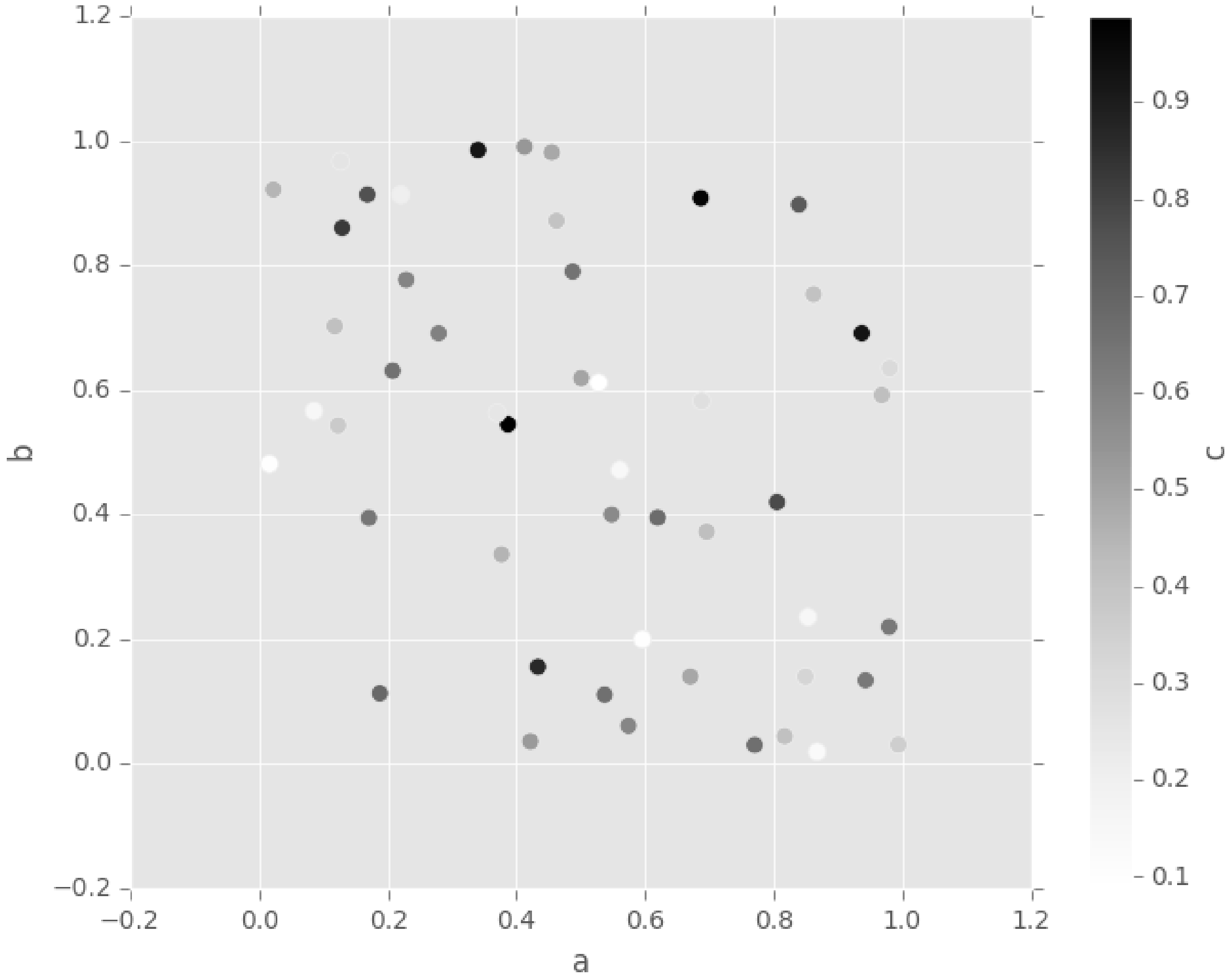
To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

```
In [60]: ax = df.plot(kind='scatter', x='a', y='b',
   ....:              color='DarkBlue', label='Group 1');
   ....:

In [61]: df.plot(kind='scatter', x='c', y='d',
   ....:         color='DarkGreen', label='Group 2', ax=ax);
   ....:
```



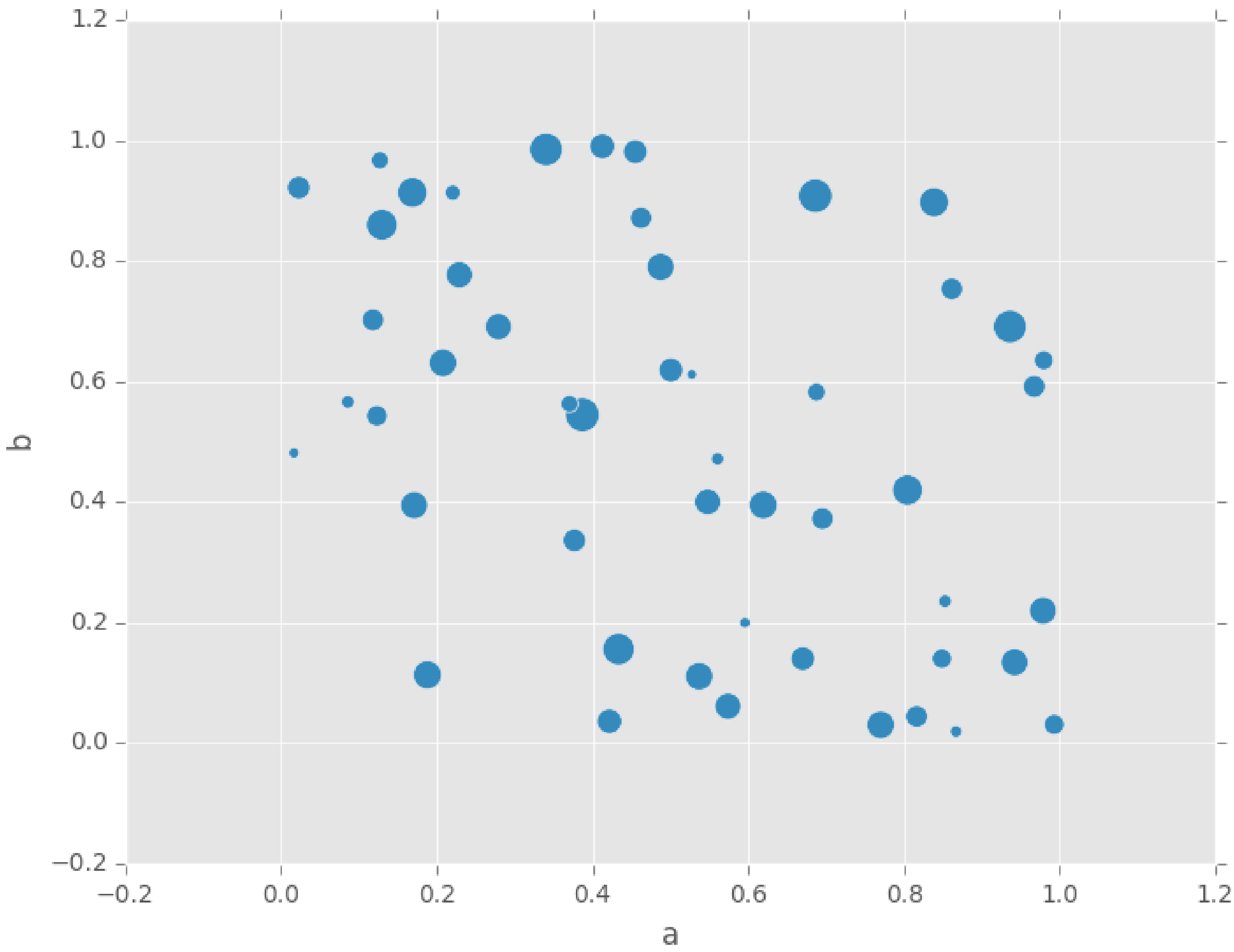
The keyword `c` may be given as the name of a column to provide colors for each point:

```
In [62]: df.plot(kind='scatter', x='a', y='b', c='c', s=50);
```



You can pass other keywords supported by matplotlib `scatter`. Below example shows a bubble chart using a dataframe column values as bubble size.

```
In [63]: df.plot(kind='scatter', x='a', y='b', s=df['c']*200);
```



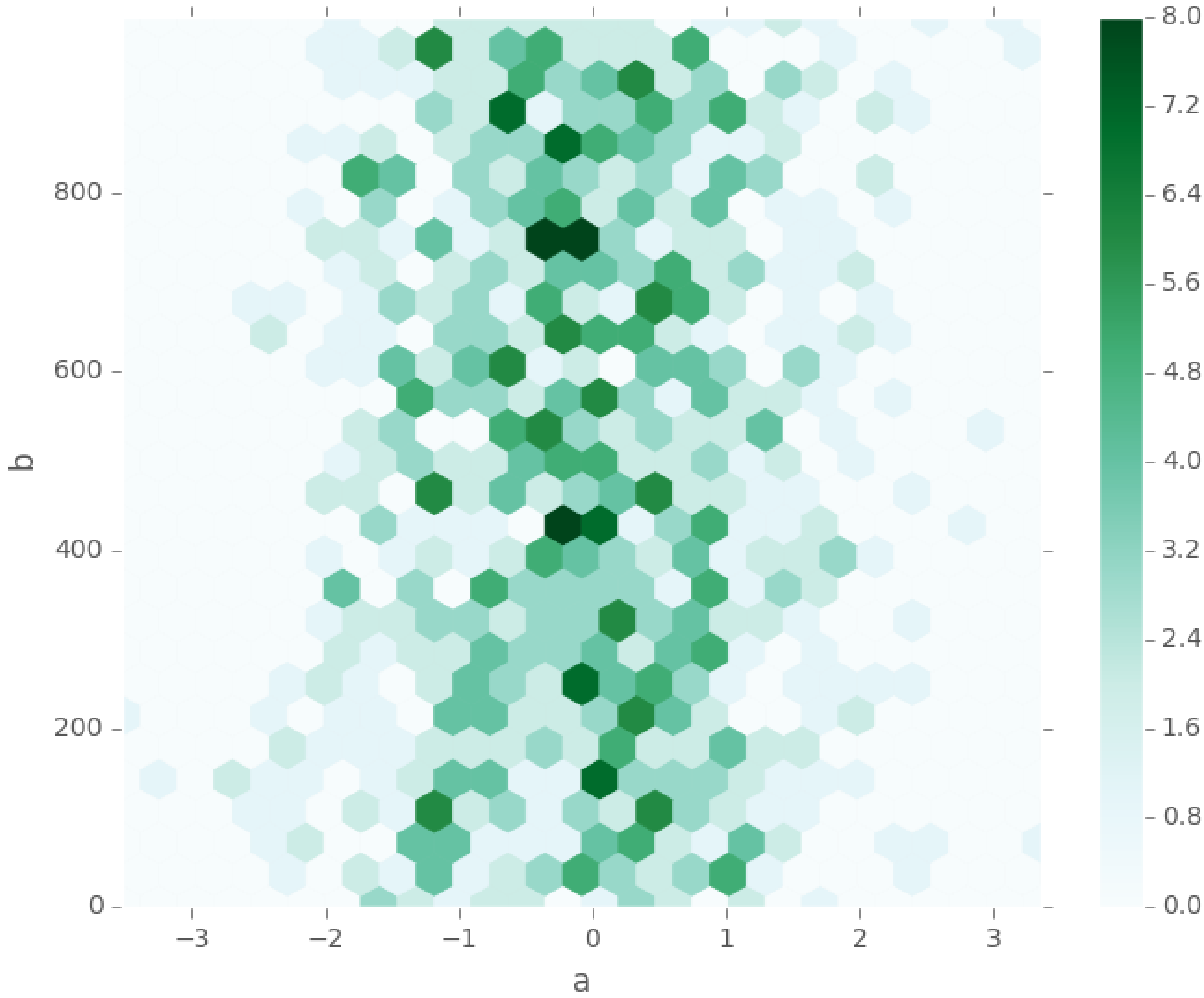
See the `scatter` method and the matplotlib scatter documentation for more.

Hexagonal Bin Plot

New in version 0.14.

You can create hexagonal bin plots with `DataFrame.plot()` and `kind='hexbin'`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [64]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

In [65]: df['b'] = df['b'] + np.arange(1000)

In [66]: df.plot(kind='hexbin', x='a', y='b', gridsize=25)
Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x9c6e2fcc>
```



A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

By default, a histogram of the counts around each `(x, y)` point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each `(x, y)` point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g. `mean`, `max`, `sum`, `std`). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with numpy's `max` function.

```
In [67]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

In [68]: df['b'] = df['b'] = df['b'] + np.arange(1000)

In [69]: df['z'] = np.random.uniform(0, 3, 1000)

In [70]: df.plot(kind='hexbin', x='a', y='b', C='z', reduce_C_function=np.max,
   ....:         gridsize=25)
   ....:
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x9cbedccc>
```

_images/hexbin_plot_agg.png

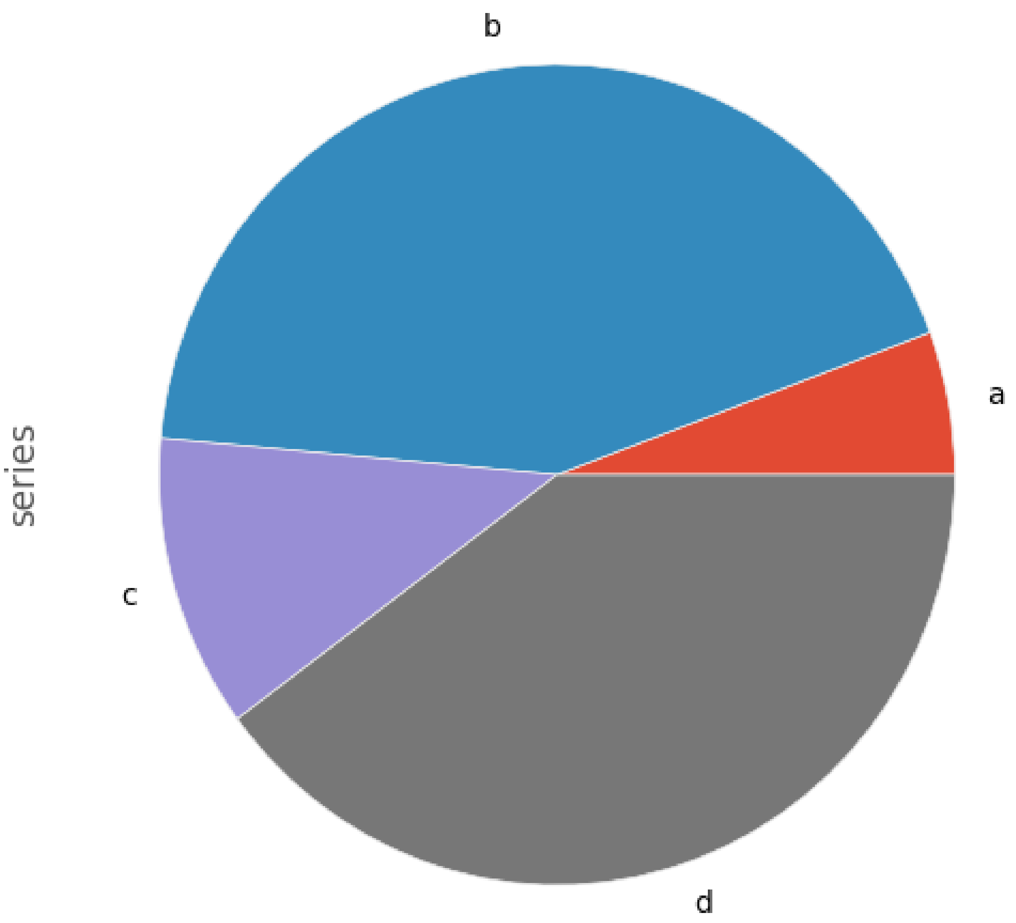
See the `hexbin` method and the matplotlib hexbin documentation for more.

Pie plot

New in version 0.14.

You can create a pie plot with `DataFrame.plot()` or `Series.plot()` with `kind='pie'`. If your data includes any `NaN`, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

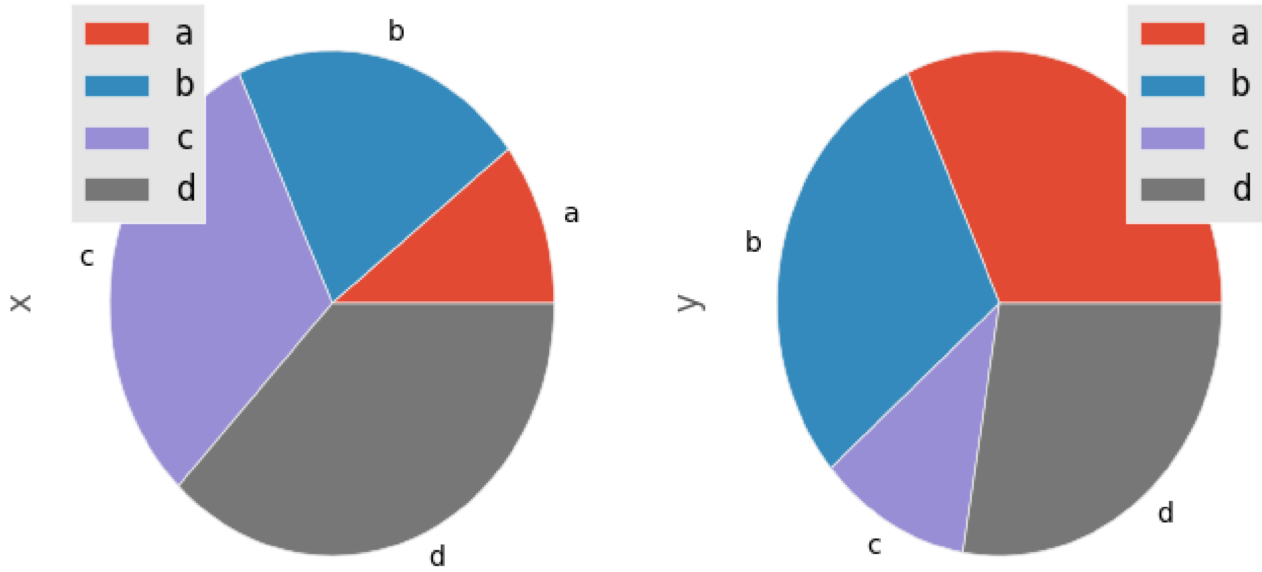
```
In [71]: series = pd.Series(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], name='series')

In [72]: series.plot(kind='pie', figsize=(6, 6))
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0x9cd248cc>
```



For pie plots it's best to use square figures, one's with an equal aspect ratio. You can create the figure with equal width and height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned `axes` object.

Note that pie plot with `DataFrame` requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```
In [73]: df = pd.DataFrame(3 * np.random.rand(4, 2), index=['a', 'b', 'c', 'd'], columns=['x',

In [74]: df.plot(kind='pie', subplots=True, figsize=(8, 4))
Out[74]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0x9cd0c4cc>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x9d67412c>], dtype=object)
```

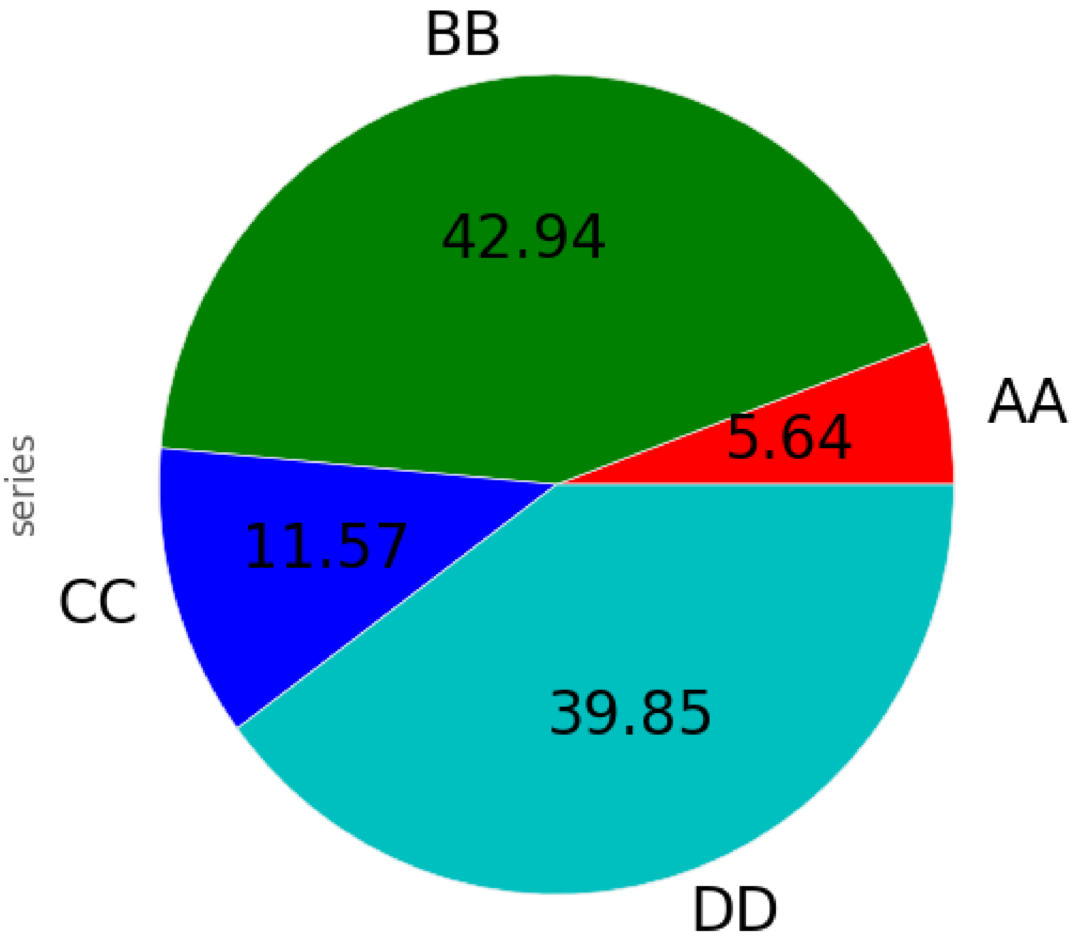


You can use the `labels` and `colors` keywords to specify the labels and colors of each wedge.

Warning: Most pandas plots use the the `label` and `color` arguments (note the lack of "s" on those). To be consistent with `matplotlib.pyplot.pie()` you must use `labels` and `colors`.

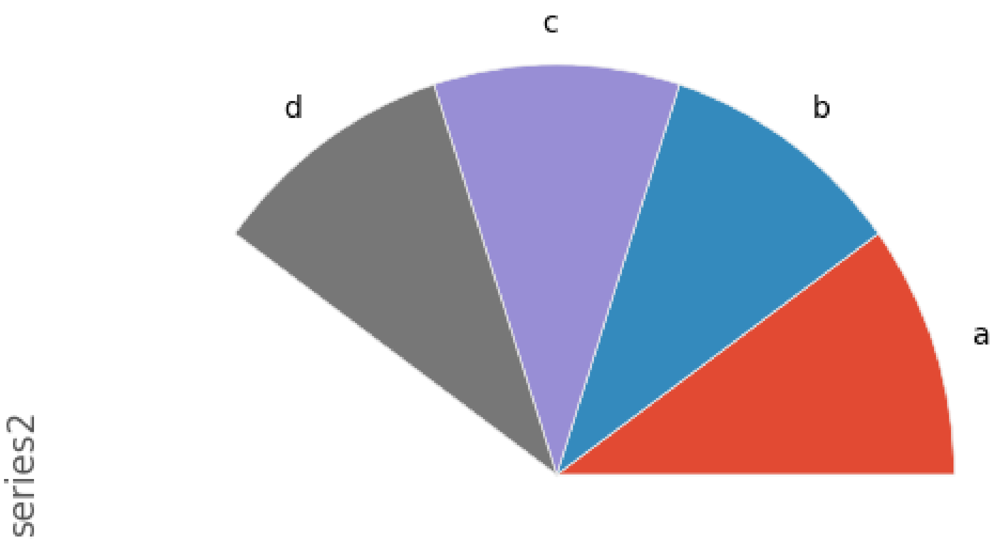
If you want to hide wedge labels, specify `labels=None`. If `fontsize` is specified, the value will be applied to wedge labels. Also, other keywords supported by `matplotlib.pyplot.pie()` can be used.

```
In [75]: series.plot(kind='pie', labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
   ....:             autopct='%.2f', fontsize=20, figsize=(6, 6))
   ....:
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x9d27f80c>
```



If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [76]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')

In [77]: series.plot(kind='pie', figsize=(6, 6))
Out[77]: <matplotlib.axes._subplots.AxesSubplot at 0x9d1ca44c>
```



See the matplotlib pie documentation for more.

Plotting with Missing Data

Pandas tries to be pragmatic about plotting DataFrames or Series that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

Plot Type	NaN Handling
Line	Leave gaps at NaNs
Line (stacked)	Fill 0's
Bar	Fill 0's
Scatter	Drop NaNs
Histogram	Drop NaNs (column-wise)
Box	Drop NaNs (column-wise)
Area	Fill 0's
KDE	Drop NaNs (column-wise)
Hexbin	Drop NaNs
Pie	Fill 0's

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using `fillna()` or `dropna()` before plotting.

Plotting Tools

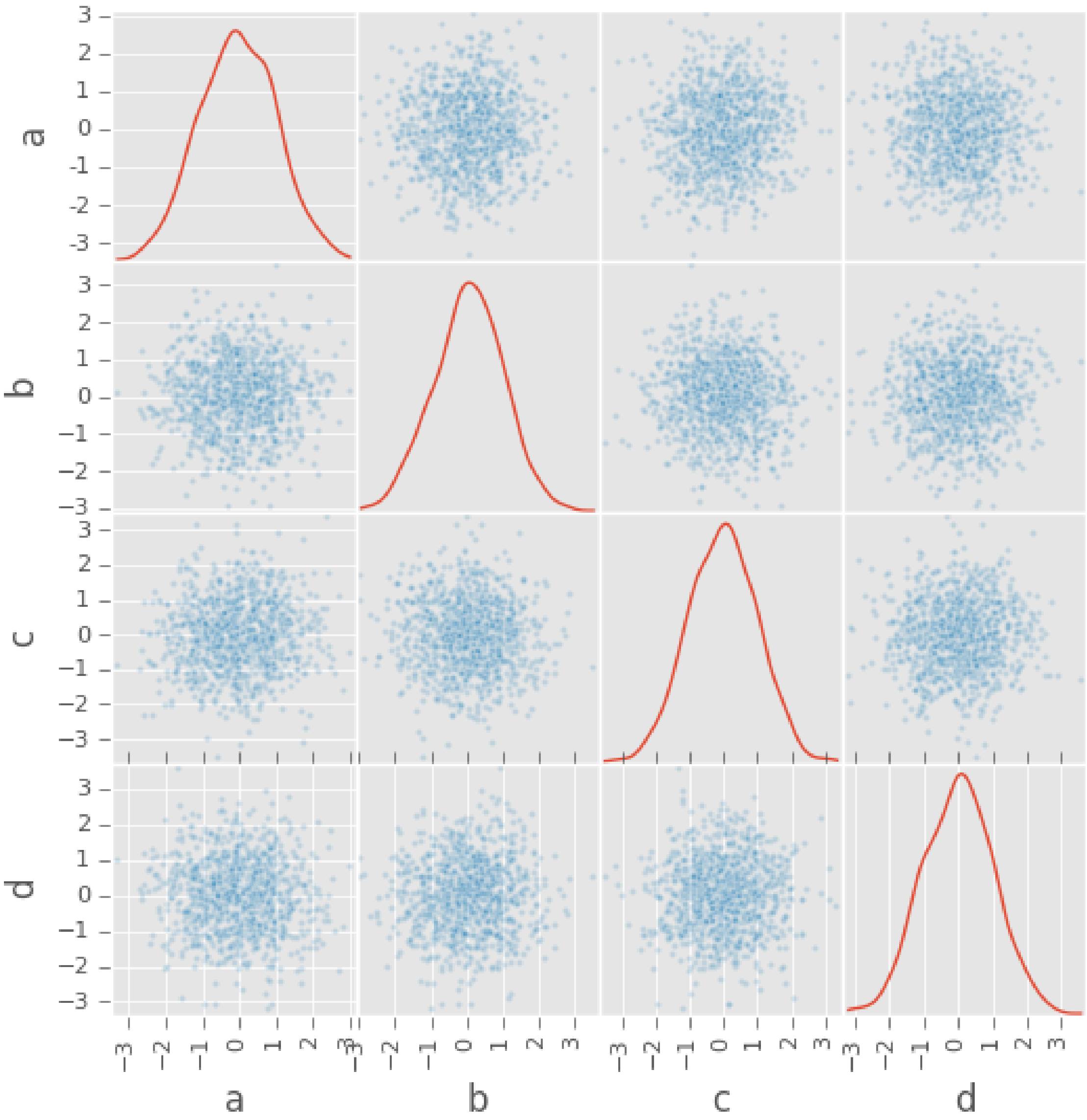
These functions can be imported from `pandas.tools.plotting` and take a `Series` or `DataFrame` as an argument.

Scatter Matrix Plot

New in version 0.7.3.

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.tools.plotting`:

```
In [78]: from pandas.tools.plotting import scatter_matrix

In [79]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])

In [80]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')
Out[80]: 
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x9d4f276c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9d229cec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9d39f2ac>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9cf9b78c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9ce526ec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9d5332cc>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9d5f750c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9d009fcc>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9ce1628c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9ce0c88c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9e0d68cc>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9df71eac>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x9cd5a8cc>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9e7cfb0c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9c584b0c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x9c5fd14c>]], dtype=object)
```

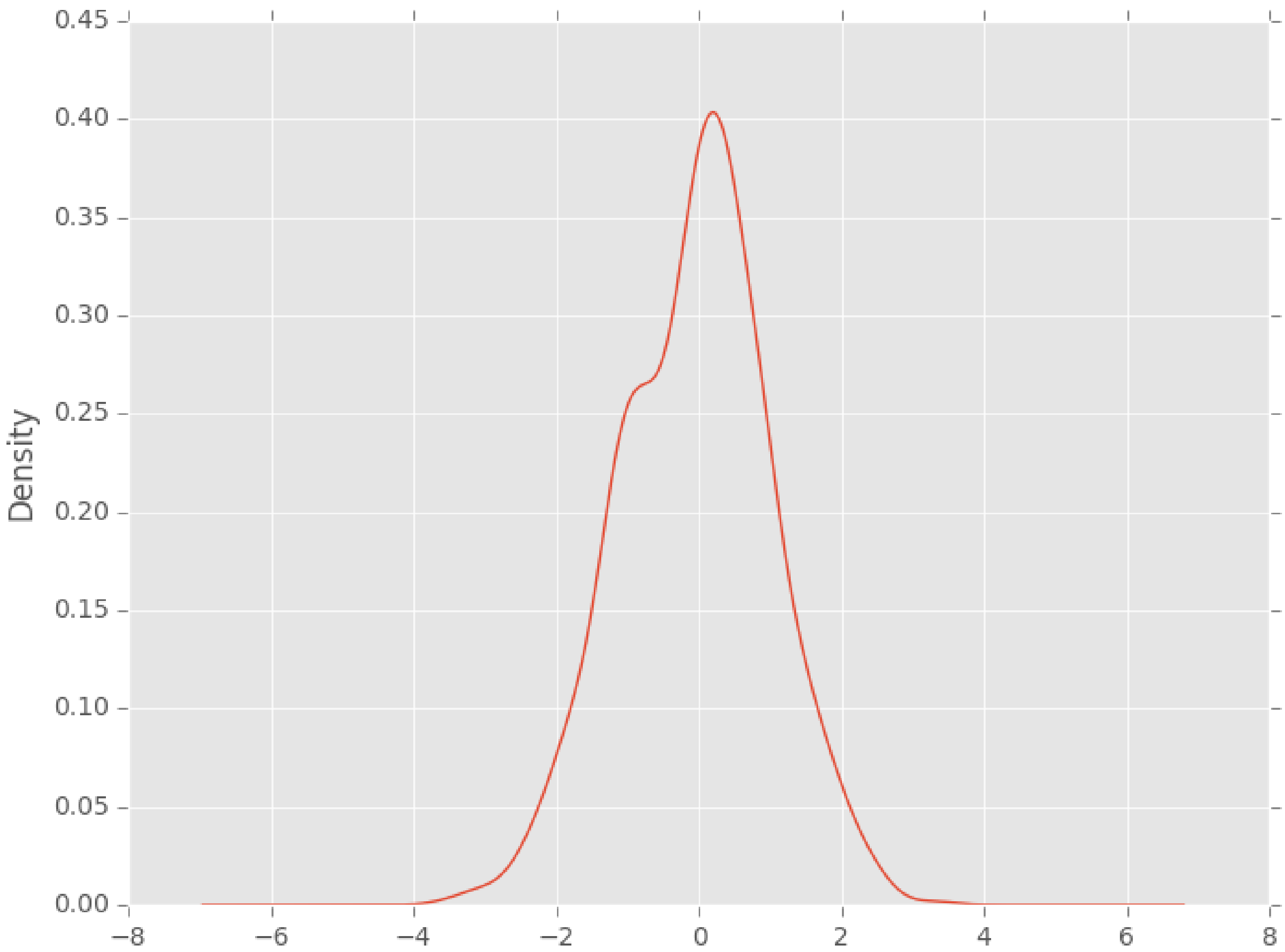


Density Plot

New in version 0.8.0.

You can create density plots using the Series/DataFrame.plot and setting `kind='kde'`:

```
In [81]: ser = pd.Series(np.random.randn(1000))

In [82]: ser.plot(kind='kde')
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x9dfbbdac>
```

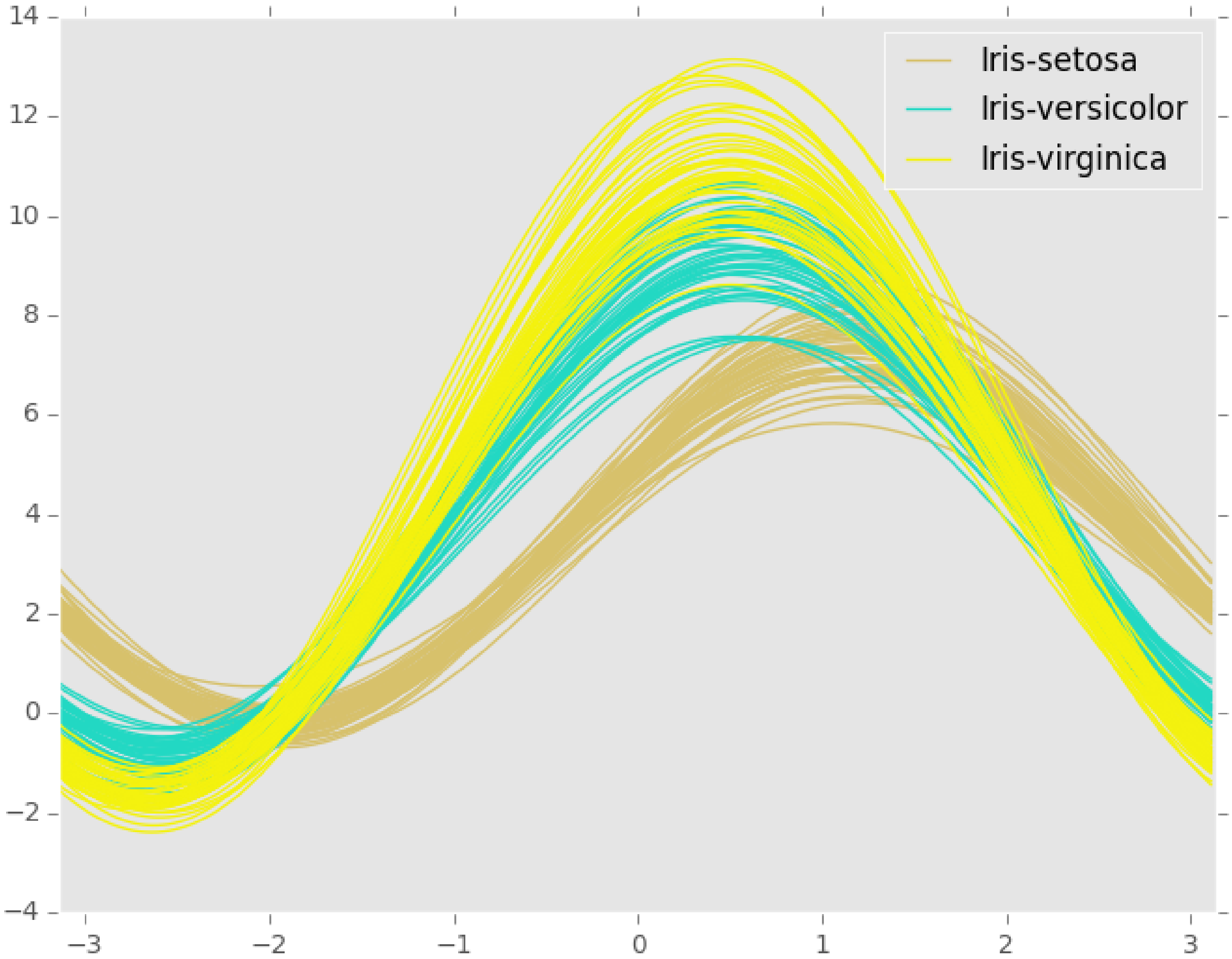


Andrews Curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

Note: The "Iris" dataset is available here.

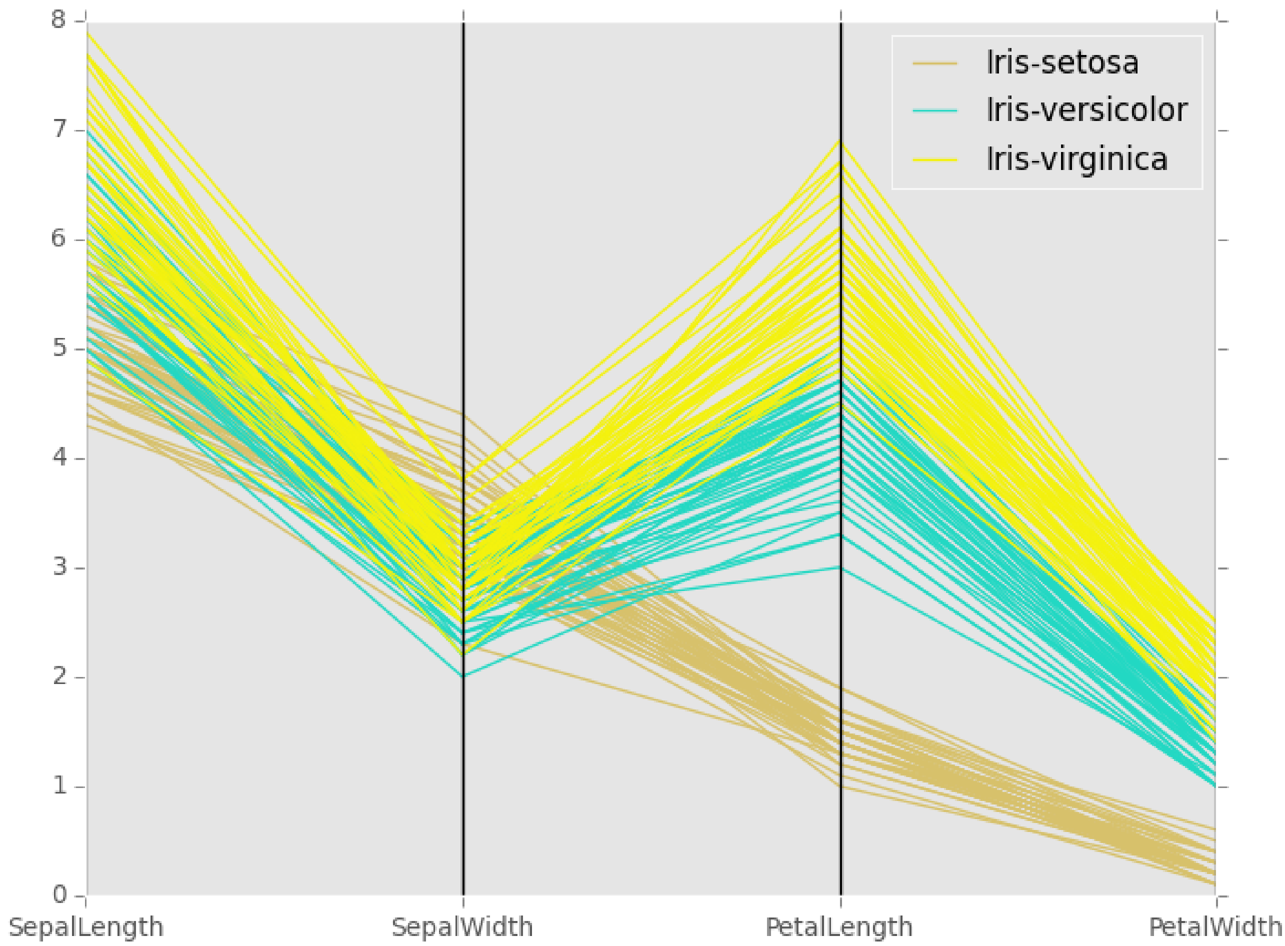
```
In [83]: from pandas.tools.plotting import andrews_curves

In [84]: data = pd.read_csv('data/iris.data')

In [85]: plt.figure()
Out[85]: <matplotlib.figure.Figure at 0x9e633acc>

In [86]: andrews_curves(data, 'Name')
Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x9ea8890c>
```



Parallel Coordinates

Parallel coordinates is a plotting technique for plotting multivariate data. It allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

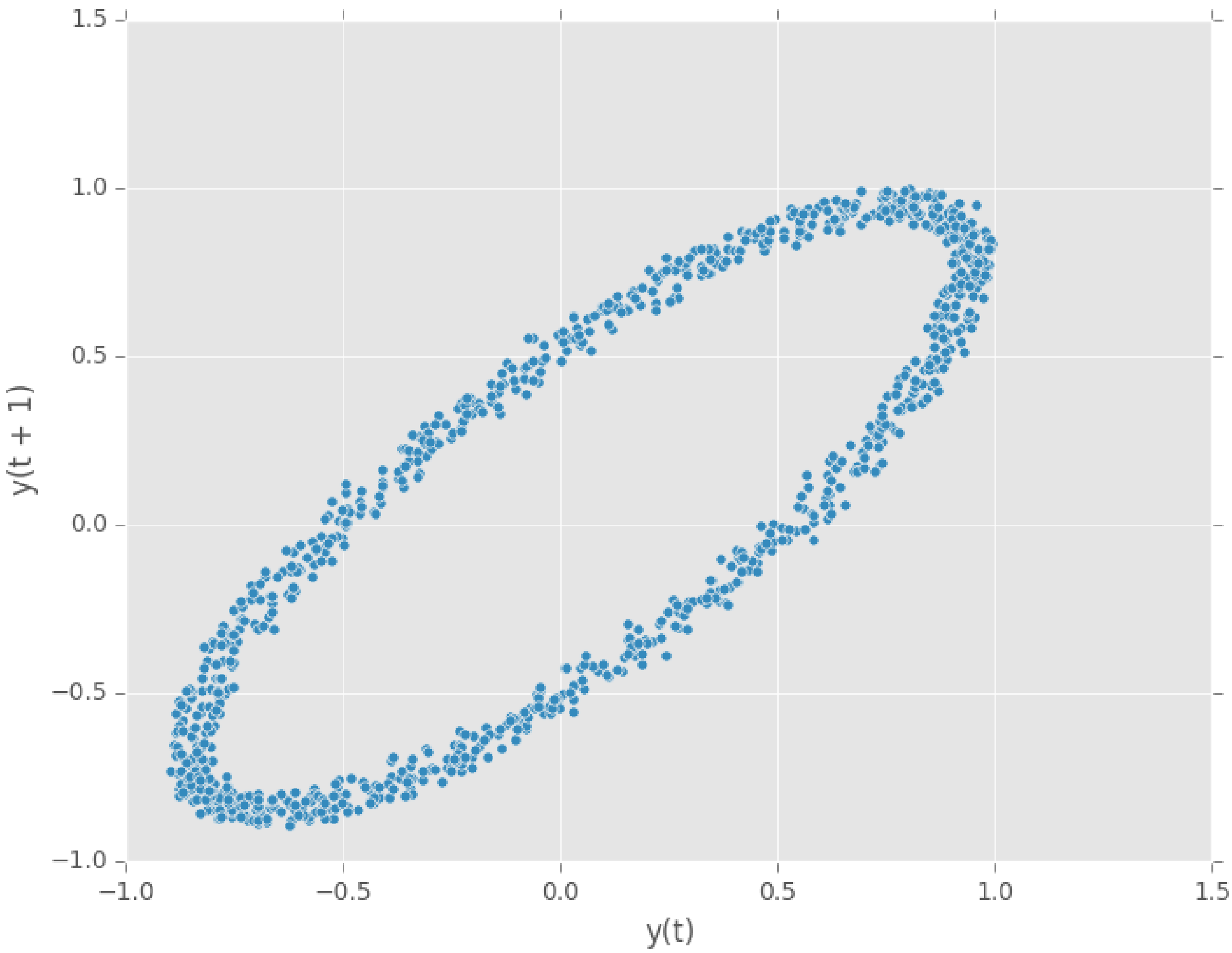
```
In [87]: from pandas.tools.plotting import parallel_coordinates

In [88]: data = pd.read_csv('data/iris.data')

In [89]: plt.figure()
Out[89]: <matplotlib.figure.Figure at 0x9e07b96c>

In [90]: parallel_coordinates(data, 'Name')
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x9e416fac>
```



Lag Plot

Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random.

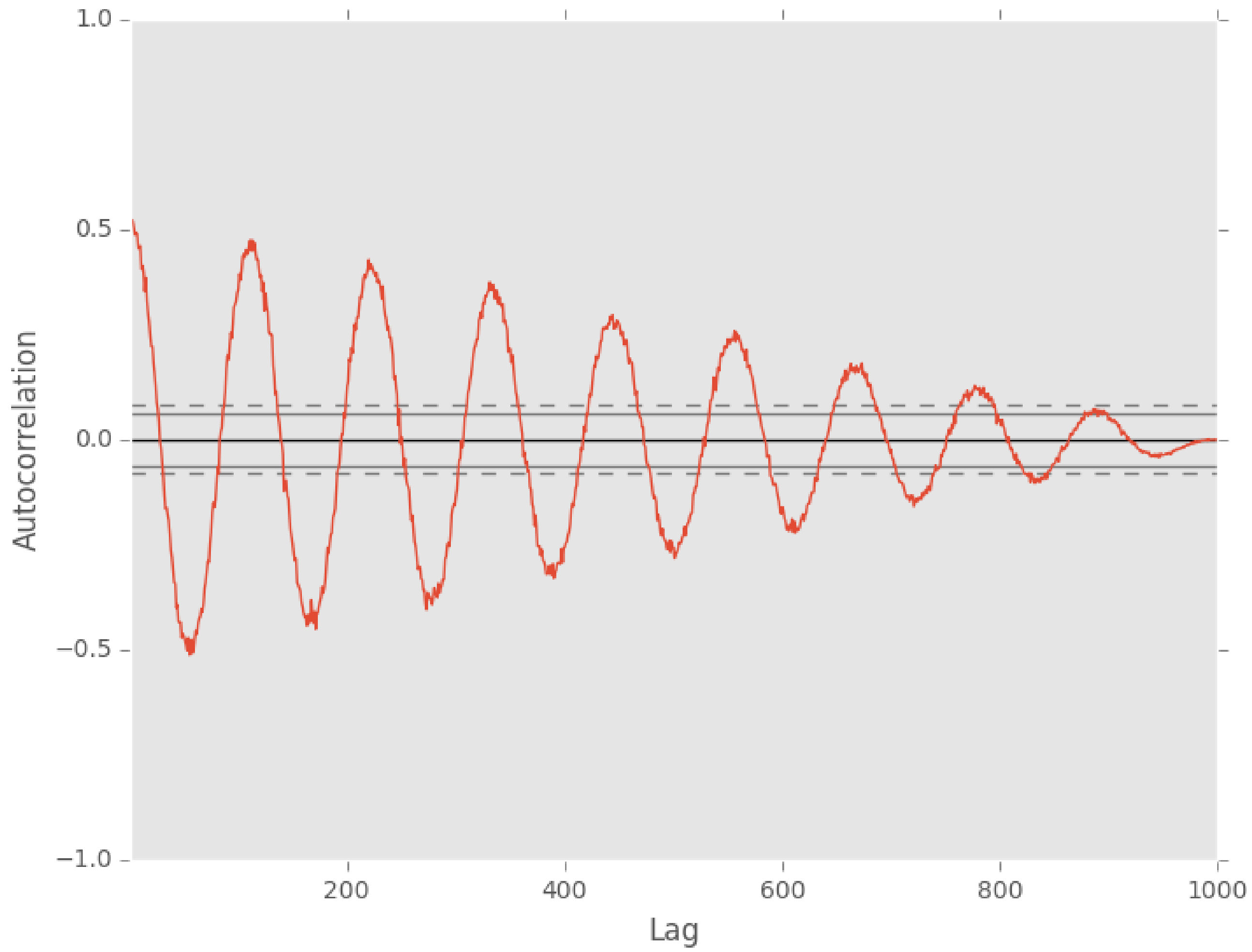
```
In [91]: from pandas.tools.plotting import lag_plot

In [92]: plt.figure()
Out[92]: <matplotlib.figure.Figure at 0xb083614c>

In [93]: data = pd.Series(0.1 * np.random.rand(1000) +
   ....:     0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))
   ....:

In [94]: lag_plot(data)
Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0xb08b1d2c>
```



Autocorrelation Plot

Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band.

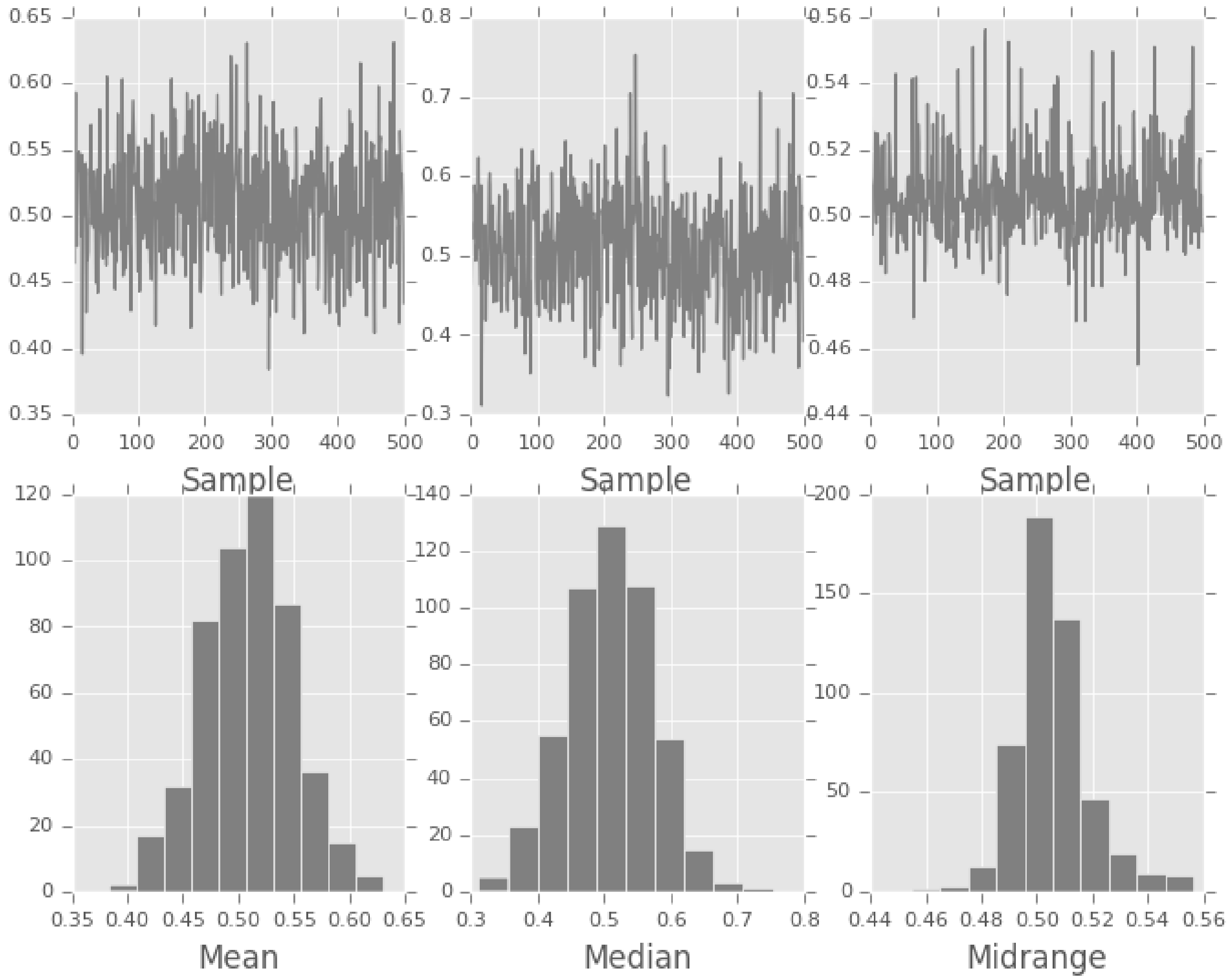
```
In [95]: from pandas.tools.plotting import autocorrelation_plot

In [96]: plt.figure()
Out[96]: <matplotlib.figure.Figure at 0xb08c0f8c>

In [97]: data = pd.Series(0.7 * np.random.rand(1000) +
   ....:    0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
   ....:

In [98]: autocorrelation_plot(data)
Out[98]: <matplotlib.axes._subplots.AxesSubplot at 0xb098778c>
```



Bootstrap Plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [99]: from pandas.tools.plotting import bootstrap_plot

In [100]: data = pd.Series(np.random.rand(1000))

In [101]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[101]: <matplotlib.figure.Figure at 0xb0897c8c>
```

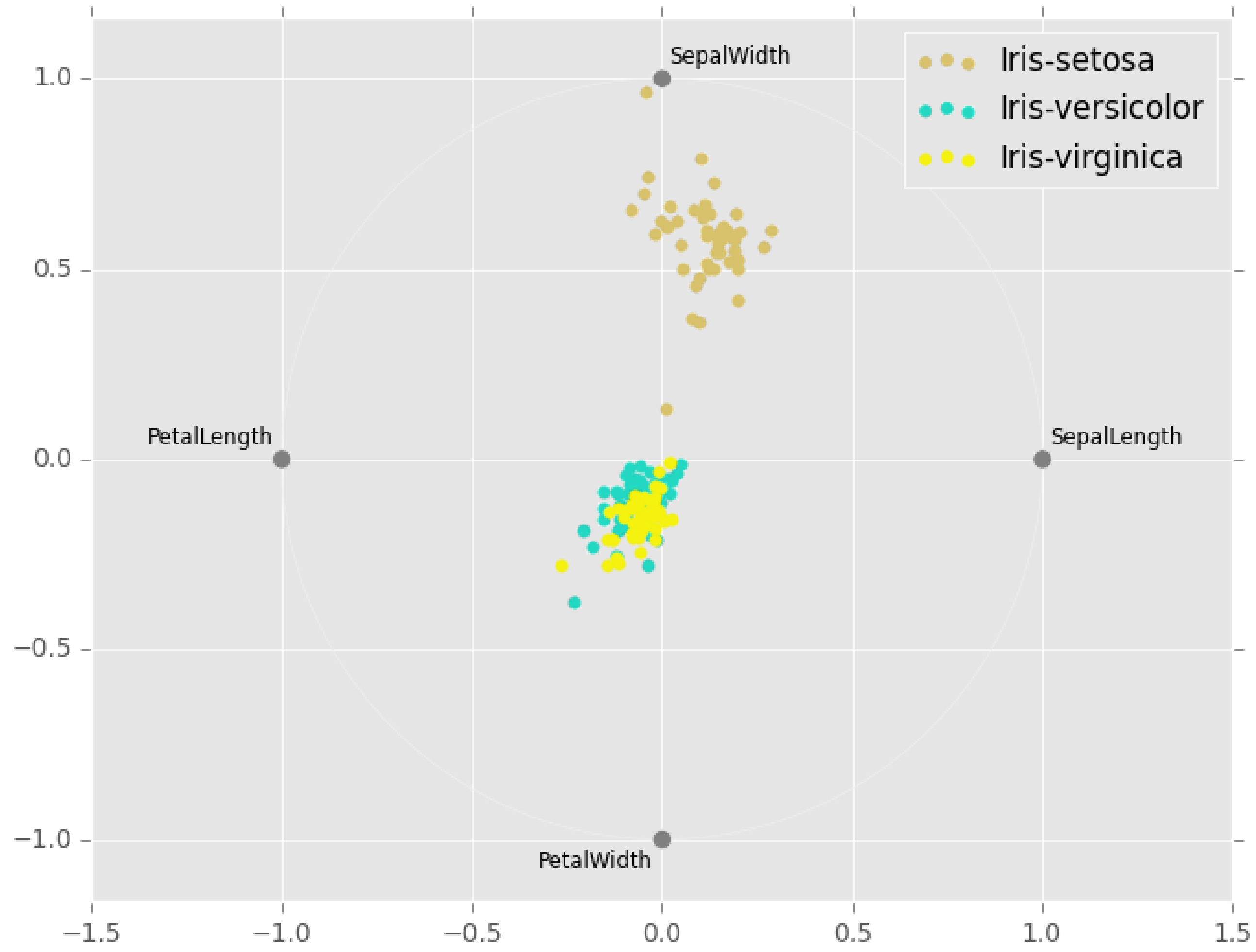


RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs it will be colored differently.

Note: The “Iris” dataset is available here.

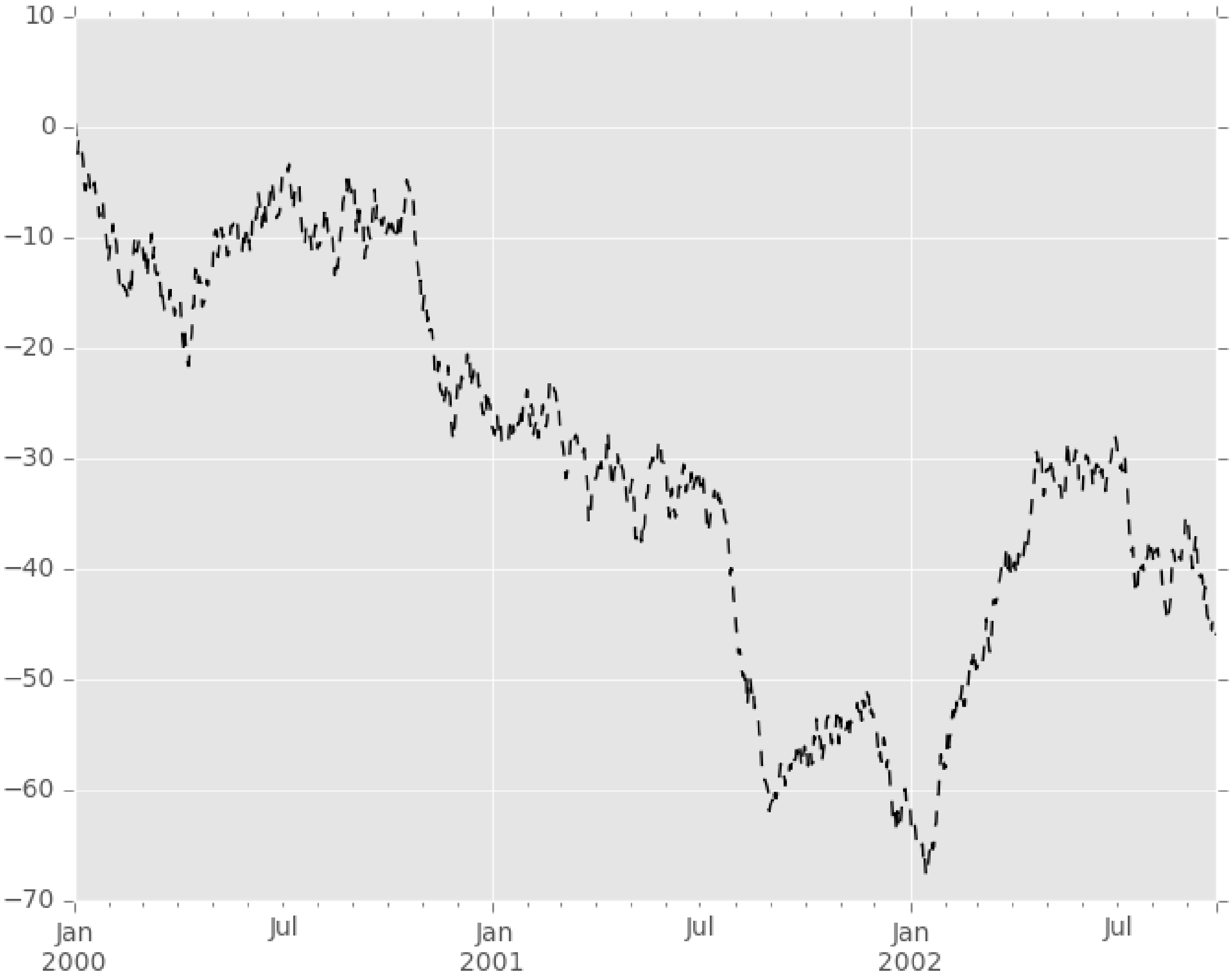
```
In [102]: from pandas.tools.plotting import radviz

In [103]: data = pd.read_csv('data/iris.data')

In [104]: plt.figure()
Out[104]: <matplotlib.figure.Figure at 0x9ce79e8c>

In [105]: radviz(data, 'Name')
Out[105]: <matplotlib.axes._subplots.AxesSubplot at 0x9ce6ec2c>
```



Plot Formatting

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [106]: plt.figure(); ts.plot(style='k--', label='Series');
```

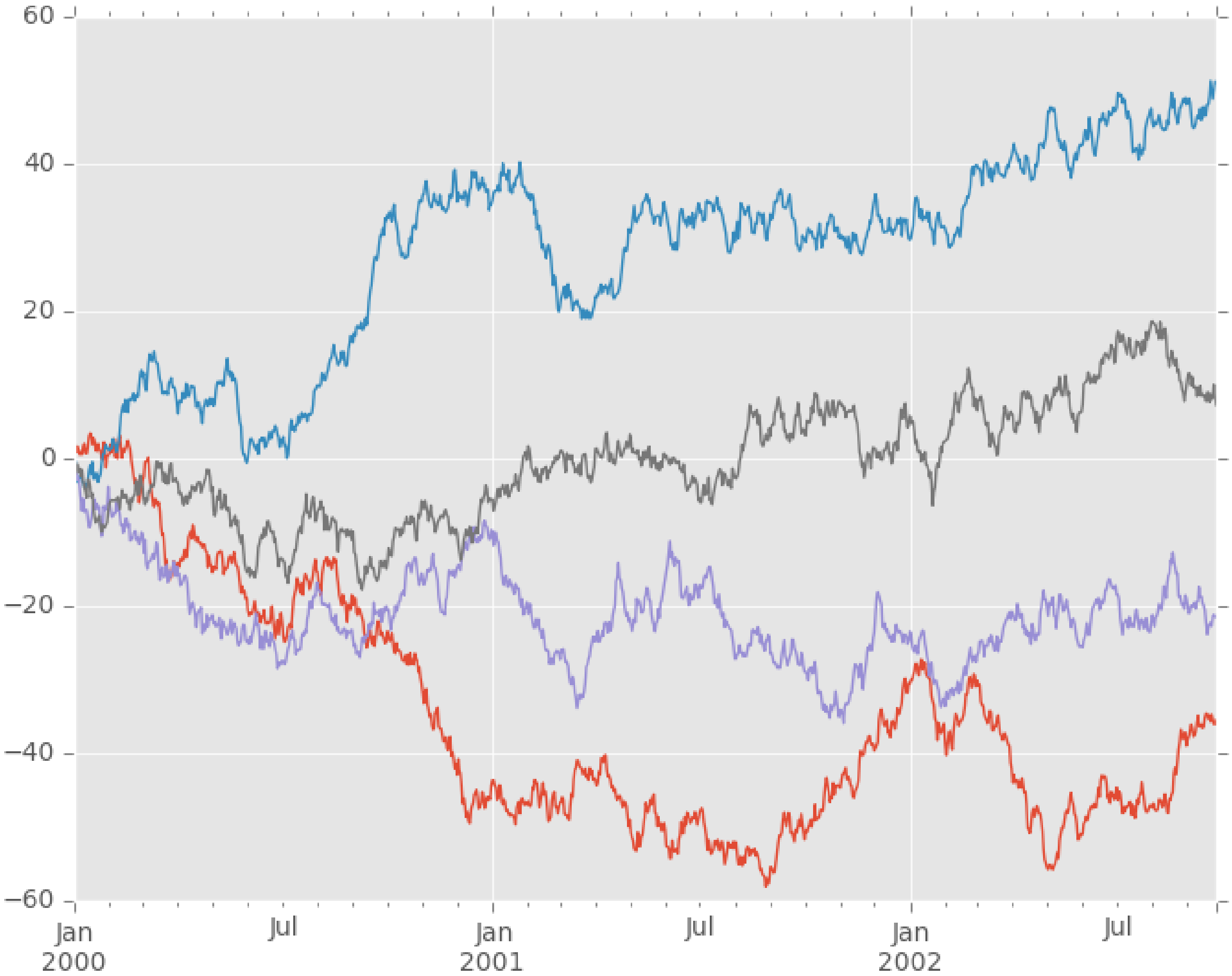


For each kind of plot (e.g. *line*, *bar*, *scatter*) any additional arguments keywords are passed along to the corresponding matplotlib function (`ax.plot()`, `ax.bar()`, `ax.scatter()`). These can be used to control additional styling, beyond what pandas provides.

Controlling the Legend

You may set the `legend` argument to `False` to hide the legend, which is shown by default.

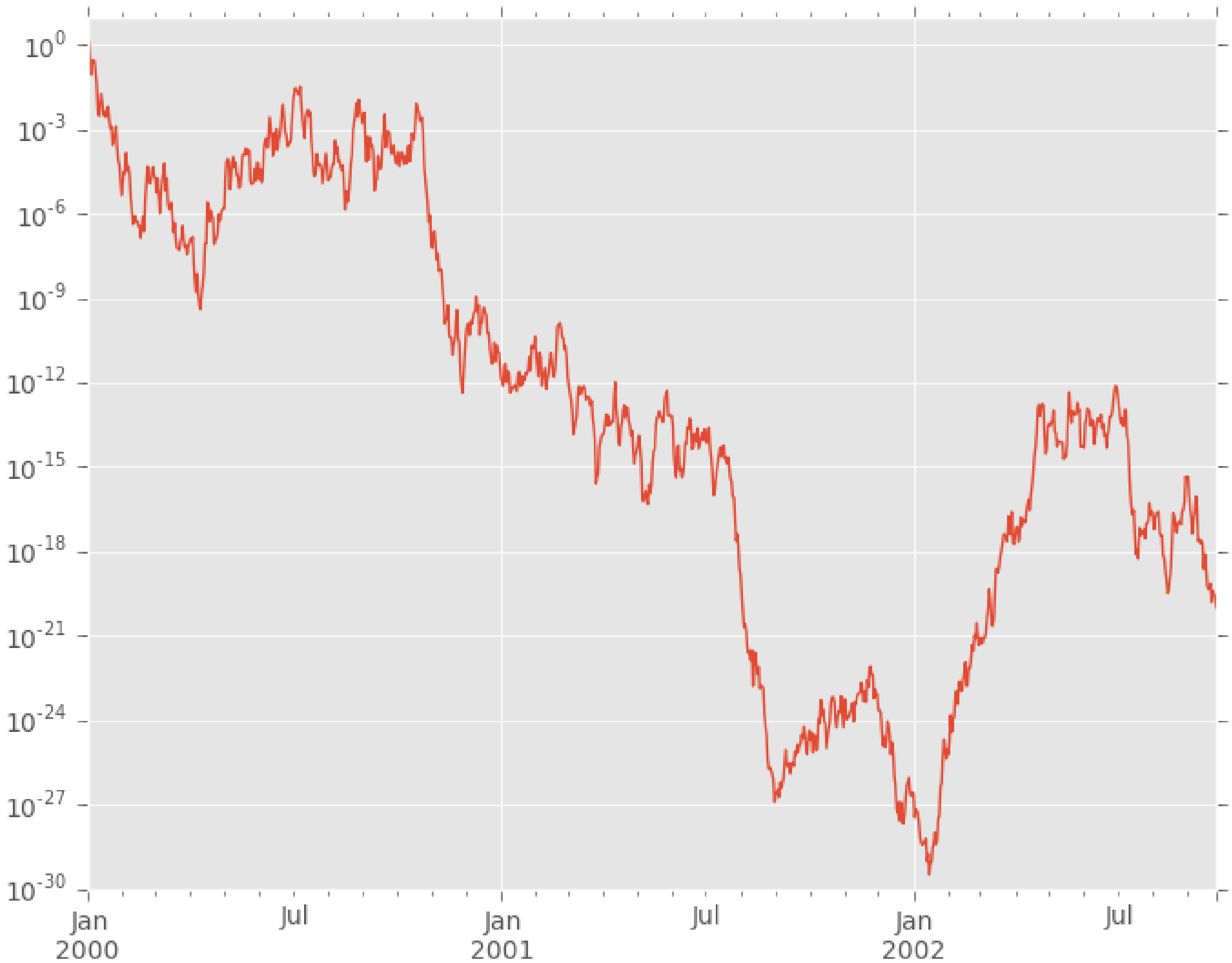
```
In [107]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))

In [108]: df = df.cumsum()

In [109]: df.plot(legend=False)
Out[109]: <matplotlib.axes._subplots.AxesSubplot at 0xb083620c>
```



Scales

You may pass `logy` to get a log-scale Y axis.

```
In [110]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))

In [111]: ts = np.exp(ts.cumsum())

In [112]: ts.plot(logy=True)
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x9e4871ac>
```

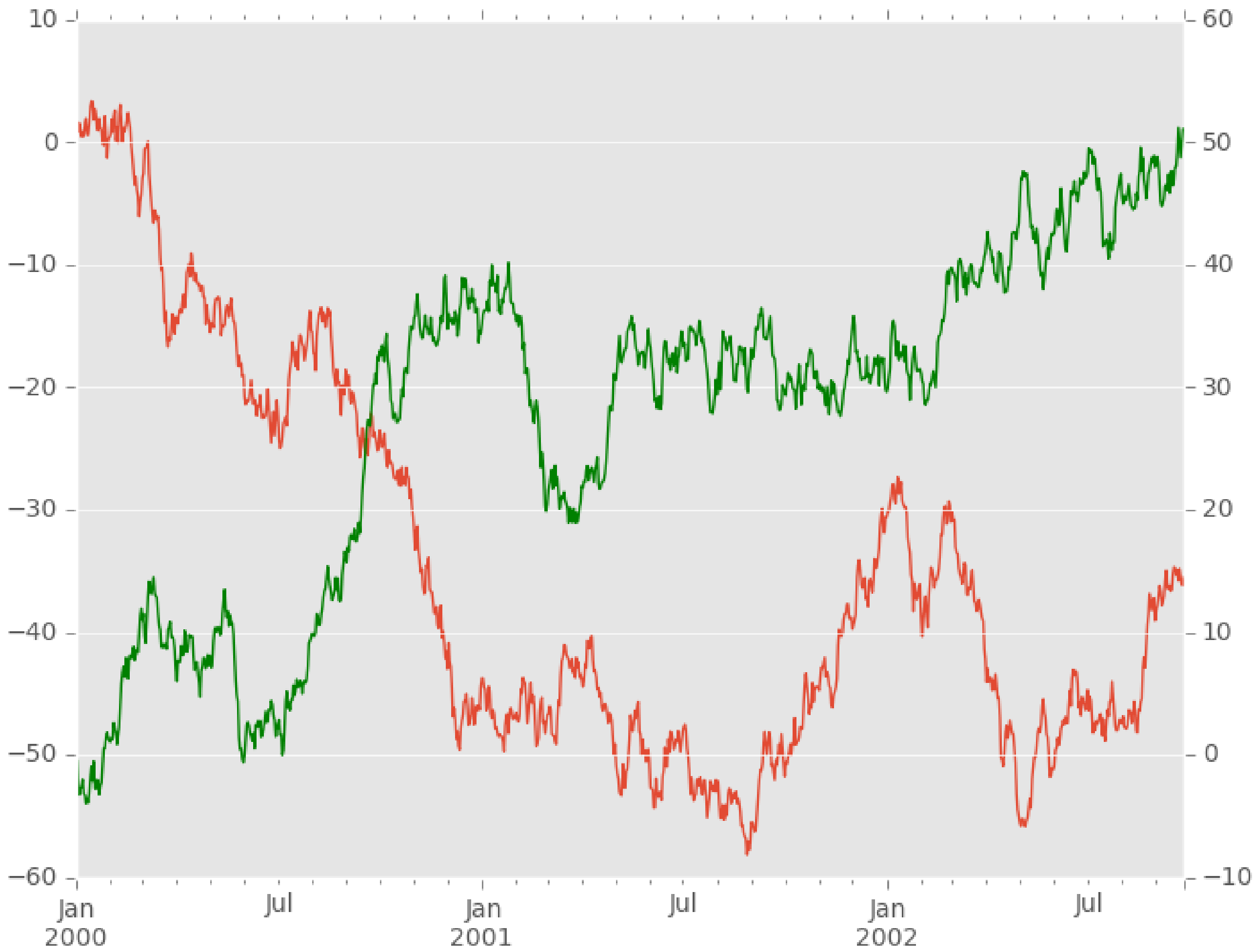


See also the `logx` and `loglog` keyword arguments.

Plotting on a Secondary Y-axis

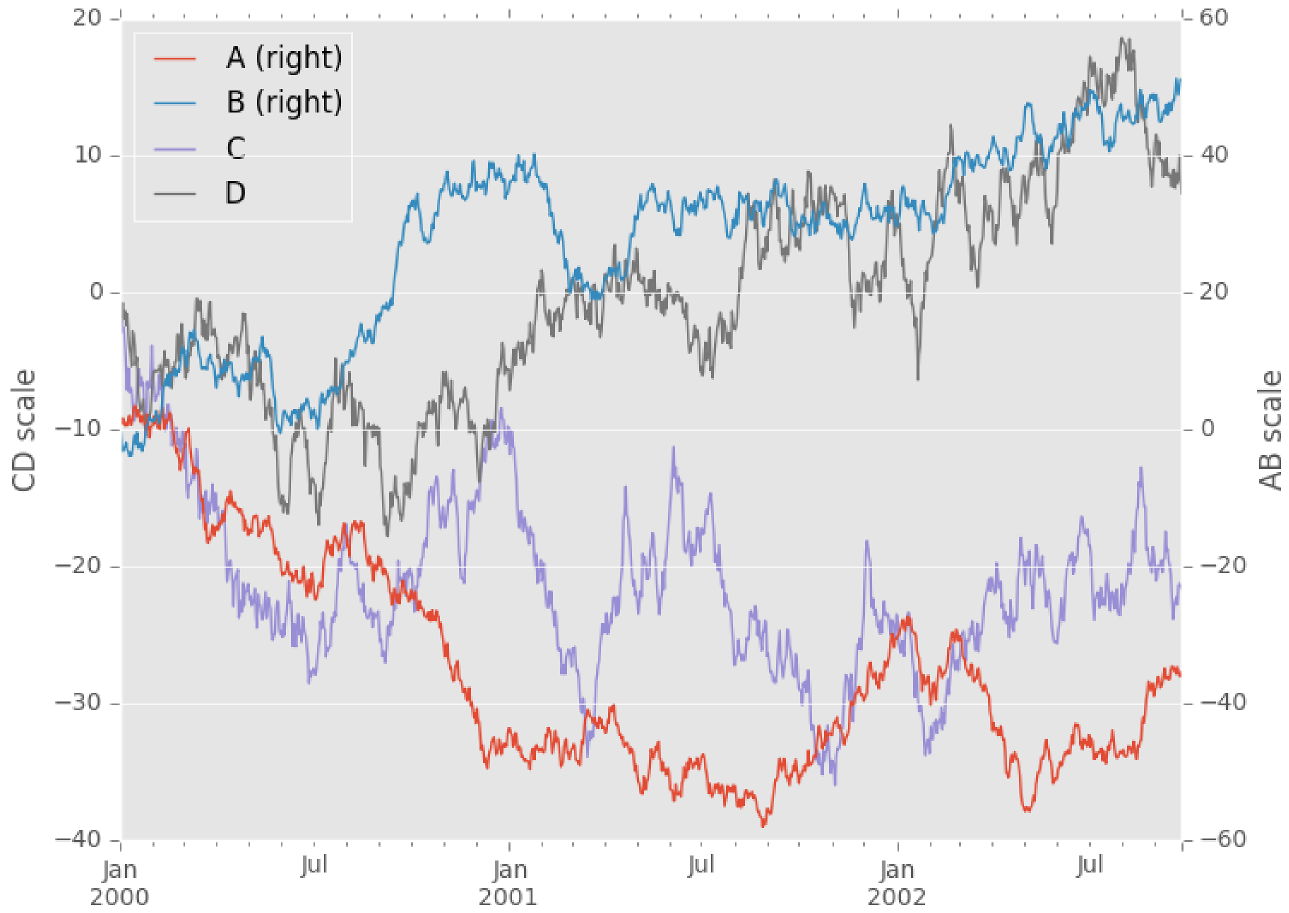
To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [113]: df.A.plot()
Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x9e40918c>

In [114]: df.B.plot(secondary_y=True, style='g')
Out[114]: <matplotlib.axes._subplots.AxesSubplot at 0x9d4d5aac>
```



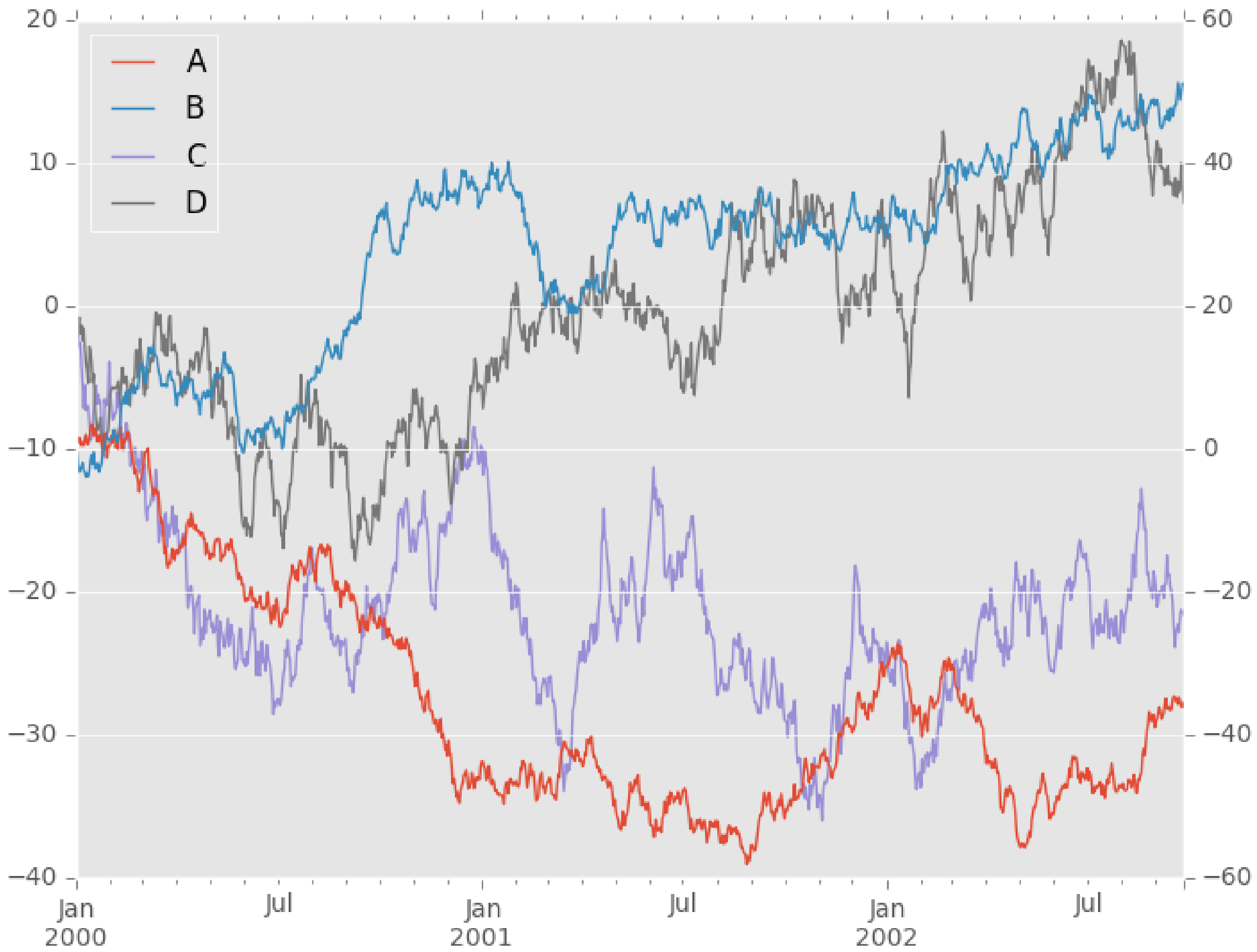
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [115]: plt.figure()
Out[115]: <matplotlib.figure.Figure at 0x9e95e40c>

In [116]: ax = df.plot(secondary_y=['A', 'B'])

In [117]: ax.set_ylabel('CD scale')
Out[117]: <matplotlib.text.Text at 0x9f09e1cc>

In [118]: ax.right_ax.set_ylabel('AB scale')
Out[118]: <matplotlib.text.Text at 0x9ed2f2cc>
```



Note that the columns plotted on the secondary y-axis is automatically marked with “(right)” in the legend. To turn off the automatic marking, use the `mark_right=False` keyword:

```
In [119]: plt.figure()
Out[119]: <matplotlib.figure.Figure at 0x9cda83cc>

In [120]: df.plot(secondary_y=['A', 'B'], mark_right=False)
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0x9cd82a0c>
```



Suppressing Tick Resolution Adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

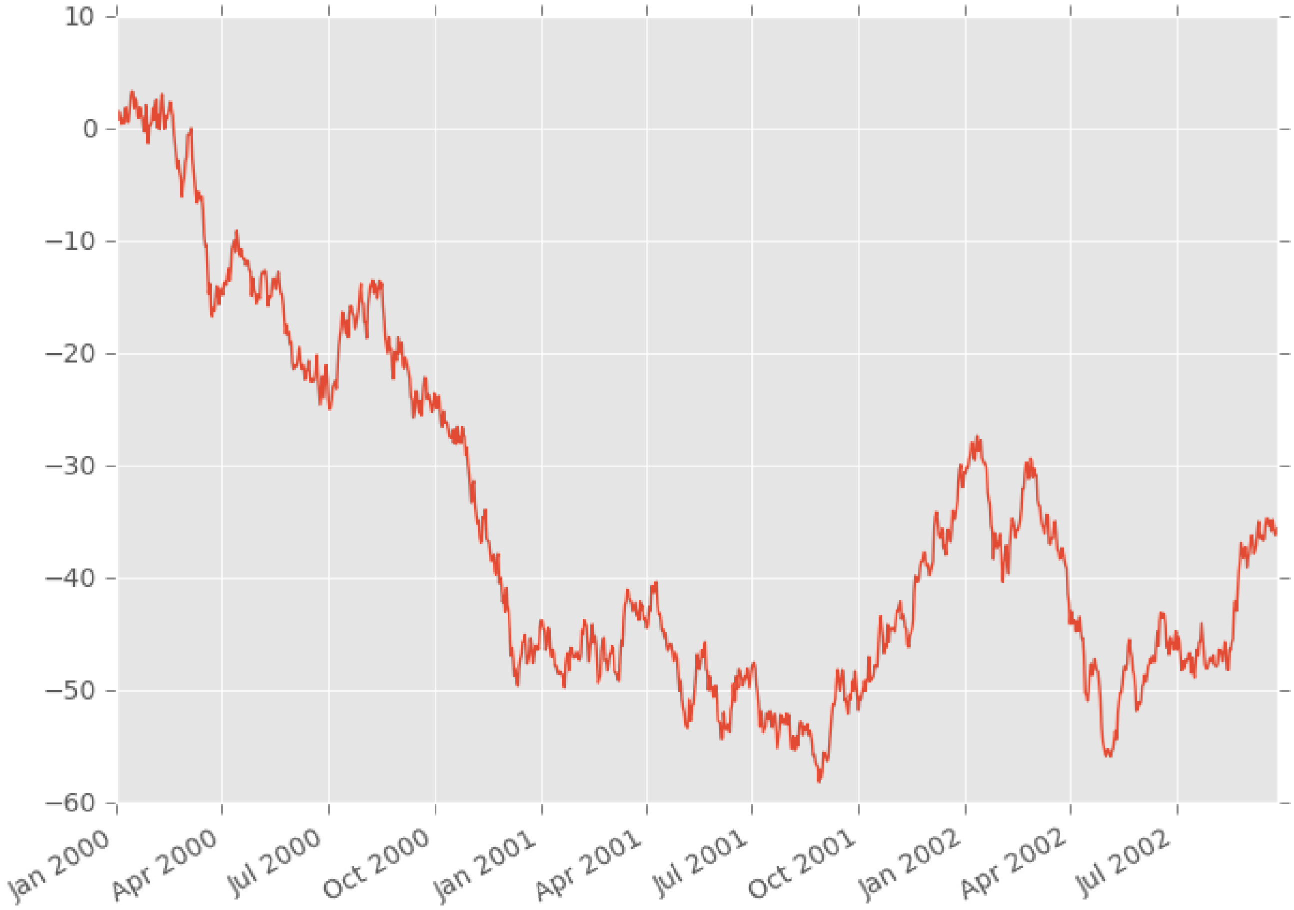
Here is the default behavior, notice how the x-axis tick labelling is performed:

```
In [121]: plt.figure()
Out[121]: <matplotlib.figure.Figure at 0x9e95e8ac>

In [122]: df.A.plot()
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0x9f04a32c>
```

_images/ser_plot_suppress.png

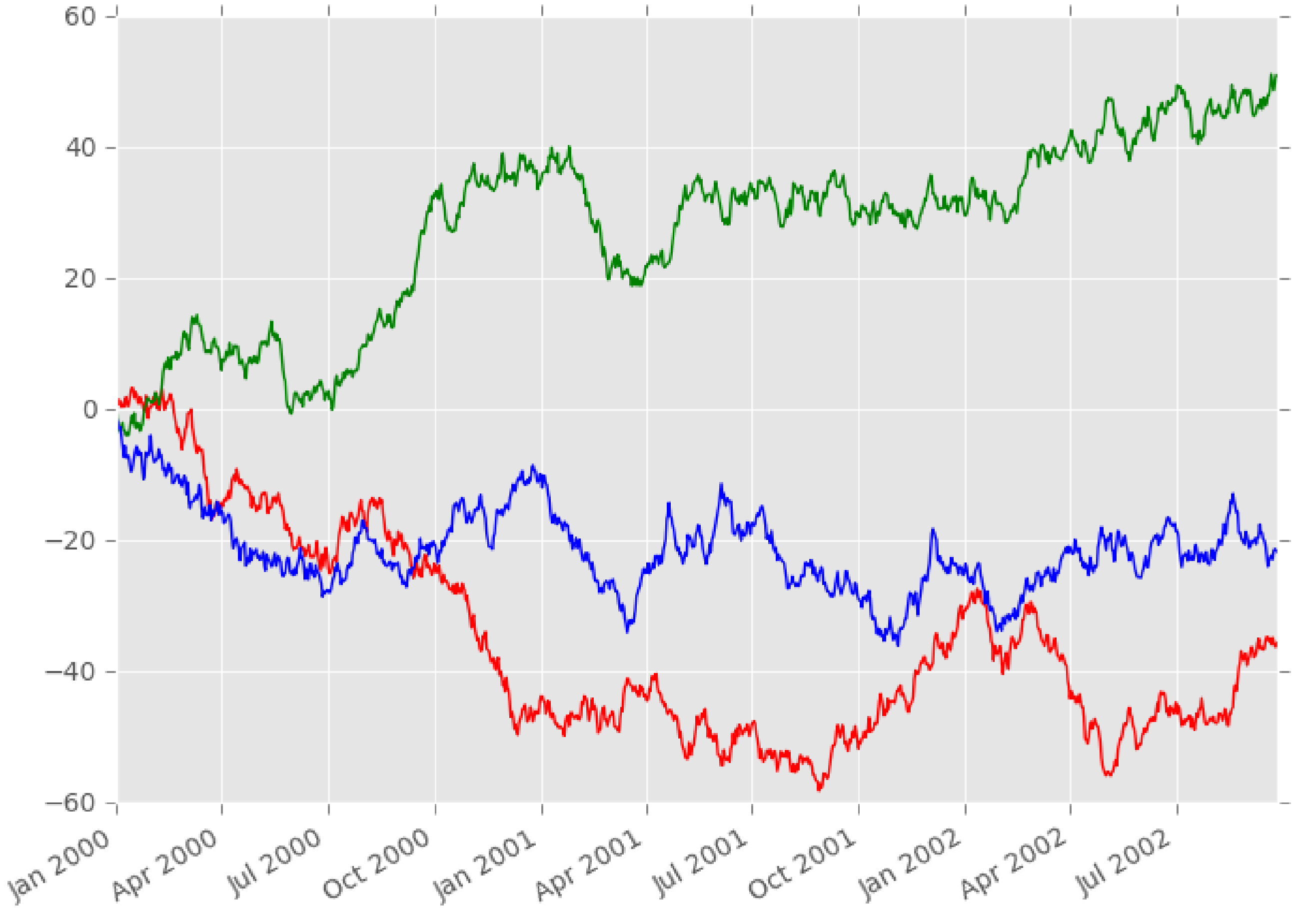
Using the `x_compat` parameter, you can suppress this behavior:

```
In [123]: plt.figure()
Out[123]: <matplotlib.figure.Figure at 0x9f205d8c>

In [124]: df.A.plot(x_compat=True)
Out[124]: <matplotlib.axes._subplots.AxesSubplot at 0x9f20556c>
```



If you have more than one plot that needs to be suppressed, the `use` method in `pandas.plot_params` can be used in a *with statement*:

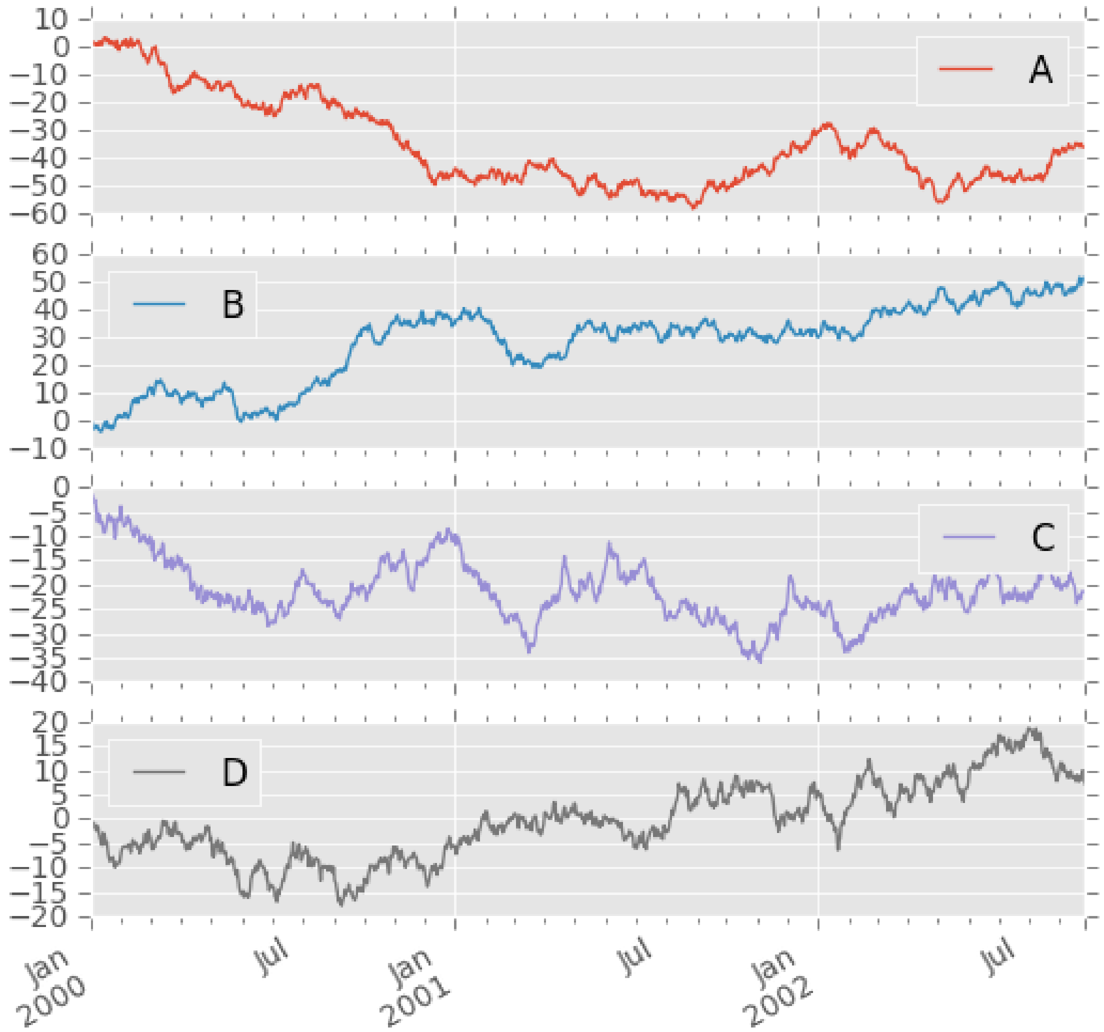
```
In [125]: plt.figure()
Out[125]: <matplotlib.figure.Figure at 0x9da6ceac>

In [126]: with pd.plot_params.use('x_compat', True):
   .....:     df.A.plot(color='r')
   .....:     df.B.plot(color='g')
   .....:     df.C.plot(color='b')
   .....:
```



Subplots

Each Series in a DataFrame can be plotted on a different axis with the `subplots` keyword:

```
In [127]: df.plot(subplots=True, figsize=(6, 6));
```

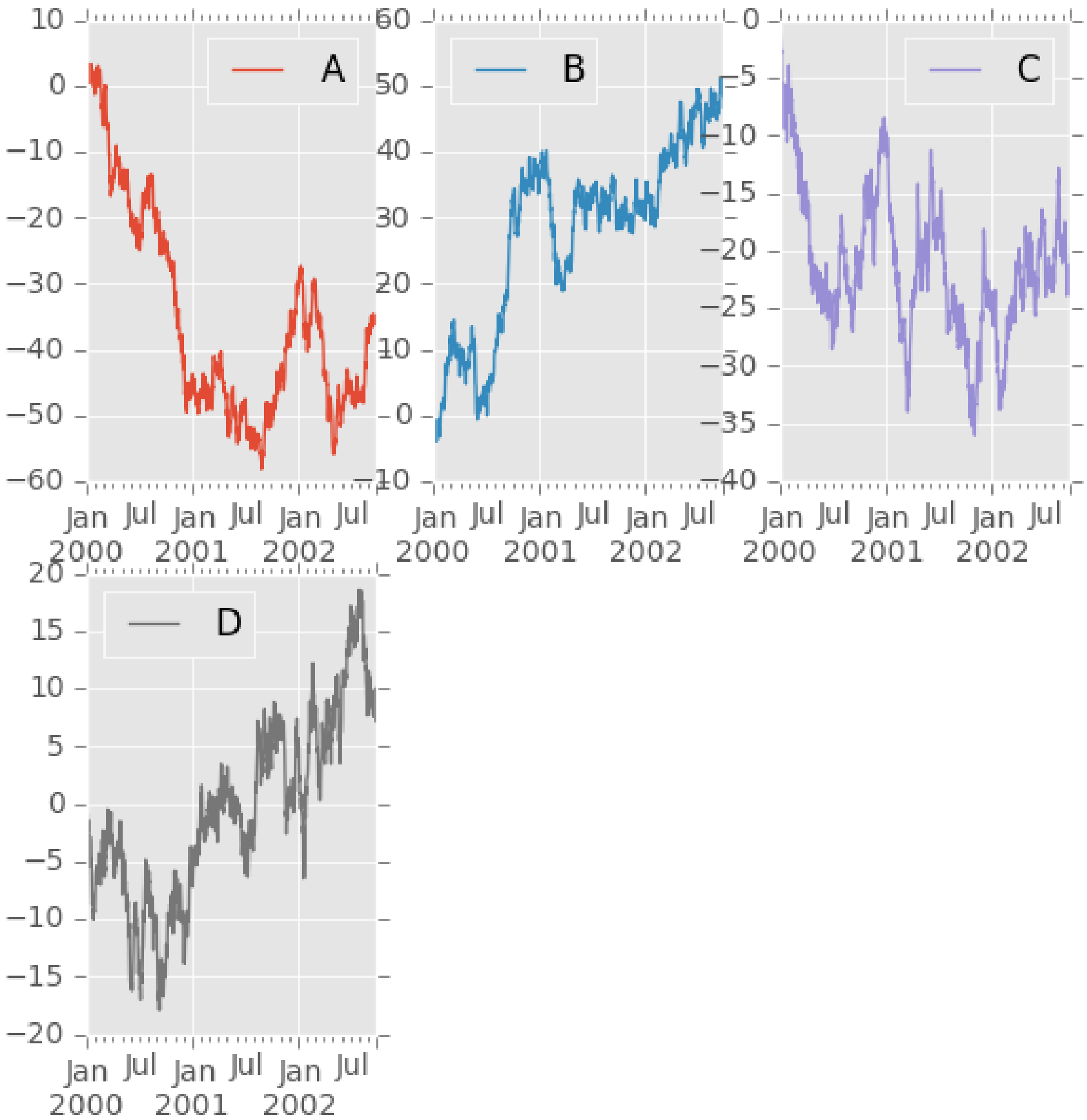


Using Layout and Targetting Multiple Axes

The layout of subplots can be specified by `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If input is invalid, `ValueError` will be raised.

The number of axes which can be contained by rows x columns specified by `layout` must be larger than the number of required subplots. If layout can contain more axes than required, blank axes are not drawn. Similar to a numpy array's `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [128]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```



The above example is identical to using

```
In [129]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

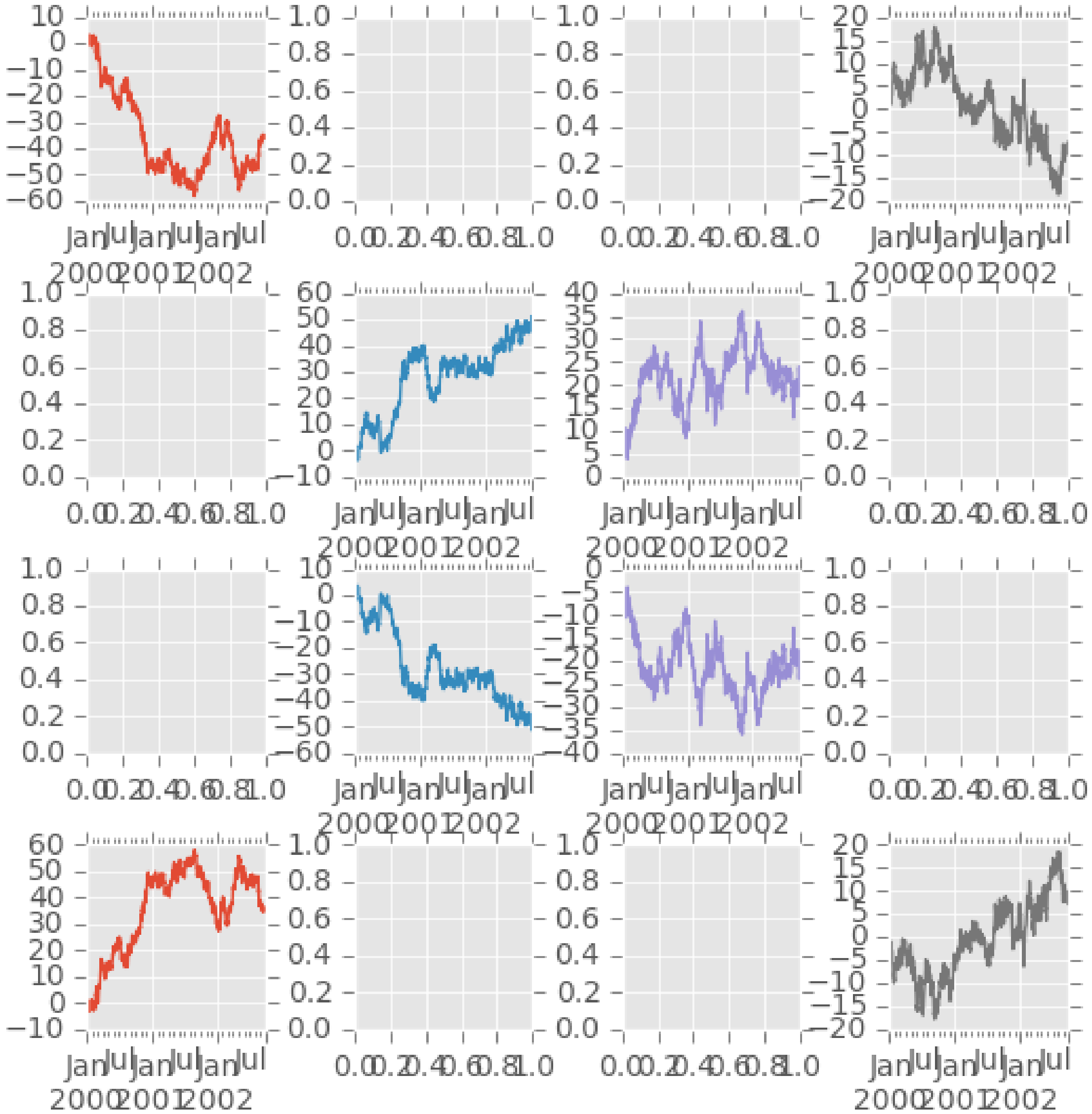
The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

Also, you can pass multiple axes created beforehand as list-like via `ax` keyword. This allows to use more complicated layout. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via `ax` keyword, `layout`, `sharex` and `sharey` keywords don't affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

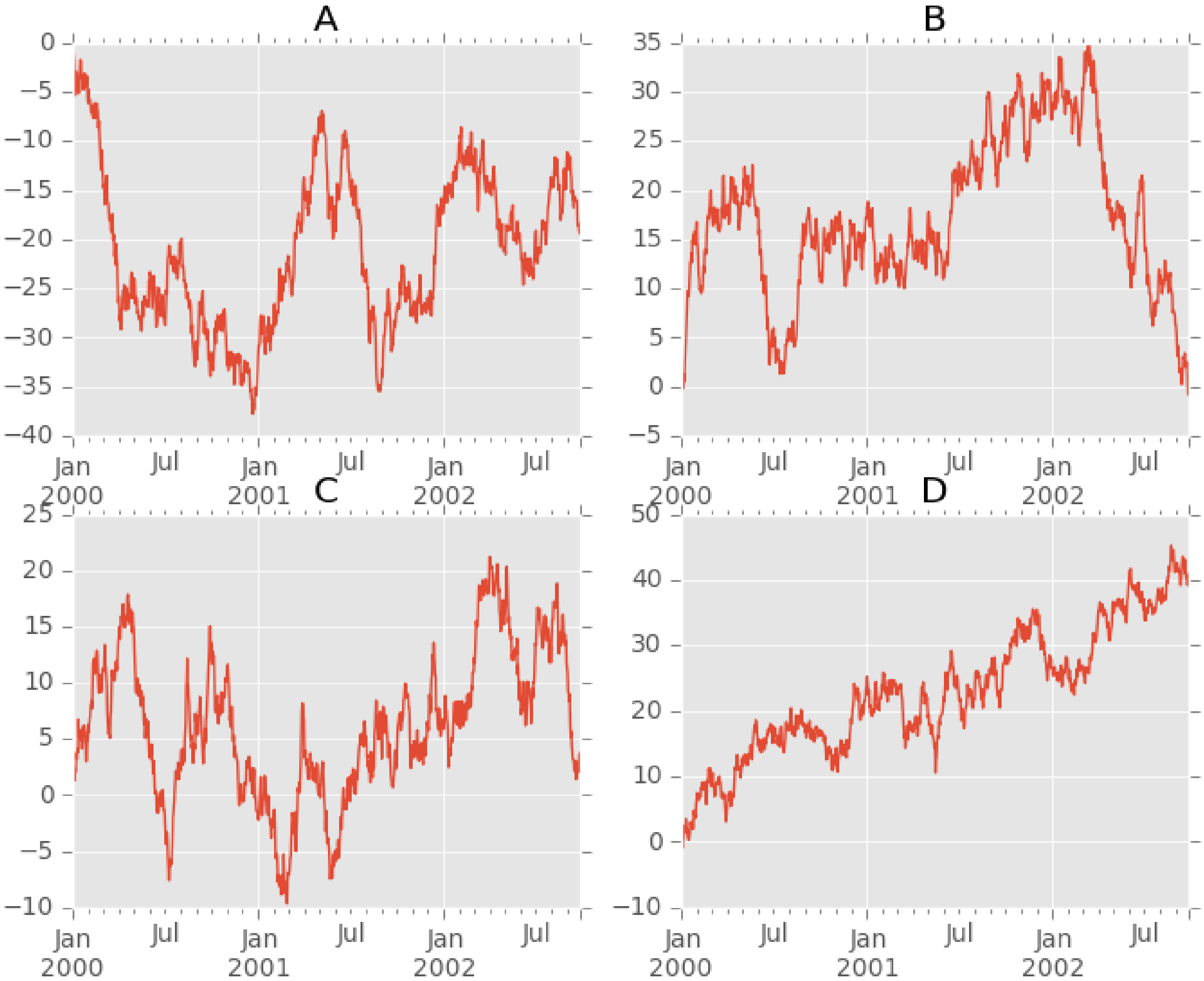
```
In [130]: fig, axes = plt.subplots(4, 4, figsize=(6, 6));

In [131]: plt.subplots_adjust(wspace=0.5, hspace=0.5);

In [132]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]
```

```
In [133]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]

In [134]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);

In [135]: (-df).plot(subplots=True, ax=target2, legend=False, sharex=False, sharey=False);
```



Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

```
In [136]: fig, axes = plt.subplots(nrows=2, ncols=2)

In [137]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A');

In [138]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B');

In [139]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C');

In [140]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D');
```



Plotting With Error Bars

New in version 0.14.

Plotting with error bars is now supported in the `DataFrame.plot()` and `Series.plot()`

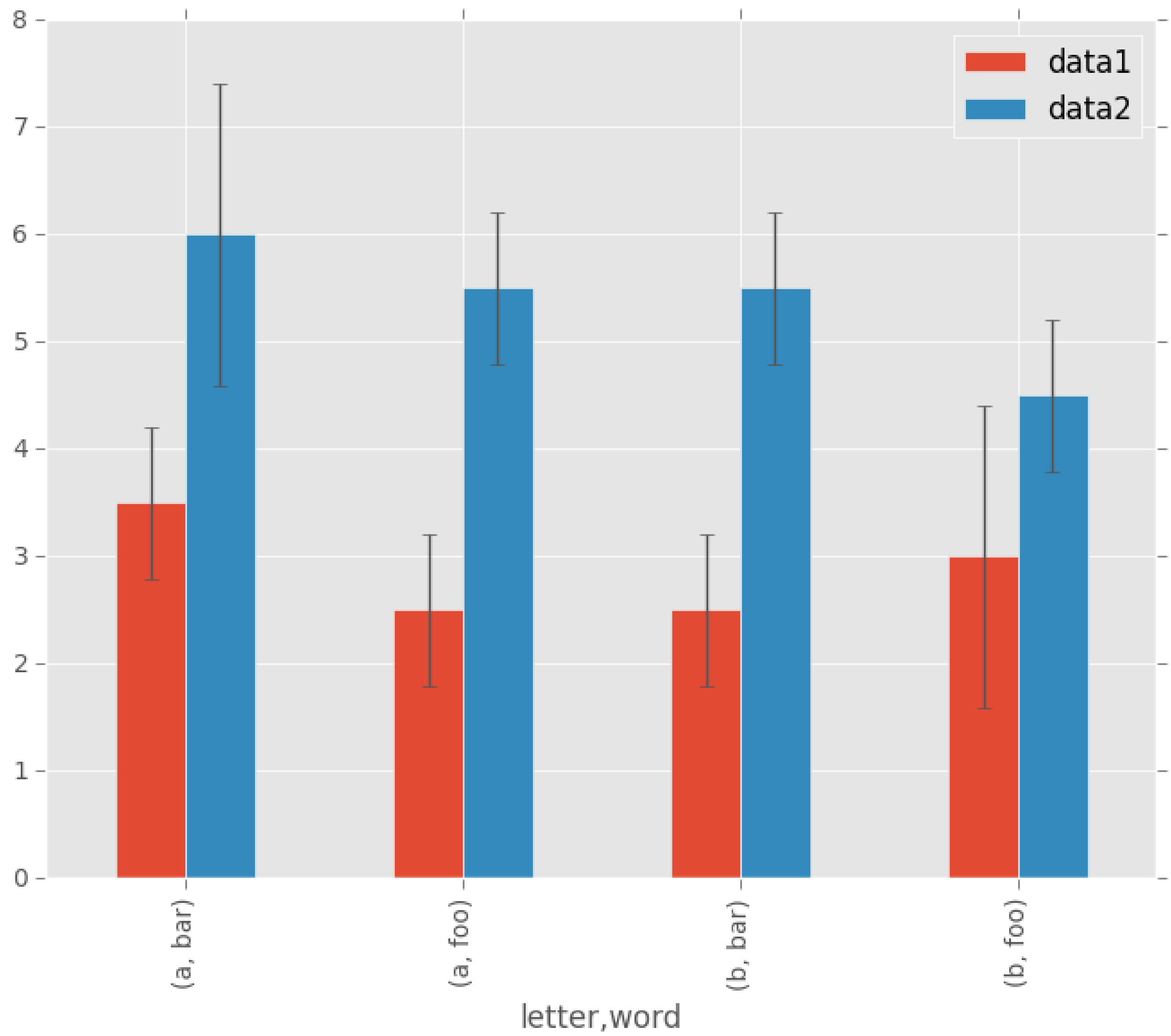
Horizontal and vertical errorbars can be supplied to the `xerr` and `yerr` keyword arguments to `plot()`. The error values can be specified using a variety of formats.

- As a `DataFrame` or `dict` of errors with column names matching the `columns` attribute of the plotting `DataFrame` or matching the `name` attribute of the `Series`
- As a `str` indicating which of the columns of plotting `DataFrame` contain the error values
- As raw values (`list`, `tuple`, or `np.ndarray`). Must be the same length as the plotting `DataFrame`/`Series`

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For a `M` length `Series`, a `Mx2` array should be provided indicating lower and upper (or left and right) errors. For a `MxN` `DataFrame`, asymmetrical errors should be in a `Mx2xN` array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.

```
# Generate the data
In [141]: ix3 = pd.MultiIndex.from_arrays([['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'], ['foo', '

In [142]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2], 'data2': [6, 5, 7, 5, 4, 5, 6

# Group by index labels and take the means and standard deviations for each group
In [143]: gp3 = df3.groupby(level=('letter', 'word'))

In [144]: means = gp3.mean()

In [145]: errors = gp3.std()

In [146]: means
Out[146]:
             data1  data2
letter word
a      bar     3.5    6.0
       foo     2.5    5.5
b      bar     2.5    5.5
       foo     3.0    4.5

In [147]: errors
Out[147]:
                data1     data2
letter word
a      bar   0.707107  1.414214
       foo   0.707107  0.707107
b      bar   0.707107  0.707107
       foo   1.414214  0.707107

# Plot
In [148]: fig, ax = plt.subplots()

In [149]: means.plot(yerr=errors, ax=ax, kind='bar')
Out[149]: <matplotlib.axes._subplots.AxesSubplot at 0x9ad6050c>
```

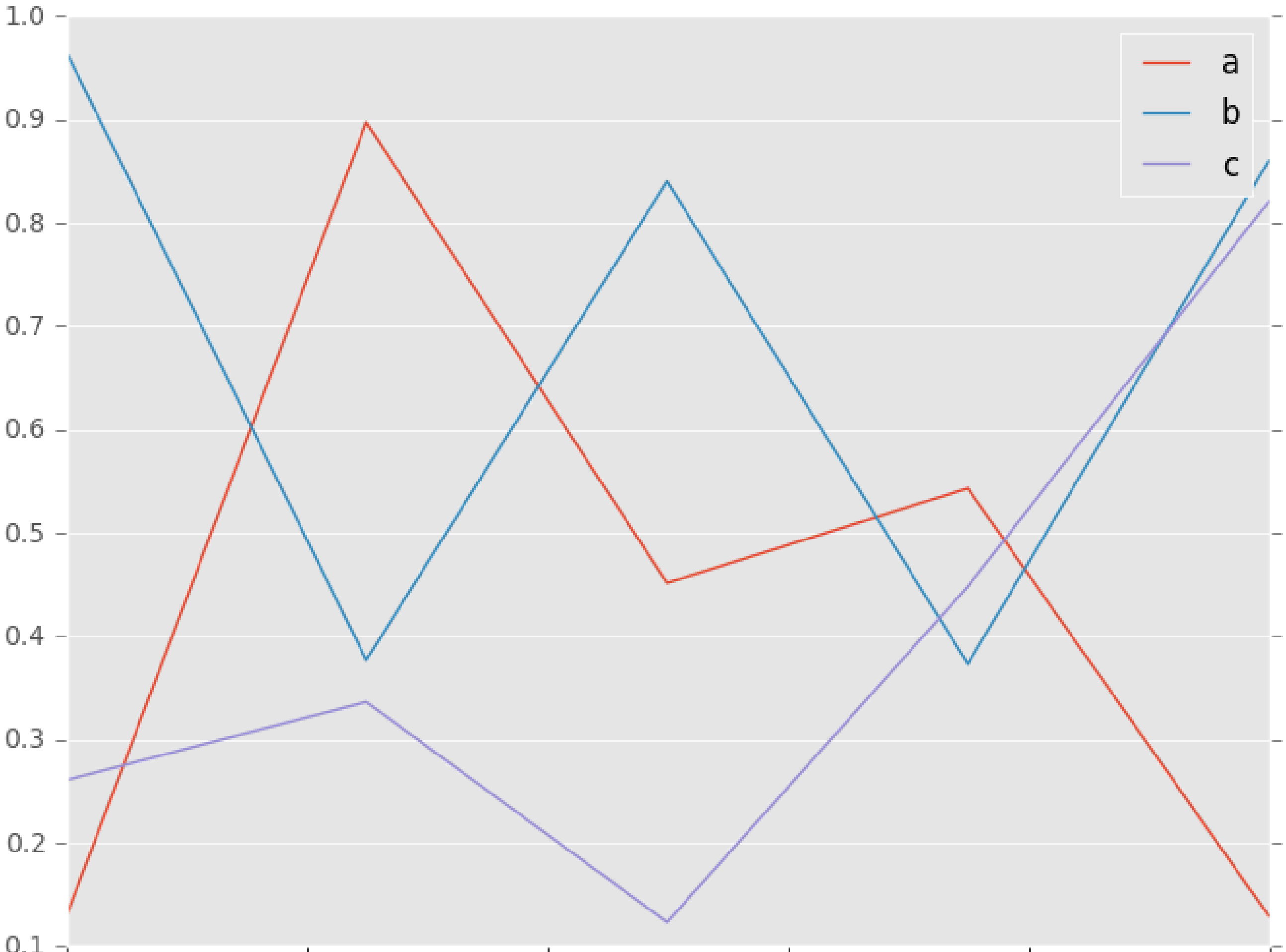


Plotting Tables

New in version 0.14.

Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

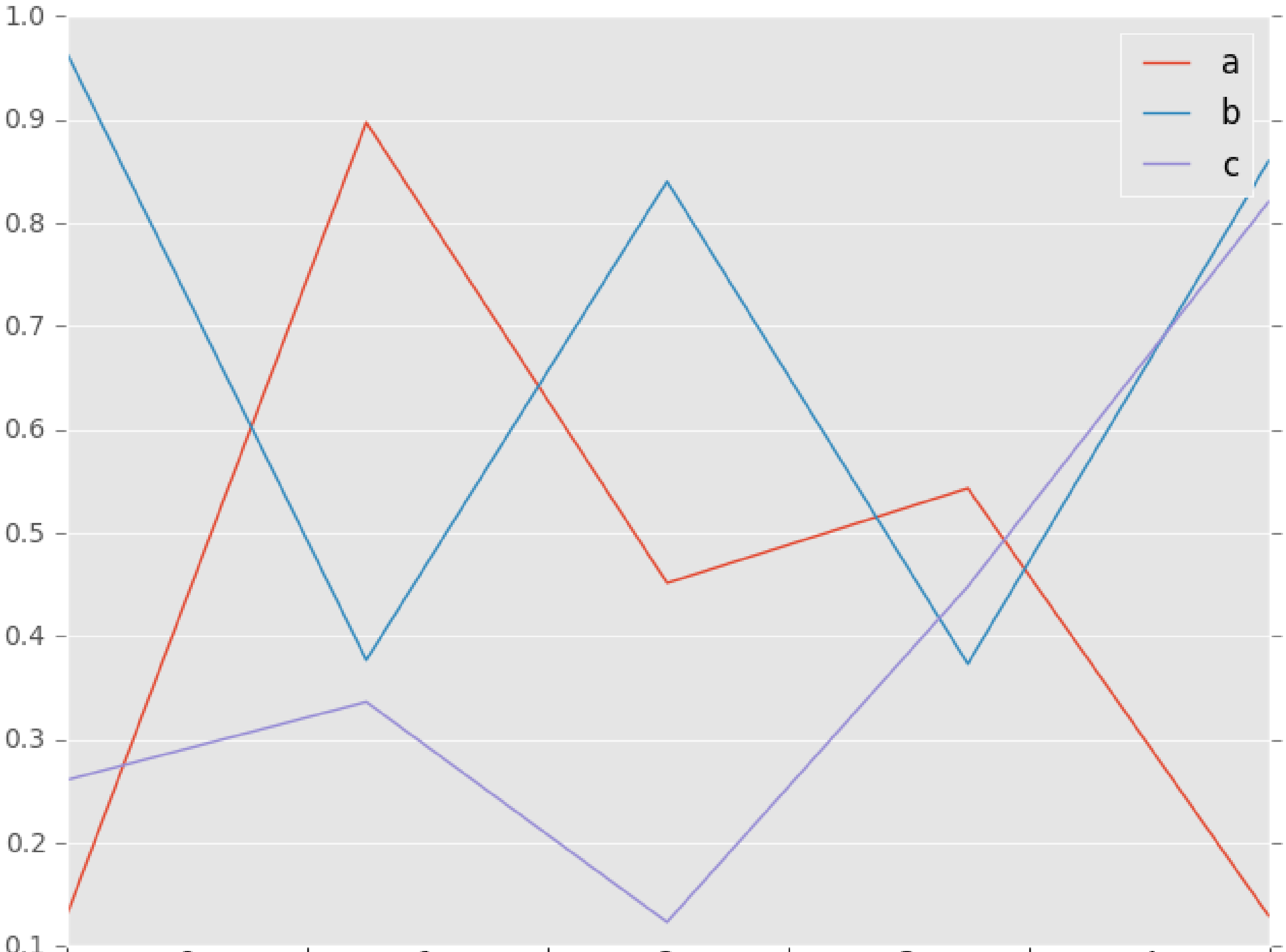
```
In [150]: fig, ax = plt.subplots(1, 1)

In [151]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])

In [152]: ax.get_xaxis().set_visible(False)   # Hide Ticks

In [153]: df.plot(table=True, ax=ax)
Out[153]: <matplotlib.axes._subplots.AxesSubplot at 0x9959708c>
```



	0	1	2	3	4
a	0.126969833038	0.897236524365	0.451376470475	0.543026202047	0.129440679718
b	0.966717838482	0.37674971619	0.840255083261	0.373012225221	0.85987870658
c	0.260476005866	0.336221744334	0.123102144288	0.447996824686	0.82038836312

Also, you can pass different `DataFrame` or `Series` for `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as below example.

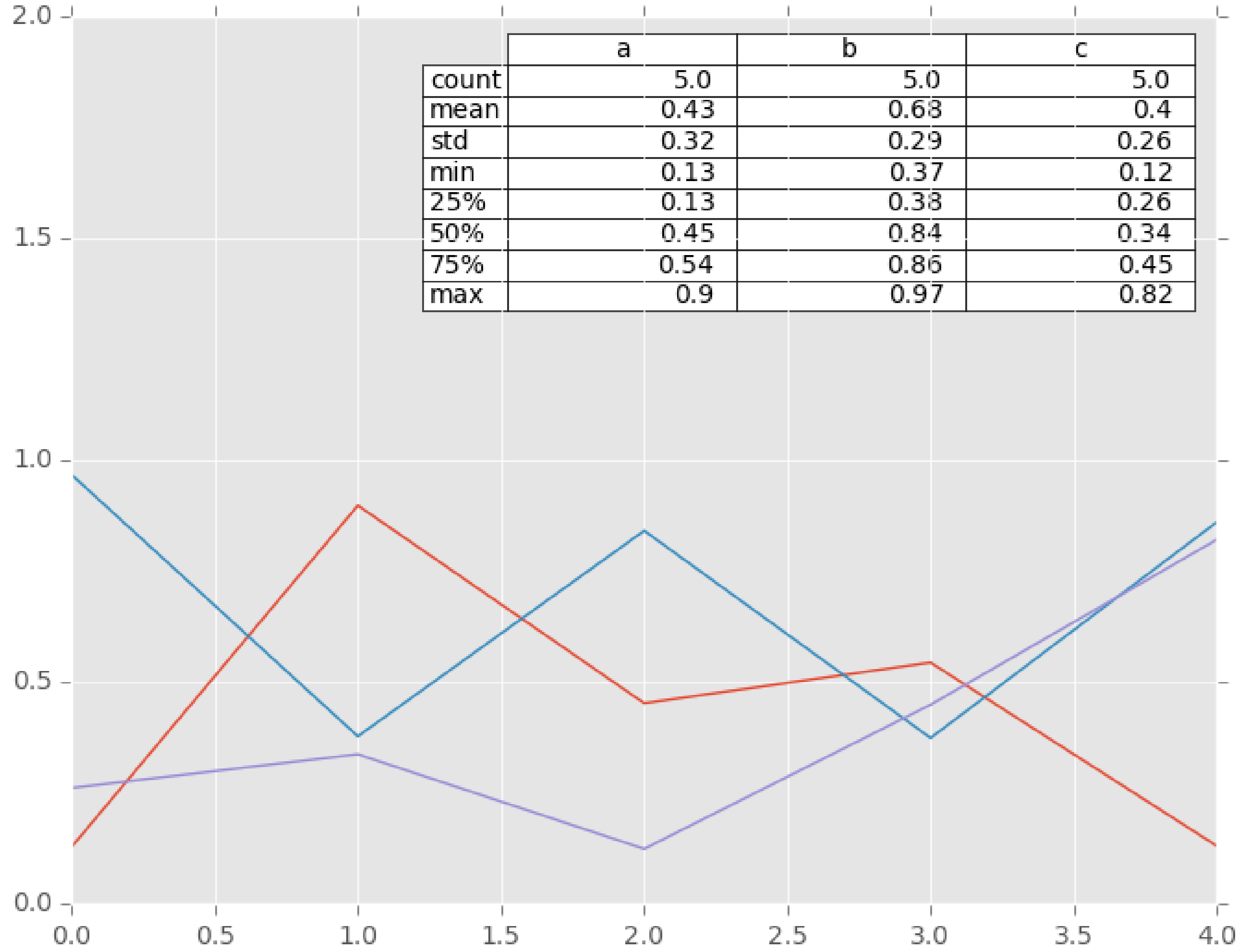
```
In [154]: fig, ax = plt.subplots(1, 1)

In [155]: ax.get_xaxis().set_visible(False)   # Hide Ticks

In [156]: df.plot(table=np.round(df.T, 2), ax=ax)
Out[156]: <matplotlib.axes._subplots.AxesSubplot at 0x9aec176c>
```



	0	1	2	3	4
a	0.13	0.9	0.45	0.54	0.13
b	0.97	0.38	0.84	0.37	0.86
c	0.26	0.34	0.12	0.45	0.82

Finally, there is a helper function `pandas.tools.plotting.table` to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`. This function can accept keywords which matplotlib table has.

```
In [157]: from pandas.tools.plotting import table

In [158]: fig, ax = plt.subplots(1, 1)

In [159]: table(ax, np.round(df.describe(), 2),
   .....:       loc='upper right', colWidths=[0.2, 0.2, 0.2])
   .....:
Out[159]: <matplotlib.table.Table at 0x968bda6c>

In [160]: df.plot(ax=ax, ylim=(0, 2), legend=None)
Out[160]: <matplotlib.axes._subplots.AxesSubplot at 0x9d7ef38c>
```



	a	b	c
count	5.0	5.0	5.0
mean	0.43	0.68	0.4
std	0.32	0.29	0.26
min	0.13	0.37	0.12
25%	0.13	0.38	0.26
50%	0.45	0.84	0.34
75%	0.54	0.86	0.45
max	0.9	0.97	0.82

Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the matplotlib table documentation for more.

Colormaps

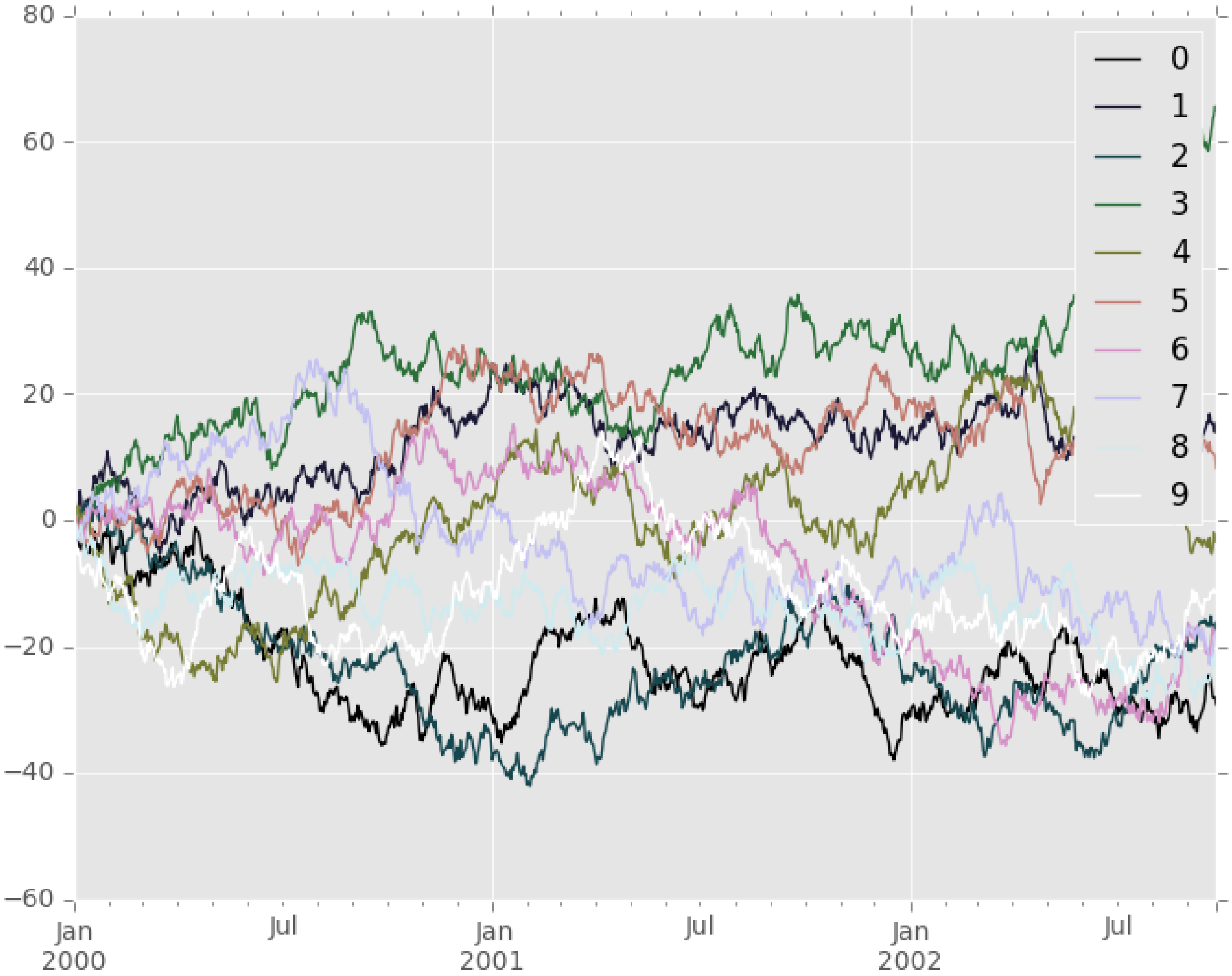
A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, DataFrame plotting supports the use of the `colormap=` argument, which accepts either a Matplotlib colormap or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available here.

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the DataFrame. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

To use the cubehelix colormap, we can simply pass `'cubehelix'` to `colormap=`

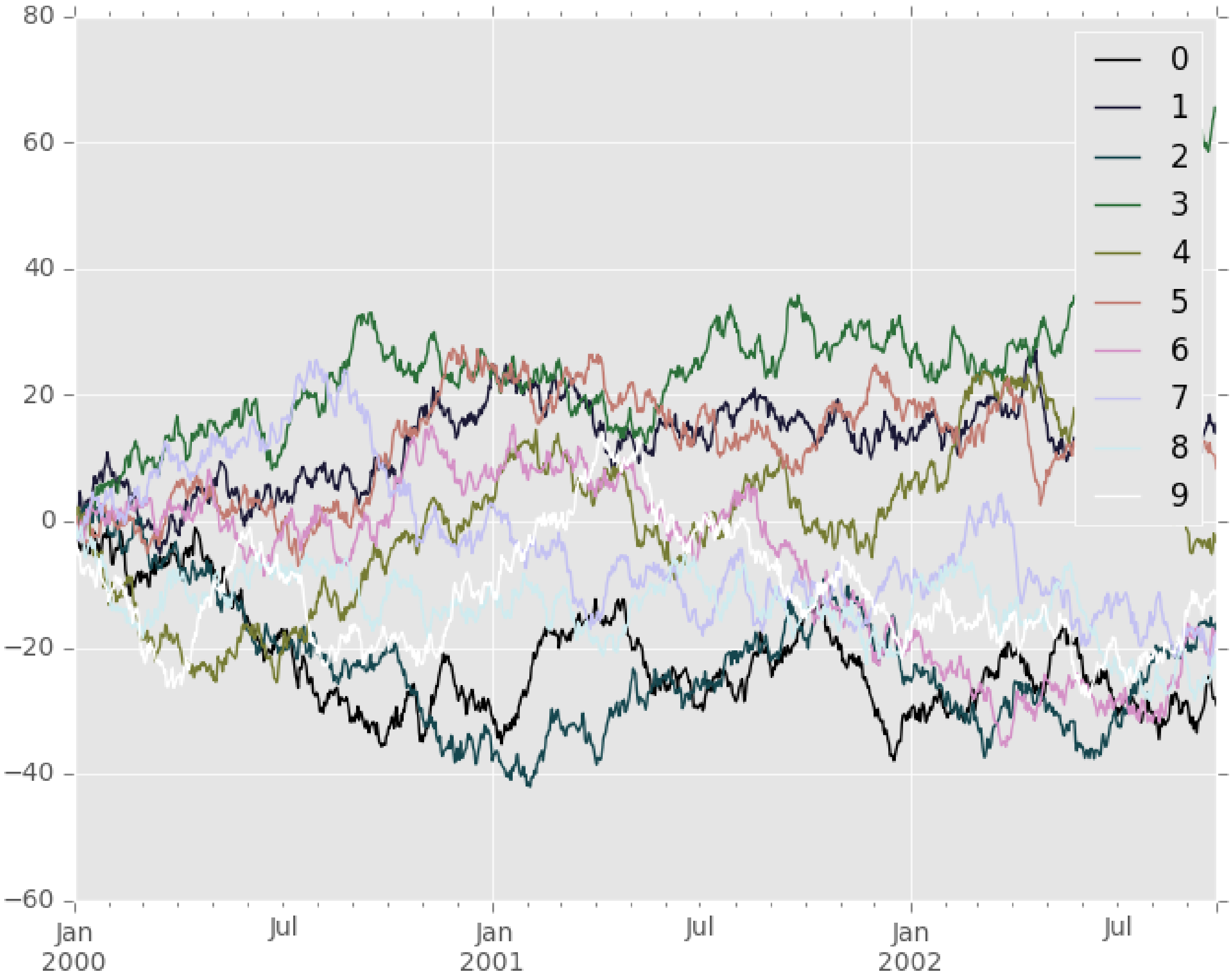
```
In [161]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)

In [162]: df = df.cumsum()

In [163]: plt.figure()
Out[163]: <matplotlib.figure.Figure at 0x9689b7ec>
```

```
In [164]: df.plot(colormap='cubehelix')
Out[164]: <matplotlib.axes._subplots.AxesSubplot at 0x9689f62c>
```



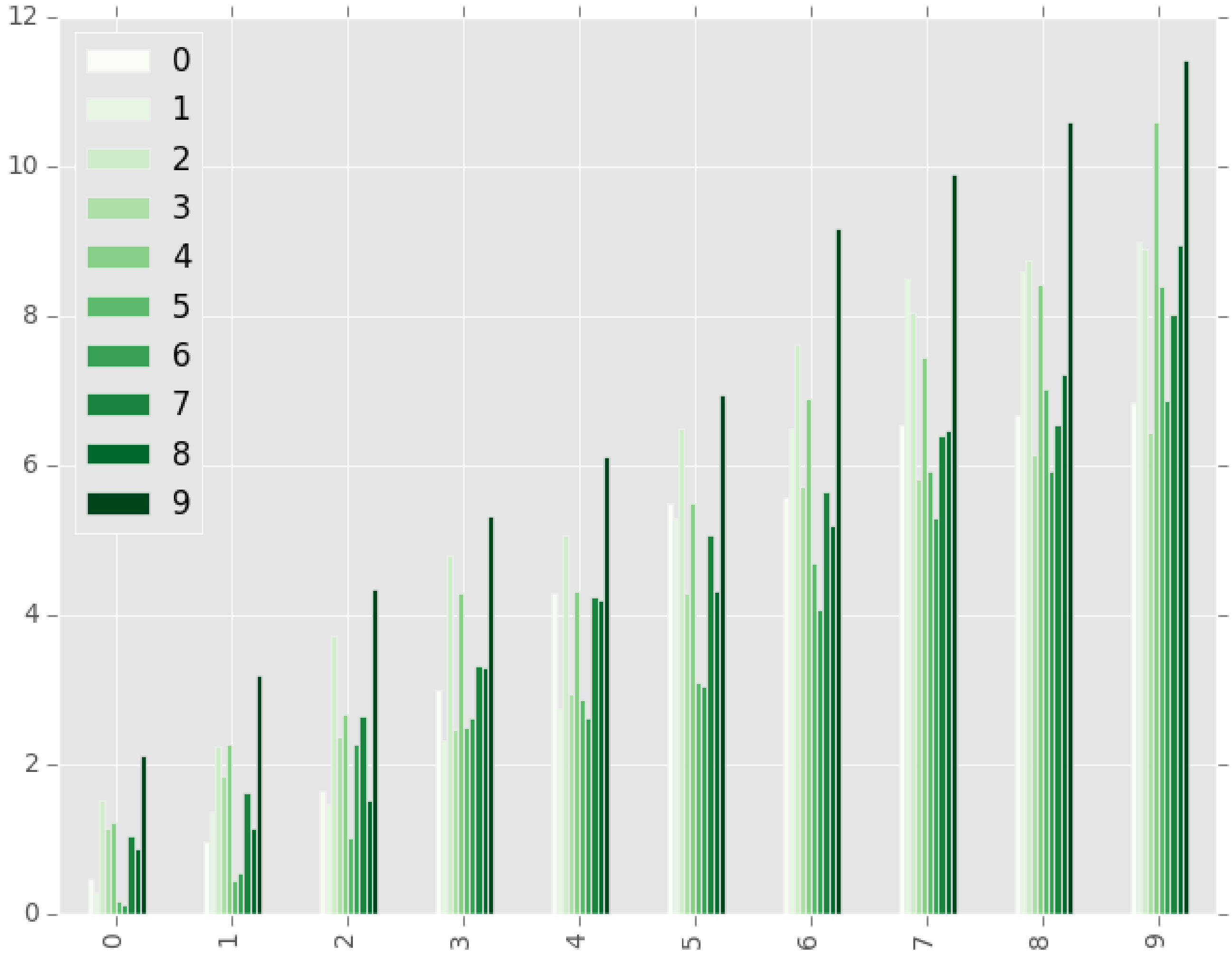
or we can pass the colormap itself

```
In [165]: from matplotlib import cm

In [166]: plt.figure()
Out[166]: <matplotlib.figure.Figure at 0x967a2c8c>

In [167]: df.plot(colormap=cm.cubehelix)
Out[167]: <matplotlib.axes._subplots.AxesSubplot at 0x9679758c>
```



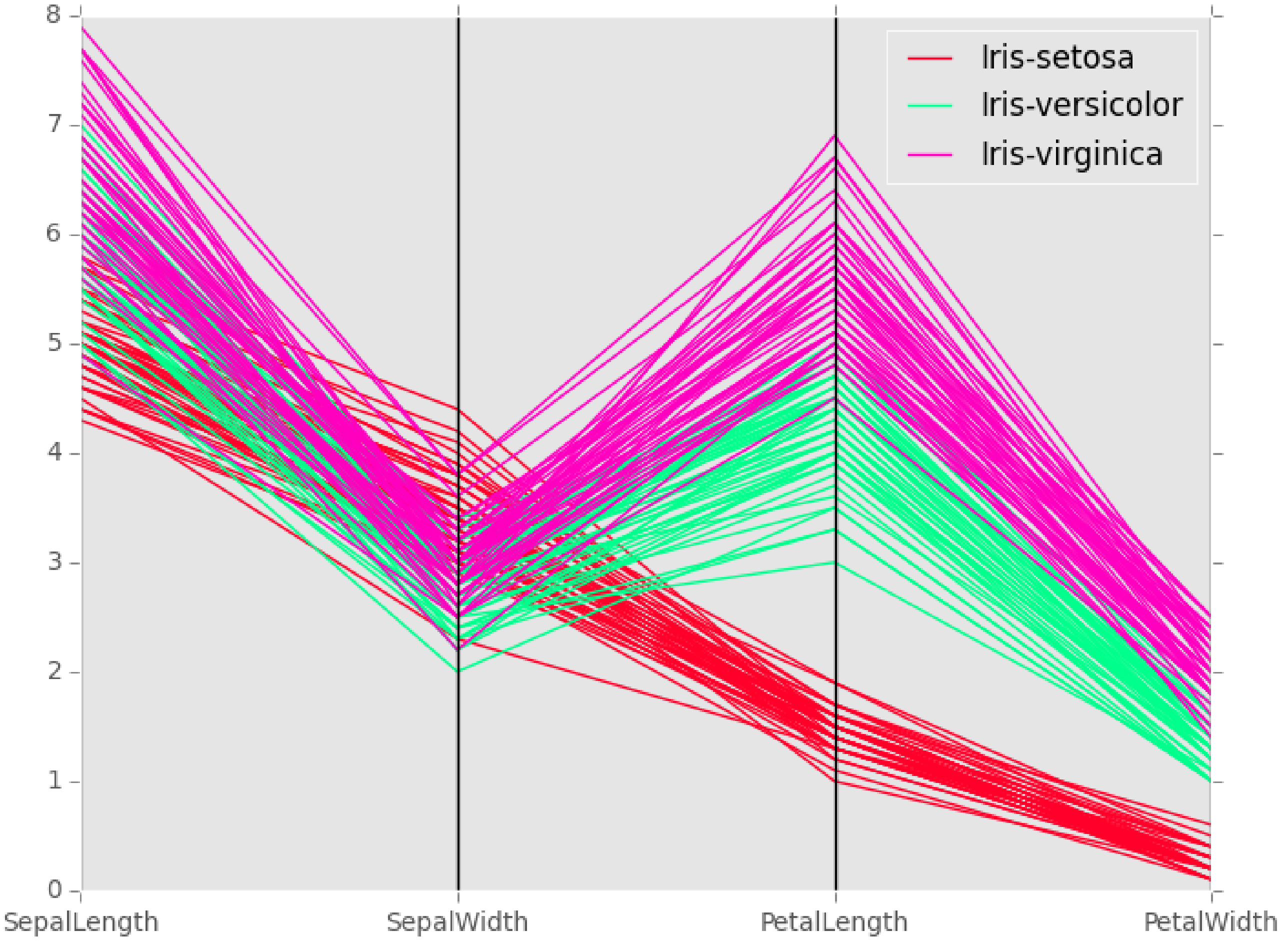
Colormaps can also be used other plot types, like bar charts:

```
In [168]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)

In [169]: dd = dd.cumsum()

In [170]: plt.figure()
Out[170]: <matplotlib.figure.Figure at 0x96507f4c>

In [171]: dd.plot(kind='bar', colormap='Greens')
Out[171]: <matplotlib.axes._subplots.AxesSubplot at 0x964eeccc>
```



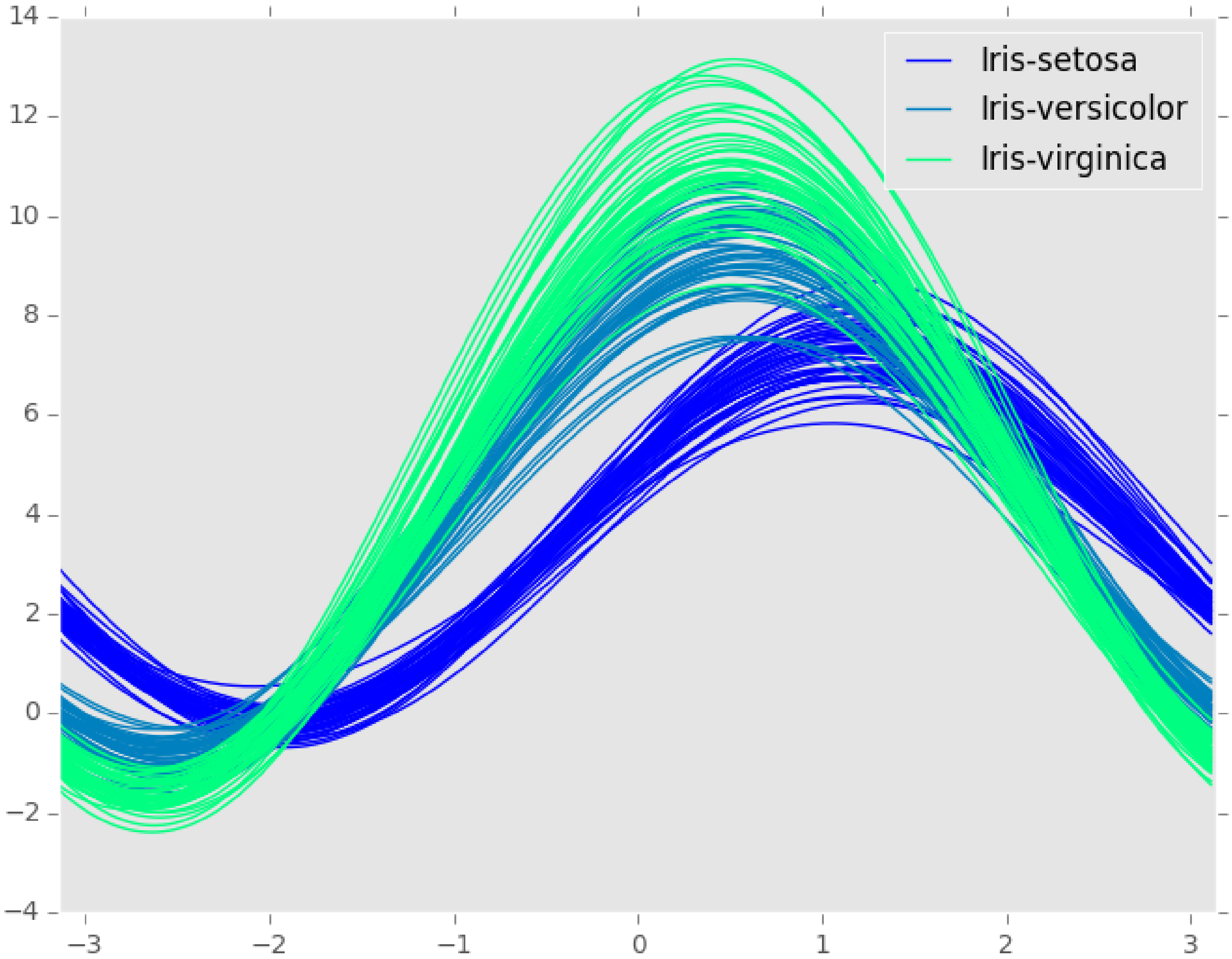
Parallel coordinates charts:

```
In [172]: plt.figure()
Out[172]: <matplotlib.figure.Figure at 0x963f104c>

In [173]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0x9607eecc>
```



Andrews curves charts:

```
In [174]: plt.figure()
Out[174]: <matplotlib.figure.Figure at 0x95c94e6c>

In [175]: andrews_curves(data, 'Name', colormap='winter')
Out[175]: <matplotlib.axes._subplots.AxesSubplot at 0x95c9474c>
```



Plotting directly with matplotlib

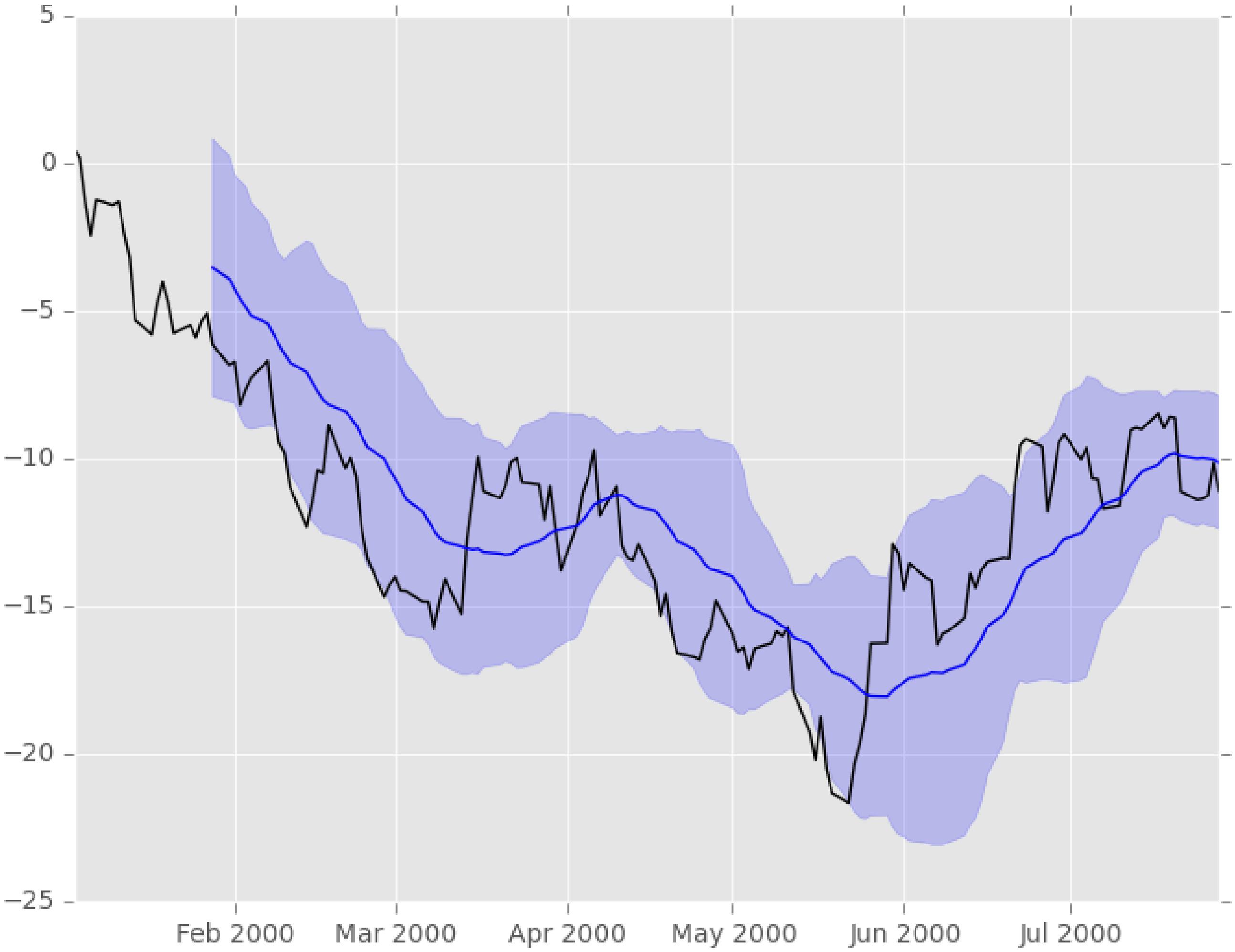
In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. Series and DataFrame objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

Note: The speed up for large data sets only applies to pandas 0.14.0 and later.

```
In [176]: price = pd.Series(np.random.randn(150).cumsum(),
   .....:                   index=pd.date_range('2000-1-1', periods=150, freq='B'))
   .....:

In [177]: ma = pd.rolling_mean(price, 20)

In [178]: mstd = pd.rolling_std(price, 20)

In [179]: plt.figure()
```

```
Out[179]: <matplotlib.figure.Figure at 0x9591d54c>

In [180]: plt.plot(price.index, price, 'k')
Out[180]: [<matplotlib.lines.Line2D at 0x95938cac>]

In [181]: plt.plot(ma.index, ma, 'b')
Out[181]: [<matplotlib.lines.Line2D at 0x958dbaac>]

In [182]: plt.fill_between(mstd.index, ma-2*mstd, ma+2*mstd, color='b', alpha=0.2)
Out[182]: <matplotlib.collections.PolyCollection at 0x958e21cc>
```



Trellis plotting interface

Warning: The `rplot` trellis plotting interface is **deprecated and will be removed in a future version**. We refer to external packages like seaborn for similar but more refined functionality.

The docs below include some example on how to convert your existing code to `seaborn`.

Note: The tips data set can be downloaded here. Once you download it execute

```
tips_data = pd.read_csv('tips.csv')
```

from the directory where you downloaded the file.

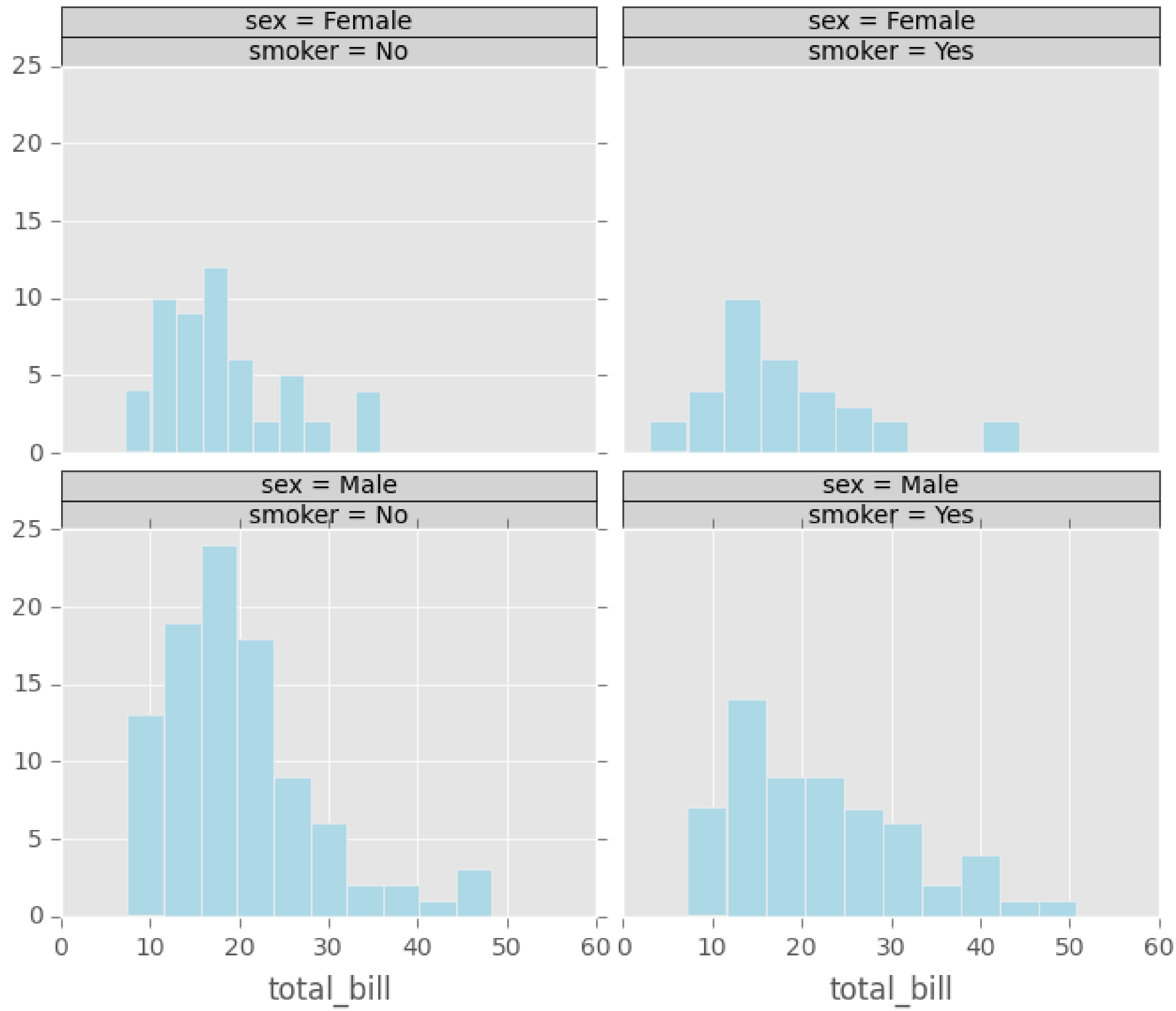
We import the rplot API:

```
In [183]: import pandas.tools.rplot as rplot
```

Examples

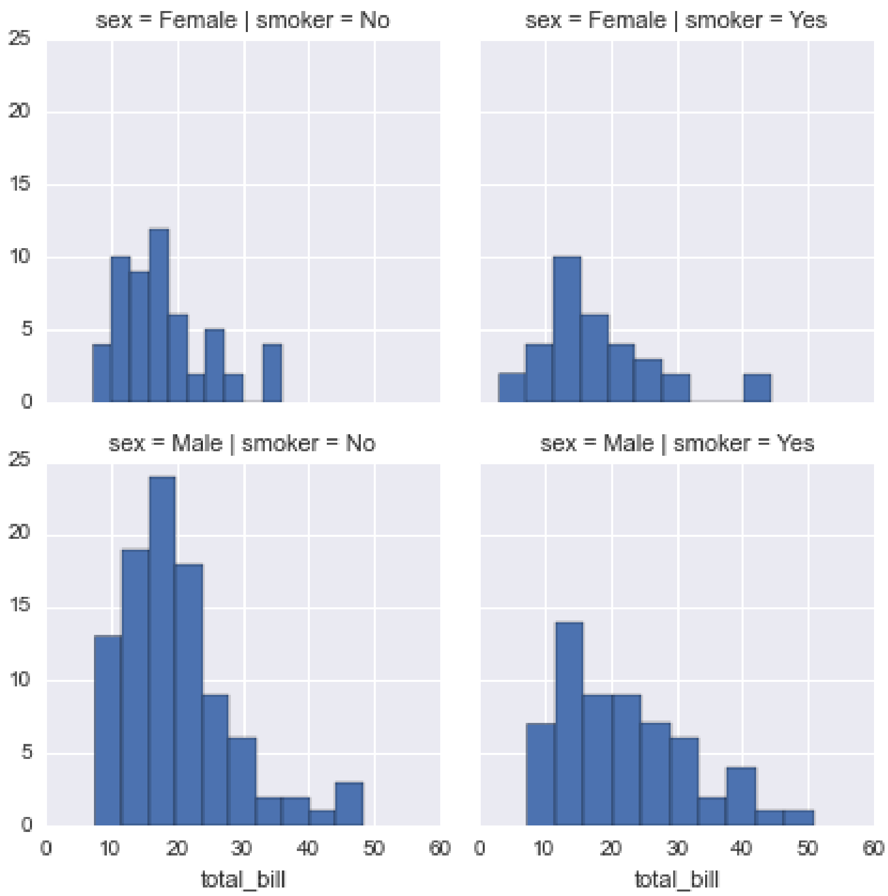
RPlot was an API for producing Trellis plots. These plots allow you toμ arrange data in a rectangular grid by values of certain attributes. In the example below, data from the tips data set is arranged by the attributes ‘sex’ and ‘smoker’. Since both of those attributes can take on one of two values, the resulting grid has two columns and two rows. A histogram is displayed for each cell of the grid.

```
In [184]: plt.figure()
Out[184]: <matplotlib.figure.Figure at 0x9590982c>

In [185]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [186]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [187]: plot.add(rplot.GeomHistogram())

In [188]: plot.render(plt.gcf())
Out[188]: <matplotlib.figure.Figure at 0x9590982c>
```



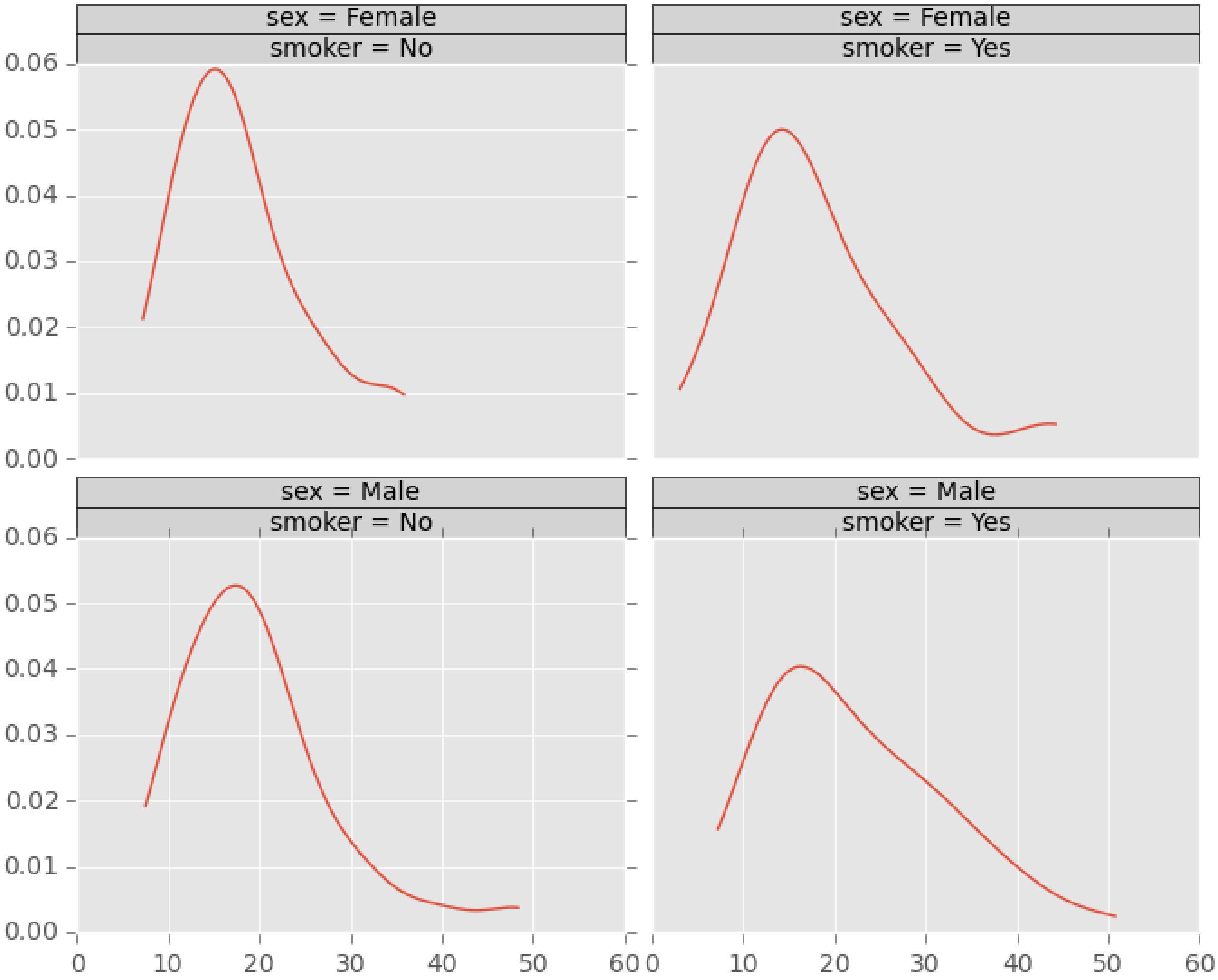
A similar plot can be made with `seaborn` using the `FacetGrid` object, resulting in the following image:

```
import seaborn as sns
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.hist, "total_bill")
```

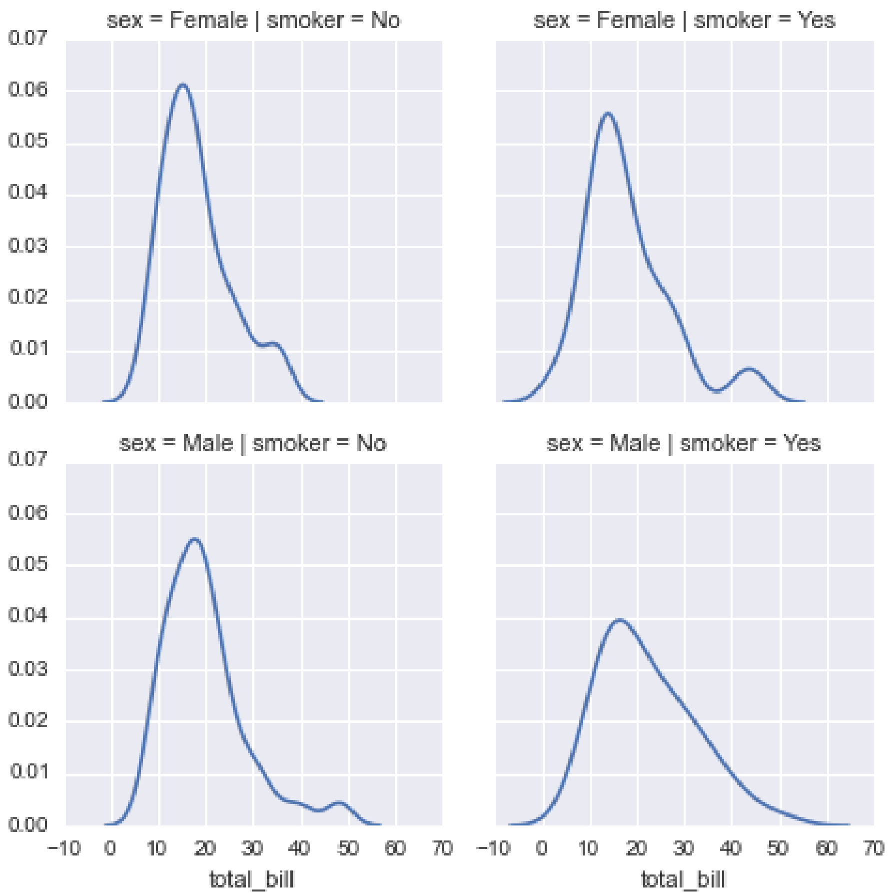


Example below is the same as previous except the plot is set to kernel density estimation. A `seaborn` example is included beneath.

```
In [189]: plt.figure()
Out[189]: <matplotlib.figure.Figure at 0x955cf62c>

In [190]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [191]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [192]: plot.add(rplot.GeomDensity())

In [193]: plot.render(plt.gcf())
Out[193]: <matplotlib.figure.Figure at 0x955cf62c>
```

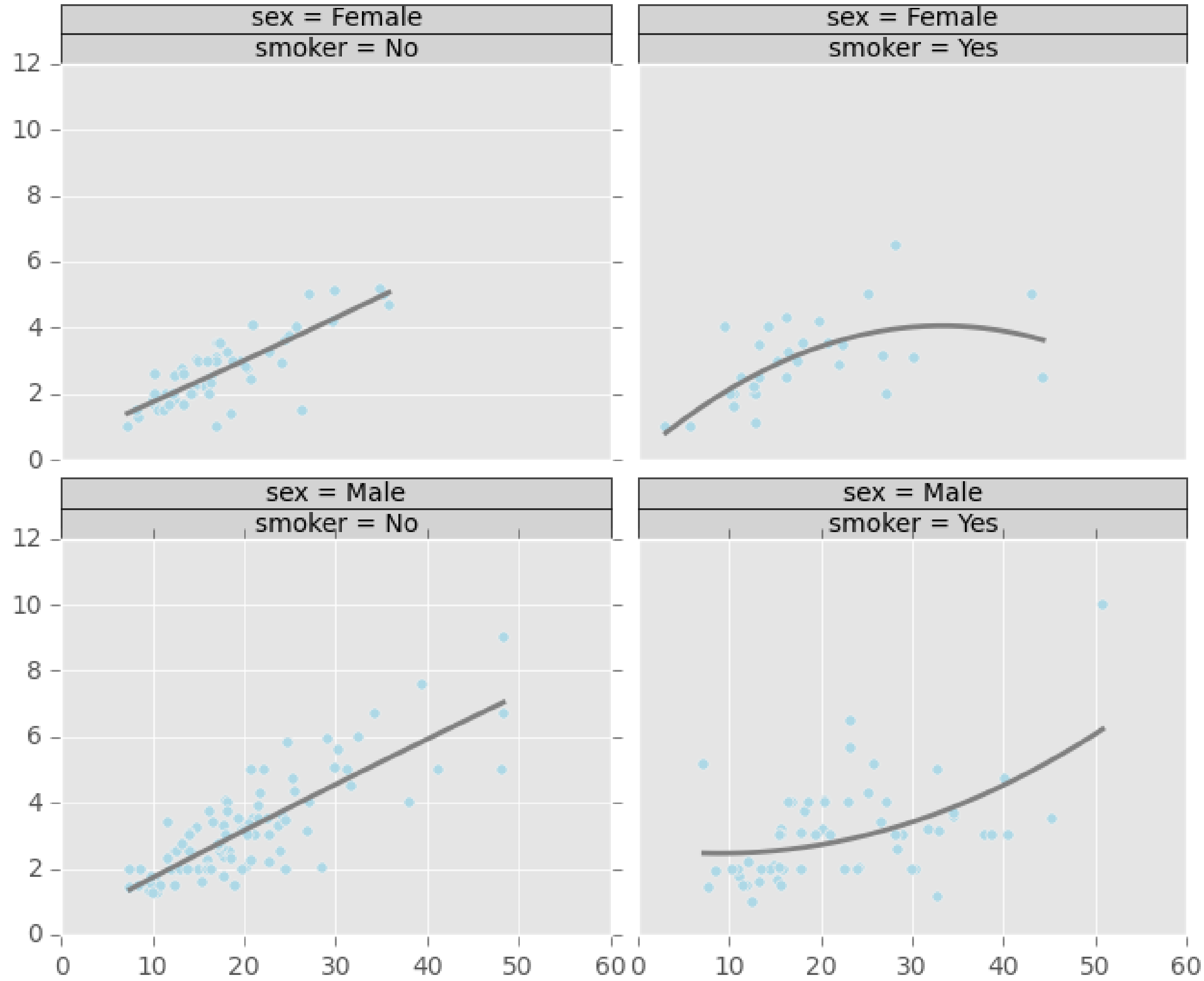



```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(sns.kdeplot, "total_bill")
```



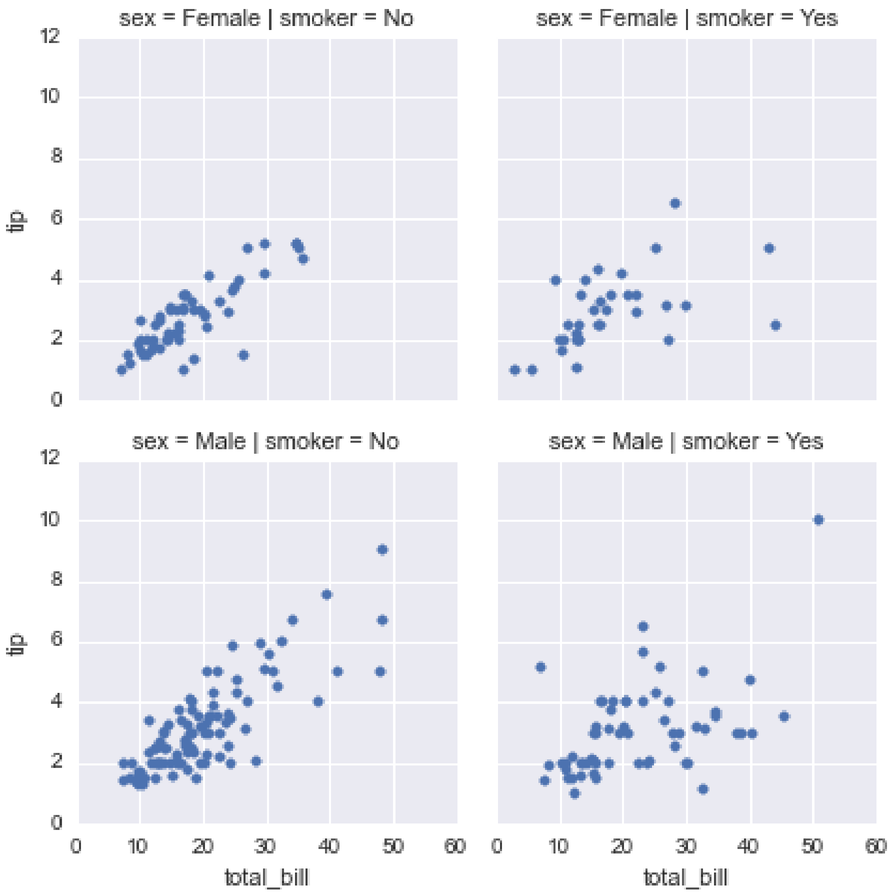
The plot below shows that it is possible to have two or more plots for the same data displayed on the same Trellis grid cell.

```
In [194]: plt.figure()
Out[194]: <matplotlib.figure.Figure at 0x952166ac>

In [195]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [196]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [197]: plot.add(rplot.GeomScatter())

In [198]: plot.add(rplot.GeomPolyFit(degree=2))

In [199]: plot.render(plt.gcf())
Out[199]: <matplotlib.figure.Figure at 0x952166ac>
```



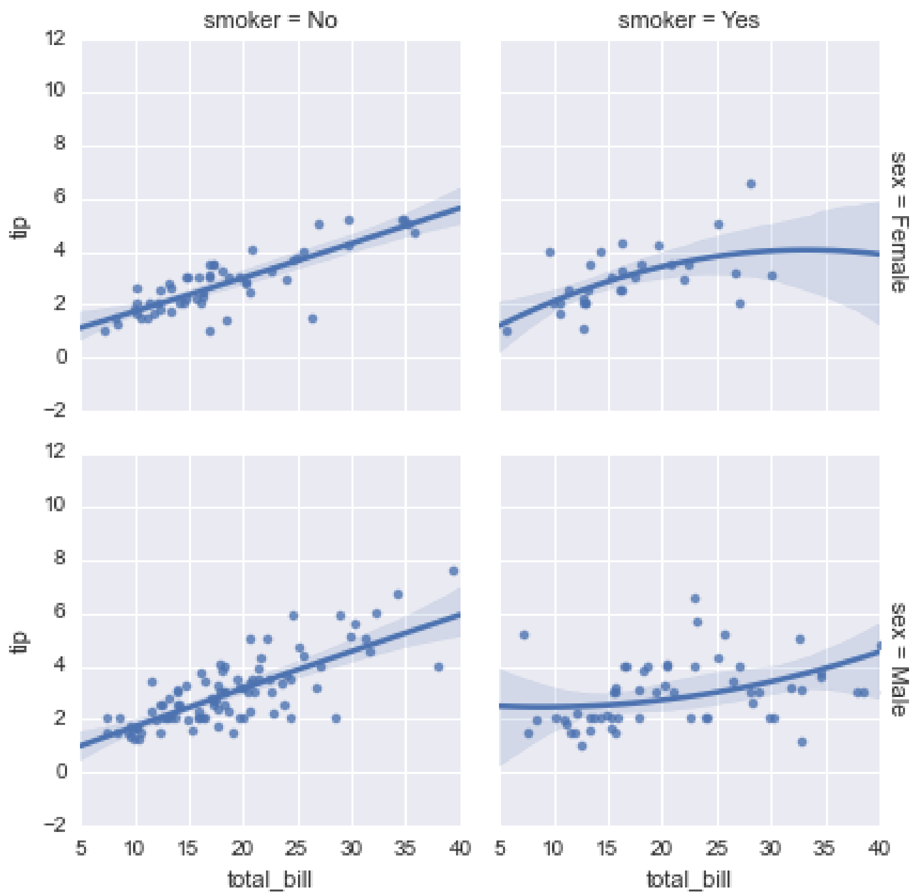
A seaborn equivalent for a simple scatter plot:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
```



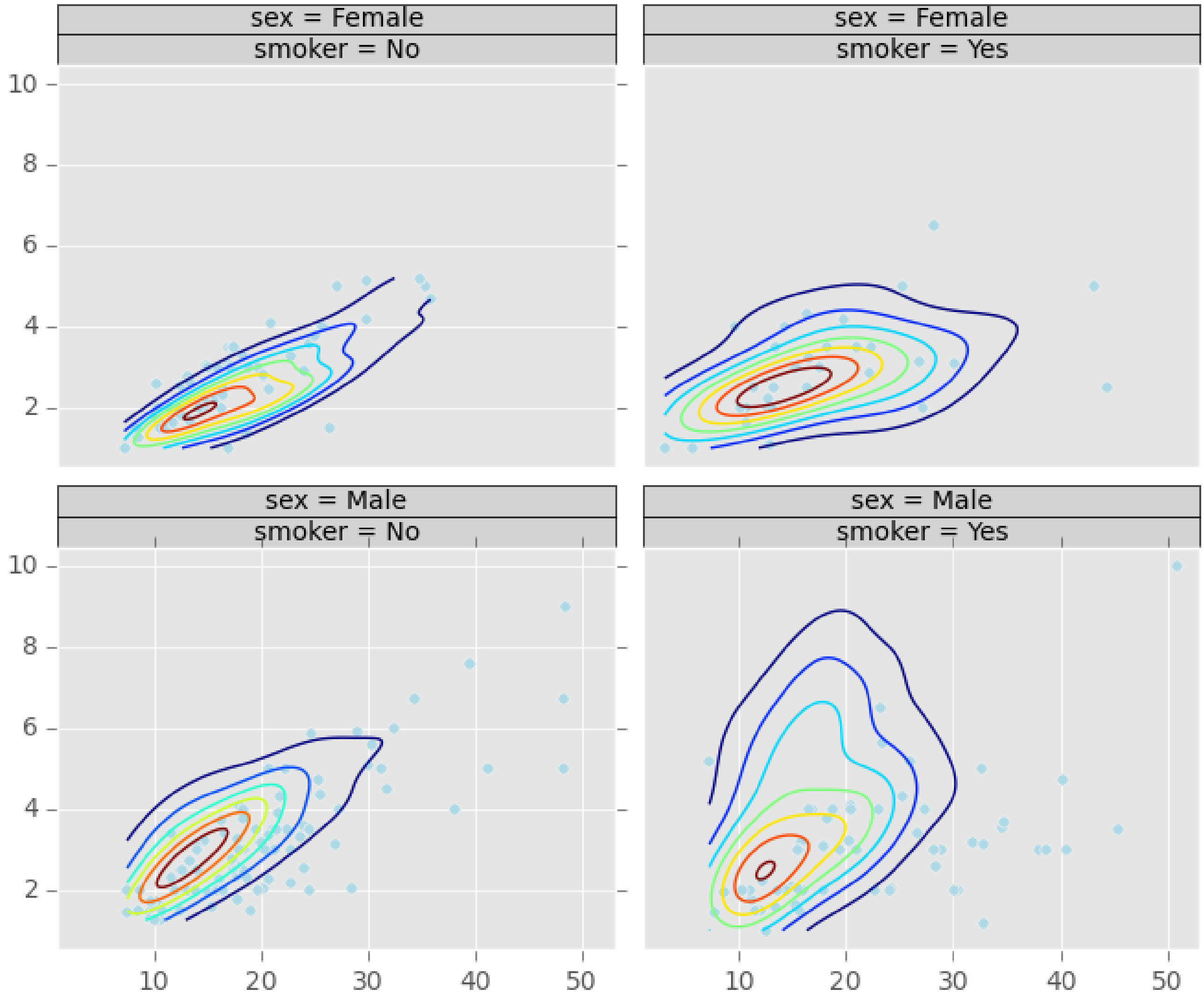
and with a regression line, using the dedicated `seaborn` `regplot` function:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", margin_titles=True)
g.map(sns.regplot, "total_bill", "tip", order=2)
```

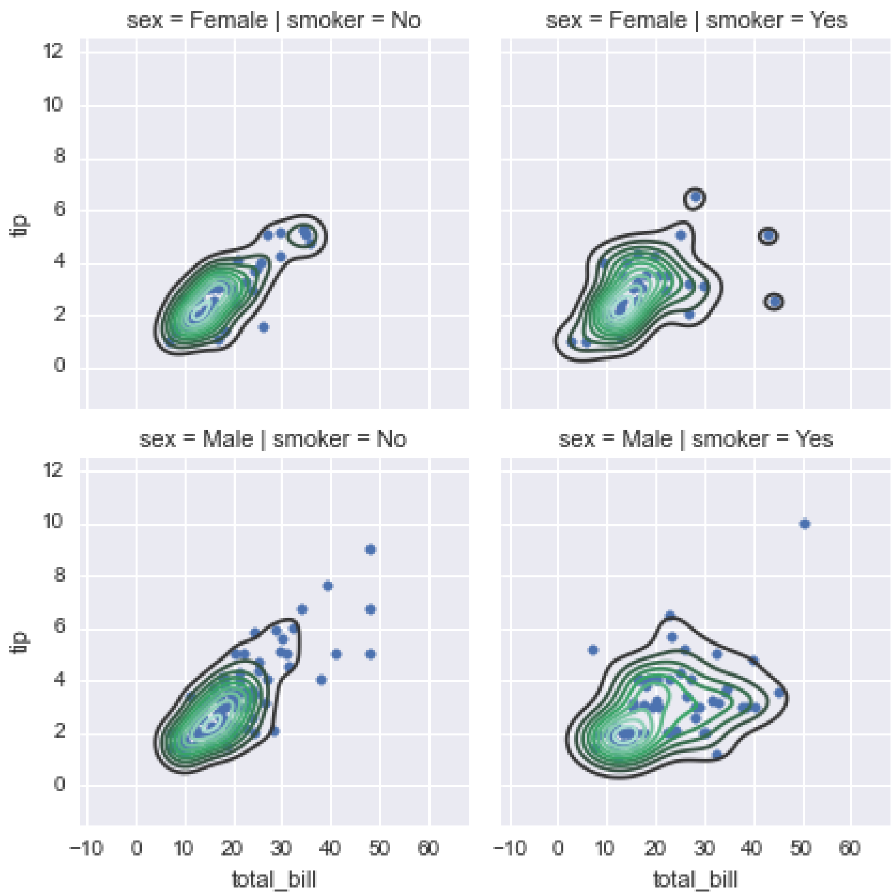


Below is a similar plot but with 2D kernel density estimation plot superimposed, followed by a `seaborn` equivalent:

```
In [200]: plt.figure()
Out[200]: <matplotlib.figure.Figure at 0x94ebebec>

In [201]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [202]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [203]: plot.add(rplot.GeomScatter())

In [204]: plot.add(rplot.GeomDensity2D())

In [205]: plot.render(plt.gcf())
Out[205]: <matplotlib.figure.Figure at 0x94ebebec>
```

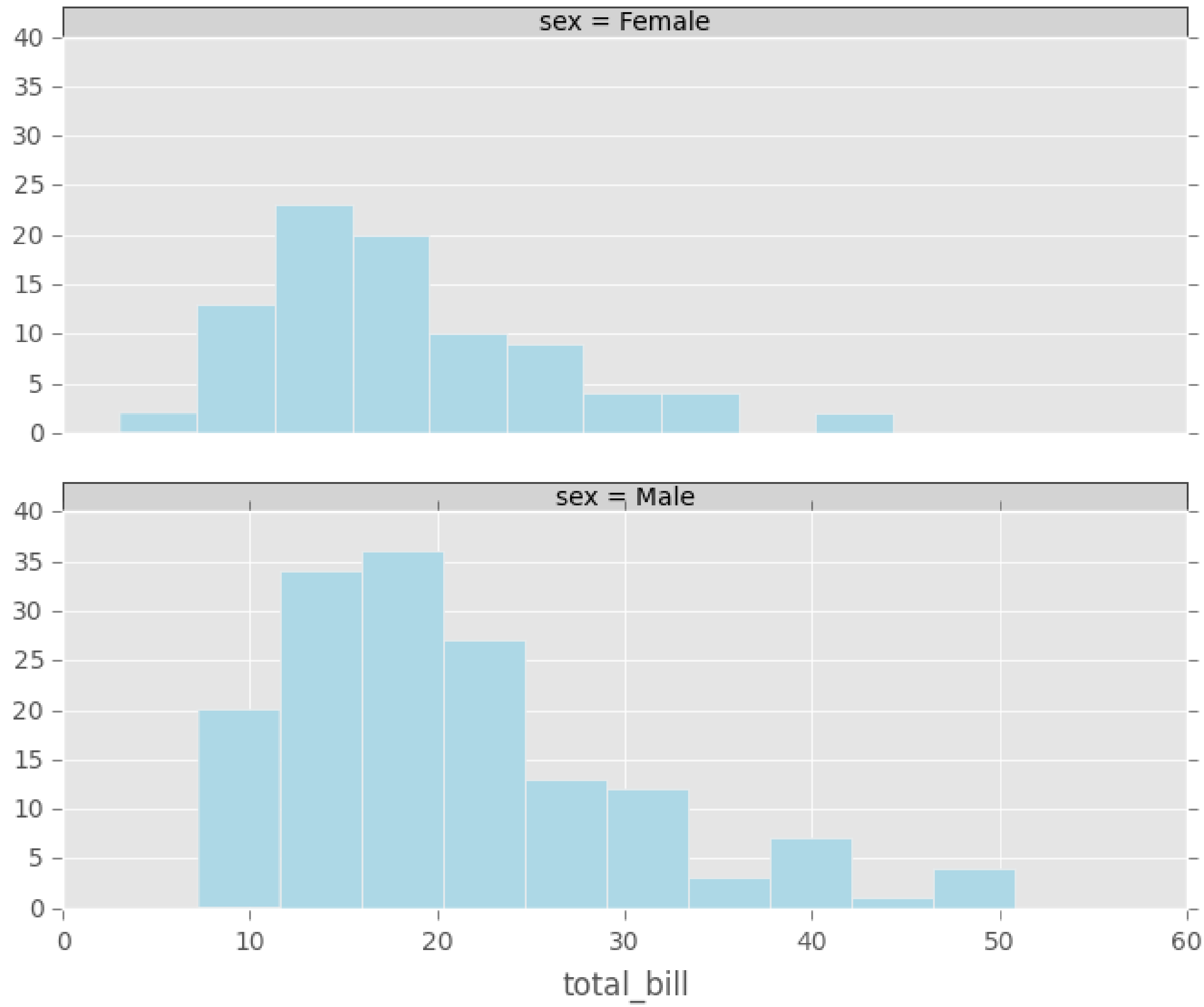



```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
g.map(sns.kdeplot, "total_bill", "tip")
```



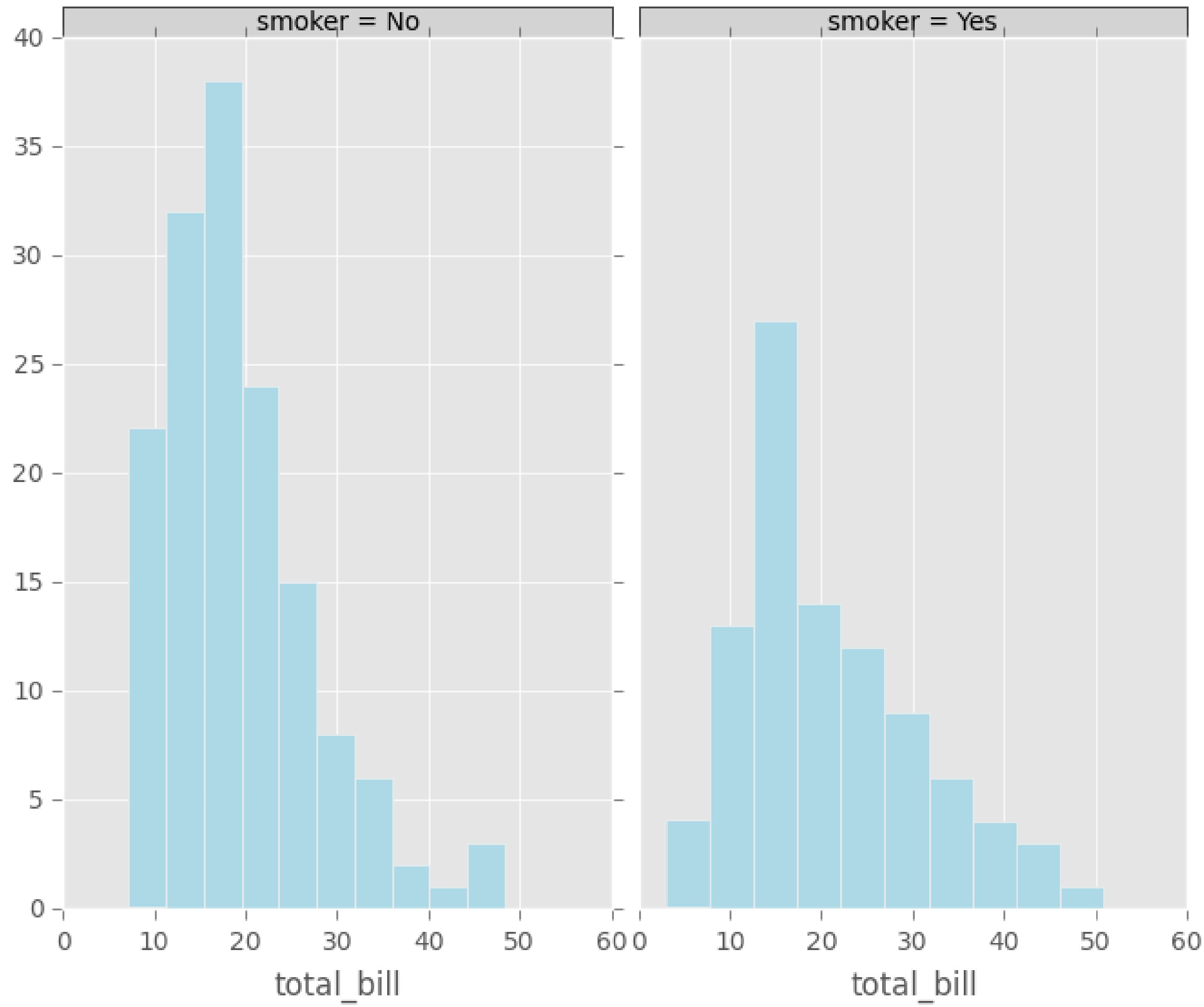
It is possible to only use one attribute for grouping data. The example above only uses 'sex' attribute. If the second grouping attribute is not specified, the plots will be arranged in a column.

```
In [206]: plt.figure()
Out[206]: <matplotlib.figure.Figure at 0x94b528ac>

In [207]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [208]: plot.add(rplot.TrellisGrid(['sex', '.']))

In [209]: plot.add(rplot.GeomHistogram())

In [210]: plot.render(plt.gcf())
Out[210]: <matplotlib.figure.Figure at 0x94b528ac>
```



If the first grouping attribute is not specified the plots will be arranged in a row.

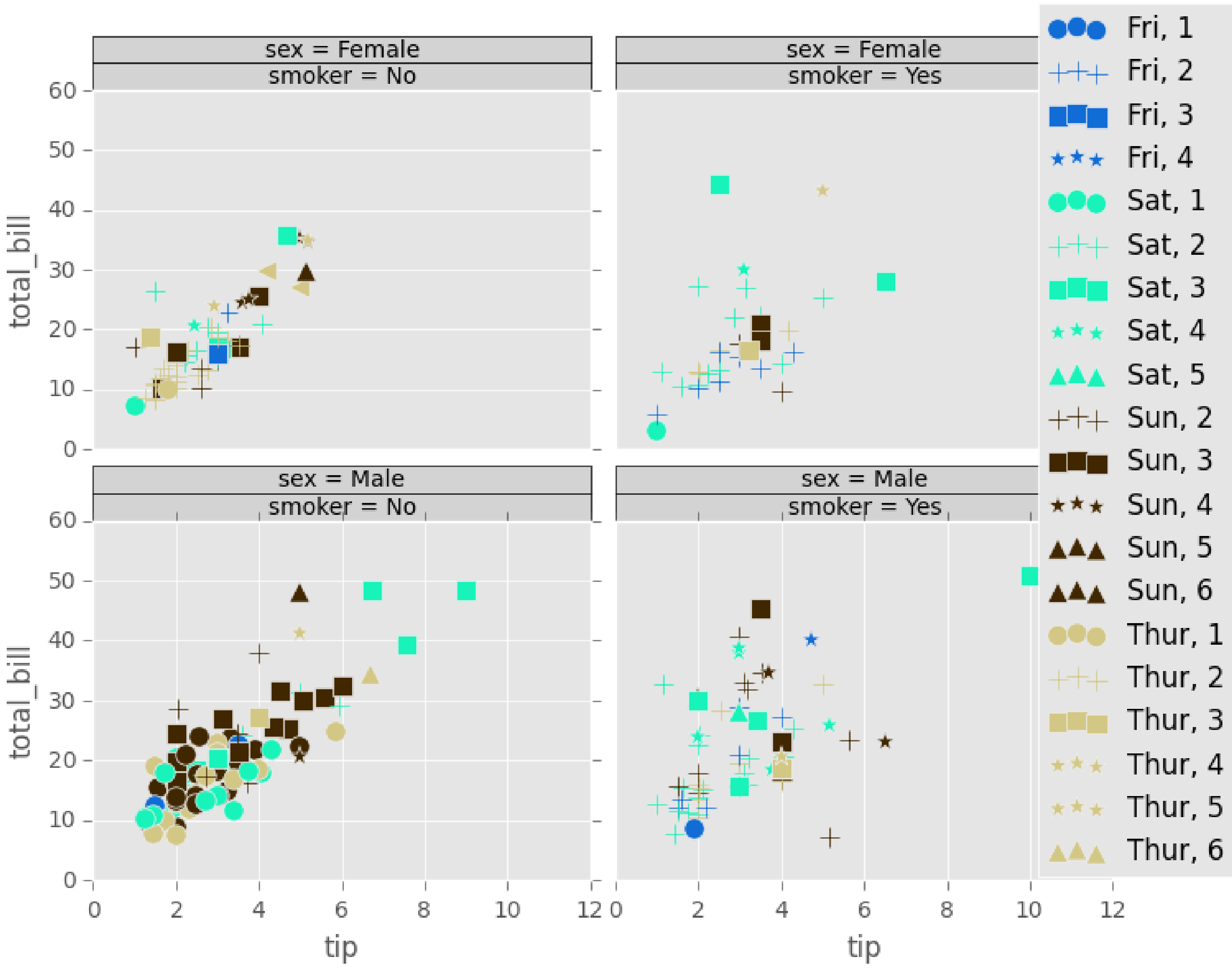
```
In [211]: plt.figure()
Out[211]: <matplotlib.figure.Figure at 0x94b9ddac>

In [212]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [213]: plot.add(rplot.TrellisGrid(['.', 'smoker']))

In [214]: plot.add(rplot.GeomHistogram())

In [215]: plot.render(plt.gcf())
Out[215]: <matplotlib.figure.Figure at 0x94b9ddac>
```



In `seaborn`, this can also be done by only specifying one of the `row` and `col` arguments.

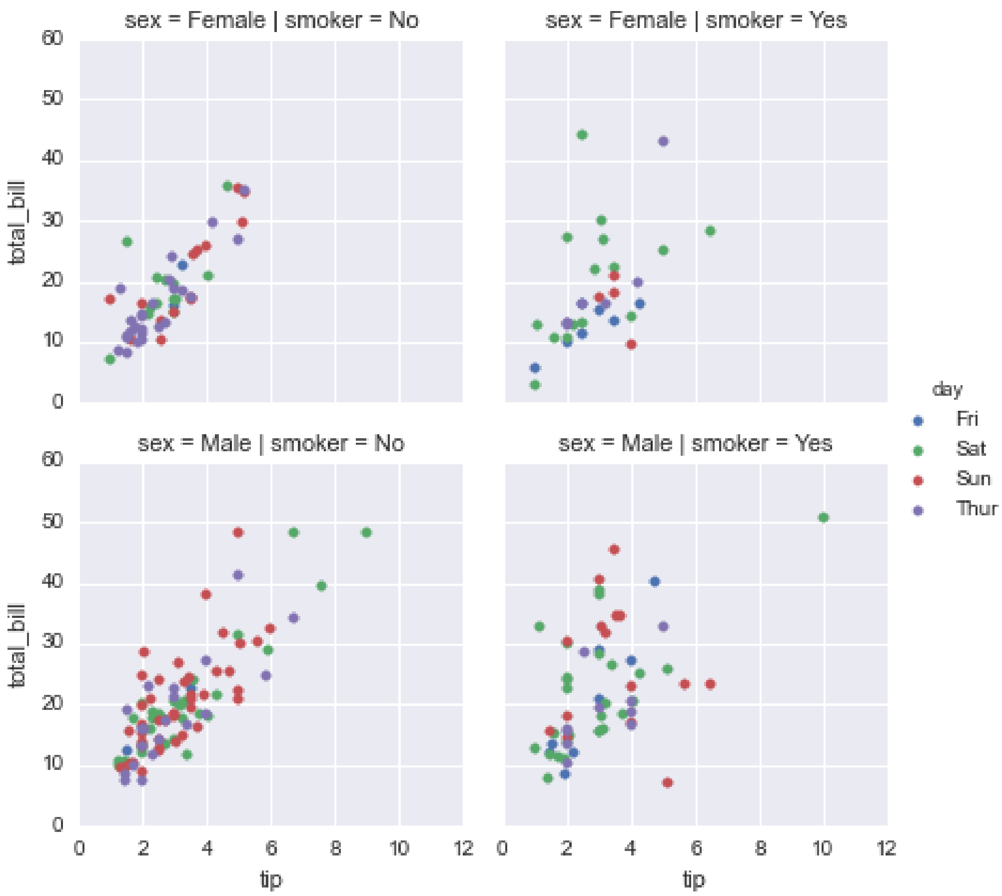
In the example below the colour and shape of the scatter plot graphical objects is mapped to 'day' and 'size' attributes respectively. You use scale objects to specify these mappings. The list of scale classes is given below with initialization arguments for quick reference.

```
In [216]: plt.figure()
Out[216]: <matplotlib.figure.Figure at 0x94ee56ac>

In [217]: plot = rplot.RPlot(tips_data, x='tip', y='total_bill')

In [218]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [219]: plot.add(rplot.GeomPoint(size=80.0, colour=rplot.ScaleRandomColour('day'), shape=rp

In [220]: plot.render(plt.gcf())
Out[220]: <matplotlib.figure.Figure at 0x94ee56ac>
```



This can also be done in `seaborn`, at least for 3 variables:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", hue="day")
g.map(plt.scatter, "tip", "total_bill")
g.add_legend()
```


sex = Female | smoker = No
sex = Female | smoker = Yes
sex = Male | smoker = No
sex = Male | smoker = Yes
total_bill
tip
day
Fri
Sat
Sun
Thur