Data Analysis with Python

Jared Garst

February 2, 2016

Python is a high level scripting language. While there are many reasons to like or dislike Python, we are introducing it to you because it is becoming the lingua franca of science. This means that increasingly you can expect other people to understand your code, and for many of your problems to already be solved and documented in Python. Briefly, some exceptional Python features are:

Beautiful Syntax
: Python will make your life easier, by encouraging simple, clean, easy to read code.

Interpreted
: The code you write is the code that runs. Nothing will be changed, nothing will be checked, nothing will be optimised.

No Types
: There is no easy way to specify how code will operate on your data.

Program Control Through Indentation
: Other languages use curly brackets `{}` to determine program flow, and tabs by convention for readability. Python conflates the two.

Batteries Included
: Python makes it easy to do common tasks, has an extensive set of additional libraries, and a vibrant community maintaining them.

IPython is an interactive version of python, designed for a more exploratory approach to programming and analysis. ~~IPython~~ Jupyter notebooks allow you to quickly visualize your analysis, and provide an easy record of your process. Like any tools, you can become expert in Jupyter notebooks and IPython syntax, but you won't need to for this course, and we won't cover those skills.

There are two versions of Python that you will encounter in the wild, Python 2 and Python 3. Python 3 is a take-no-prisoners reimagining of the the language. The result is a smoother language, that breaks everything down to the print statement in Python 2. Most libraries support both Python 2 and 3, but most code is in Python 2. This means the appropriate version will depend on how old your project is. This introduction will use Python 2 — but for this course there aren't huge differences between the choices.

Setup and Startup

If you have never set up a programming environment before, the easiest way to start is to install Anaconda. This modified python environment will install the most common python libraries. It is distributed for free in hopes of later selling packages that speed up your python code, but you can simply use it as a convenient installation tool. If you want to try a grittier, more controlled installation of Python and its many friends, you can schedule some time with Jared.

Once you have completed the installation, run `ipython notebook` in the terminal, or the Anaconda IPython Notebook executable. A web browser will automatically start with your notebook. Managing directories in notebooks is clumsy. Either make sure to run IPython in the directory you want, or change the default directory.

There are a few flavors of help commands available in IPython. Familiarity with the options allows you to reference the manuals, or explore specific parts of the language.

help() is the native python help command. Type `help()` into the first cell, and execute with shift-enter. This is a good place to spend time getting familiar with the language, but you can also ask it about specific objects. For example, run `help(list)` to see some common list manipulations.

? is IPython's own help command, and it is often nicer to use than `help`. Try running `?` to see an introduction to IPython. Like help you can also ask more specific commands, run `import numpy; numpy?` to see an overview of the exceptionally useful numpy module. If you need all the gory details of an object, `numpy??` will give you the source code.

<regex>? allows you to use `?` to search through an object. Try running `numpy.*cos*?` to see every function in numpy related to cos.

%quickref is a 'magic function', unique to IPython. They are usually used to change the behavior of the notebook — this one will list of all special IPython commands, including the magic functions.

<tab> will provide code completion. Type `numpy.arc<tab>` and IPython will suggest a list of inverse trig functions.

Control-m h Provides a list of hotkeys for IPython notebooks. If you spend a lot of time in the notebook, these are worth putting in your fingers.

help commands

```
help()

help(list)

?

import numpy;
numpy?

numpy??

numpy.*cos*?

numpy.arc<tab>

<ctrl>-m h

%quickref
```

First Steps

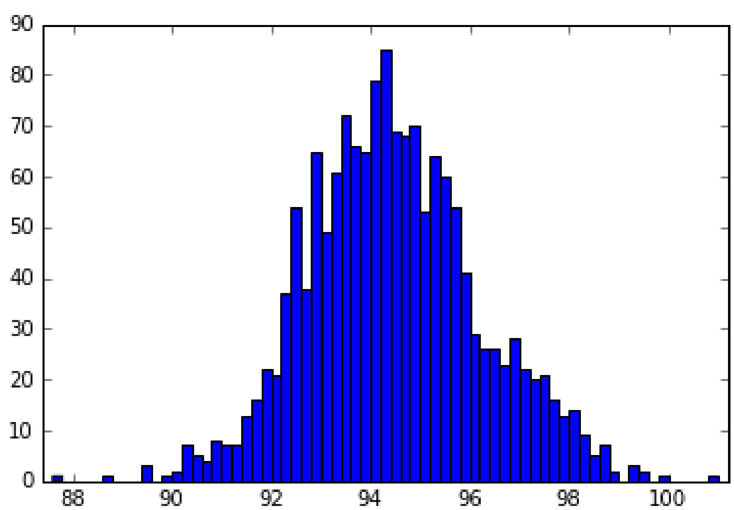
```
In [1]: # Libraries at the top
        # Display graphs immediately
        %matplotlib inline
        import numpy as np                     # Math functions
        import matplotlib.pyplot as plt       # Plotting functions
        import scipy.stats as st               # Common distributions
        import pandas as pd                    # For handaling data
        from IPython.display import display   # Display complex objects
```

```
In [2]: # Convert data from a file to a big list
        capacitor_data = (pd.read_csv('first_example.csv')
                            .as_matrix().flatten())
        capacitor_data
```

```
Out[2]: array([ 97. ,  92.7,  94.5, ...,  93.4,  95.5,  97.4])
```

```
In [3]: # Set bin size for histogram
        bin_width = 0.2;
        cmin = capacitor_data.min();
        cmax = capacitor_data.max();
        # Create a list of each bin location
        # The bin location is the smallest number it contains.
        bins = np.arange(cmin, cmax, bin_width)
```

```
In [4]: # Get figure objects to keep and work on
        fig, ax = plt.subplots();
        ax.set_xlim((cmin - bin_width, cmax + bin_width));
        ax.hist(capacitor_data, bins=bins);
```

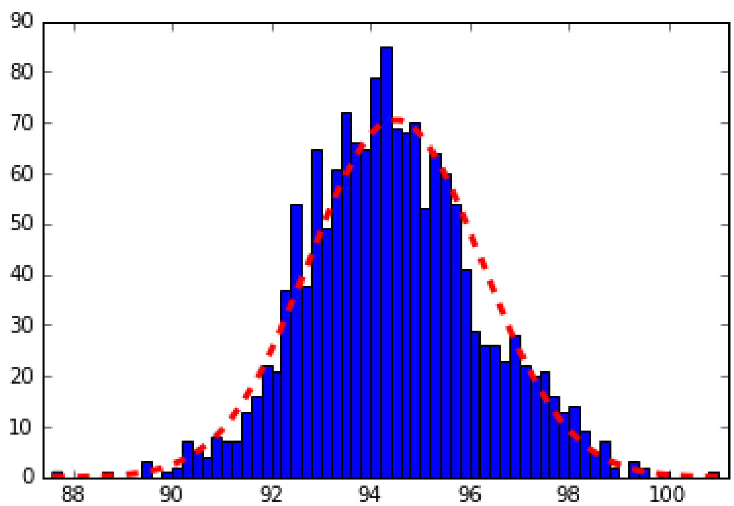


```
In [5]: # Find some statistical parameters
        N = len(capacitor_data)
        mu = np.mean(capacitor_data)
        variance = np.var(capacitor_data)

In [6]: # Print the variance to two decimal places
        'variance is {0:.2f}'.format(variance)

Out[6]: 'variance is 3.02'

In [7]: # Add fitting
        area = N * bin_width
        std = np.sqrt(variance)
        fit = area * st.norm(loc=mu, scale=std).pdf(bins)
        ax.plot(bins, fit, 'r--', linewidth=3);
        display(fig)
```



Python Gotchas

Some of the ways that python makes your life easier can send your program off the rails, if you don't understand what the computer is doing.

TYPES still exist in python, even if you can't enforce them. Consider the following python code:

```
In [1]: print 3/2, 3.0/2.0

        1 1.5
```

In the underlying C code, an operation on two integers always returns an integer, because floating point[1] math is much slower. In python, you can check a type with type(object), and enforce a type with **assert** and isinstance.

Float stands for floating point number', otherwise known as a decimal number. Though not usually relevant for data analysis, be aware that `int` and `float` have detailed differences in precision and speed.

In the underlying C code, an operation on two integers always returns an you can check a type with `type(object)`, and enforce a type with `assert` and `isinstance`.

```
In [1]: print 3/2, 3.0/2.0

        1 1.5

In [2]: print type(3), type(3.0)

        <type 'int'> <type 'float'>

In [3]: assert isinstance(3, int)
```

`assert` will stop the program with an error if the next statement is not true. Python 3 is smarter about division, and will return 1.5 for both calculations. In the likely event that you cannot use python 3, you can still import the behavior by including

```
In [1]: from __future__ import division
```

at the top of your file or notebook.

COPYING OBJECTS can be done in two distinct ways, shown abstractly in Figure 1. The more common method is to copy the object reference, so that it can be used in a different part of the code. The second method is when you want to have two distinct copies, so that you can have both an original version and a modified version. In the first case it is appropriate to duplicate the pointer. In the second case it is necessary to duplicate the object itself. Because the first case is common and the second case is expensive, python duplicates the reference by default.

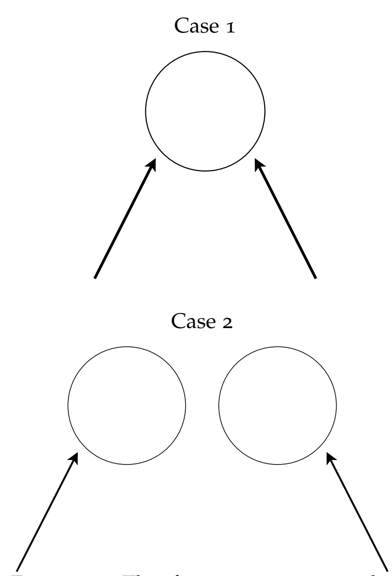


Figure 1: The finger pointing at the moon is not the moon

```
In [1]: import numpy as np
        lst1 = np.array(['An Object'], dtype=object);
        lstcpy = lst1; lst2 = lst1.copy()

In [2]: print lst1, lstcpy, lst2

        ['An Object'] ['An Object'] ['An Object']

In [3]: lstcpy[0] = 'A New Object'

In [4]: print lst1, lstcpy, lst2

        ['A New Object'] ['A New Object'] ['An Object']
```

THE NOTEBOOK STATE is changed every time you run a command, not every time you add a cell. This allows you to create confusing code, by removing cells or executing them in a strange order.

```
In [3]: message = ('IPython does not have to run from '
                   'top to bottom')

In [1]: message = 'Good luck debugging this'

In [4]: print message

        IPython does not have to run from top to bottom

In [2]: print message

        Good luck debugging this
```

You can debug this problem by paying attention to the numbers in front of the cells. Commands are executed in sequence with their numbers, not their position. Try to keep your notebook linear, by not changing cells that have already successfully executed.

Problems

1 DOCUMENTATION FROM PYTHON

Use the help commands to locate the `scipy.stats` documentation on the Poisson distribution. Is the distribution a function or an object? Plot[1] the expected number of counts for 10 trials of a poisson process, each with an average of 3 counts per trial.

[1] You will need the syntax for matplotlib. You can find everything with the help commands, or can get syntax and ideas from example plots that others have made.

2 DOCUMENTATION FROM GOOGLE

Try calling the poisson distribution function from `scipy.stats` with no arguments. You will get an error message saying one argument was passed, but two were needed. Use google to explain these strange parameter counts.

3 USING PYTHON TO CALCULATE

Reproduce the mean, variance, and standard deviation of the data using your own functions.

4 OBSERVE THE CENTRAL LIMIT THEOREM

Write a function `data_avg(list, int)` that returns a new list $\bar{x}_n$, containing all possible averages of n values selected from the list. Use this to plot $\bar{x}_2$, $\bar{x}_{10}$ and $\bar{x}_{100}$. What are the means of these averaged distributions? What are the variances? How do these compare to the mean and variance of x?

More Reading

Data Structures and List Maniupulation

Units and Errors

Source control: Mercurial and Git