Python Quick Start for Economists

Chicago Federal Reserve Workshop

John Stachurski

May 2016

This Morning

- 9:00–10:30 Lecture
- 10:30–11:00 Coffee break
- 11:00–12:30 Exercises

Lecture topics:

- Introduction
- A first program
- Some language features
- Scientific programming

Set Up

Use Anaconda!

- Bundles Python and the main scientific libraries
- Free from `http://continuum.io/downloads`
- Make it your default Python distribution

Keeping up to date:

- In a terminal type `conda update anaconda`
  - On Windows, terminal = `cmd`

Downloads

Documents for today's lecture available from

- https://github.com/QuantEcon/ChicagoFed_workshop

Download the whole repo using `Download ZIP` (or `git`)

In `Tuesday_morning` you'll find

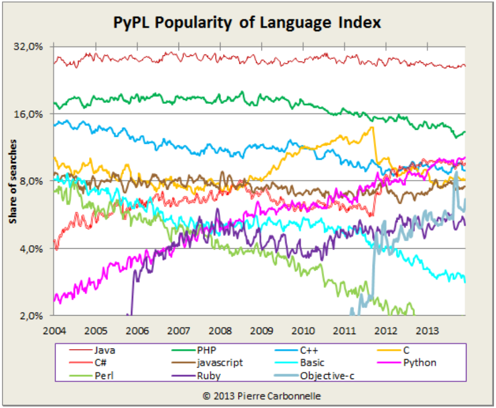
- these lecture slides (PDF)
- `scientific_python_quickstart.ipynb`
- `python_exercises.ipynb`

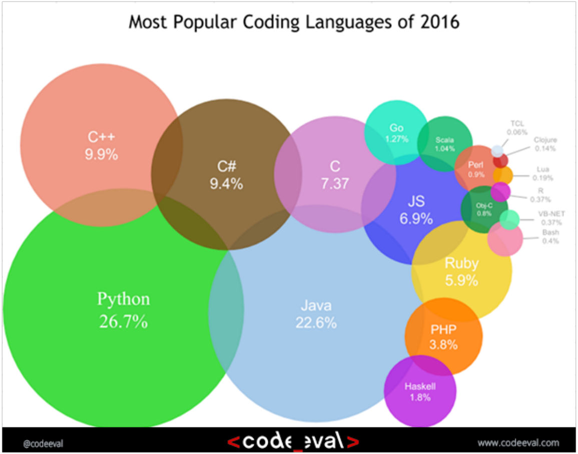
What's Python?

A high level, general purpose programming language

Used extensively by

- Tech firms (YouTube, Dropbox, Reddit, etc., etc.)
- Hedge funds and finance industry
- Gov't agencies (NASA, CERN, etc.)
- Academia


PyPL Popularity of Language Index
Share of searches
32,0%
16,0%
8,0%
4,0%
2,0%
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
Java
PHP
C++
C
C#
javascript
Basic
Python
Perl
Ruby
Objective-c
© 2013 Pierre Carbonnelle


Most Popular Coding Languages of 2016
C++
9.9%
C#
9.4%
C
7.37
Go
1.27%
Scala
1.04%
Perl
0.9%
TCL
0.06%
Clojure
0.14%
Lua
0.19%
R
0.37%
JS
6.9%
Obj-C
0.8%
VB-NET
0.37%
Bash
0.4%
Ruby
5.9%
Python
26.7%
Java
22.6%
PHP
3.8%
Haskell
1.8%
@codeeval
www.codeeval.com

Noted for

- Elegant, modern design
- Clean syntax, readability
- High productivity

Often used to teach first courses in comp sci and programming

- MIT, Stanford, Chicago, NYU, Yale, etc.
- Udacity, edX, etc.

Very popular in "data science" / machine learning

Why I Like Python

1. Well designed language
    - Elegant, readable, expressive
2. General purpose
    - meets all my coding needs
    - large set of mature libraries
3. Other awesomeness
    - Numba, Jupyter, etc
4. Open source
    - no license hassles
    - can read / edit source code

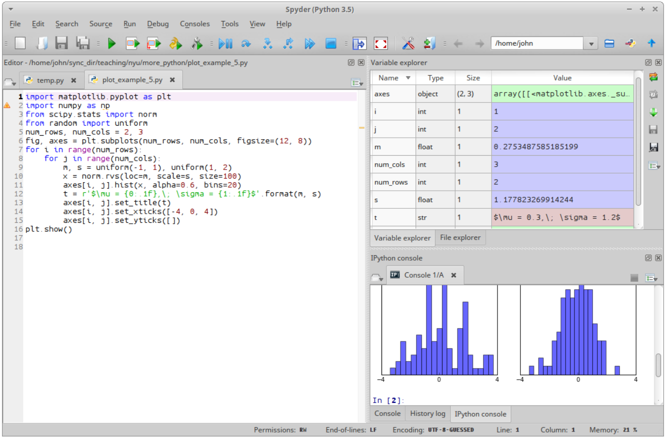
Interacting with Python

How do we write / run code in Python?

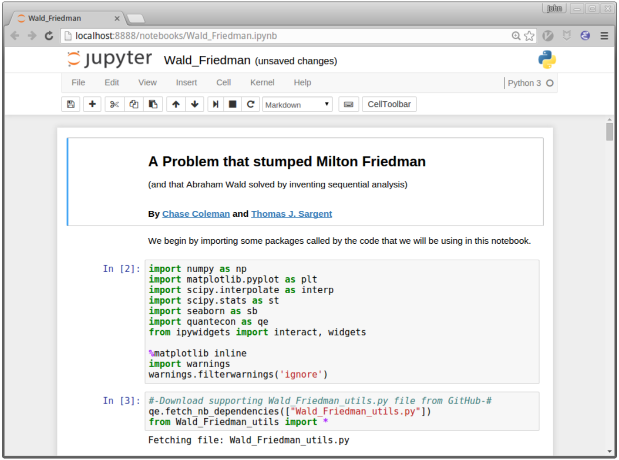
Options

- IDE
- Text editor plus REPL
- Jupyter notebooks
- etc.

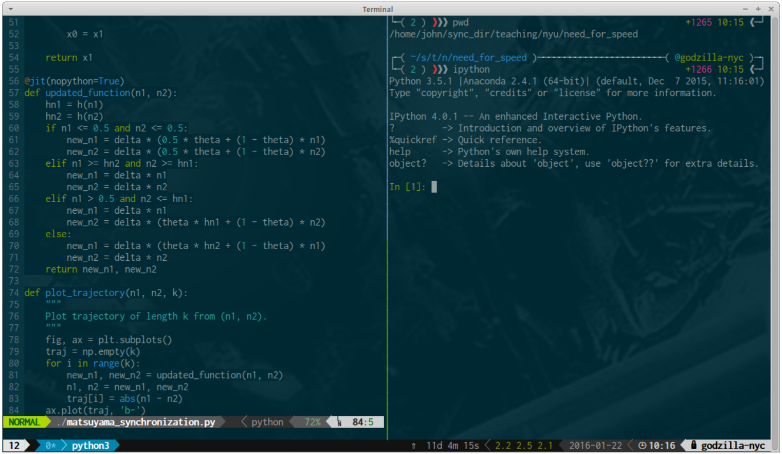
Spyder


Spyder (Python 3.5)
File Edit Search Source Run Debug Consoles Tools View Help
/home/john
Editor - /home/john/sync_dir/teaching/nyu/more_python/plot_example_5.py
temp.py
plot_example_5.py
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import norm
from random import uniform
num_rows, num_cols = 2, 3
fig, axes = plt.subplots(num_rows, num_cols, figsize=(12, 8))
for i in range(num_rows):
for j in range(num_cols):
m, s = uniform(-1, 1), uniform(1, 2)
x = norm.rvs(loc=m, scale=s, size=100)
axes[i, j].hist(x, alpha=0.6, bins=20)
t = r'$\mu = {0:.1f},\; \sigma = {1:.1f}$'.format(m, s)
axes[i, j].set_title(t)
axes[i, j].set_xticks([-4, 0, 4])
axes[i, j].set_yticks([])
plt.show()
Variable explorer
Name Type Size Value
axes object (2, 3) array([[<matplotlib.axes._su...
i int 1 1
j int 1 2
m float 1 0.2753487585185199
num_cols int 1 3
num_rows int 1 2
s float 1 1.177823269914244
t str 1 $\mu = 0.3,\; \sigma = 1.2$
Variable explorer File explorer
IPython console
Console 1/A
In [2]:
Console History log IPython console
Permissions: RW End-of-lines: LF Encoding: UTF-8-GUESSED Line: 1 Column: 1 Memory: 21 %

Jupyter notebooks



My set up (Linux terminal, Tmux, Vim, IPython REPL)



Jupyter Notebooks

Today we'll interact with Python using Jupyter notebooks

- A browser based front end to Python, Julia, R, etc.
- Stores output as well as input
- Allows for rich text, graphics, etc.
- Easy to run remotely on servers / in cloud

To show

- Editing modes, execution
- Markdown
- Inline figures
- Language agnostic

- Ref: http://quant-econ.net/py/getting_started.html

- Examples: http://notebooks.quantecon.org/

An Easy Python Program

Next step: write and pick apart small Python program

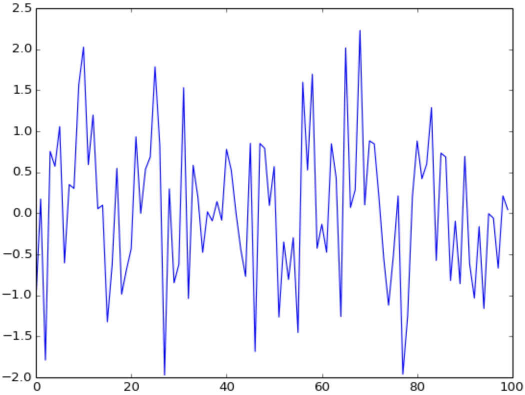
Aim: To simulate and plot

$$\epsilon_0, \epsilon_1, \ldots, \epsilon_T \quad \text{where} \quad \{\epsilon_t\} \stackrel{\text{IID}}{\sim} N(0,1)$$

Notes

1. Like all first programs, to some extent contrived
2. We focus as much as possible on pure Python

Desired output (modulo randomness)



First pass

```
import matplotlib.pyplot as plt
from random import normalvariate

ts_length = 100
epsilon_values = []
for i in range(ts_length):
    e = normalvariate(0, 1)
    epsilon_values.append(e)
plt.plot(epsilon_values, 'b-')
plt.show()
```

- http://quant-econ.net/py/python_by_example.html

Import Statements

Consider the lines

```
import matplotlib.pyplot as plt
from random import normalvariate
```

We are importing functionality from two modules

- module = file containing Python code

Importing a module causes Python to

- run the code in those files
- set up a matching **namespace** to store variables

```
In [1]: import random

In [2]: random.normalvariate(0, 1)
Out[2]: 0.18415513098683509

In [3]: random.uniform(0, 1)
Out[3]: 0.11883707116624409
```

You can also just import the names directly:

```
In [4]: from random import normalvariate, uniform

In [5]: normalvariate(0, 1)
Out[5]: -0.7248742909651001

In [6]: uniform(0, 4)
Out[6]: 0.24696251658189228
```

Lists

Statement `epsilon_values = []` creates an empty list

Lists: a Python data structure used to group objects

```
In [7]: x = [10, 'foo']

In [8]: type(x)
Out[8]: list
```

Note that different types of objects can be combined in a single list

Adding a value to a list: `list_name.append(some_value)`

```
In [10]: x
Out[10]: [10, 'foo']

In [11]: x.append(0.5)

In [12]: x
Out[12]: [10, 'foo', 0.5]
```

Here `append()` is an example of a **method**

- a function "attached to" an object

Another example of a list method:

```
In [13]: x
Out[13]: [10, 'foo', 0.5]

In [14]: x.pop()
Out[14]: 0.5

In [15]: x
Out[15]: [10, 'foo']
```

To see all list methods, type `x.` and hit “Tab”

Lists in Python are **zero based**

- Like C, Java, Ruby, Go, etc.

```
In [16]: x
Out[16]: [10, 'foo']

In [17]: x[0]
Out[17]: 10

In [18]: x[1]
Out[18]: 'foo'
```

Looping

Consider again these lines from `test_program_1.py`

```
6 for i in range(ts_length):
7     e = normalvariate(0, 1)
8     epsilon_values.append(e)
9 plt.plot(epsilon_values, 'b-')
```

Lines 7–8 are the **code block** of the `for` loop

Reduced indentation signals end of code block

Comments on Indentation

In Python **all** code blocks are delimited by indentation

Pros: more consistency, less clutter

Cons: a bit fragile

Notes:

- Line before start of code block always ends in a colon
- All lines in a code block must have same indentation
- The Python standard is 4 spaces

Extension 1: Same result but using a function:

```
import matplotlib.pyplot as plt
from random import normalvariate

def generate_data(n):
    epsilon_values = []
    for i in range(n):
        e = normalvariate(0, 1)
        epsilon_values.append(e)
    return epsilon_values

data = generate_data(100)
plt.plot(data, 'b-')
plt.show()
```

Extension 2: A more flexible function:

```
import matplotlib.pyplot as plt
from random import normalvariate, uniform

def generate_data(n, generator_type):
    epsilon_values = []
    for i in range(n):
        e = generator_type(0, 1)
        epsilon_values.append(e)
    return epsilon_values

data = generate_data(100, uniform)
plt.plot(data, 'b-')
plt.show()
```

Language Features

Now let's turn to some features of the Python language

- Common data types
- Objects and methods
- Name and variables

Data Types

Some native Python data types

```
In [1]: s = 'foo'
In [2]: type(s)
Out[2]: str

In [3]: x = 0.1
In [4]: type(x)
Out[4]: float

In [5]: y = ['foo', 'bar']
In [6]: type(y)
Out[6]: list
```

Type is important in Python

```
In [1]: 1 + 1
Out[1]: 2
```

```
In [2]: 'foo' + 'bar'
Out[2]: 'foobar'
```

```
In [3]: ['foo', 'bar'] + [10, 20]
Out[3]: ['foo', 'bar', 10, 20]
```

Each data type has its own methods

```
In [7]: y = ['foo', 'bar']
In [8]: y.reverse()
In [9]: y
Out[9]: ['bar', 'foo']
```

An example of a string method:

```
In [10]: s = 'foobar'
In [11]: s.capitalize()
Out[11]: 'Foobar'
```

Another data type is a **tuple** — similar to a list

```
In [1]: x = ['a', 'b']  # Square brackets for lists
In [2]: type(x)
Out[2]: list

In [3]: x = ('a', 'b')  # Round brackets for tuples
In [4]: type(x)
Out[4]: tuple

In [5]: x = 'a', 'b'    # No brackets is identical
In [6]: type(x)
Out[6]: tuple
```

In fact tuples are **immutable** lists

Immutable means internal state cannot be altered

```
In [1]: x = (10, 20)

In [2]: x[0] = 'foo'
---------------------------------------------------------------
TypeError
Traceback (most recent call last)
<ipython-input-2-ff02f57fd8a0> in <module>()
----> 1 x[0] = 'foo'
TypeError: 'tuple' object does not support item assignment
```

Functions

Some are built-in:

```
In [1]: max(10, 20, -2)
Out[1]: 20

In [2]: max
Out[2]: <function max>
```

Others are imported:

```
In [3]: from math import sqrt

In [4]: sqrt
Out[4]: <function math.sqrt>
```

We can also write our own functions

```
In [1]: def f(x):
   ...:     return x + 42
   ...:

In [2]: f(1)
Out[2]: 43
```

One line functions using the `lambda` keyword:

```
In [3]: f = lambda x: x + 42
```

Object Oriented Programming

Traditional programming paradigm is called **procedural**

- A program has state (values of its variables)
- Functions are called to act on this state
- Data is passed around via function calls

In **OOP**, data and functions bundled together into **objects**

These bundled functions are called **methods**

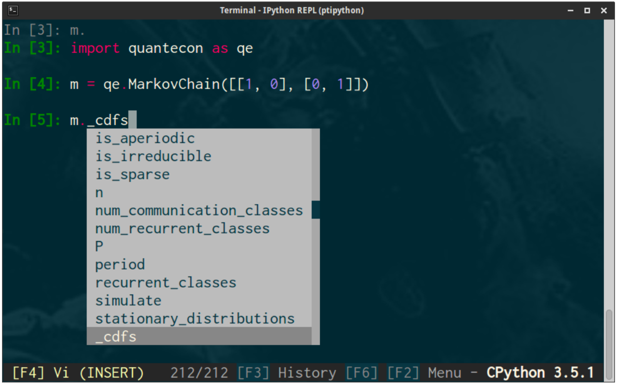
Example: Lists = list data + list methods

```
In [1]: x = []

In [2]: x.append('foo')
In [3]: x
Out[3]: ['foo']
```

Compare with Julia:

```
julia> x = Any[]
0-element Array{Any,1}

julia> push!(x, "foo")
1-element Array{Any,1}:
 "foo"
```

One advantage: introspection



We can build our own objects using the keyword `class`

```
import random

class Dice:

    def __init__(self, face):

        self.face = face

    def roll(self):

        new_face = random.choice((1, 2, 3, 4, 5, 5, 6))
        self.face = new_face
```

Names and Objects

Consider this assignment statement

```
x = 42
```

We are **binding** the **name** `x` to the object on the right hand side

Thus, **names are symbols bound to objects stored in memory**

Python is **dynamically typed** — names are not specific to type

```
s = 'foo'   # Bind s to a string
s = 100     # and now to an integer
```

Consider this (frightening?) code example

```
In [1]: x = ['foo', 'bar']

In [2]: y = x

In [3]: y[0] = 'fee'

In [4]: x
Out[4]: ['fee', 'bar']
```

Works because

- `x` and `y` are bound to the **same object**
- that object is **mutable**

Scientific Programming with Python

Rapid adoption by the scientific community

- engineering
- computational biology
- chemistry
- physics, etc., etc.

More recently

- AI, machine learning, “data science”

Key Scientific Libraries

NumPy

- basic data types
- simple array processing operations

SciPy

- built on top of NumPy
- provides additional functionality

Matplotlib

- 2D and 3D figures

NumPy

NumPy Example: Mean and standard dev of an array

```
In [1]: import numpy as np

In [2]: a = np.random.randn(100)

In [3]: a.mean()
Out[3]: -0.091480787986957607

In [4]: a.std()
Out[4]: 1.09303761548889
```

Previous Example Using NumPy

Let's redo our earlier example using NumPy

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

epsilon_values = np.random.randn(100)
plt.plot(epsilon_values, 'b-')
plt.show()
```

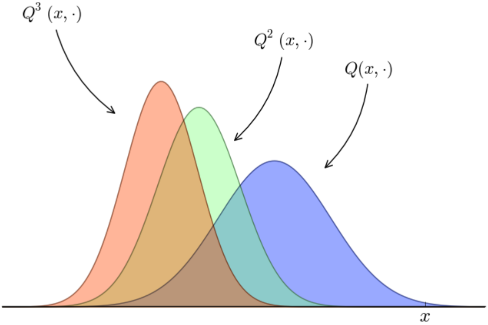
SciPy

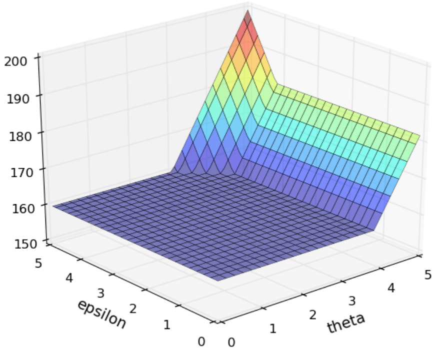
SciPy Example: Calculate

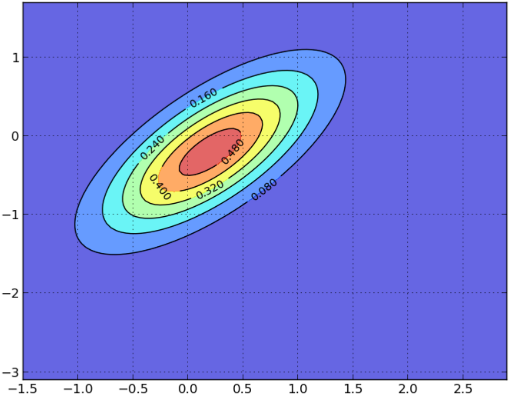
$$\int_{-2}^{2} \phi(z)dz \quad \text{where} \quad \phi \sim N(0,1)$$

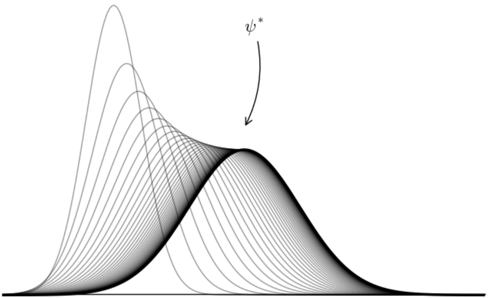
```
In [1]: from scipy.stats import norm
In [2]: from scipy.integrate import quad

In [3]: phi = norm(0, 1)

In [4]: value, error = quad(phi.pdf, -2, 2)

In [5]: value
Out[5]: 0.9544997361036417
```

Matplotlib examples




200
190
180
170
160
150
5
4
3
2
1
0
epsilon
0
1
2
3
4
5
theta


0.160
0.240
0.480
0.400
0.320
0.080
1
0
−1
−2
−3
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5


ψ^*

Other Scientific Libraries

Pandas

- statistics and data analysis

SymPy

- symbolic manipulations à la Mathematica

Still more:

- **statsmodels** — statistics / econometrics
- **scikit-learn** — machine learning in Python

Python Libraries for Econ

QuantEcon (http://quantecon.org/) provides

- Markov chains
- Dynamic programming
- LQ control
- etc

Dolo for quantitative macro

- A modeling language
- Many solution methods

Other Scientific Tools

Also tools for

- working with graphs (as in networks)
- parallel processing, GPUs
- manipulating large data sets
- interfacing with C / C++ / Fortran
- cloud computing
- database interaction
- bindings to high level languages like R and Julia
- etc.

Further Resources

Further discussion and links available at `http://quant-econ.net`

- Basic instructions
- Python lectures
- Scientific Python
- Lots of economic examples

Exercise Session

Inside the `Tuesday_morning` dir of

- https://github.com/QuantEcon/ChicagoFed_workshop

you will find

1. `scientific_python_quickstart.ipynb`
2. `python_exercises.ipynb`

Work through these notebooks in order

To do so,

1. start `jupyter-notebook`
2. click 'Upload'
3. navigate to file