matplotlib

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Version 3.0.0

Usage Guide

This tutorial covers some basic usage patterns and best-practices to help you get started with Matplotlib.

General Concepts

`matplotlib` has an extensive codebase that can be daunting to many new users. However, most of matplotlib can be understood with a fairly simple conceptual framework and knowledge of a few important points.

Plotting requires action on a range of levels, from the most general (e.g., 'contour this 2-D array') to the most specific (e.g., 'color this screen pixel red'). The purpose of a plotting package is to assist you in visualizing your data as easily as possible, with all the necessary control -- that is, by using relatively high-level commands most of the time, and still have the ability to use the low-level commands when needed.

Therefore, everything in matplotlib is organized in a hierarchy. At the top of the hierarchy is the matplotlib "state-machine environment" which is provided by the `matplotlib.pyplot` module. At this level, simple functions are used to add plot elements (lines, images, text, etc.) to the current axes in the current figure.

Note

Pyplot's state-machine environment behaves similarly to MATLAB and should be most familiar to users with MATLAB experience.

The next level down in the hierarchy is the first level of the object-oriented interface, in which pyplot is used only for a few functions such as figure creation, and the user explicitly creates and keeps track of the figure and axes objects. At this level, the user uses pyplot to create figures, and through those figures, one or more axes objects can be created. These axes objects are then used for most plotting actions.

For even more control -- which is essential for things like embedding matplotlib plots in GUI applications -- the pyplot level may be dropped completely, leaving a purely object-oriented approach.

```
# sphinx_gallery_thumbnail_number = 3
import matplotlib.pyplot as plt
import numpy as np
```

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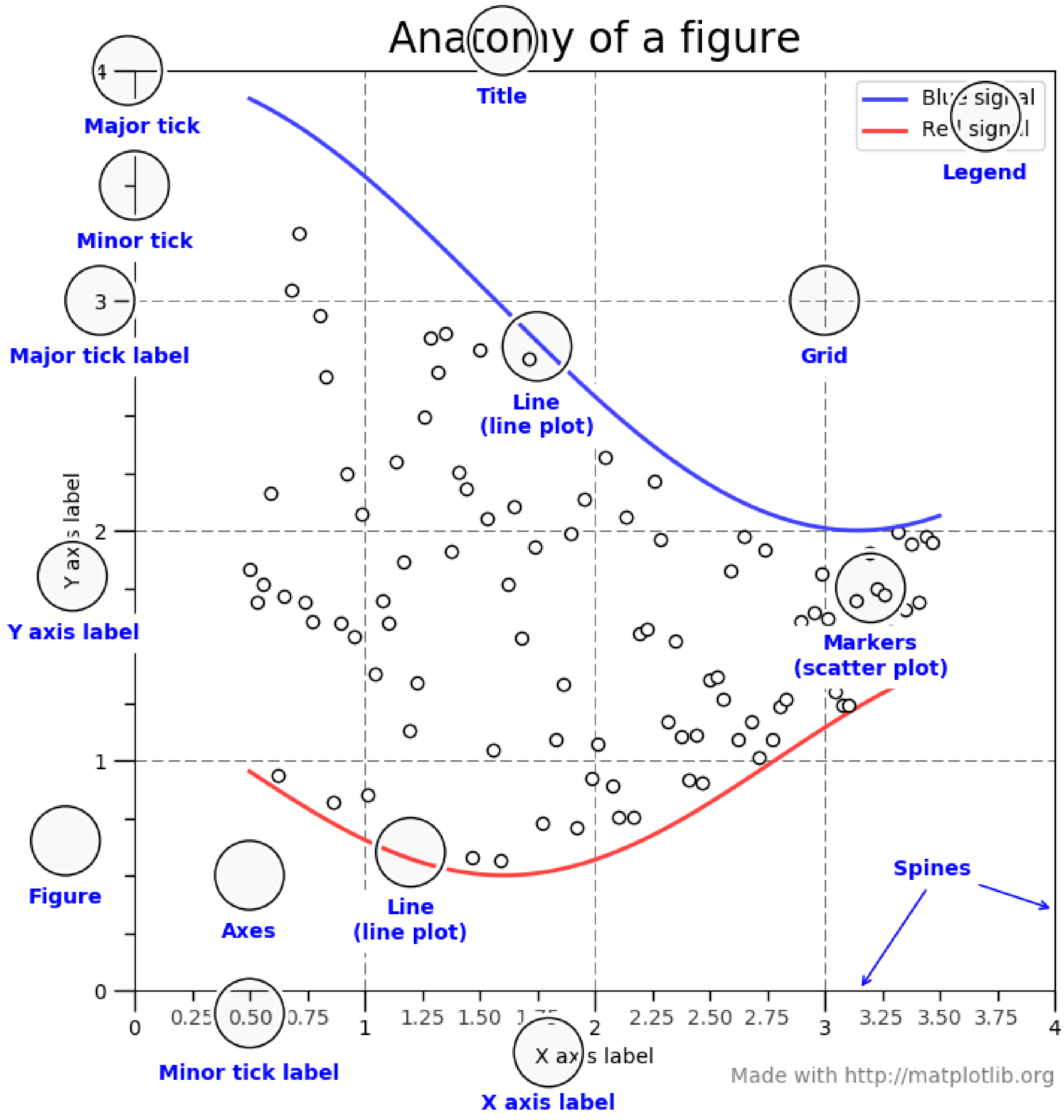
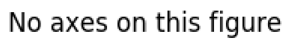


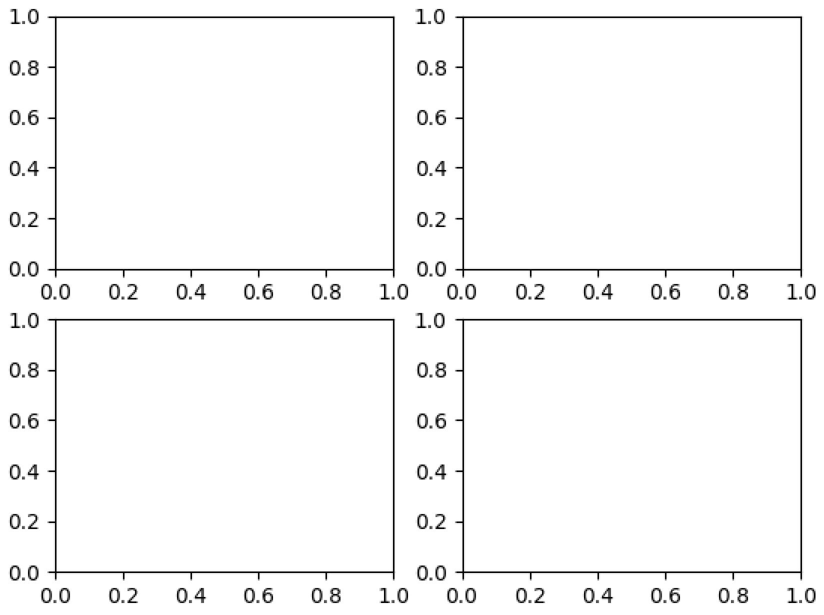
Figure

The **whole** figure. The figure keeps track of all the child `Axes`, a smattering of 'special' artists (titles, figure legends, etc), and the **canvas**. (Don't worry too much about the canvas, it is crucial as it is the object that actually does the drawing to get you your plot, but as the user it is more-or-less invisible to you). A figure can have any number of `Axes`, but to be useful should have at least one.

The easiest way to create a new figure is with pyplot:

```
fig = plt.figure()  # an empty figure with no axes
fig.suptitle('No axes on this figure')  # Add a title so we know which it

fig, ax_lst = plt.subplots(2, 2)  # a figure with a 2x2 grid of Axes
```





Axes

This is what you think of as 'a plot', it is the region of the image with the data space. A given figure can contain many Axes, but a given `Axes` object can only be in one `Figure`. The Axes contains two (or three in the case of 3D) `Axis` objects (be aware of the difference between **Axes** and **Axis**) which take care of the data limits (the data limits can also be controlled via set via the `set_xlim()` and `set_ylim()` `Axes` methods). Each `Axes` has a title (set via `set_title()`), an x-label (set via `set_xlabel()`), and a y-label set via `set_ylabel()`).

The `Axes` class and it's member functions are the primary entry point to working with the OO interface.

`Axis`

These are the number-line-like objects. They take care of setting the graph limits and generating the ticks (the marks on the axis) and ticklabels (strings labeling the ticks). The location of the ticks is determined by a `Locator` object and the ticklabel strings are formatted by a `Formatter`. The combination of the correct `Locator` and `Formatter` gives very fine control over the tick locations and labels.

`Artist`

Basically everything you can see on the figure is an artist (even the `Figure`, `Axes`, and `Axis` objects). This includes `Text` objects, `Line2D` objects, `collection` objects, `Patch` objects ... (you get the idea). When the figure is rendered, all of the artists are drawn to the **canvas**. Most Artists are tied to an Axes; such an Artist cannot be shared by multiple Axes, or moved from one to another.

Types of inputs to plotting functions

All of plotting functions expect `np.array` or `np.ma.masked_array` as input. Classes that are 'array-like' such as `pandas` data objects and `np.matrix` may or may not work as intended. It is best to convert these to `np.array` objects prior to plotting.

For example, to convert a `pandas.DataFrame`

```
a = pandas.DataFrame(np.random.rand(4,5), columns = list('abcde'))
a_asndarray = a.values
```

and to covert a `np.matrix`

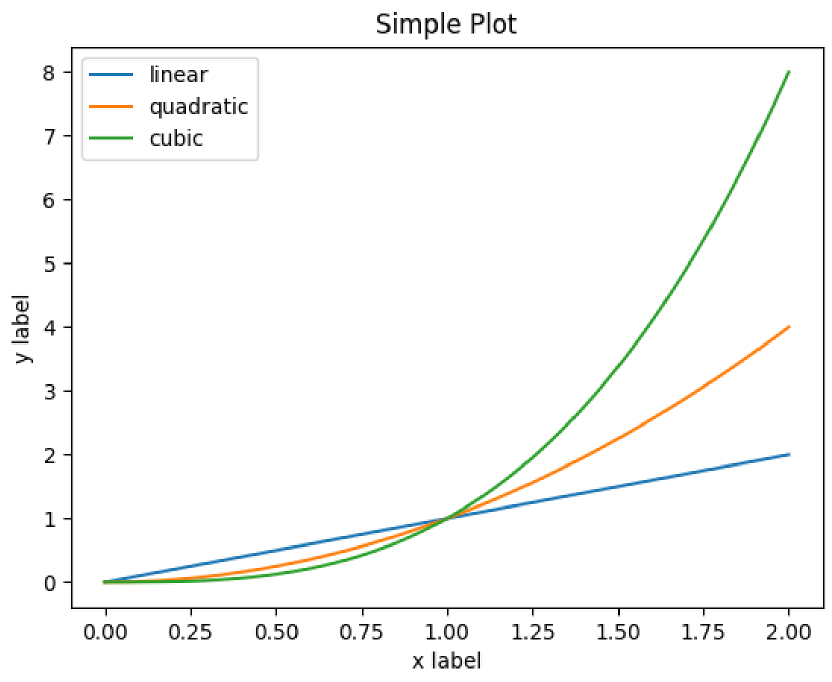
```
b = np.matrix([[1,2],[3,4]])
b_asarray = np.asarray(b)
```

Matplotlib, pyplot and pylab: how are they related?

Matplotlib is the whole package; `matplotlib.pyplot` is a module in matplotlib; and `pylab` is a module that gets installed alongside `matplotlib`.

Pyplot provides the state-machine interface to the underlying object-oriented plotting library. The state-machine implicitly and automatically creates figures and axes to achieve the desired plot. For example:

```
x = np.linspace(0, 2, 100)

plt.plot(x, x, label='linear')
plt.plot(x, x**2, label='quadratic')
plt.plot(x, x**3, label='cubic')

plt.xlabel('x label')
plt.ylabel('y label')

plt.title("Simple Plot")

plt.legend()
plt.show()
```



The first call to `plt.plot` will automatically create the necessary figure and axes to achieve the desired plot. Subsequent calls to `plt.plot` re-use the current axes and each add another line. Setting the title, legend, and axis labels also automatically use the current axes and set the title, create the legend, and label the axis respectively.

`pylab` is a convenience module that bulk imports `matplotlib.pyplot` (for plotting) and `numpy` (for mathematics and working with arrays) in a single name space. pylab is deprecated and its use is strongly discouraged because of namespace pollution. Use pyplot instead.

For non-interactive plotting it is suggested to use pyplot to create the figures and then the OO interface for plotting.

Coding Styles

When viewing this documentation and examples, you will find different coding styles and usage patterns. These styles are perfectly valid and have their pros and cons. Just about all of the examples can be converted into another style and achieve the same results. The only caveat is to avoid mixing the coding styles for your own code.

Note

Developers for matplotlib have to follow a specific style and guidelines. See The Matplotlib Developers' Guide.

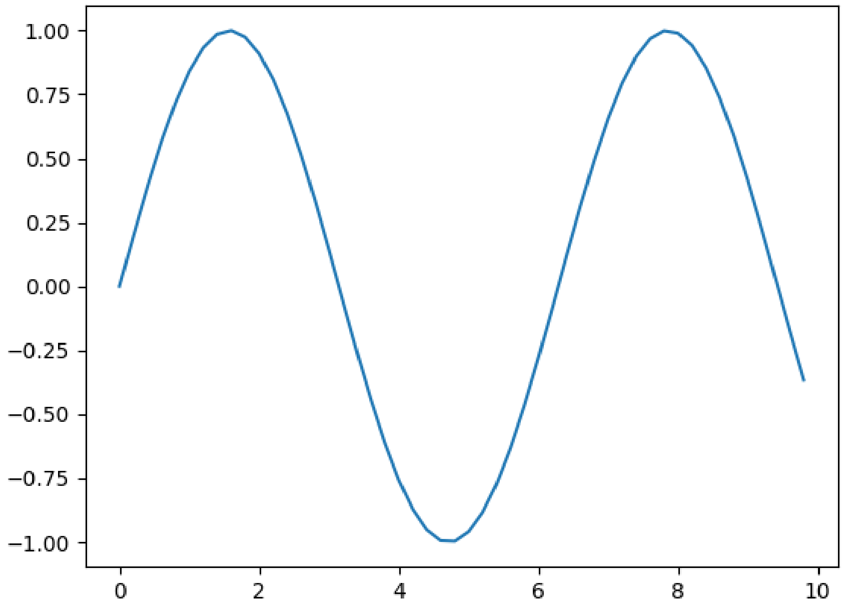
Of the different styles, there are two that are officially supported. Therefore, these are the preferred ways to use matplotlib.

For the pyplot style, the imports at the top of your scripts will typically be:

```
import matplotlib.pyplot as plt
import numpy as np
```

Then one calls, for example, np.arange, np.zeros, np.pi, plt.figure, plt.plot, plt.show, etc. Use the pyplot interface for creating figures, and then use the object methods for the rest:

```
x = np.arange(0, 10, 0.2)
y = np.sin(x)
fig, ax = plt.subplots()
ax.plot(x, y)
plt.show()
```

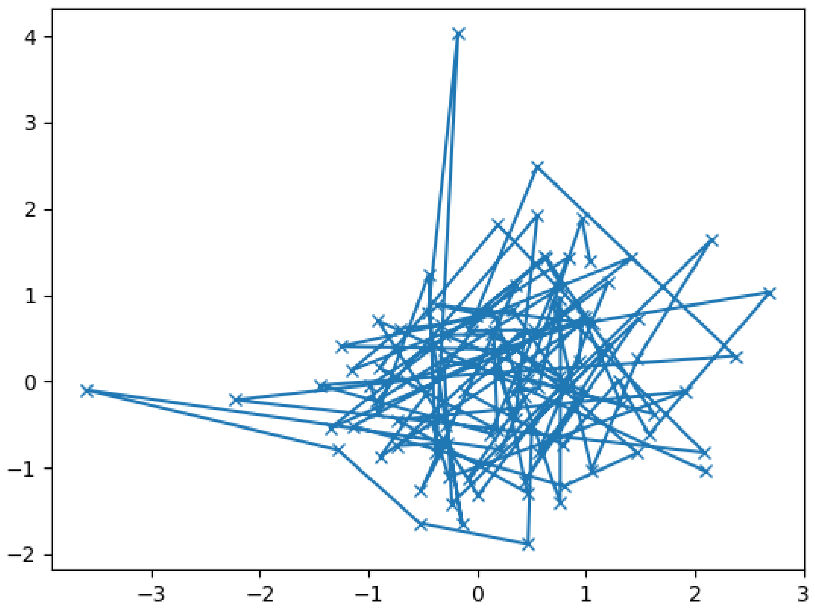


So, why all the extra typing instead of the MATLAB-style (which relies on global state and a flat namespace)? For very simple things like this example, the only advantage is academic: the wordier styles are more explicit, more clear as to where things come from and what is going on. For more complicated applications, this explicitness and clarity becomes increasingly valuable, and the richer and more complete object-oriented interface will likely make the program easier to write and maintain.

Typically one finds oneself making the same plots over and over again, but with different data sets, which leads to needing to write specialized functions to do the plotting. The recommended function signature is something like:

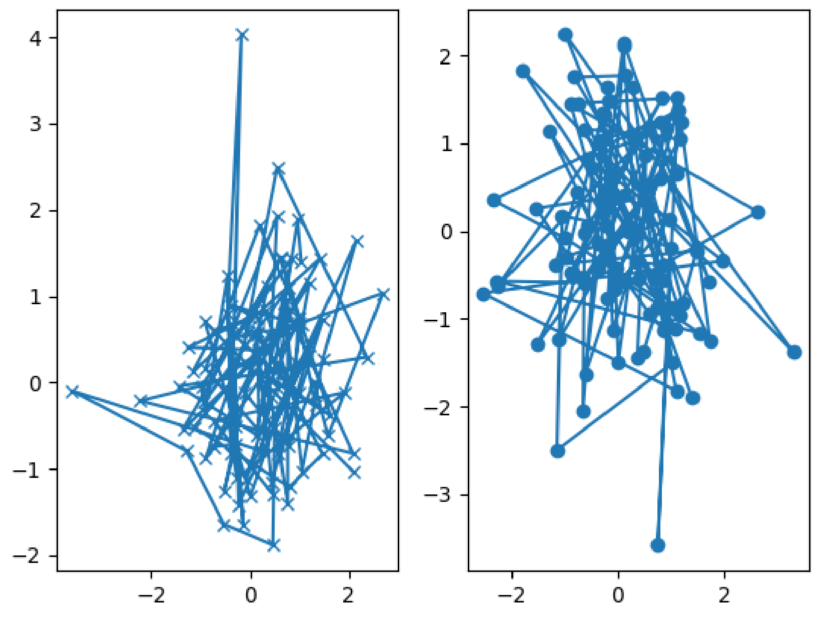
```
def my_plotter(ax, data1, data2, param_dict):
    """
    A helper function to make a graph

    Parameters
    ----------
    ax : Axes
        The axes to draw to

    data1 : array
```

```
        The x data

    data2 : array
        The y data

    param_dict : dict
        Dictionary of kwargs to pass to ax.plot

    Returns
    -------
    out : list
        list of artists added
    """
    out = ax.plot(data1, data2, **param_dict)
    return out

# which you would then use as:

data1, data2, data3, data4 = np.random.randn(4, 100)
fig, ax = plt.subplots(1, 1)
my_plotter(ax, data1, data2, {'marker': 'x'})
```



or if you wanted to have 2 sub-plots:

```
fig, (ax1, ax2) = plt.subplots(1, 2)
my_plotter(ax1, data1, data2, {'marker': 'x'})
my_plotter(ax2, data3, data4, {'marker': 'o'})
```



Again, for these simple examples this style seems like overkill, however once the graphs get slightly more complex it pays off.

Backends

What is a backend?

A lot of documentation on the website and in the mailing lists refers to the "backend" and many new users are confused by this term. matplotlib targets many different use cases and output formats. Some people use matplotlib interactively from the python shell and have plotting windows pop up when they type commands. Some people run Jupyter notebooks and draw inline plots for quick data analysis. Others embed matplotlib into graphical user interfaces like wxpython or pygtk to build rich applications. Some people use matplotlib in batch scripts to generate postscript images from numerical simulations, and still others run web application servers to dynamically serve up graphs.

To support all of these use cases, matplotlib can target different outputs, and each of these capabilities is called a backend; the "frontend" is the user facing code, i.e., the plotting code, whereas the "backend" does all the hard work behind-the-scenes to make the figure. There are two types of backends: user interface backends (for use in pygtk, wxpython, tkinter, qt4, or macosx; also referred to as "interactive backends") and hardcopy backends to make image files (PNG, SVG, PDF, PS; also referred to as "non-interactive backends").

There are four ways to configure your backend. If they conflict each other, the method mentioned last in the following list will be used, e.g. calling `use()` will override the setting in your `matplotlibrc`.

1. The `backend` parameter in your `matplotlibrc` file (see Customizing Matplotlib with style sheets and rcParams):

```
backend : WXAgg   # use wxpython with antigrain (agg) rendering
```

2. Setting the `MPLBACKEND` environment variable, either for your current shell or for a single script. On Unix:

   ```
   > export MPLBACKEND=module://my_backend
   > python simple_plot.py

   > MPLBACKEND="module://my_backend" python simple_plot.py
   ```

   On Windows, only the former is possible:

   ```
   > set MPLBACKEND=module://my_backend
   > python simple_plot.py
   ```

   Setting this environment variable will override the `backend` parameter in *any* `matplotlibrc`, even if there is a `matplotlibrc` in your current working directory. Therefore setting `MPLBACKEND` globally, e.g. in your `.bashrc` or `.profile`, is discouraged as it might lead to counter-intuitive behavior.

3. If your script depends on a specific backend you can use the `use()` function:

   ```
   import matplotlib
   matplotlib.use('PS')   # generate postscript output by default
   ```

   If you use the `use()` function, this must be done before importing `matplotlib.pyplot`. Calling `use()` after pyplot has been imported will have no effect. Using `use()` will require changes in your code if users want to use a different backend. Therefore, you should avoid explicitly calling `use()` unless absolutely necessary.

> **Note**
>
> Backend name specifications are not case-sensitive; e.g., 'GTK3Agg' and 'gtk3agg' are equivalent.

With a typical installation of matplotlib, such as from a binary installer or a linux distribution package, a good default backend will already be set, allowing both interactive work and plotting from scripts, with output to the screen and/or to a file, so at least initially you will not need to use any of the methods given above.

If, however, you want to write graphical user interfaces, or a web application server (Matplotlib in a web application server), or need a better understanding of what is going on, read on. To make things a little more customizable for graphical user interfaces, matplotlib separates the concept of the renderer (the thing that actually does the drawing) from the canvas (the place where the drawing goes). The canonical renderer for user interfaces is `Agg` which uses the Anti-Grain Geometry C++ library to make a raster (pixel) image of the figure. All of the user interfaces except `macosx` can be used with agg rendering, e.g., `WXAgg`, `GTK3Agg`, `QT4Agg`, `QT5Agg`, `TkAgg`. In addition, some of the user interfaces support other rendering engines. For example, with GTK+ 3, you can also select Cairo rendering (backend `GTK3Cairo`).

For the rendering engines, one can also distinguish between vector or raster renderers. Vector graphics languages issue drawing commands like "draw a line from this point to this point" and hence are scale free, and raster backends generate a pixel representation of the line whose accuracy depends on a DPI setting.

Here is a summary of the matplotlib renderers (there is an eponymous backed for each; these are *non-interactive backends*, capable of writing to a file):

Renderer	Filetypes	Description
AGG	png	raster graphics -- high quality images using the Anti-Grain Geometry engine
PS	ps eps	vector graphics -- Postscript output
PDF	pdf	vector graphics -- Portable Document Format
SVG	svg	vector graphics -- Scalable Vector Graphics
Cairo	png ps pdf svg	raster graphics and vector graphics -- using the Cairo graphics library

And here are the user interfaces and renderer combinations supported; these are *interactive backends*, capable of displaying to the screen and of using appropriate renderers from the table above to write to a file:

Backend	Description
Qt5Agg	Agg rendering in a Qt5 canvas (requires PyQt5). This backend can be activated in IPython with `%matplotlib qt5`.
ipympl	Agg rendering embedded in a Jupyter widget. (requires ipympl). This backend can be enabled in a Jupyter notebook with `%matplotlib ipympl`.
GTK3Agg	Agg rendering to a GTK 3.x canvas (requires PyGObject, and pycairo or cairocffi). This backend can be activated in IPython with `%matplotlib gtk3`.
macosx	Agg rendering into a Cocoa canvas in OSX. This backend can be activated in IPython with `%matplotlib osx`.
TkAgg	Agg rendering to a Tk canvas (requires TkInter). This backend can be activated in IPython with `%matplotlib tk`.
nbAgg	Embed an interactive figure in a Jupyter classic notebook. This backend can be enabled in Jupyter notebooks via `%matplotlib notebook`.
WebAgg	On `show()` will start a tornado server with an interactive figure.
GTK3Cairo	Cairo rendering to a GTK 3.x canvas (requires PyGObject, and pycairo or cairocffi).
Qt4Agg	Agg rendering to a Qt4 canvas (requires PyQt4 or `pyside`). This backend can be activated in IPython with `%matplotlib qt4`.
WXAgg	Agg rendering to a wxWidgets canvas (requires wxPython 4). This backend can be activated in IPython with `%matplotlib wx`.

ipympl

The Jupyter widget ecosystem is moving too fast to support directly in Matplotlib. To install ipympl

```
pip install ipympl
jupyter nbextension enable --py --sys-prefix ipympl
```

or

```
conda install ipympl -c conda-forge
```

See jupyter-matplotlib for more details.

GTK and Cairo

`GTK3` backends (*both* `GTK3Agg` and `GTK3Cairo`) depend on Cairo (pycairo>=1.11.0 or cairocffi).

How do I select PyQt4 or PySide?

The `QT_API` environment variable can be set to either `pyqt` or `pyside` to use `PyQt4` or `PySide`, respectively.

Since the default value for the bindings to be used is `PyQt4`, `matplotlib` first tries to import it, if the import fails, it tries to import `PySide`.

What is interactive mode?

Use of an interactive backend (see What is a backend?) permits--but does not by itself require or ensure--plotting to the screen. Whether and when plotting to the screen occurs, and whether a script or shell session continues after a plot is drawn on the screen, depends on the functions and methods that are called, and on a state variable that determines whether matplotlib is in "interactive mode". The default Boolean value is set by the `matplotlibrc` file, and may be customized like any other configuration parameter (see Customizing Matplotlib with style sheets and rcParams). It may also be set via `matplotlib.interactive()`, and its value may be queried via `matplotlib.is_interactive()`. Turning interactive mode on and off in the middle of a stream of plotting commands, whether in a script or in a shell, is rarely needed and potentially confusing, so in the following we will assume all plotting is done with interactive mode either on or off.

> **Note**
>
> Major changes related to interactivity, and in particular the role and behavior of `show()`, were made in the transition to matplotlib version 1.0, and bugs were fixed in 1.0.1. Here we describe the version 1.0.1 behavior for the primary interactive backends, with the partial exception of *macosx*.

Interactive mode may also be turned on via `matplotlib.pyplot.ion()`, and turned off via `matplotlib.pyplot.ioff()`.

> **Note**
>
> Interactive mode works with suitable backends in ipython and in the ordinary python shell, but it does *not* work in the IDLE IDE. If the default backend does not support interactivity, an interactive backend can be explicitly activated using any of the methods discussed in What is a backend?.

Interactive example

From an ordinary python prompt, or after invoking ipython with no options, try this:

```
import matplotlib.pyplot as plt
plt.ion()
plt.plot([1.6, 2.7])
```

Assuming you are running version 1.0.1 or higher, and you have an interactive backend installed and selected by default, you should see a plot, and your terminal prompt should also be active; you can type additional commands such as:

```
plt.title("interactive test")
plt.xlabel("index")
```

and you will see the plot being updated after each line. Since version 1.5, modifying the plot by other means *should* also automatically update the display on most backends. Get a reference to the `Axes` instance, and call a method of that instance:

```
ax = plt.gca()
ax.plot([3.1, 2.2])
```

If you are using certain backends (like `macosx`), or an older version of matplotlib, you may not see the new line added to the plot immediately. In this case, you need to explicitly call `draw()` in order to update the plot:

```
plt.draw()
```

Non-interactive example

Start a fresh session as in the previous example, but now turn interactive mode off:

```
import matplotlib.pyplot as plt
plt.ioff()
plt.plot([1.6, 2.7])
```

Nothing happened--or at least nothing has shown up on the screen (unless you are using *macosx* backend, which is anomalous). To make the plot appear, you need to do this:

```
plt.show()
```

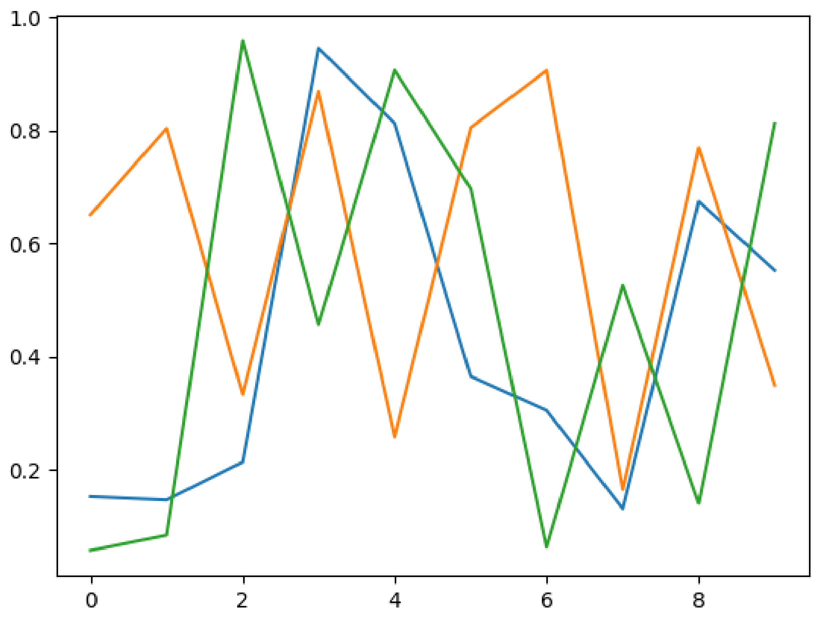
Now you see the plot, but your terminal command line is unresponsive; the `show()` command *blocks* the input of additional commands until you manually kill the plot window.

What good is this--being forced to use a blocking function? Suppose you need a script that plots the contents of a file to the screen. You want to look at that plot, and then end the script. Without some blocking command such as show(), the script would flash up the plot and then end immediately, leaving nothing on the screen.

In addition, non-interactive mode delays all drawing until show() is called; this is more efficient than redrawing the plot each time a line in the script adds a new feature.

Prior to version 1.0, show() generally could not be called more than once in a single script (although sometimes one could get away with it); for version 1.0.1 and above, this restriction is lifted, so one can write a script like this:

```
import numpy as np
import matplotlib.pyplot as plt

plt.ioff()
for i in range(3):
    plt.plot(np.random.rand(10))
    plt.show()
```



which makes three plots, one at a time.

Summary

In interactive mode, pyplot functions automatically draw to the screen.

When plotting interactively, if using object method calls in addition to pyplot functions, then call `draw()` whenever you want to refresh the plot.

Use non-interactive mode in scripts in which you want to generate one or more figures and display them before ending or generating a new set of figures. In that case, use `show()` to display the figure(s) and to block execution until you have manually destroyed them.

Performance

Whether exploring data in interactive mode or programmatically saving lots of plots, rendering performance can be a painful bottleneck in your pipeline. Matplotlib provides a couple ways to greatly reduce rendering time at the cost of a slight change (to a settable tolerance) in your plot's appearance. The methods available to reduce rendering time depend on the type of plot that is being created.

Line segment simplification

For plots that have line segments (e.g. typical line plots, outlines of polygons, etc.), rendering performance can be controlled by the `path.simplify` and `path.simplify_threshold` parameters in your `matplotlibrc` file (see Customizing Matplotlib with style sheets and rcParams for more information about the `matplotlibrc` file). The `path.simplify` parameter is a boolean indicating whether or not line segments are simplified at all. The `path.simplify_threshold` parameter controls how much line segments are simplified; higher thresholds result in quicker rendering.

The following script will first display the data without any simplification, and then display the same data with simplification. Try interacting with both of them:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl

# Setup, and create the data to plot
y = np.random.rand(100000)
y[50000:] *= 2
y[np.logspace(1, np.log10(50000), 400).astype(int)] = -1
mpl.rcParams['path.simplify'] = True

mpl.rcParams['path.simplify_threshold'] = 0.0
plt.plot(y)
plt.show()

mpl.rcParams['path.simplify_threshold'] = 1.0
plt.plot(y)
plt.show()
```

Matplotlib currently defaults to a conservative simplification threshold of `1/9`. If you want to change your default settings to use a different value, you can change your `matplotlibrc` file. Alternatively, you could create a new style for interactive plotting (with maximal simplification) and another style for publication quality plotting (with minimal simplification) and activate them as necessary. See Customizing Matplotlib with style sheets and rcParams for instructions on how to perform these actions.

The simplification works by iteratively merging line segments into a single vector until the next line segment's perpendicular distance to the vector (measured in display-coordinate space) is greater than the `path.simplify_threshold` parameter.

> **Note**
>
> Changes related to how line segments are simplified were made in version 2.1. Rendering time will still be improved by these parameters prior to 2.1, but rendering time for some kinds of data will be vastly improved in versions 2.1 and greater.

Marker simplification

Markers can also be simplified, albeit less robustly than line segments. Marker simplification is only available to `Line2D` objects (through the `markevery` property). Wherever `Line2D` construction parameter are passed through, such as `matplotlib.pyplot.plot()` and `matplotlib.axes.Axes.plot()`, the `markevery` parameter can be used:

```
plt.plot(x, y, markevery=10)
```

The markevery argument allows for naive subsampling, or an attempt at evenly spaced (along the *x* axis) sampling. See the Markevery Demo for more information.

Splitting lines into smaller chunks

If you are using the Agg backend (see What is a backend?), then you can make use of the `agg.path.chunksize` rc parameter. This allows you to specify a chunk size, and any lines with greater than that many vertices will be split into multiple lines, each of which have no more than `agg.path.chunksize` many vertices. (Unless `agg.path.chunksize` is zero, in which case there is no chunking.) For some kind of data, chunking the line up into reasonable sizes can greatly decrease rendering time.

The following script will first display the data without any chunk size restriction, and then display the same data with a chunk size of 10,000. The difference can best be seen when the figures are large, try maximizing the GUI and then interacting with them:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
mpl.rcParams['path.simplify_threshold'] = 1.0

# Setup, and create the data to plot
y = np.random.rand(100000)
y[50000:] *= 2
y[np.logspace(1,np.log10(50000), 400).astype(int)] = -1
mpl.rcParams['path.simplify'] = True

mpl.rcParams['agg.path.chunksize'] = 0
plt.plot(y)
plt.show()

mpl.rcParams['agg.path.chunksize'] = 10000
plt.plot(y)
plt.show()
```

Using the *fast* style

The *fast* style can be used to automatically set simplification and chunking parameters to reasonable settings to speed up plotting large amounts of data. It can be used simply by running:

```
import matplotlib.style as mplstyle
mplstyle.use('fast')
```

It is very light weight, so it plays nicely with other styles, just make sure the fast style is applied last so that other styles do not overwrite the settings:

```
mplstyle.use(['dark_background', 'ggplot', 'fast'])
```

`Download Python source code: usage.py`

`Download Jupyter notebook: usage.ipynb`