Python Programming for Economics and Finance

Thomas J. Sargent & John Stachurski

Dec 20, 2023

CONTENTS

This website presents a set of lectures on Python programming for economics and finance.

This is the first text in the series, which focuses on programming in Python.

For an overview of the series, see this page

Part I

Introduction to Python

CHAPTER

ONE

ABOUT PYTHON

Contents

> "Python has gotten sufficiently weapons grade that we don't descend into R anymore. Sorry, R people. I used to be one of you but we no longer descend into R." – Chris Wiggins

1.1 Overview

In this lecture we will

- outline what Python is
- compare it to some other languages
- showcase some of its abilities.

At this stage, it's **not** our intention that you try to replicate all you see.

We will work through what follows at a slow pace later in the lecture series.

Our only objective for this lecture is to give you some feel of what Python is, and what it can do.

1.2 What's Python?

Python is a general-purpose programming language conceived in 1989 by Dutch programmer Guido van Rossum.

Python is free and open source, with development coordinated through the Python Software Foundation.

Python has experienced rapid adoption in the last decade and is now one of the most popular programming languages.

1.2.1 Common Uses

Python is a general-purpose language used in almost all application domains such as

- communications
- web development
- CGI and graphical user interfaces
- game development
- resource planning
- multimedia, data science, security, etc., etc., etc.

Used and supported extensively by Internet services and high-tech companies including

- Google
- Netflix
- Meta
- Dropbox
- Amazon
- Reddit

For reasons we will discuss, Python is particularly popular within the scientific community and behind many scientific achievements in

- Space Science
- Particle Physics
- Genetics

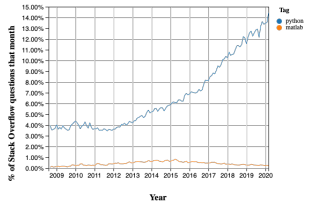
and practically all branches of academia.

Meanwhile, Python is also very beginner-friendly and is found to be suitable for students learning programming and recommended to introduce computational methods to students in fields other than computer science.

Python is also replacing familiar tools like Excel as an essential skill in the fields of finance and banking.

1.2.2 Relative Popularity

The following chart, produced using Stack Overflow Trends, shows one measure of the relative popularity of Python

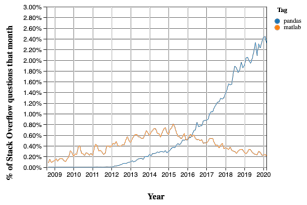


The figure indicates not only that Python is widely used but also that adoption of Python has accelerated significantly since 2012.

We suspect this is driven at least in part by uptake in the scientific domain, particularly in rapidly growing fields like data science.

For example, the popularity of pandas, a library for data analysis with Python has exploded, as seen here.

(The corresponding time path for MATLAB is shown for comparison)



Note that pandas takes off in 2012, which is the same year that we see Python's popularity begin to spike in the first figure.

Overall, it's clear that

- Python is one of the most popular programming languages worldwide.
- Python is a major tool for scientific computing, accounting for a rapidly rising share of scientific work around the globe.

1.2.3 Features

Python is a high-level language suitable for rapid development.

It has a relatively small core language supported by many libraries.

Other features of Python:

- multiple programming styles are supported (procedural, object-oriented, functional, etc.)
- it is interpreted rather than compiled.

1.2.4 Syntax and Design

One nice feature of Python is its elegant syntax — we'll see many examples later on.

Elegant code might sound superfluous but in fact it's highly beneficial because it makes the syntax easy to read and easy to remember.

Remembering how to read from files, sort dictionaries and other such routine tasks means that you don't need to break your flow in order to hunt down correct syntax.

Closely related to elegant syntax is an elegant design.

Features like iterators, generators, decorators and list comprehensions make Python highly expressive, allowing you to get more done with less code.

Namespaces improve productivity by cutting down on bugs and syntax errors.

1.3 Scientific Programming

Python has become one of the core languages of scientific computing.

It's either the dominant player or a major player in

- machine learning and data science
- astronomy
- chemistry
- computational biology
- meteorology
- natural language processing

Its popularity in economics is also beginning to rise.

This section briefly showcases some examples of Python for scientific programming.

- All of these topics below will be covered in detail later on.

1.3.1 Numerical Programming

Fundamental matrix and array processing capabilities are provided by the excellent NumPy library.

NumPy provides the basic array data type plus some simple processing operations.

For example, let's build some arrays

```
import numpy as np                      # Load the library

a = np.linspace(-np.pi, np.pi, 100)     # Create even grid from -π to π
b = np.cos(a)                           # Apply cosine to each element of a
c = np.sin(a)                           # Apply sin to each element of a
```

Now let's take the inner product

```
b @ c
```

```
9.853229343548264e-16
```

The number you see here might vary slightly but it's essentially zero.

(For older versions of Python and NumPy you need to use the np.dot function)

The SciPy library is built on top of NumPy and provides additional functionality.

For example, let's calculate $\int_{-2}^{2} \phi(z)dz$ where ϕ is the standard normal density.

```
from scipy.stats import norm
from scipy.integrate import quad

ϕ = norm()
value, error = quad(ϕ.pdf, -2, 2)  # Integrate using Gaussian quadrature
value
```

```
0.9544997361036417
```

SciPy includes many of the standard routines used in

- linear algebra
- integration
- interpolation
- optimization
- distributions and statistical techniques
- signal processing

See them all here.

1.3.2 Graphics

The most popular and comprehensive Python library for creating figures and graphs is Matplotlib, with functionality including

- plots, histograms, contour images, 3D graphs, bar charts etc.
- output in many formats (PDF, PNG, EPS, etc.)
- LaTeX integration

Example 2D plot with embedded LaTeX annotations

Example contour plot

Example 3D plot

More examples can be found in the Matplotlib thumbnail gallery.

Other graphics libraries include

- Plotly
- seaborn — a high-level interface for matplotlib
- Altair
- Bokeh

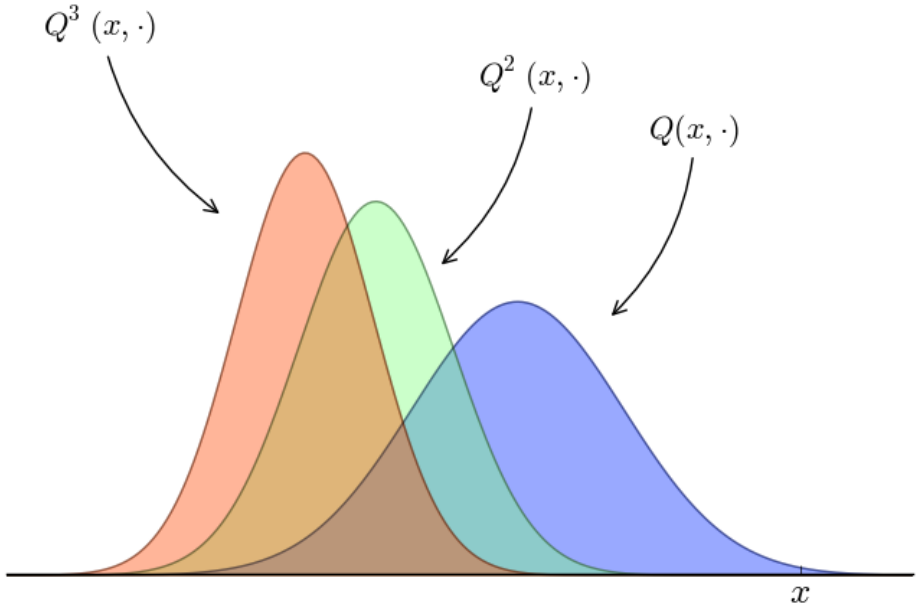
You can visit the Python Graph Gallery for more example plots drawn using a variety of libraries.

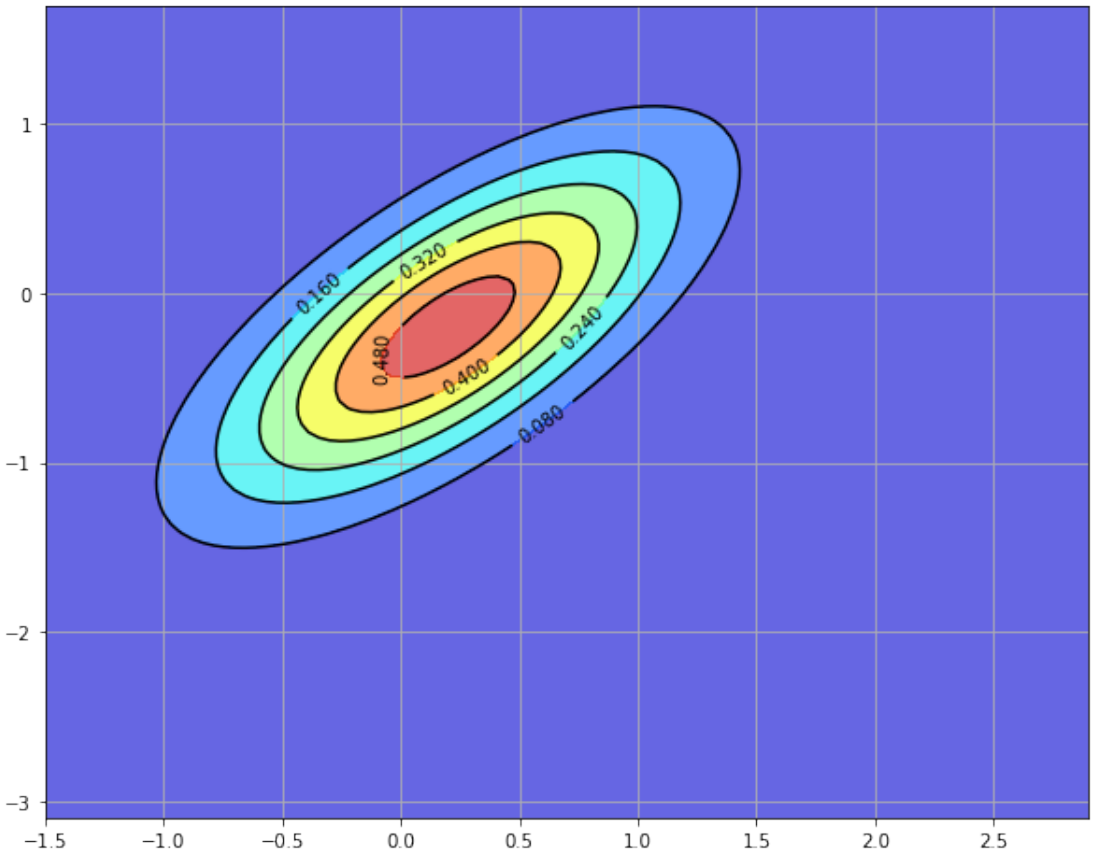
1.3.3 Symbolic Algebra

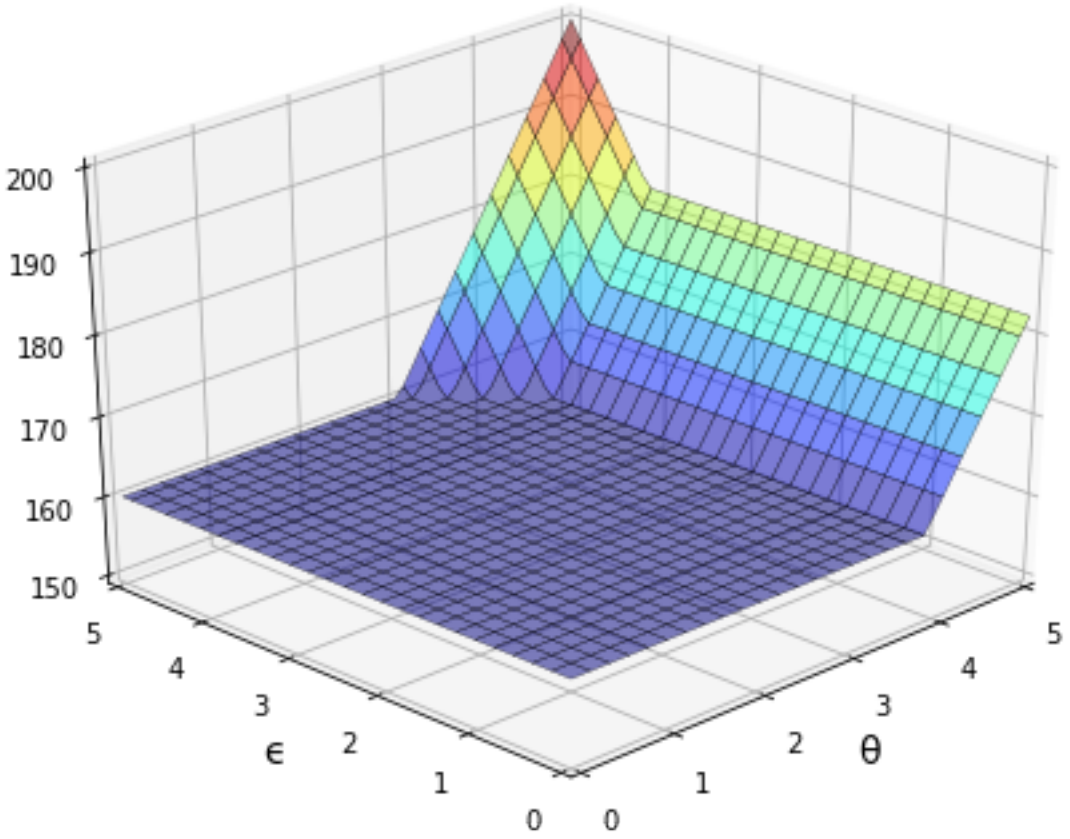
It's useful to be able to manipulate symbolic expressions, as in Mathematica or Maple.

The SymPy library provides this functionality from within the Python shell.

```
from sympy import Symbol

x, y = Symbol('x'), Symbol('y')  # Treat 'x' and 'y' as algebraic symbols
x + x + x + y
```


$Q^3\ (x, \cdot)$
$Q^2\ (x, \cdot)$
$Q(x, \cdot)$
x


0.160
0.320
0.480
0.400
0.240
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


200
190
180
170
160
150
5
4
3
ϵ
2
1
0
0
1
2
θ
3
4
5

$$3x + y$$

We can manipulate expressions

```
expression = (x + y)**2
expression.expand()
```

$$x^2 + 2xy + y^2$$

solve polynomials

```
from sympy import solve

solve(x**2 + x + 2)
```

```
[-1/2 - sqrt(7)*I/2, -1/2 + sqrt(7)*I/2]
```

and calculate limits, derivatives and integrals

```
from sympy import limit, sin, diff, integrate

limit(1 / x, x, 0)
```

$$\infty$$

```
limit(sin(x) / x, x, 0)
```

$$1$$

```
diff(sin(x), x)
```

$$\cos(x)$$

```
integrate(sin(x) * x, x)
```

$$-x\cos(x) + \sin(x)$$

The beauty of importing this functionality into Python is that we are working within a fully fledged programming language. We can easily create tables of derivatives, generate LaTeX output, add that output to figures and so on.

1.3.4 Statistics

Python's data manipulation and statistics libraries have improved rapidly over the last few years to tackle specific problems in data science.

Pandas

One of the most popular libraries for working with data is pandas.

Pandas is fast, efficient, flexible and well designed.

Here's a simple example, using some dummy data generated with Numpy's excellent `random` functionality.

```
import pandas as pd
np.random.seed(1234)

data = np.random.randn(5, 2)  # 5x2 matrix of N(0, 1) random draws
dates = pd.date_range('2010-12-28', periods=5)

df = pd.DataFrame(data, columns=('price', 'weight'), index=dates)
print(df)
```

```
                price    weight
2010-12-28  0.471435 -1.190976
2010-12-29  1.432707 -0.312652
2010-12-30 -0.720589  0.887163
2010-12-31  0.859588 -0.636524
2011-01-01  0.015696 -2.242685
```

```
df.mean()
```

```
price     0.411768
weight   -0.699135
dtype: float64
```

Other Useful Statistics and Data Science Libraries

- statsmodels — various statistical routines
- scikit-learn — Machine Learning in Python
- PyTorch — Deep learning framework in Python and other major competitors in the field including TensorFlow and Keras
- Pyro and PyStan — for Bayesian data analysis building on Pytorch and stan respectively
- lifelines — for survival analysis
- GeoPandas — for spatial data analysis

1.3.5 Networks and Graphs

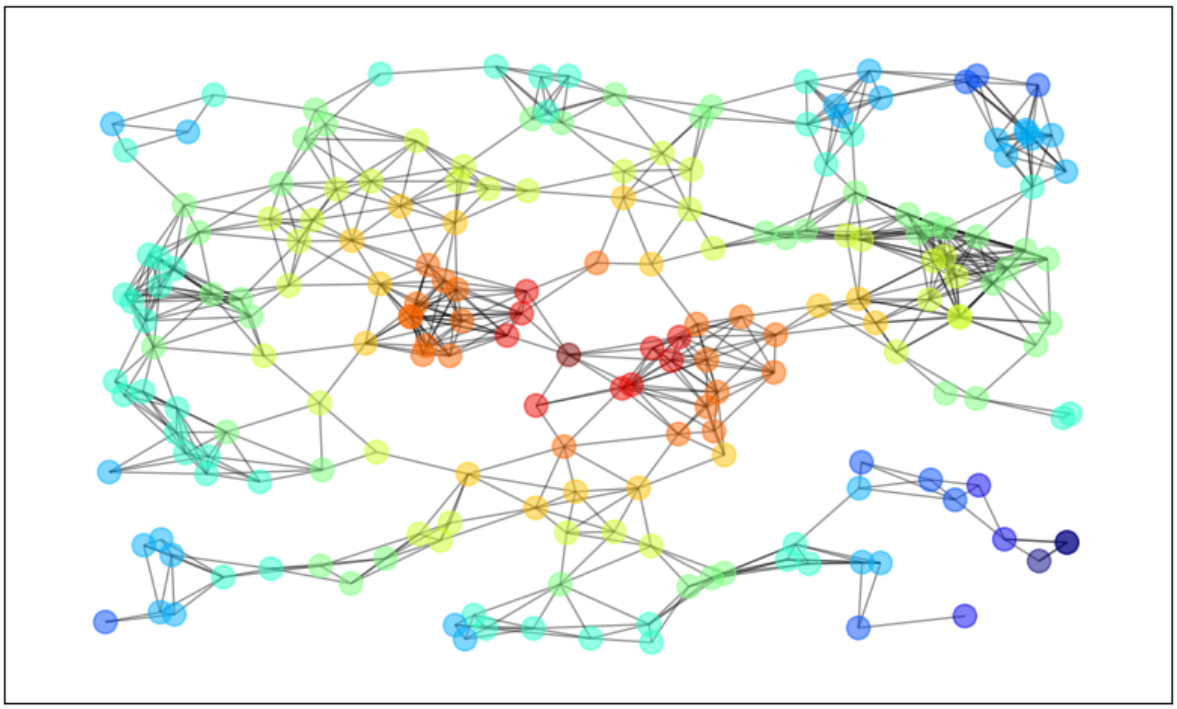
Python has many libraries for studying graphs.

One well-known example is NetworkX. Its features include, among many other things:

- standard graph algorithms for analyzing networks
- plotting routines

Here's some example code that generates and plots a random graph, with node color determined by the shortest path length from a central node.

```
%matplotlib inline
import networkx as nx
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
np.random.seed(1234)

# Generate a random graph
p = dict((i, (np.random.uniform(0, 1), np.random.uniform(0, 1)))
         for i in range(200))
g = nx.random_geometric_graph(200, 0.12, pos=p)
pos = nx.get_node_attributes(g, 'pos')

# Find node nearest the center point (0.5, 0.5)
dists = [(x - 0.5)**2 + (y - 0.5)**2 for x, y in list(pos.values())]
ncenter = np.argmin(dists)

# Plot graph, coloring by path length from central node
p = nx.single_source_shortest_path_length(g, ncenter)
plt.figure()
nx.draw_networkx_edges(g, pos, alpha=0.4)
nx.draw_networkx_nodes(g,
                       pos,
                       nodelist=list(p.keys()),
                       node_size=120, alpha=0.5,
                       node_color=list(p.values()),
                       cmap=plt.cm.jet_r)
plt.show()
```



1.3.6 Cloud Computing

Running your Python code on massive servers in the cloud is becoming easier and easier.

An excellent example of the portability of python in a cloud computing environment is Google Colab. It hosts the Jupyter notebook on cloud servers with no pre-configuration necessary to run Python code using cloud servers.

There are also commercial applications of cloud computing using Python:

- Anaconda Enterprise
- Amazon Web Services
- Google Cloud
- Digital Ocean

1.3.7 Parallel Processing

Apart from the cloud computing options listed above, you might like to consider

- Parallel computing through IPython clusters.
- Dask parallelises PyData and Machine Learning in Python.
- GPU programming through JAX, PyCuda, PyOpenCL, Rapids, etc.

Here is more about recent developments in high-performance computing (HPC) in scientific computing and how HPC helps researchers in different fields.

1.3.8 Other Developments

There are many other interesting developments with scientific programming in Python.

Some representative examples include

- Jupyter — Python in your browser with interactive code cells, embedded images and other useful features.
- Numba — make Python run at the same speed as native machine code!
- CVXPY — convex optimization in Python.
- PyTables — manage large data sets.
- scikit-image and OpenCV — process and analyse scientific image data.
- FLAML — automate machine learning and hyperparameter tuning.
- BeautifulSoup — extract data from HTML and XML files.
- PyInstaller — create packaged app from python script.

1.4 Learn More

- Browse some Python projects on GitHub.
- Read more about Python's history and rise in popularity and version history.
- Have a look at some of the Jupyter notebooks people have shared on various scientific topics.
- Visit the Python Package Index.
- View some of the questions people are asking about Python on Stackoverflow.
- Keep up to date on what's happening in the Python community with the Python subreddit.

CHAPTER

TWO

GETTING STARTED

Contents

2.1 Overview

In this lecture, you will learn how to

1. use Python in the cloud
2. get a local Python environment up and running
3. execute simple Python commands
4. run a sample program
5. install the code libraries that underpin these lectures

2.2 Python in the Cloud

The easiest way to get started coding in Python is by running it in the cloud.

(That is, by using a remote server that already has Python installed.)

There are many options for doing this, both free and paid.

At present Google Colab seems to be the most reliable.

Colab offers a free tier and also has the advantage of providing GPUs.

The free-tier GPUs are adequate and better ones can be accessed by signing up for Colab Pro.

Tutorials on how to get started with Google Colab can be found by searching.

Written examples include

- Google Colab Tutorial for Beginners
- Intro to Google Colab

Videos on the same topic can be found by searching on Youtube.

Most of our lectures include a "Launch notebook" (play icon) button on the top right that allows you to easily run them in Colab.

2.3 Local Install

Local installs are preferable if you have access to a suitable machine and plan to do a substantial amount of Python programming.

At the same time, local installs require more work than a cloud option like Colab.

The rest of this lecture runs you through the details.

2.3.1 The Anaconda Distribution

The core Python package is easy to install but *not* what you should choose for these lectures.

These lectures require the entire scientific programming ecosystem, which

- the core installation doesn't provide
- is painful to install one piece at a time.

Hence the best approach for our purposes is to install a Python distribution that contains

1. the core Python language **and**
2. compatible versions of the most popular scientific libraries.

The best such distribution is Anaconda.

Anaconda is

- very popular
- cross-platform
- comprehensive
- completely unrelated to the Nicki Minaj song of the same name

Anaconda also comes with a great package management system to organize your code libraries.

All of what follows assumes that you adopt this recommendation!

2.3.2 Installing Anaconda

To install Anaconda, download the binary and follow the instructions.

Important points:

- Install the latest version!
- Find the correct distribution for your system.
- If you are asked during the installation process whether you'd like to make Anaconda your default Python installation, say yes.

2.3.3 Updating Anaconda

Anaconda supplies a tool called `conda` to manage and upgrade your Anaconda packages.

One `conda` command you should execute regularly is the one that updates the whole Anaconda distribution.

As a practice run, please execute the following

1. Open up a terminal
2. Type `conda update anaconda`

For more information on conda, type conda help in a terminal.

2.4 Jupyter Notebooks

Jupyter notebooks are one of the many possible ways to interact with Python and the scientific libraries.

They use a *browser-based* interface to Python with

- The ability to write and execute Python commands.
- Formatted output in the browser, including tables, figures, animation, etc.
- The option to mix in formatted text and mathematical expressions.

Because of these features, Jupyter is now a major player in the scientific computing ecosystem.

Here's an image showing execution of some code (borrowed from here) in a Jupyter notebook

While Jupyter isn't the only way to code in Python, it's great for when you wish to

- start coding in Python
- test new ideas or interact with small pieces of code
- use powerful online interactive environments such as Google Colab
- share or collaborate scientific ideas with students or colleagues

These lectures are designed for executing in Jupyter notebooks.

Home Page - Select or

Demo - Jupyter Noteb

localhost:8888/notebooks/Demo.ipy

90%

jupyter Demo

Logout

File Edit View Insert Cell Kernel Widgets Help Trusted

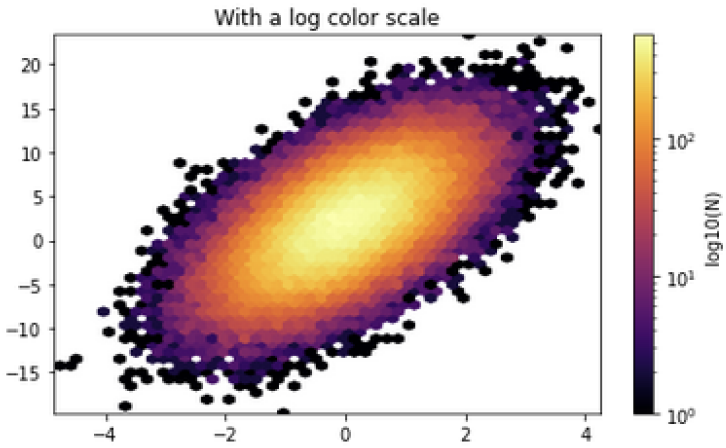
Python 3 (ipykernel)

Run Code

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

In [2]:
```
np.random.seed(0)
n = 100000
x = np.random.standard_normal(n)
y = 2.0 + 3.0 * x + 4.0 * np.random.standard_normal(n)
xmin = x.min()
xmax = x.max()
ymin = y.min()
ymax = y.max()
```

In [3]:
```
fig, axs = plt.subplots(figsize=(7, 4))
ax = axs
hb = ax.hexbin(x, y, gridsize=50, bins='log', cmap='inferno')
ax.axis([xmin, xmax, ymin, ymax])
ax.set_title("With a log color scale")
cb = fig.colorbar(hb, ax=ax)
cb.set_label('log10(N)')

plt.show()
```



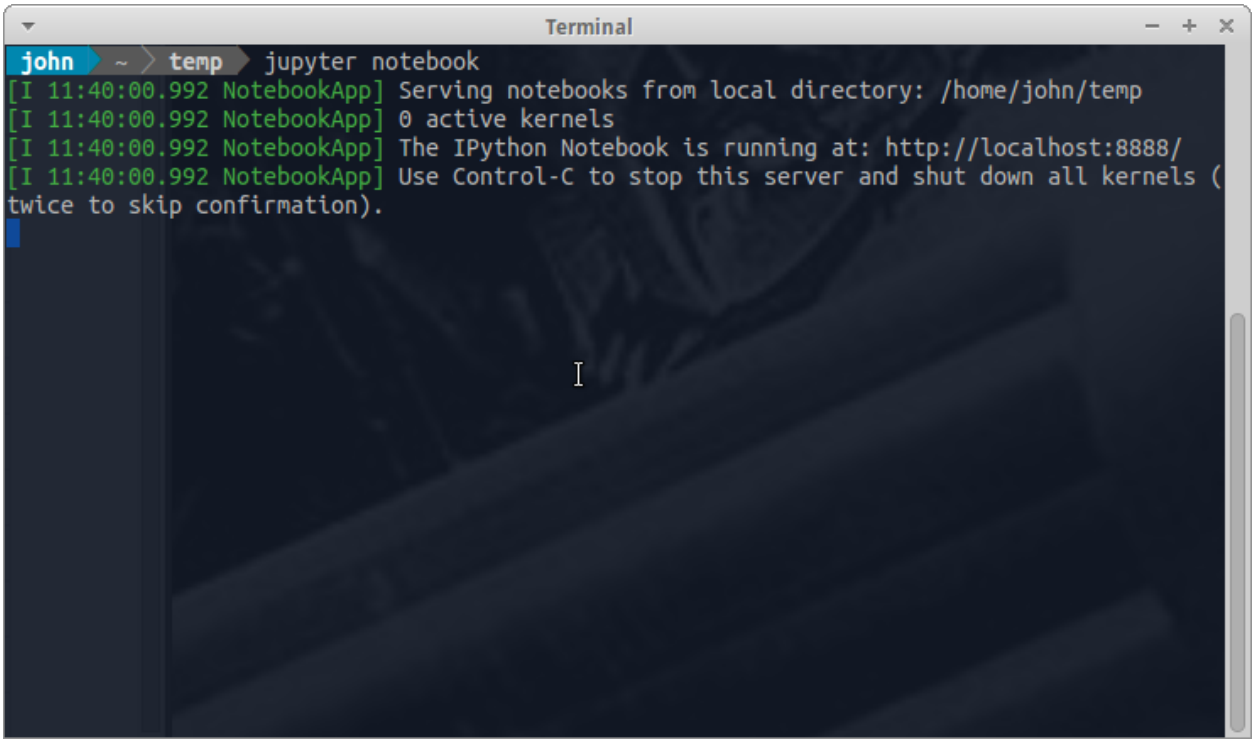
2.4.1 Starting the Jupyter Notebook

Once you have installed Anaconda, you can start the Jupyter notebook.

Either

- search for Jupyter in your applications menu, or
- open up a terminal and type `jupyter notebook`
  - Windows users should substitute "Anaconda command prompt" for "terminal" in the previous line.

If you use the second option, you will see something like this



The output tells us the notebook is running at `http://localhost:8888/`

- `localhost` is the name of the local machine
- `8888` refers to port number 8888 on your computer

Thus, the Jupyter kernel is listening for Python commands on port 8888 of our local machine.

Hopefully, your default browser has also opened up with a web page that looks something like this

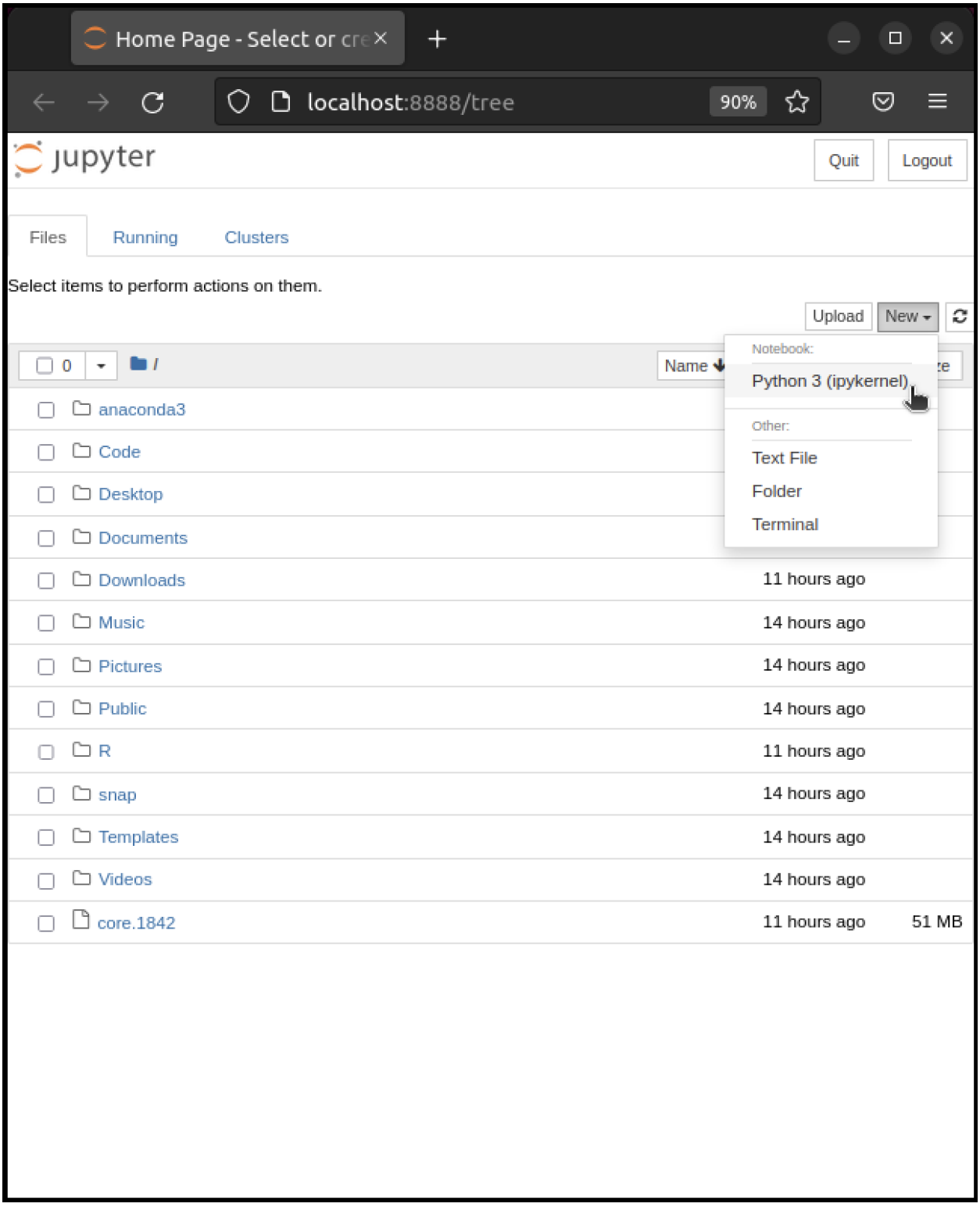
What you see here is called the Jupyter *dashboard*.

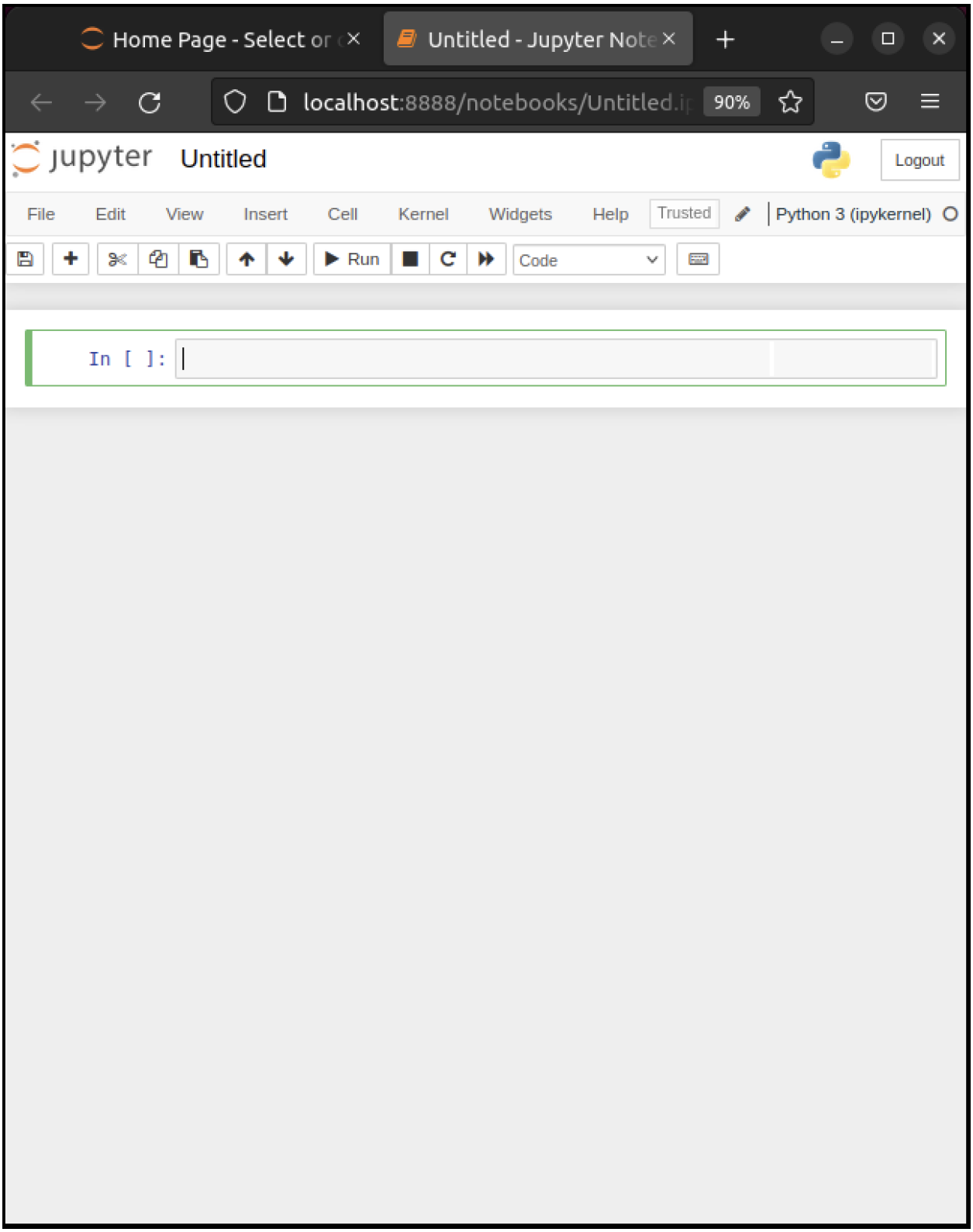
If you look at the URL at the top, it should be `localhost:8888` or similar, matching the message above.

Assuming all this has worked OK, you can now click on `New` at the top right and select `Python 3` or similar.

Here's what shows up on our machine:

The notebook displays an *active cell*, into which you can type Python commands.


Home Page - Select or cre
localhost:8888/tree
90%
jupyter
Quit
Logout
Files
Running
Clusters
Select items to perform actions on them.
Upload
New
Notebook:
Python 3 (ipykernel)
Other:
Text File
Folder
Terminal
0
/
Name
anaconda3
Code
Desktop
Documents
Downloads
11 hours ago
Music
14 hours ago
Pictures
14 hours ago
Public
14 hours ago
R
11 hours ago
snap
14 hours ago
Templates
14 hours ago
Videos
14 hours ago
core.1842
11 hours ago
51 MB


Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.i
90%
jupyter
Untitled
Logout
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3 (ipykernel)
Run
Code
In [ ]:

2.4.2 Notebook Basics

Let's start with how to edit code and run simple programs.

Running Cells

Notice that, in the previous figure, the cell is surrounded by a green border.

This means that the cell is in *edit mode*.

In this mode, whatever you type will appear in the cell with the flashing cursor.

When you're ready to execute the code in a cell, hit `Shift-Enter` instead of the usual `Enter`.

Note: There are also menu and button options for running code in a cell that you can find by exploring.

Modal Editing

The next thing to understand about the Jupyter notebook is that it uses a *modal* editing system.

This means that the effect of typing at the keyboard **depends on which mode you are in**.

The two modes are

1. Edit mode
    - Indicated by a green border around one cell, plus a blinking cursor
    - Whatever you type appears as is in that cell
2. Command mode
    - The green border is replaced by a blue border
    - Keystrokes are interpreted as commands — for example, typing `b` adds a new cell below the current one

To switch to

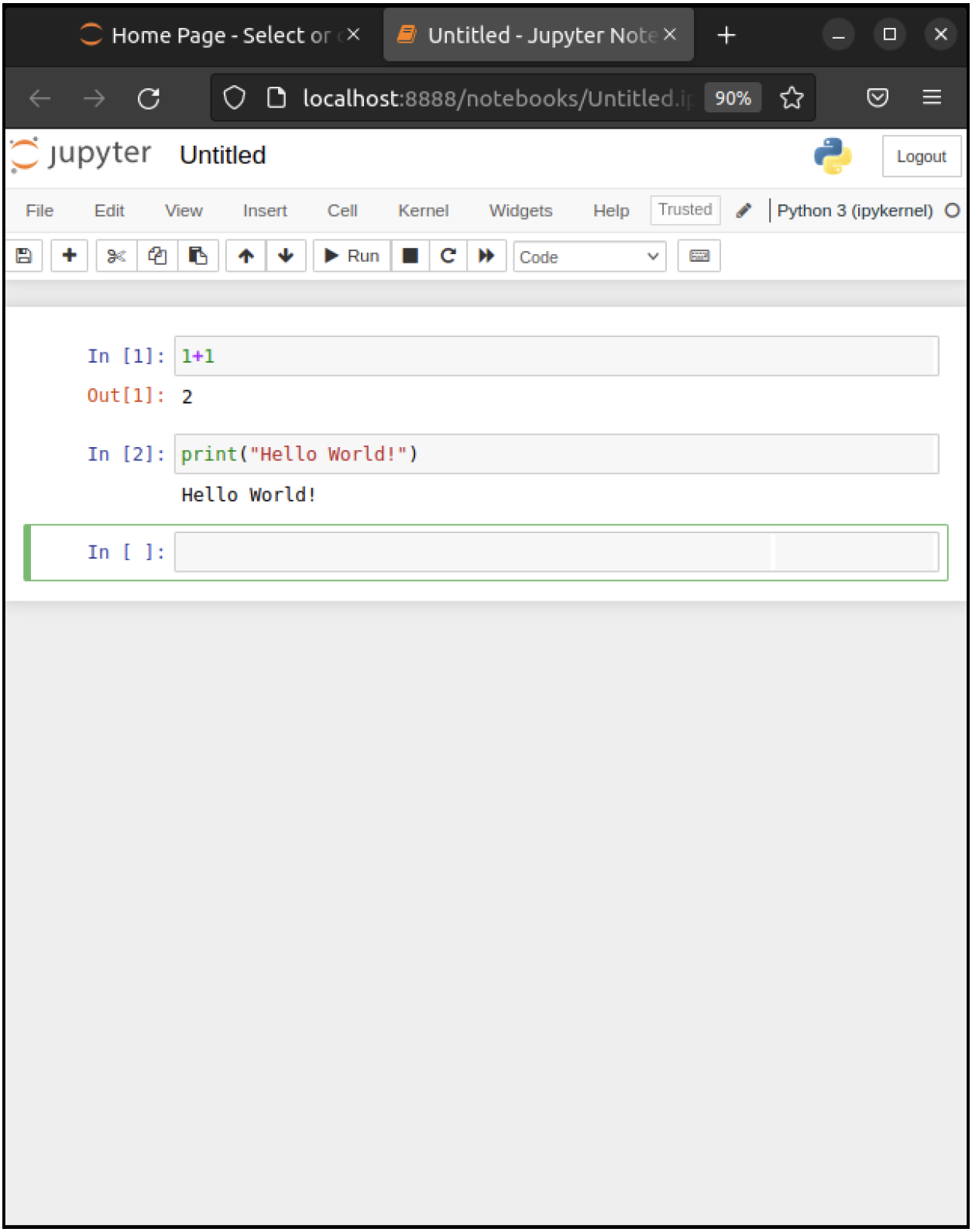
- command mode from edit mode, hit the `Esc` key or `Ctrl-M`
- edit mode from command mode, hit `Enter` or click in a cell

The modal behavior of the Jupyter notebook is very efficient when you get used to it.

Inserting Unicode (e.g., Greek Letters)

Python supports unicode, allowing the use of characters such as α and β as names in your code.

In a code cell, try typing `\alpha` and then hitting the tab key on your keyboard.


Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.ip
90%
jupyter
Untitled
Logout
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3 (ipykernel)
Run
Code
In [1]: 1+1
Out[1]: 2
In [2]: print("Hello World!")
Hello World!
In [ ]:

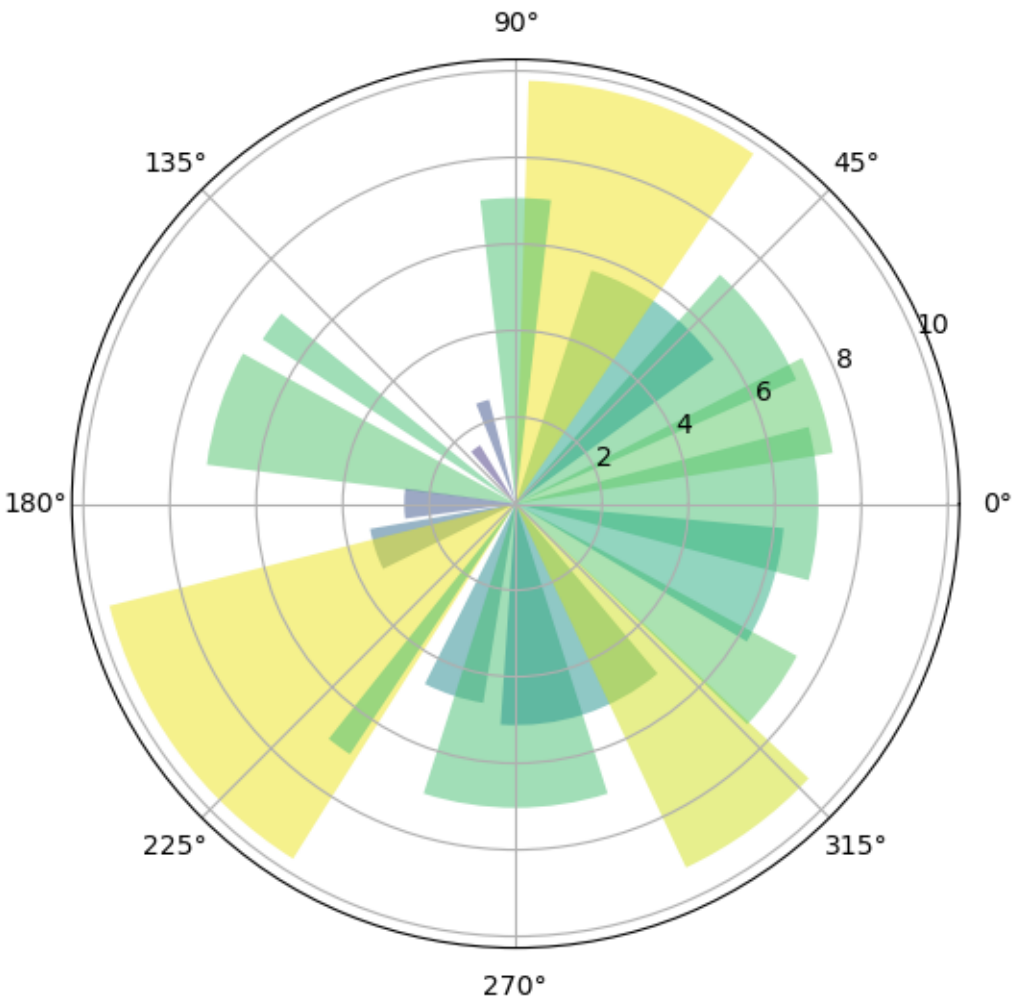
A Test Program

Let's run a test program.

Here's an arbitrary program we can use: http://matplotlib.org/3.1.1/gallery/pie_and_polar_charts/polar_bar.html.

On that page, you'll see the following code

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = (10,6)

# Fixing random state for reproducibility
np.random.seed(19680801)

# Compute pie slices
N = 20
θ = np.linspace(0.0, 2 * np.pi, N, endpoint=False)
radii = 10 * np.random.rand(N)
width = np.pi / 4 * np.random.rand(N)
colors = plt.cm.viridis(radii / 10.)

ax = plt.subplot(111, projection='polar')
ax.bar(θ, radii, width=width, bottom=0.0, color=colors, alpha=0.5)

plt.show()
```



Don't worry about the details for now — let's just run it and see what happens.

The easiest way to run this code is to copy and paste it into a cell in the notebook.

Hopefully you will get a similar plot.

2.4.3 Working with the Notebook

Here are a few more tips on working with Jupyter notebooks.

Tab Completion

In the previous program, we executed the line `import numpy as np`

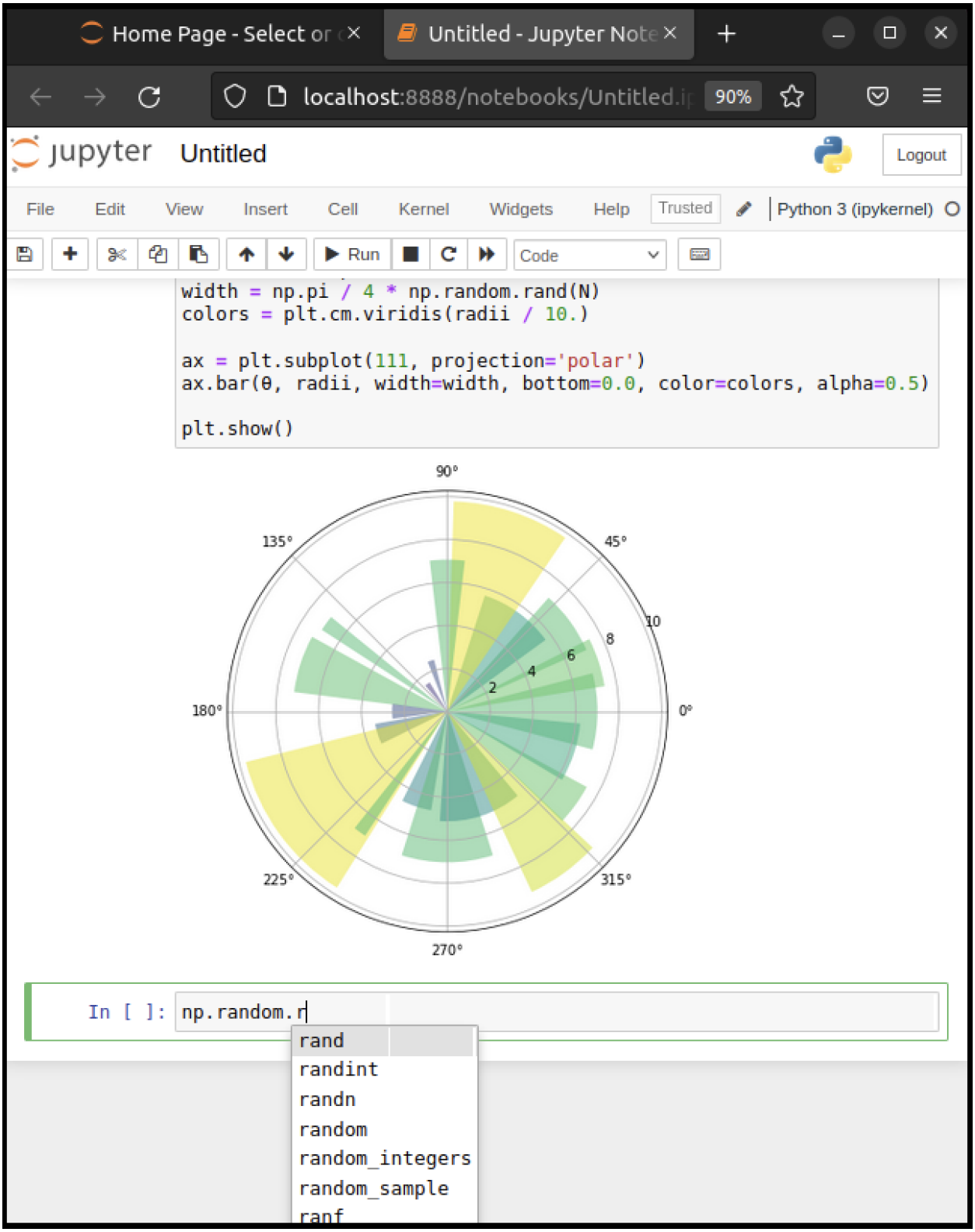
- NumPy is a numerical library we'll work with in depth.

After this import command, functions in NumPy can be accessed with `np.function_name` type syntax.

- For example, try `np.random.randn(3)`.

We can explore these attributes of `np` using the `Tab` key.

For example, here we type `np.random.r` and hit Tab


Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.ip
90%
jupyter
Untitled
Logout
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3 (ipykernel)
Run
Code
width = np.pi / 4 * np.random.rand(N)
colors = plt.cm.viridis(radii / 10.)
ax = plt.subplot(111, projection='polar')
ax.bar(θ, radii, width=width, bottom=0.0, color=colors, alpha=0.5)
plt.show()
90°
45°
135°
180°
0°
225°
315°
270°
2
4
6
8
10
In [ ]:
np.random.r
rand
randint
randn
random
random_integers
random_sample
ranf

Jupyter offers several possible completions for you to choose from.

In this way, the Tab key helps remind you of what's available and also saves you typing.

On-Line Help

To get help on `np.random.randn`, we can execute `np.random.randn?`.

Documentation appears in a split window of the browser, like so

Clicking on the top right of the lower split closes the on-line help.

We will learn more about how to create documentation like this *later*!

Other Content

In addition to executing code, the Jupyter notebook allows you to embed text, equations, figures and even videos in the page.

For example, we can enter a mixture of plain text and LaTeX instead of code.

Next we `Esc` to enter command mode and then type `m` to indicate that we are writing Markdown, a mark-up language similar to (but simpler than) LaTeX.

(You can also use your mouse to select `Markdown` from the `Code` drop-down box just below the list of menu items)

Now we `Shift+Enter` to produce this

2.4.4 Debugging Code

Debugging is the process of identifying and removing errors from a program.

You will spend a lot of time debugging code, so it is important to learn how to do it effectively.

If you are using a newer version of Jupyter, you should see a bug icon on the right end of the toolbar.

Clicking this icon will enable the Jupyter debugger.

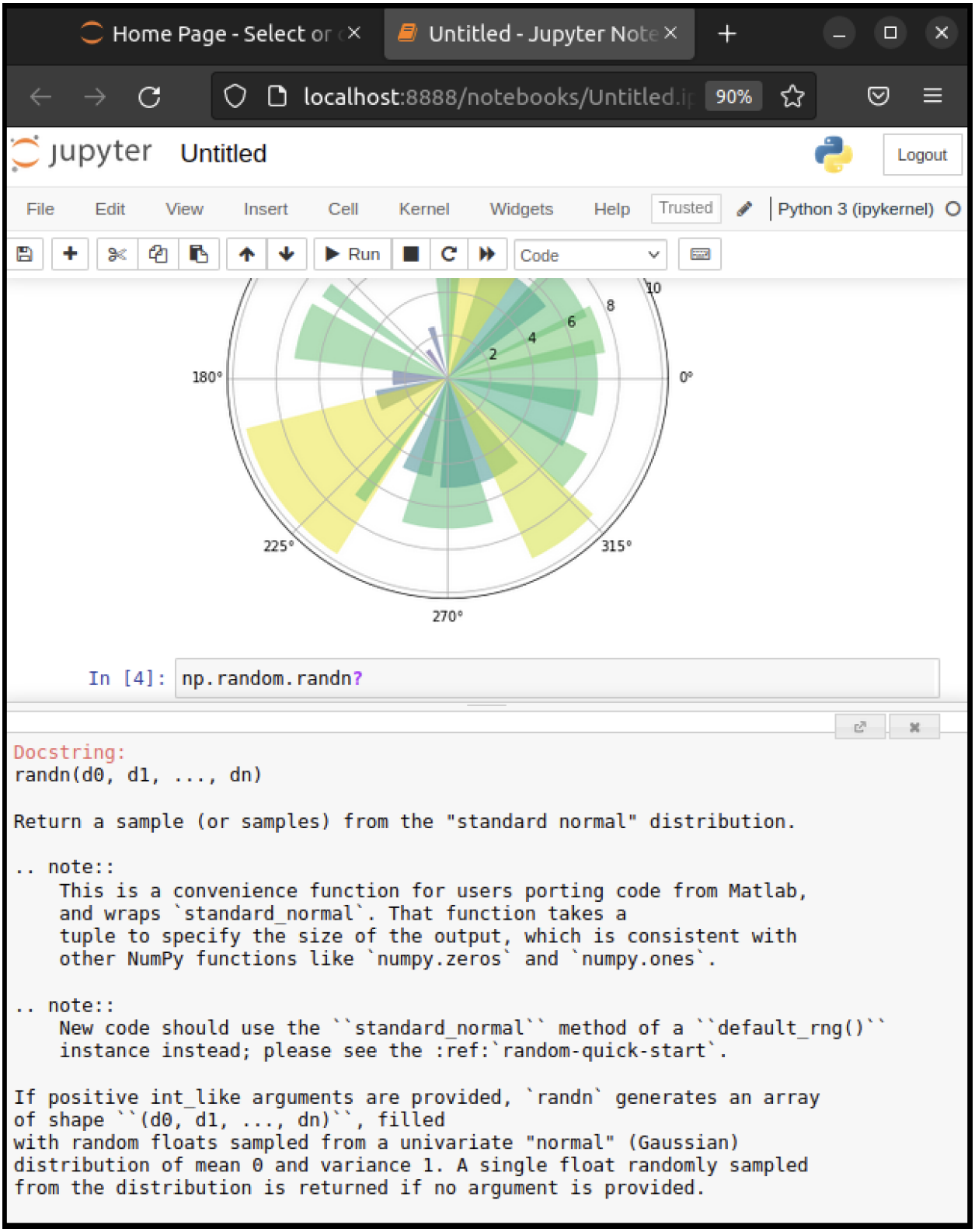
Note: You may also need to open the Debugger Panel (View -> Debugger Panel).

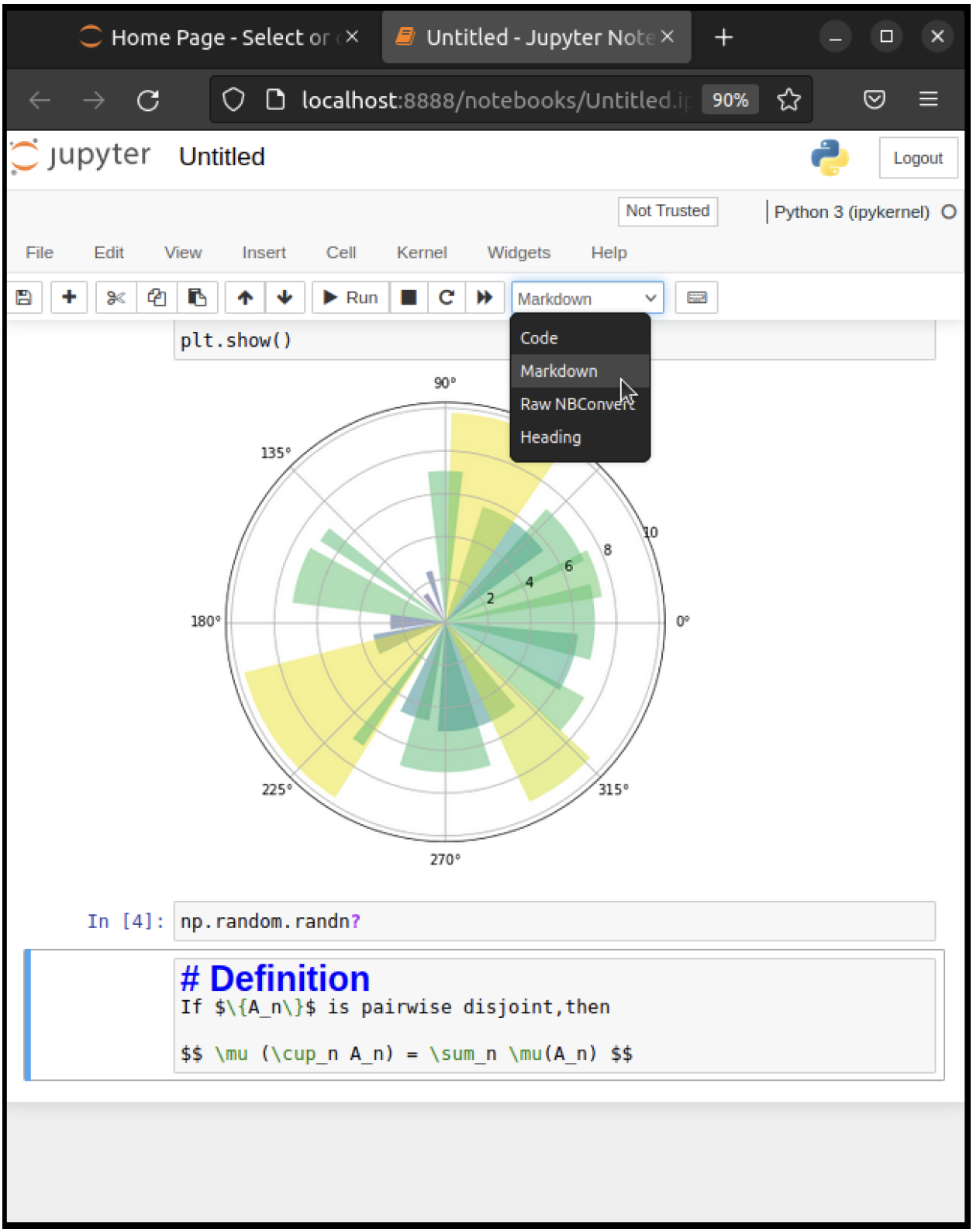
You can set breakpoints by clicking on the line number of the cell you want to debug.

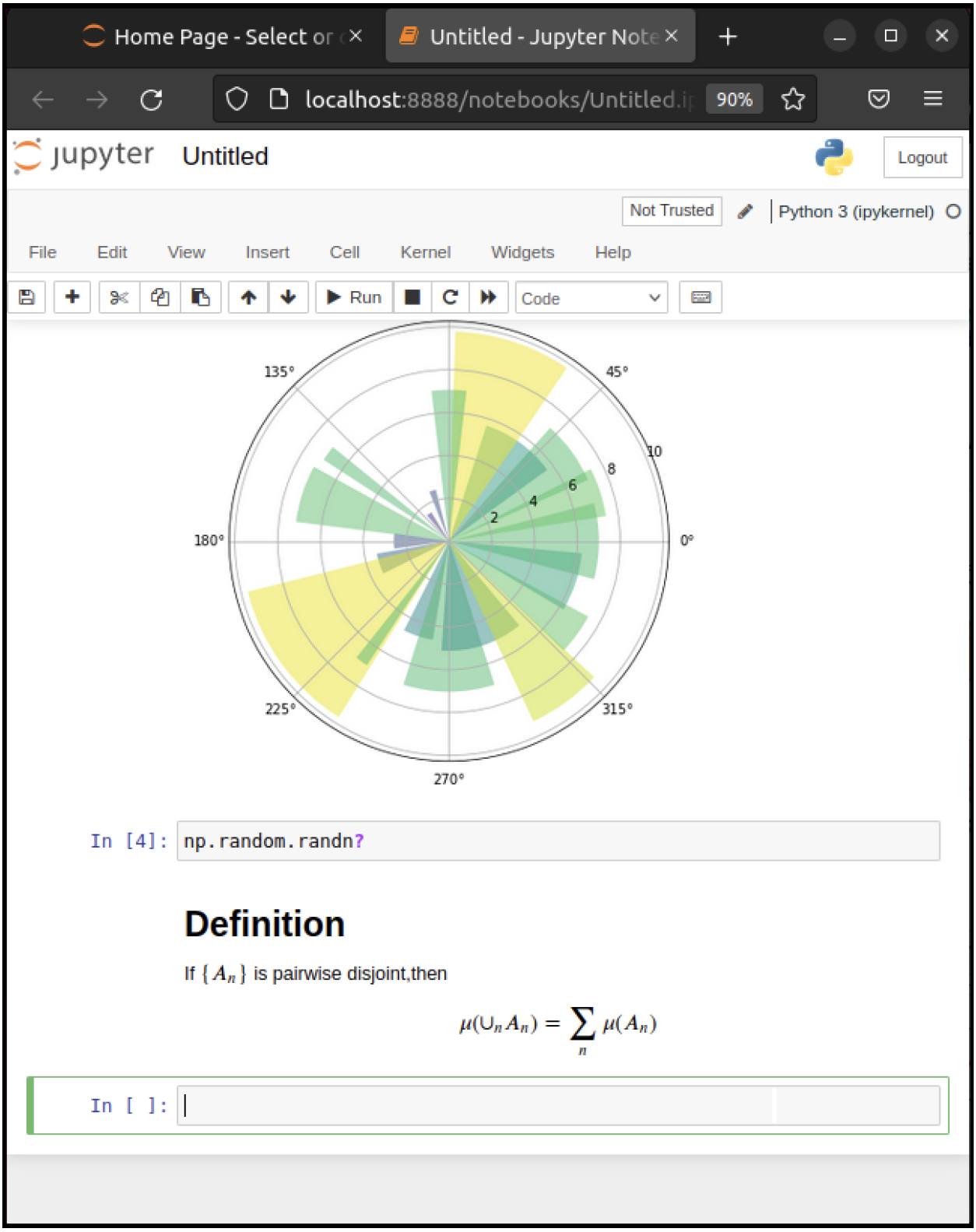
When you run the cell, the debugger will stop at the breakpoint.

You can then step through the code line by line using the buttons on the "Next" button on the CALLSTACK toolbar (located in the right hand window).

You can explore more functionality of the debugger in the Jupyter documentation.

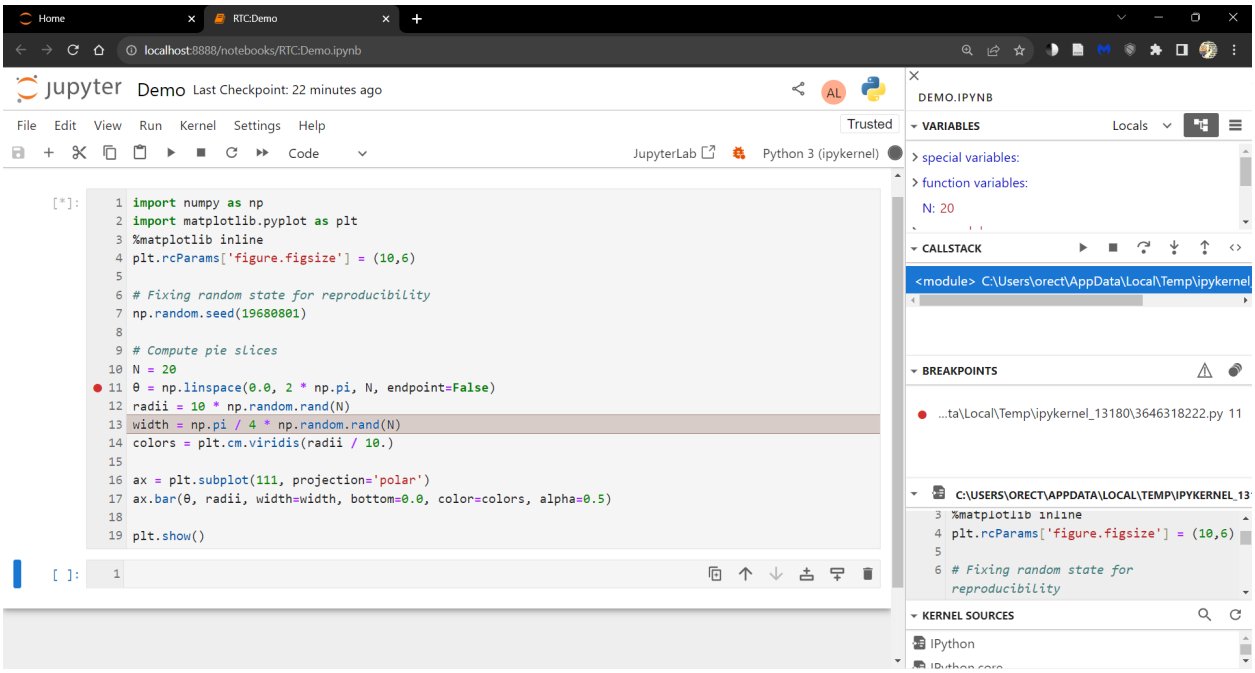

Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.ip
90%
jupyter
Untitled
Logout
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Trusted
Python 3 (ipykernel)
Run
Code
10
8
6
4
2
180°
0°
225°
315°
270°
In [4]:
np.random.randn?
Docstring:
randn(d0, d1, ..., dn)
Return a sample (or samples) from the "standard normal" distribution.
.. note::
This is a convenience function for users porting code from Matlab,
and wraps `standard_normal`. That function takes a
tuple to specify the size of the output, which is consistent with
other NumPy functions like `numpy.zeros` and `numpy.ones`.
.. note::
New code should use the ``standard_normal`` method of a ``default_rng()``
instance instead; please see the :ref:`random-quick-start`.
If positive int_like arguments are provided, `randn` generates an array
of shape ``(d0, d1, ..., dn)``, filled
with random floats sampled from a univariate "normal" (Gaussian)
distribution of mean 0 and variance 1. A single float randomly sampled
from the distribution is returned if no argument is provided.


Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.ip
90%
jupyter
Untitled
Logout
Not Trusted
Python 3 (ipykernel)
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Run
Markdown
Code
Markdown
Raw NBConvert
Heading
plt.show()
90°
135°
180°
0°
225°
315°
270°
2
4
6
8
10
In [4]:
np.random.randn?
Definition
If $\{A_n\}$ is pairwise disjoint,then
$$ \mu (\cup_n A_n) = \sum_n \mu(A_n) $$


Home Page - Select or
Untitled - Jupyter Note
localhost:8888/notebooks/Untitled.ip
90%
jupyter
Untitled
Logout
Not Trusted
Python 3 (ipykernel)
File
Edit
View
Insert
Cell
Kernel
Widgets
Help
Run
Code
135°
45°
180°
0°
225°
315°
270°
2
4
6
8
10
In [4]:
np.random.randn?
Definition
If $\{A_n\}$ is pairwise disjoint,then
$$\mu(\cup_n A_n) = \sum_n \mu(A_n)$$
In [ ]:

Trusted

JupyterLab Python 3 (ipykernel)



2.4.5 Sharing Notebooks

Notebook files are just text files structured in JSON and typically ending with `.ipynb`.

You can share them in the usual way that you share files — or by using web services such as nbviewer.

The notebooks you see on that site are **static** html representations.

To run one, download it as an `ipynb` file by clicking on the download icon at the top right.

Save it somewhere, navigate to it from the Jupyter dashboard and then run as discussed above.

Note: If you are interested in sharing notebooks containing interactive content, you might want to check out Binder.

To collaborate with other people on notebooks, you might want to take a look at

- Google Colab
- Kaggle

To keep the code private and to use the familiar JupyterLab and Notebook interface, look into the JupyterLab Real-Time Collaboration extension.

2.4.6 QuantEcon Notes

QuantEcon has its own site for sharing Jupyter notebooks related to economics – QuantEcon Notes.

Notebooks submitted to QuantEcon Notes can be shared with a link, and are open to comments and votes by the community.

2.5 Installing Libraries

Most of the libraries we need come in Anaconda.

Other libraries can be installed with `pip` or `conda`.

One library we'll be using is QuantEcon.py.

You can install QuantEcon.py by starting Jupyter and typing

```
!conda install quantecon
```

into a cell.

Alternatively, you can type the following into a terminal

```
conda install quantecon
```

More instructions can be found on the library page.

To upgrade to the latest version, which you should do regularly, use

```
conda upgrade quantecon
```

Another library we will be using is interpolation.py.

This can be installed by typing in Jupyter

```
!conda install -c conda-forge interpolation
```

2.6 Working with Python Files

So far we've focused on executing Python code entered into a Jupyter notebook cell.

Traditionally most Python code has been run in a different way.

Code is first saved in a text file on a local machine

By convention, these text files have a `.py` extension.

We can create an example of such a file as follows:

```
%%writefile foo.py

print("foobar")
```

```
Writing foo.py
```

This writes the line `print("foobar")` into a file called `foo.py` in the local directory.

Here `%%writefile` is an example of a cell magic.

2.6.1 Editing and Execution

If you come across code saved in a `*.py` file, you'll need to consider the following questions:

1. how should you execute it?
2. How should you modify or edit it?

Option 1: JupyterLab

JupyterLab is an integrated development environment built on top of Jupyter notebooks.

With JupyterLab you can edit and run `*.py` files as well as Jupyter notebooks.

To start JupyterLab, search for it in the applications menu or type `jupyter-lab` in a terminal.

Now you should be able to open, edit and run the file `foo.py` created above by opening it in JupyterLab.

Read the docs or search for a recent YouTube video to find more information.

Option 2: Using a Text Editor

One can also edit files using a text editor and then run them from within Jupyter notebooks.

A text editor is an application that is specifically designed to work with text files — such as Python programs.

Nothing beats the power and efficiency of a good text editor for working with program text.

A good text editor will provide

- efficient text editing commands (e.g., copy, paste, search and replace)
- syntax highlighting, etc.

Right now, an extremely popular text editor for coding is VS Code.

VS Code is easy to use out of the box and has many high quality extensions.

Alternatively, if you want an outstanding free text editor and don't mind a seemingly vertical learning curve plus long days of pain and suffering while all your neural pathways are rewired, try Vim.

2.7 Exercises

Exercise 2.7.1

If Jupyter is still running, quit by using `Ctrl-C` at the terminal where you started it.

Now launch again, but this time using `jupyter notebook --no-browser`.

This should start the kernel without launching the browser.

Note also the startup message: It should give you a URL such as `http://localhost:8888` where the notebook is running.

Now

1. Start your browser — or open a new tab if it's already running.
2. Enter the URL from above (e.g. `http://localhost:8888`) in the address bar at the top.

You should now be able to run a standard Jupyter notebook session.

This is an alternative way to start the notebook that can also be handy.

This can also work when you accidentally close the webpage as long as the kernel is still running.

CHAPTER

THREE

AN INTRODUCTORY EXAMPLE

Contents

3.1 Overview

We're now ready to start learning the Python language itself.

In this lecture, we will write and then pick apart small Python programs.

The objective is to introduce you to basic Python syntax and data structures.

Deeper concepts will be covered in later lectures.

You should have read the *lecture* on getting started with Python before beginning this one.

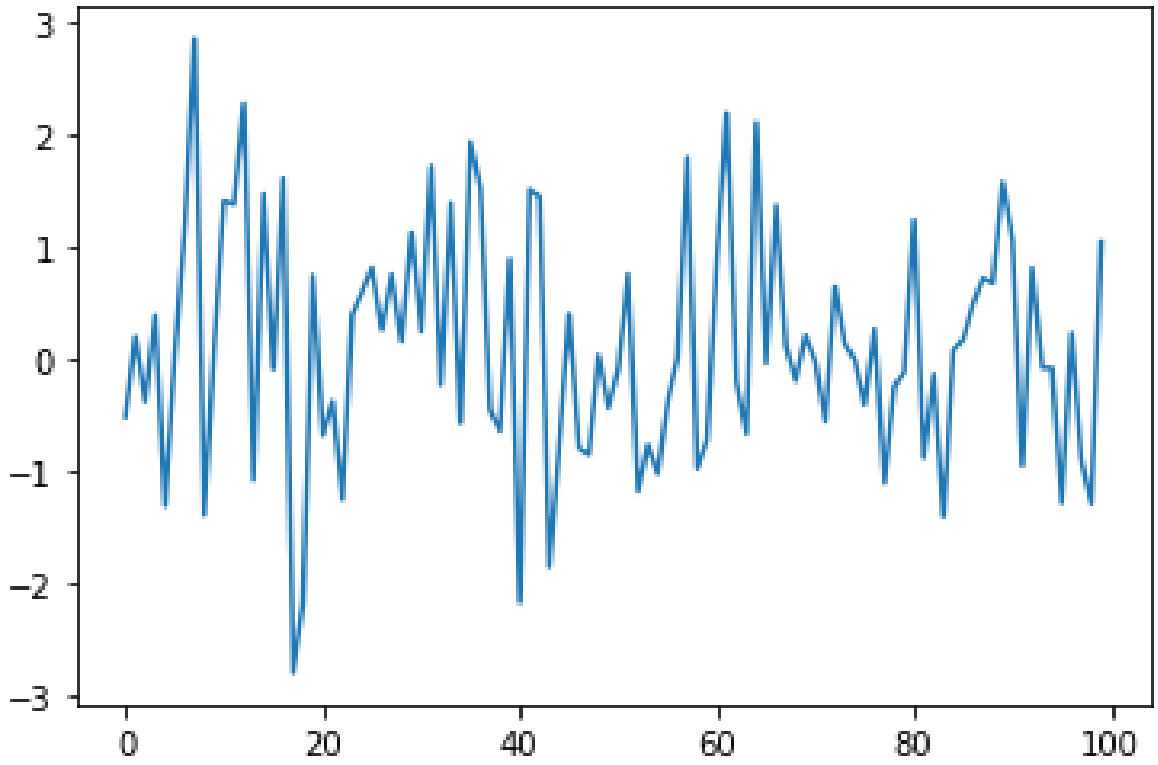
3.2 The Task: Plotting a White Noise Process

Suppose we want to simulate and plot the white noise process $\epsilon_0, \epsilon_1, \ldots, \epsilon_T$, where each draw ϵ_t is independent standard normal.

In other words, we want to generate figures that look something like this:

(Here t is on the horizontal axis and ϵ_t is on the vertical axis.)

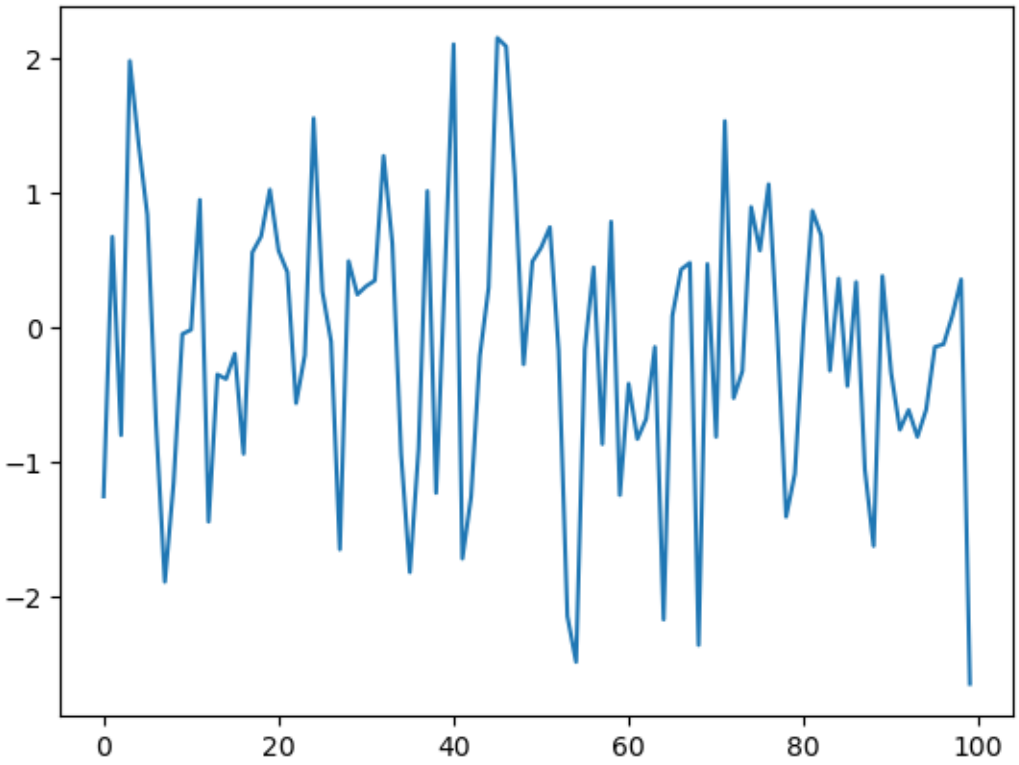
We'll do this in several different ways, each time learning something more about Python.



3.3 Version 1

Here are a few lines of code that perform the task we set

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

ϵ_values = np.random.randn(100)
plt.plot(ϵ_values)
plt.show()
```



Let's break this program down and see how it works.

3.3.1 Imports

The first two lines of the program import functionality from external code libraries.

The first line imports *NumPy*, a favorite Python package for tasks like

- working with arrays (vectors and matrices)
- common mathematical functions like `cos` and `sqrt`
- generating random numbers
- linear algebra, etc.

After `import numpy as np` we have access to these attributes via the syntax `np.attribute`.

Here's two more examples

```
np.sqrt(4)
```

```
2.0
```

```
np.log(4)
```

```
1.3862943611198906
```

We could also use the following syntax:

```
import numpy

numpy.sqrt(4)
```

```
2.0
```

But the former method (using the short name `np`) is convenient and more standard.

Why So Many Imports?

Python programs typically require several import statements.

The reason is that the core language is deliberately kept small, so that it's easy to learn and maintain.

When you want to do something interesting with Python, you almost always need to import additional functionality.

Packages

As stated above, NumPy is a Python *package*.

Packages are used by developers to organize code they wish to share.

In fact, a package is just a directory containing

1. files with Python code — called **modules** in Python speak
2. possibly some compiled code that can be accessed by Python (e.g., functions compiled from C or FORTRAN code)
3. a file called `__init__.py` that specifies what will be executed when we type `import package_name`

You can check the location of your `__init__.py` for NumPy in python by running the code:

```
import numpy as np

print(np.__file__)
```

Subpackages

Consider the line `ϵ_values = np.random.randn(100)`.

Here `np` refers to the package NumPy, while `random` is a **subpackage** of NumPy.

Subpackages are just packages that are subdirectories of another package.

For instance, you can find folder `random` under the directory of NumPy.

3.3.2 Importing Names Directly

Recall this code that we saw above

```
import numpy as np

np.sqrt(4)
```

```
2.0
```

Here's another way to access NumPy's square root function

```
from numpy import sqrt

sqrt(4)
```

```
2.0
```

This is also fine.

The advantage is less typing if we use `sqrt` often in our code.

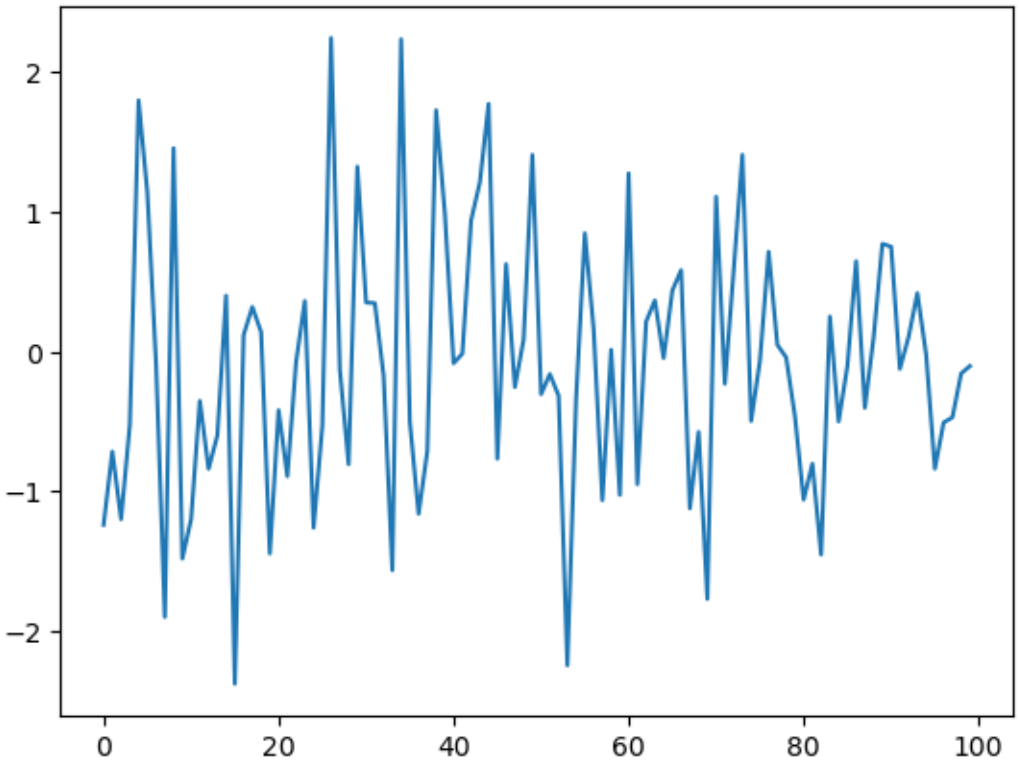
The disadvantage is that, in a long program, these two lines might be separated by many other lines.

Then it's harder for readers to know where `sqrt` came from, should they wish to.

3.3.3 Random Draws

Returning to our program that plots white noise, the remaining three lines after the import statements are

```
ϵ_values = np.random.randn(100)
plt.plot(ϵ_values)
plt.show()
```



The first line generates 100 (quasi) independent standard normals and stores them in `ϵ_values`.

The next two lines genererate the plot.

We can and will look at various ways to configure and improve this plot below.

3.4 Alternative Implementations

Let's try writing some alternative versions of *our first program*, which plotted IID draws from the standard normal distribution.

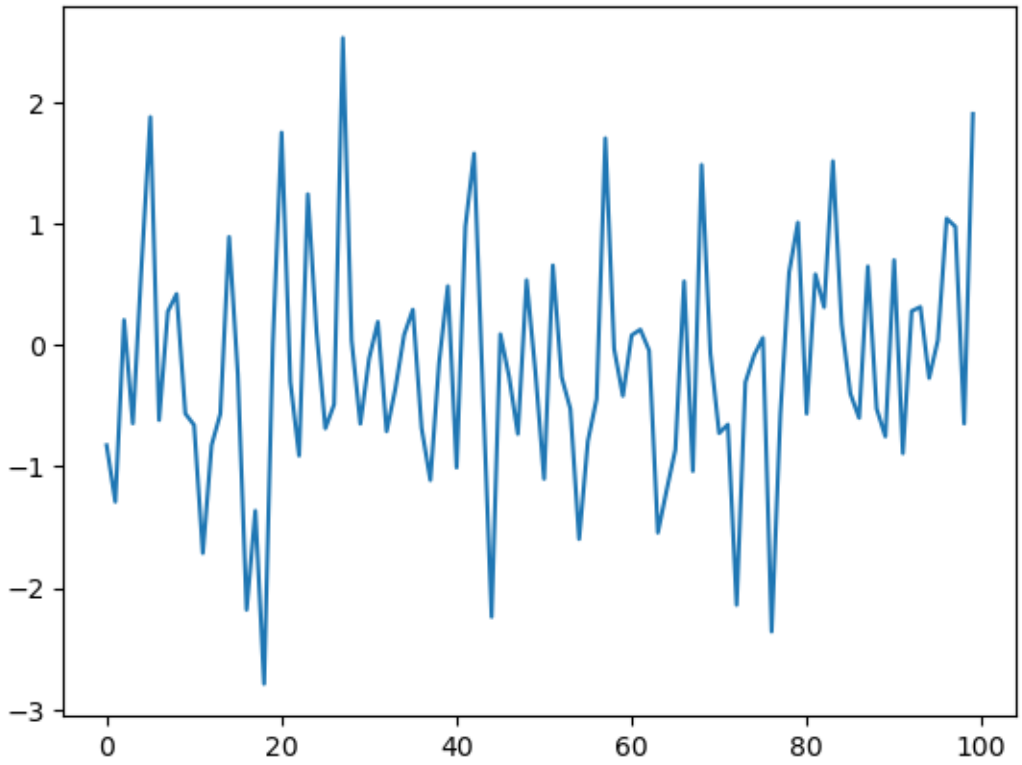
The programs below are less efficient than the original one, and hence somewhat artificial.

But they do help us illustrate some important Python syntax and semantics in a familiar setting.

3.4.1 A Version with a For Loop

Here's a version that illustrates `for` loops and Python lists.

```
ts_length = 100
ϵ_values = []   # empty list

for i in range(ts_length):
    e = np.random.randn()
    ϵ_values.append(e)

plt.plot(ϵ_values)
plt.show()
```



In brief,

- The first line sets the desired length of the time series.
- The next line creates an empty *list* called `ϵ_values` that will store the ϵ_t values as we generate them.
- The statement `# empty list` is a *comment*, and is ignored by Python's interpreter.
- The next three lines are the `for` loop, which repeatedly draws a new random number ϵ_t and appends it to the end of the list `ϵ_values`.
- The last two lines generate the plot and display it to the user.

Let's study some parts of this program in more detail.

3.4.2 Lists

Consider the statement `ϵ_values = []`, which creates an empty list.

Lists are a *native Python data structure* used to group a collection of objects.

Items in lists are ordered, and duplicates are allowed in lists.

For example, try

```
x = [10, 'foo', False]
type(x)
```

```
list
```

The first element of `x` is an integer, the next is a string, and the third is a Boolean value.

When adding a value to a list, we can use the syntax `list_name.append(some_value)`

```
x
```

```
[10, 'foo', False]
```

```
x.append(2.5)
x
```

```
[10, 'foo', False, 2.5]
```

Here `append()` is what's called a *method*, which is a function "attached to" an object—in this case, the list `x`.

We'll learn all about methods *later on*, but just to give you some idea,

- Python objects such as lists, strings, etc. all have methods that are used to manipulate the data contained in the object.
- String objects have string methods, list objects have list methods, etc.

Another useful list method is `pop()`

```
x
```

```
[10, 'foo', False, 2.5]
```

```
x.pop()
```

```
2.5
```

```
x
```

```
[10, 'foo', False]
```

Lists in Python are zero-based (as in C, Java or Go), so the first element is referenced by `x[0]`

```
x[0]   # first element of x
```

```
10
```

```
x[1]   # second element of x
```

```
'foo'
```

3.4.3 The For Loop

Now let's consider the `for` loop from *the program above*, which was

```
for i in range(ts_length):
    e = np.random.randn()
    ϵ_values.append(e)
```

Python executes the two indented lines `ts_length` times before moving on.

These two lines are called a `code block`, since they comprise the "block" of code that we are looping over.

Unlike most other languages, Python knows the extent of the code block *only from indentation*.

In our program, indentation decreases after line `ϵ_values.append(e)`, telling Python that this line marks the lower limit of the code block.

More on indentation below—for now, let's look at another example of a `for` loop

```
animals = ['dog', 'cat', 'bird']
for animal in animals:
    print("The plural of " + animal + " is " + animal + "s")
```

```
The plural of dog is dogs
The plural of cat is cats
The plural of bird is birds
```

This example helps to clarify how the `for` loop works: When we execute a loop of the form

```
for variable_name in sequence:
    <code block>
```

The Python interpreter performs the following:

- For each element of the `sequence`, it "binds" the name `variable_name` to that element and then executes the code block.

The `sequence` object can in fact be a very general object, as we'll see soon enough.

3.4.4 A Comment on Indentation

In discussing the `for` loop, we explained that the code blocks being looped over are delimited by indentation.

In fact, in Python, **all** code blocks (i.e., those occurring inside loops, if clauses, function definitions, etc.) are delimited by indentation.

Thus, unlike most other languages, whitespace in Python code affects the output of the program.

Once you get used to it, this is a good thing: It

- forces clean, consistent indentation, improving readability
- removes clutter, such as the brackets or end statements used in other languages

On the other hand, it takes a bit of care to get right, so please remember:

- The line before the start of a code block always ends in a colon
  - `for i in range(10):`

  - `if x > y:`
  - `while x < 100:`
  - etc., etc.

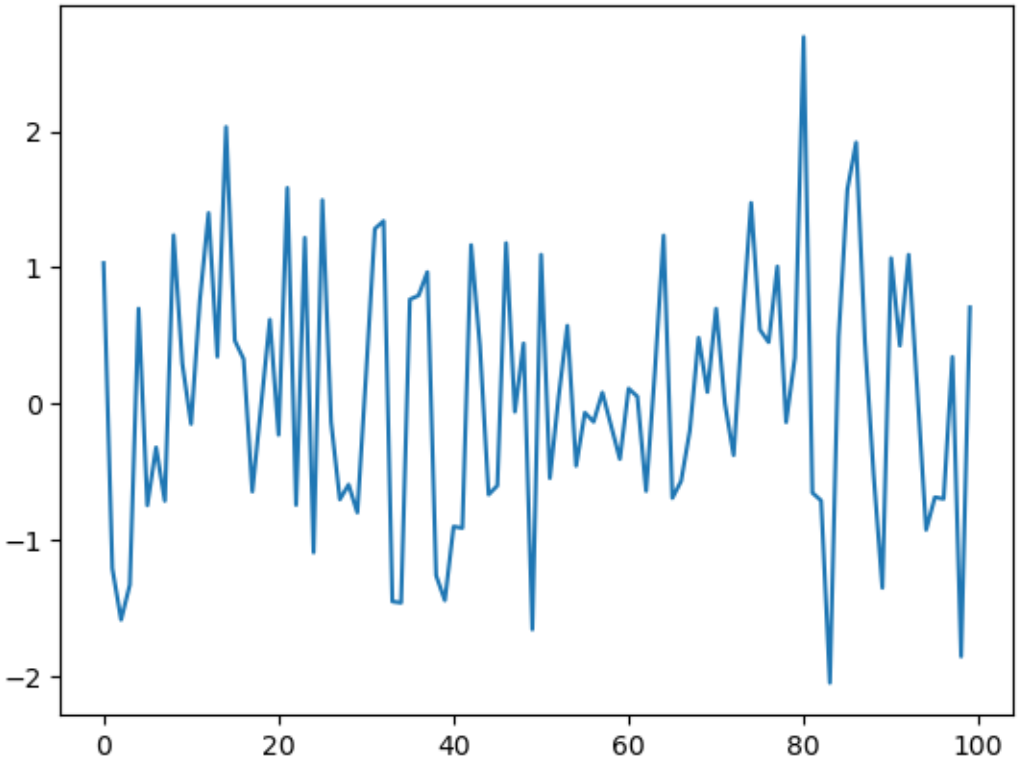
- All lines in a code block **must have the same amount of indentation**.
- The Python standard is 4 spaces, and that's what you should use.

3.4.5 While Loops

The `for` loop is the most common technique for iteration in Python.

But, for the purpose of illustration, let's modify *the program above* to use a `while` loop instead.

```
ts_length = 100
ϵ_values = []
i = 0
while i < ts_length:
    e = np.random.randn()
    ϵ_values.append(e)
    i = i + 1
plt.plot(ϵ_values)
plt.show()
```



A while loop will keep executing the code block delimited by indentation until the condition (`i < ts_length`) is satisfied.

In this case, the program will keep adding values to the list `ϵ_values` until `i` equals `ts_length`:

```
i == ts_length #the ending condition for the while loop
```

```
True
```

Note that

- the code block for the `while` loop is again delimited only by indentation.
- the statement `i = i + 1` can be replaced by `i += 1`.

3.5 Another Application

Let's do one more application before we turn to exercises.

In this application, we plot the balance of a bank account over time.

There are no withdraws over the time period, the last date of which is denoted by T.

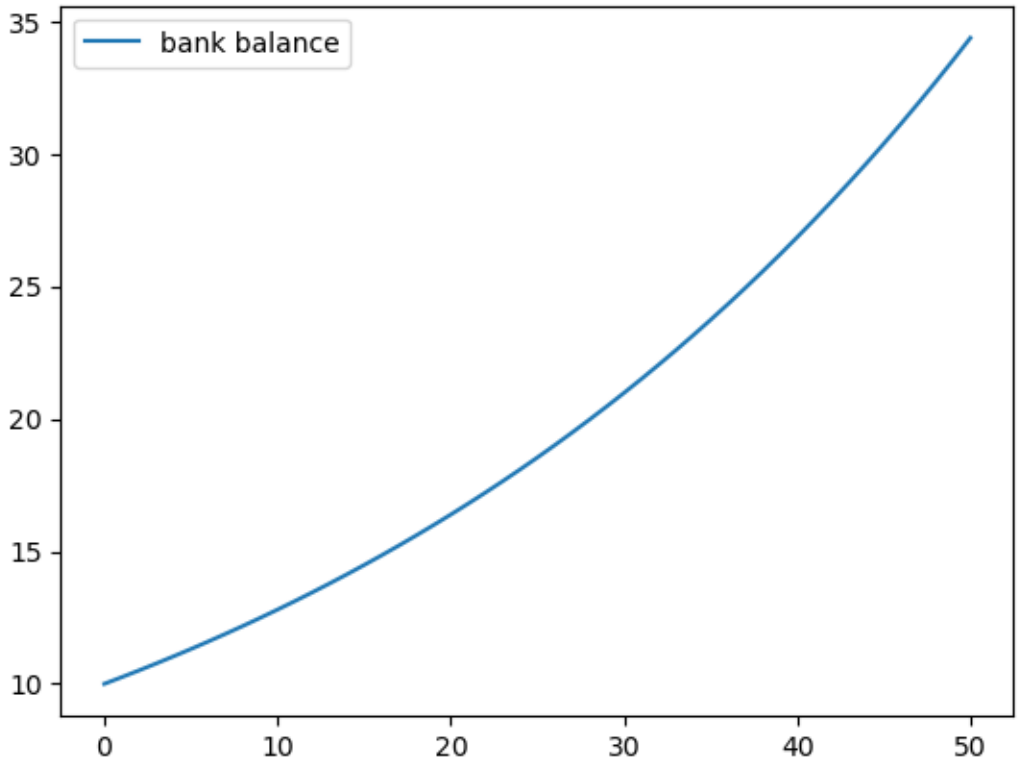
The initial balance is b_0 and the interest rate is r.

The balance updates from period t to $t+1$ according to $b_{t+1} = (1+r)b_t$.

In the code below, we generate and plot the sequence $b_0, b_1, \ldots, b_T$.

Instead of using a Python list to store this sequence, we will use a NumPy array.

```
r = 0.025         # interest rate
T = 50            # end date
b = np.empty(T+1) # an empty NumPy array, to store all b_t
b[0] = 10         # initial balance

for t in range(T):
    b[t+1] = (1 + r) * b[t]

plt.plot(b, label='bank balance')
plt.legend()
plt.show()
```



The statement `b = np.empty(T+1)` allocates storage in memory for `T+1` (floating point) numbers.

These numbers are filled in by the `for` loop.

Allocating memory at the start is more efficient than using a Python list and `append`, since the latter must repeatedly ask for storage space from the operating system.

Notice that we added a legend to the plot — a feature you will be asked to use in the exercises.

3.6 Exercises

Now we turn to exercises. It is important that you complete them before continuing, since they present new concepts we will need.

Exercise 3.6.1

Your first task is to simulate and plot the correlated time series

$$x_{t+1} = \alpha\, x_t + \epsilon_{t+1} \quad \text{where} \quad x_0 = 0 \quad \text{and} \quad t = 0, \ldots, T$$

The sequence of shocks $\{\epsilon_t\}$ is assumed to be IID and standard normal.

In your solution, restrict your import statements to

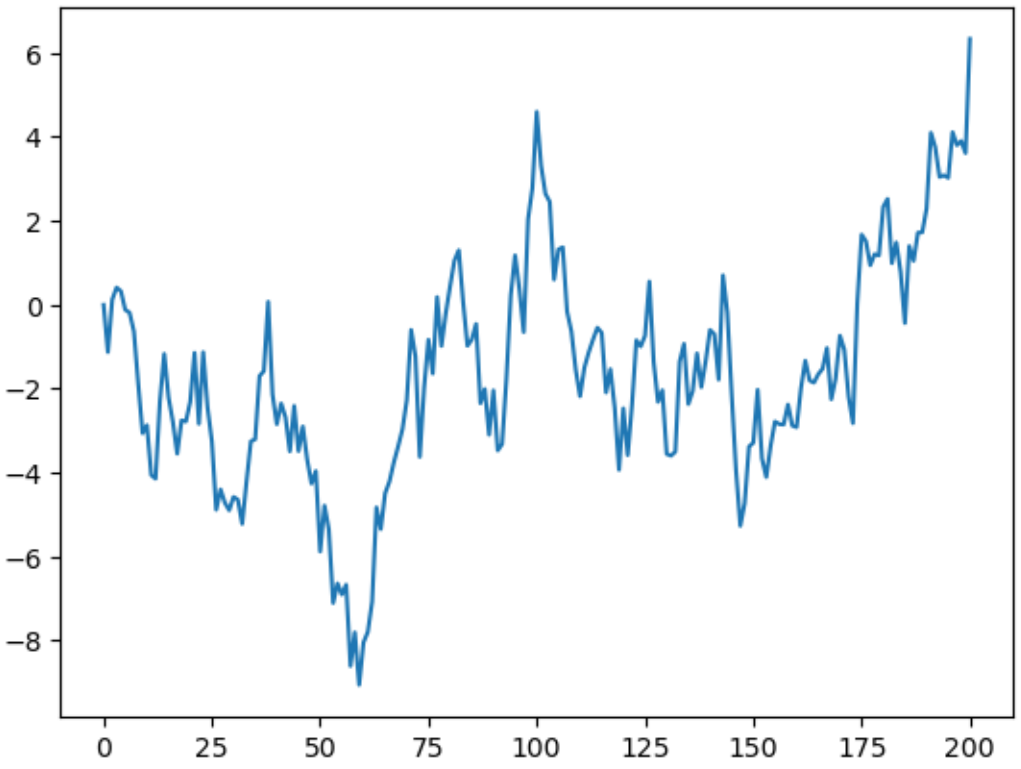
```
import numpy as np
import matplotlib.pyplot as plt
```

Set $T = 200$ and $\alpha = 0.9$.

Solution to Exercise 3.6.1

Here's one solution.

```
a = 0.9
T = 200
x = np.empty(T+1)
x[0] = 0

for t in range(T):
    x[t+1] = a * x[t] + np.random.randn()

plt.plot(x)
plt.show()
```



Exercise 3.6.2

Starting with your solution to exercise 1, plot three simulated time series, one for each of the cases $\alpha = 0$, $\alpha = 0.8$ and $\alpha = 0.98$.

Use a `for` loop to step through the α values.

If you can, add a legend, to help distinguish between the three time series.

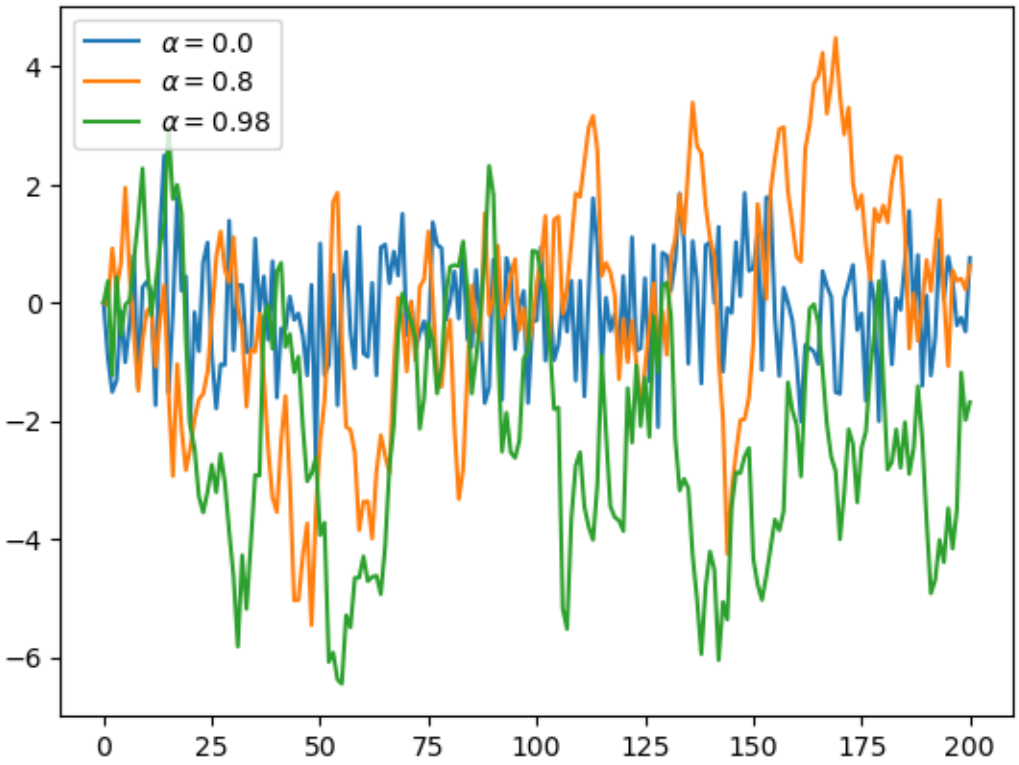
Hint:

- If you call the `plot()` function multiple times before calling `show()`, all of the lines you produce will end up on the same figure.

- For the legend, noted that suppose `var = 42`, the expression `f'foo{var}'` evaluates to `'foo42'`.

Solution to Exercise 3.6.2

```
α_values = [0.0, 0.8, 0.98]
T = 200
x = np.empty(T+1)

for α in α_values:
    x[0] = 0
    for t in range(T):
        x[t+1] = α * x[t] + np.random.randn()
    plt.plot(x, label=f'$\\alpha = {α}$')

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



Note: `f'$\\alpha = {α}$'` in the solution is an application of f-String, which allows you to use `{}` to contain an expression.

The contained expression will be evaluated, and the result will be placed into the string.

Exercise 3.6.3

Similar to the previous exercises, plot the time series

$$x_{t+1} = \alpha \, |x_t| + \epsilon_{t+1} \quad \text{where} \quad x_0 = 0 \quad \text{and} \quad t = 0, \ldots, T$$

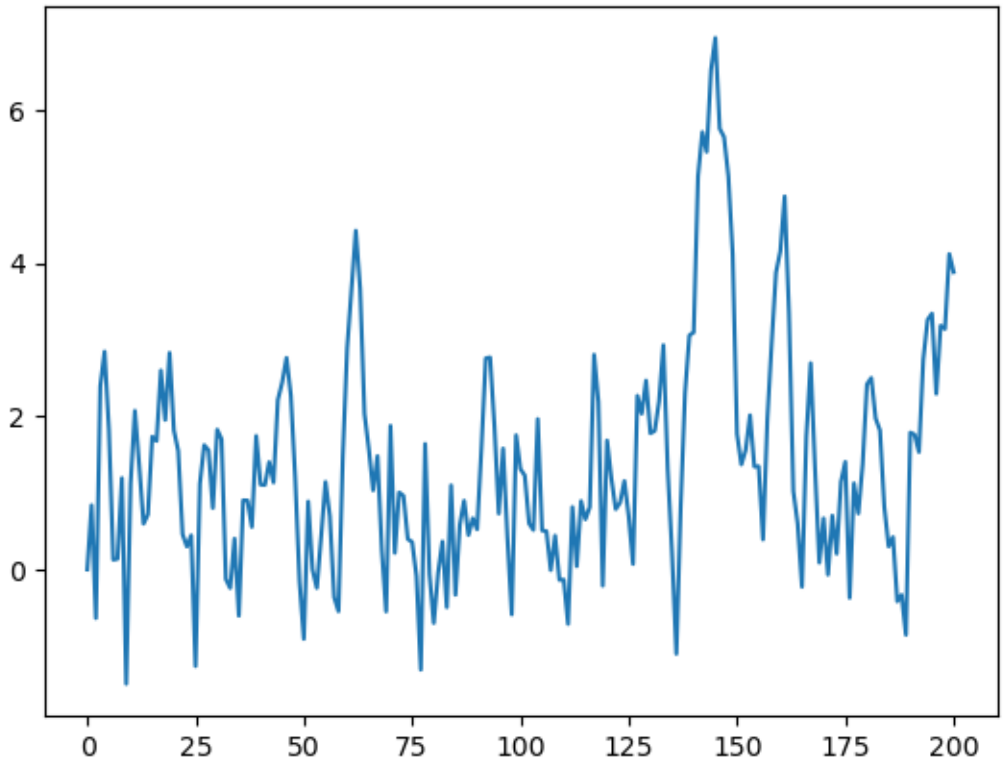
Use $T = 200$, $\alpha = 0.9$ and $\{\epsilon_t\}$ as before.

Search online for a function that can be used to compute the absolute value $|x_t|$.

Solution to Exercise 3.6.3

Here's one solution:

```
α = 0.9
T = 200
x = np.empty(T+1)
x[0] = 0

for t in range(T):
    x[t+1] = α * np.abs(x[t]) + np.random.randn()

plt.plot(x)
plt.show()
```



Exercise 3.6.4

One important aspect of essentially all programming languages is branching and conditions.

In Python, conditions are usually implemented with if–else syntax.

Here's an example, that prints -1 for each negative number in an array and 1 for each nonnegative number

```
numbers = [-9, 2.3, -11, 0]
```

```
for x in numbers:
    if x < 0:
        print(-1)
    else:
        print(1)
```

```
-1
1
-1
1
```

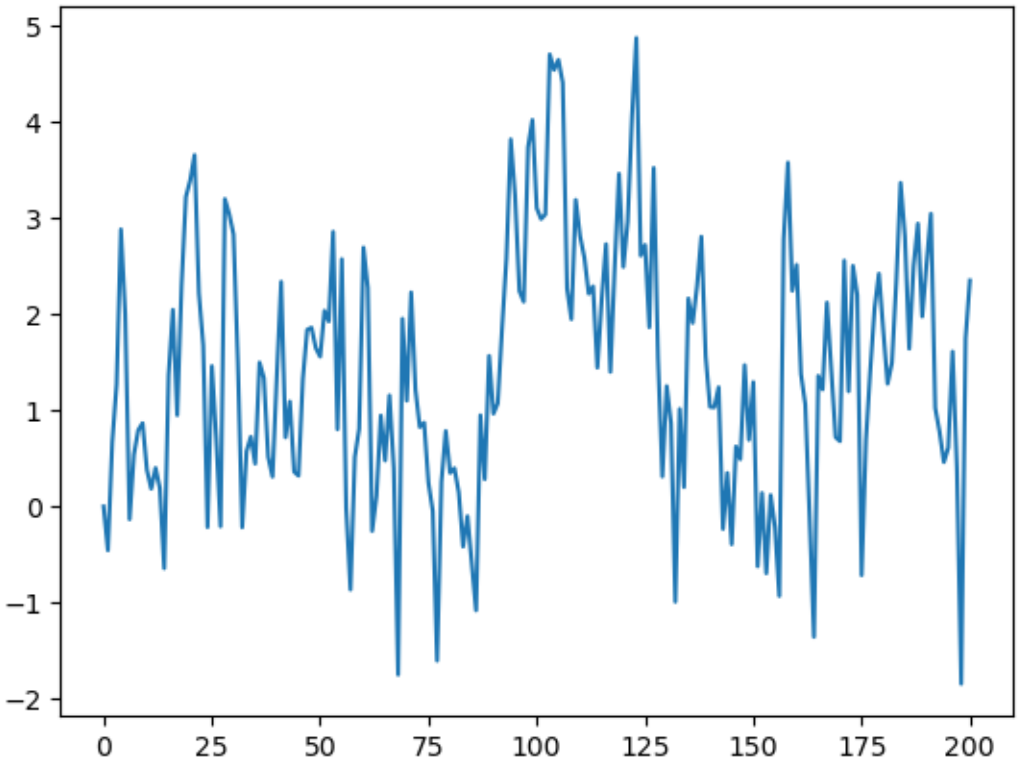
Now, write a new solution to Exercise 3 that does not use an existing function to compute the absolute value.

Replace this existing function with an if–else condition.

Solution to Exercise 3.6.4

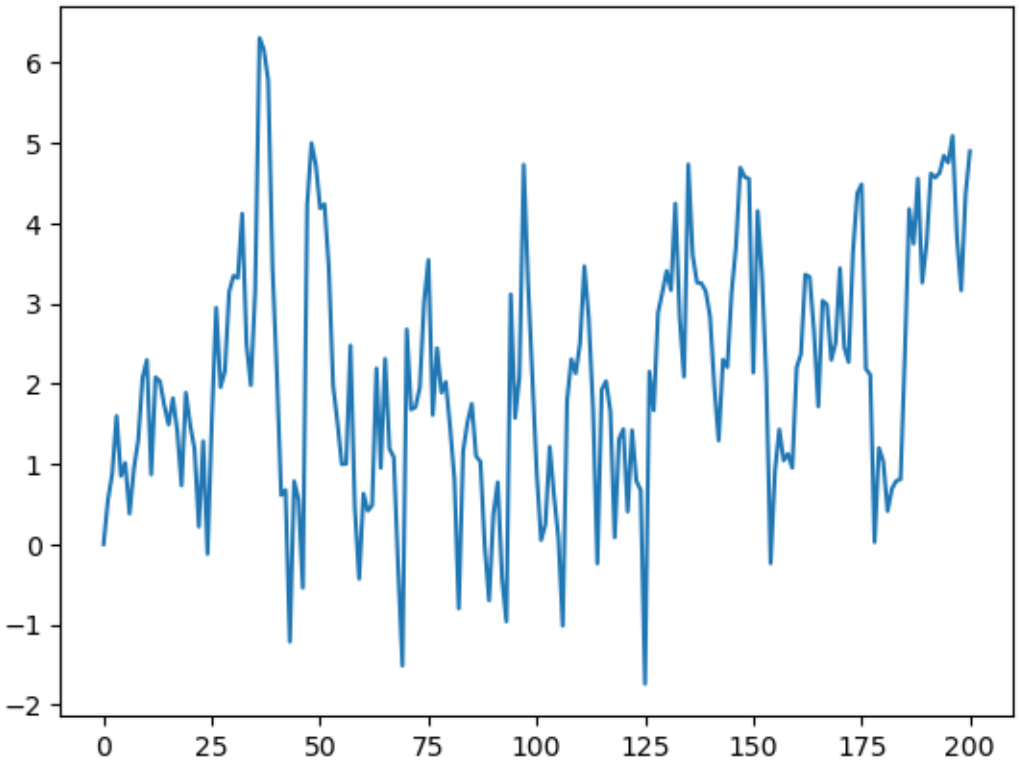
Here's one way:

```
α = 0.9
T = 200
x = np.empty(T+1)
x[0] = 0

for t in range(T):
    if x[t] < 0:
        abs_x = - x[t]
    else:
        abs_x = x[t]
    x[t+1] = α * abs_x + np.random.randn()

plt.plot(x)
plt.show()
```



Here's a shorter way to write the same thing:

```
α = 0.9
T = 200
x = np.empty(T+1)
x[0] = 0

for t in range(T):
    abs_x = - x[t] if x[t] < 0 else x[t]
    x[t+1] = α * abs_x + np.random.randn()

plt.plot(x)
plt.show()
```



Exercise 3.6.5

Here's a harder exercise, that takes some thought and planning.

The task is to compute an approximation to π using Monte Carlo.

Use no imports besides

```
import numpy as np
```

Hint: Your hints are as follows:

- If U is a bivariate uniform random variable on the unit square $(0, 1)^2$, then the probability that U lies in a subset B of $(0, 1)^2$ is equal to the area of B.
- If $U_1, \ldots, U_n$ are IID copies of U, then, as n gets large, the fraction that falls in B, converges to the probability of landing in B.
- For a circle, $area = \pi * radius^2$.

Solution to Exercise 3.6.5

Consider the circle of diameter 1 embedded in the unit square.

Let A be its area and let $r = 1/2$ be its radius.

If we know π then we can compute A via $A = \pi r^2$.

But here the point is to compute π, which we can do by $\pi = A/r^2$.

Summary: If we can estimate the area of a circle with diameter 1, then dividing by $r^2 = (1/2)^2 = 1/4$ gives an estimate of π.

We estimate the area by sampling bivariate uniforms and looking at the fraction that falls into the circle.

```
n = 1000000 # sample size for Monte Carlo simulation

count = 0
for i in range(n):

    # drawing random positions on the square
    u, v = np.random.uniform(), np.random.uniform()

    # check whether the point falls within the boundary
    # of the unit circle centred at (0.5,0.5)
    d = np.sqrt((u - 0.5)**2 + (v - 0.5)**2)

    # if it falls within the inscribed circle,
    # add it to the count
    if d < 0.5:
        count += 1

area_estimate = count / n

print(area_estimate * 4)  # dividing by radius**2
```

```
3.143436
```

CHAPTER

FOUR

FUNCTIONS

Contents

4.1 Overview

One construct that's extremely useful and provided by almost all programming languages is **functions**.

We have already met several functions, such as

- the `sqrt()` function from NumPy and
- the built-in `print()` function

In this lecture we'll treat functions systematically and begin to learn just how useful and important they are.

One of the things we will learn to do is build our own user-defined functions

We will use the following imports.

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

4.2 Function Basics

A function is a named section of a program that implements a specific task.

Many functions exist already and we can use them off the shelf.

First we review these functions and then discuss how we can build our own.

4.2.1 Built-In Functions

Python has a number of *built-in* functions that are available without `import`.

We have already met some

```
max(19, 20)
```

```
20
```

```
print('foobar')
```

```
foobar
```

```
str(22)
```

```
'22'
```

```
type(22)
```

```
int
```

Two more useful built-in functions are `any()` and `all()`

```
bools = False, True, True
all(bools)  # True if all are True and False otherwise
```

```
False
```

```
any(bools)  # False if all are False and True otherwise
```

```
True
```

The full list of Python built-ins is here.

4.2.2 Third Party Functions

If the built-in functions don't cover what we need, we either need to import functions or create our own.

Examples of importing and using functions were given in the *previous lecture*

Here's another one, which tests whether a given year is a leap year:

```
import calendar

calendar.isleap(2020)
```

```
True
```

4.3 Defining Functions

In many instances, it is useful to be able to define our own functions.

This will become clearer as you see more examples.

Let's start by discussing how it's done.

4.3.1 Basic Syntax

Here's a very simple Python function, that implements the mathematical function $f(x) = 2x + 1$

```
def f(x):
    return 2 * x + 1
```

Now that we've *defined* this function, let's *call* it and check whether it does what we expect:

```
f(1)
```

```
3
```

```
f(10)
```

```
21
```

Here's a longer function, that computes the absolute value of a given number.

(Such a function already exists as a built-in, but let's write our own for the exercise.)

```
def new_abs_function(x):

    if x < 0:
        abs_value = -x
    else:
        abs_value = x

    return abs_value
```

Let's review the syntax here.

- `def` is a Python keyword used to start function definitions.
- `def new_abs_function(x):` indicates that the function is called `new_abs_function` and that it has a single argument `x`.
- The indented code is a code block called the *function body*.
- The `return` keyword indicates that `abs_value` is the object that should be returned to the calling code.

This whole function definition is read by the Python interpreter and stored in memory.

Let's call it to check that it works:

```
print(new_abs_function(3))
print(new_abs_function(-3))
```

```
3
3
```

Note that a function can have arbitrarily many `return` statements (including zero).

Execution of the function terminates when the first return is hit, allowing code like the following example

```
def f(x):
    if x < 0:
        return 'negative'
    return 'nonnegative'
```

Functions without a return statement automatically return the special Python object `None`.

4.3.2 Keyword Arguments

In a *previous lecture*, you came across the statement

```
plt.plot(x, 'b-', label="white noise")
```

In this call to Matplotlib's `plot` function, notice that the last argument is passed in `name=argument` syntax.

This is called a *keyword argument*, with `label` being the keyword.

Non-keyword arguments are called *positional arguments*, since their meaning is determined by order

- `plot(x, 'b-', label="white noise")` is different from `plot('b-', x, label="white noise")`

Keyword arguments are particularly useful when a function has a lot of arguments, in which case it's hard to remember the right order.

You can adopt keyword arguments in user-defined functions with no difficulty.

The next example illustrates the syntax

```
def f(x, a=1, b=1):
    return a + b * x
```

The keyword argument values we supplied in the definition of `f` become the default values

```
f(2)
```

```
3
```

They can be modified as follows

```
f(2, a=4, b=5)
```

```
14
```

4.3.3 The Flexibility of Python Functions

As we discussed in the *previous lecture*, Python functions are very flexible.

In particular

- Any number of functions can be defined in a given file.
- Functions can be (and often are) defined inside other functions.
- Any object can be passed to a function as an argument, including other functions.
- A function can return any kind of object, including functions.

We will give examples of how straightforward it is to pass a function to a function in the following sections.

4.3.4 One-Line Functions: `lambda`

The `lambda` keyword is used to create simple functions on one line.

For example, the definitions

```
def f(x):
    return x**3
```

and

```
f = lambda x: x**3
```

are entirely equivalent.

To see why `lambda` is useful, suppose that we want to calculate $\int_0^2 x^3 dx$ (and have forgotten our high-school calculus).

The SciPy library has a function called `quad` that will do this calculation for us.

The syntax of the `quad` function is `quad(f, a, b)` where `f` is a function and `a` and `b` are numbers.

To create the function $f(x) = x^3$ we can use `lambda` as follows

```
from scipy.integrate import quad

quad(lambda x: x**3, 0, 2)
```

```
(4.0, 4.440892098500626e-14)
```

Here the function created by `lambda` is said to be *anonymous* because it was never given a name.

4.3.5 Why Write Functions?

User-defined functions are important for improving the clarity of your code by

- separating different strands of logic
- facilitating code reuse

(Writing the same thing twice is almost always a bad idea)

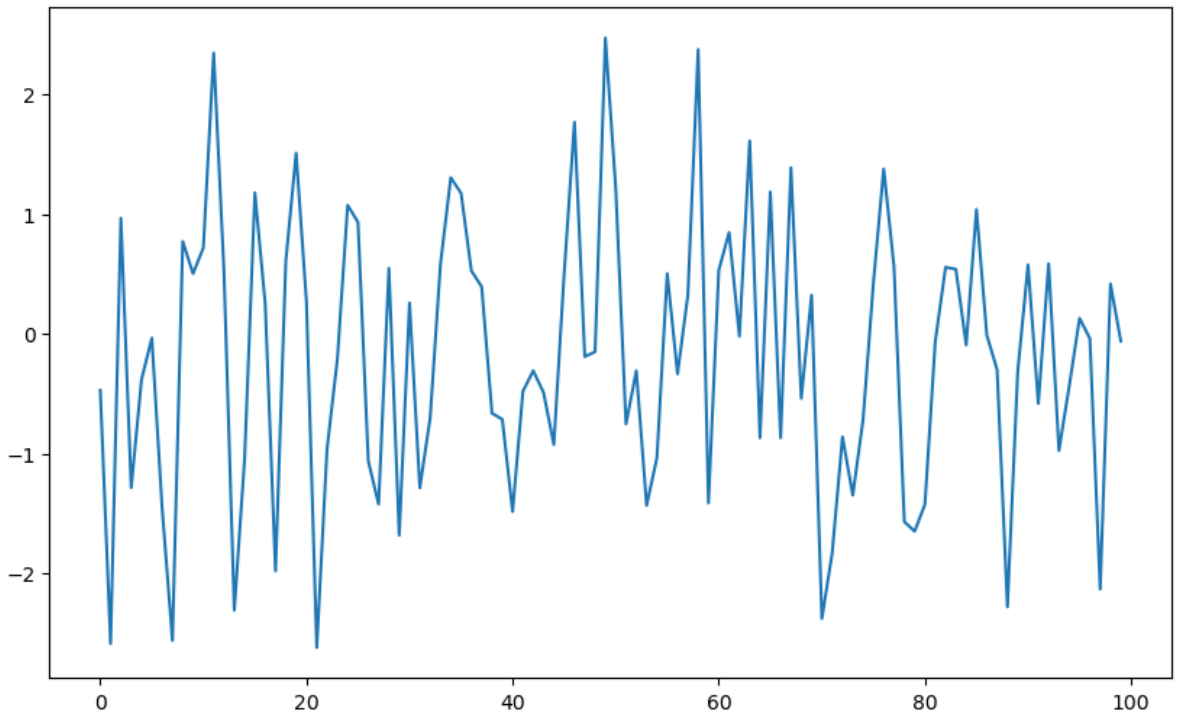
We will say more about this *later*.

4.4 Applications

4.4.1 Random Draws

Consider again this code from the *previous lecture*

```
ts_length = 100
ϵ_values = []   # empty list

for i in range(ts_length):
    e = np.random.randn()
    ϵ_values.append(e)

plt.plot(ϵ_values)
plt.show()
```

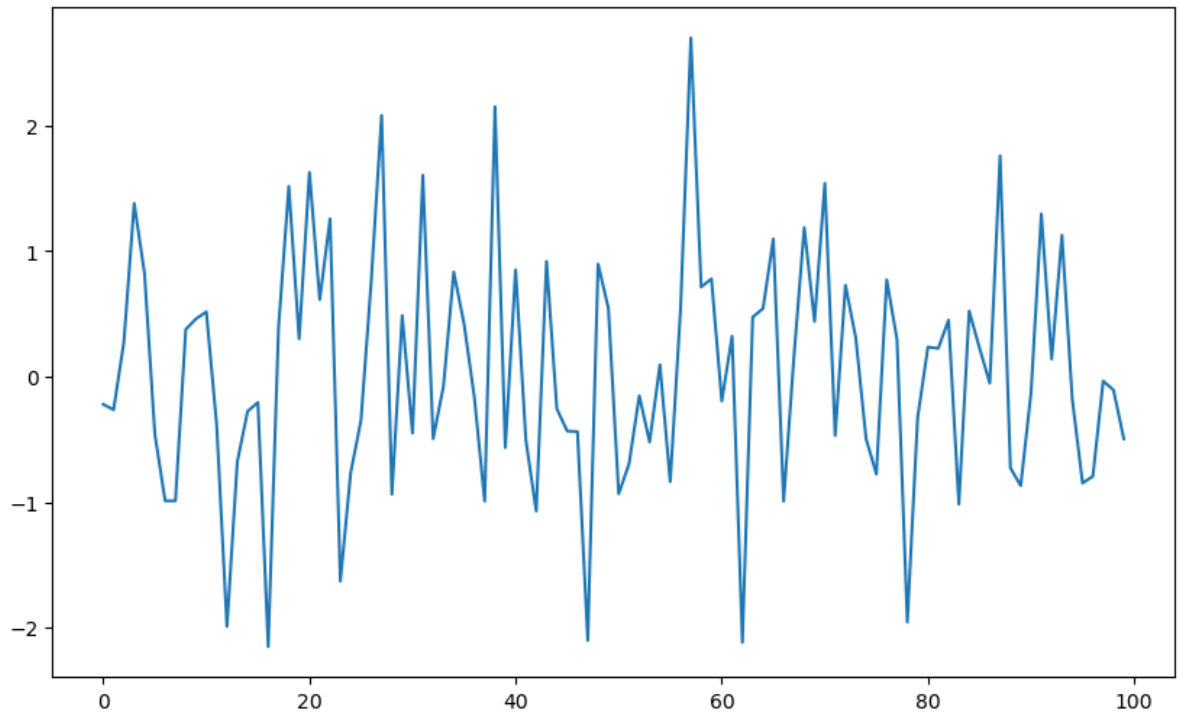


We will break this program into two parts:

1. A user-defined function that generates a list of random variables.
2. The main part of the program that
    1. calls this function to get data
    2. plots the data

This is accomplished in the next program

```
def generate_data(n):
    ϵ_values = []
    for i in range(n):
        e = np.random.randn()
        ϵ_values.append(e)
    return ϵ_values

data = generate_data(100)
plt.plot(data)
plt.show()
```



When the interpreter gets to the expression `generate_data(100)`, it executes the function body with `n` set equal to 100.

The net result is that the name `data` is *bound* to the list `ϵ_values` returned by the function.

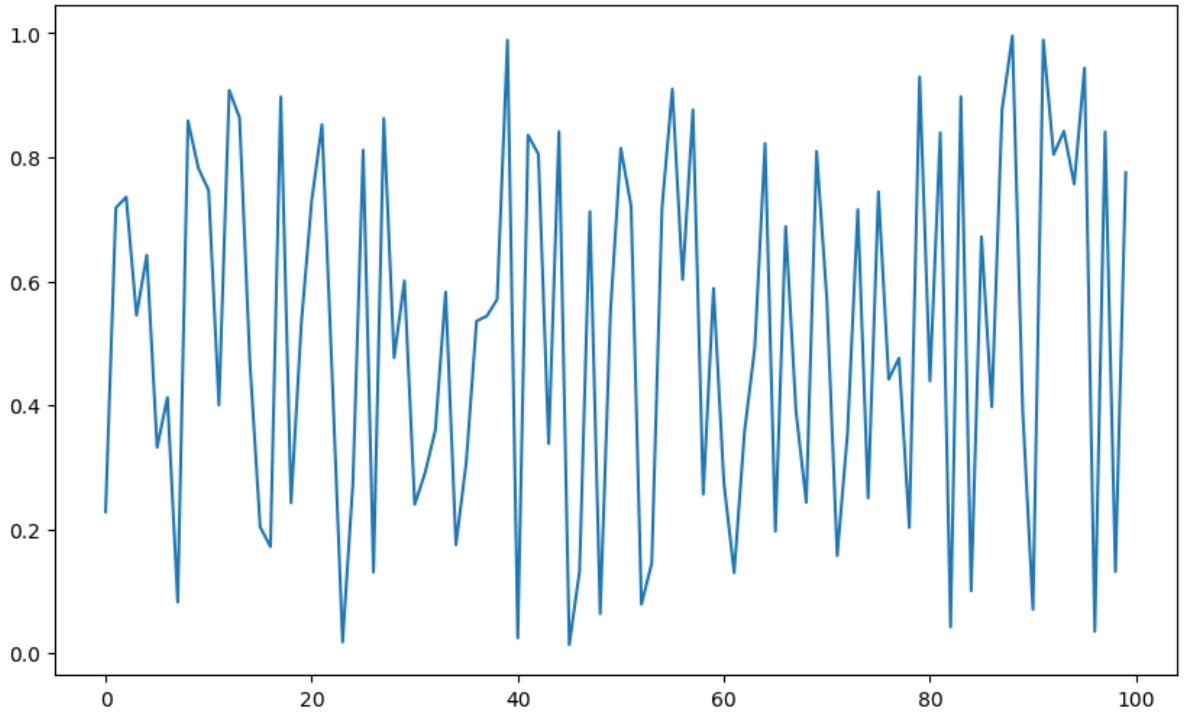
4.4.2 Adding Conditions

Our function `generate_data()` is rather limited.

Let's make it slightly more useful by giving it the ability to return either standard normals or uniform random variables on $(0, 1)$ as required.

This is achieved in the next piece of code.

```
def generate_data(n, generator_type):
    ϵ_values = []
    for i in range(n):
        if generator_type == 'U':
            e = np.random.uniform(0, 1)
        else:
            e = np.random.randn()
        ϵ_values.append(e)
    return ϵ_values

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



Hopefully, the syntax of the if/else clause is self-explanatory, with indentation again delimiting the extent of the code blocks.

Notes

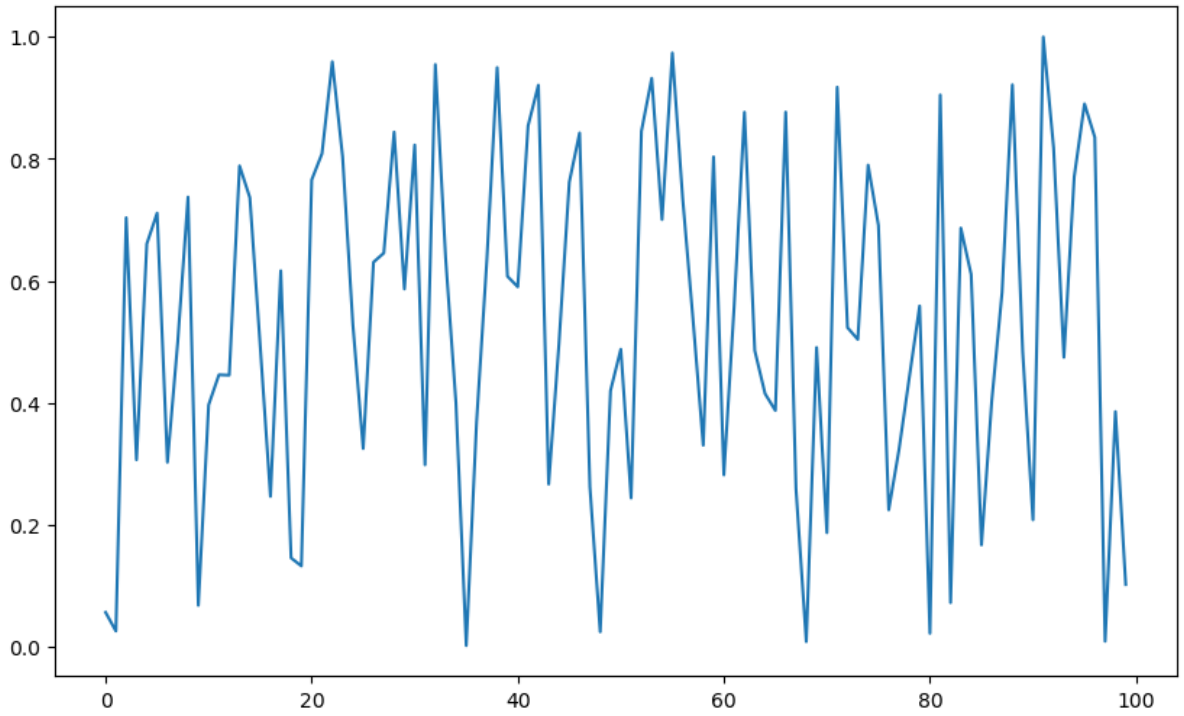
- We are passing the argument `U` as a string, which is why we write it as `'U'`.
- Notice that equality is tested with the == syntax, not =.
  - For example, the statement `a = 10` assigns the name `a` to the value `10`.
  - The expression `a == 10` evaluates to either `True` or `False`, depending on the value of `a`.

Now, there are several ways that we can simplify the code above.

For example, we can get rid of the conditionals all together by just passing the desired generator type *as a function*.

To understand this, consider the following version.

```
def generate_data(n, generator_type):
    ϵ_values = []
    for i in range(n):
        e = generator_type()
        ϵ_values.append(e)
    return ϵ_values

data = generate_data(100, np.random.uniform)
plt.plot(data)
plt.show()
```



Now, when we call the function `generate_data()`, we pass `np.random.uniform` as the second argument.

This object is a *function*.

When the function call `generate_data(100, np.random.uniform)` is executed, Python runs the function code block with `n` equal to 100 and the name `generator_type` "bound" to the function `np.random.uniform`.

- While these lines are executed, the names `generator_type` and `np.random.uniform` are "synonyms", and can be used in identical ways.

This principle works more generally—for example, consider the following piece of code

```
max(7, 2, 4)  # max() is a built-in Python function
```

```
7
```

```
m = max
m(7, 2, 4)
```

```
7
```

Here we created another name for the built-in function `max()`, which could then be used in identical ways.

In the context of our program, the ability to bind new names to functions means that there is no problem *passing a function as an argument to another function*—as we did above.

4.5 Recursive Function Calls (Advanced)

This is not something that you will use every day, but it is still useful — you should learn it at some stage.

Basically, a recursive function is a function that calls itself.

For example, consider the problem of computing x_t for some t when

$$x_{t+1} = 2x_t, \quad x_0 = 1 \tag{4.1}$$

Obviously the answer is 2^t.

We can compute this easily enough with a loop

```
def x_loop(t):
    x = 1
    for i in range(t):
        x = 2 * x
    return x
```

We can also use a recursive solution, as follows

```
def x(t):
    if t == 0:
        return 1
    else:
        return 2 * x(t-1)
```

What happens here is that each successive call uses it's own *frame* in the *stack*

- a frame is where the local variables of a given function call are held
- stack is memory used to process function calls
  - a First In Last Out (FILO) queue

This example is somewhat contrived, since the first (iterative) solution would usually be preferred to the recursive solution.

We'll meet less contrived applications of recursion later on.

4.6 Exercises

Exercise 4.6.1

Recall that $n!$ is read as "n factorial" and defined as $n! = n \times (n-1) \times \cdots \times 2 \times 1$.

We will only consider n as a positive integer here.

There are functions to compute this in various modules, but let's write our own version as an exercise.

1. In particular, write a function `factorial` such that `factorial(n)` returns $n!$ for any positive integer n.
2. In addition, try to add a new argument for your function. The argument takes a function `f` that transforms n to $f(n) = n^2 + 1$ if n is even, and $f(n) = n^2$ if n is odd. The default value should be $f(n) = n$.

For example

- The default case `factorial(3)` should return $3!$
- `factorial(3,f)` should return $9!$
- `factorial(2,f)` should return $5!$

Try to use lambda expressions to define the function `f`.

Solution to Exercise 4.6.1

Here's one solution for part 1

```
def factorial(n):
    k = 1
    for i in range(n):
        k = k * (i + 1)
    return k

factorial(4)
```

```
24
```

Adding the lambda expression

```
def factorial(n,f = lambda x: x):
    k = 1
    for i in range(f(n)):
        k = k * (i + 1)
    return k


factorial(9) # default
```

```
362880
```

```
f = lambda x: x**2 + 1 if x % 2 == 0 else x**2

factorial(3, f) # odd (equivalent to factorial(9))
```

```
362880
```

```
factorial(2, f) # even (equivalent to factorial(5))
```

```
120
```

Exercise 4.6.2

The binomial random variable $Y \sim Bin(n, p)$ represents the number of successes in n binary trials, where each trial succeeds with probability p.

Without any import besides `from numpy.random import uniform`, write a function `binomial_rv` such that `binomial_rv(n, p)` generates one draw of Y.

Hint: If U is uniform on $(0, 1)$ and $p \in (0, 1)$, then the expression `U < p` evaluates to `True` with probability p.

Solution to Exercise 4.6.2

Here is one solution:

```
from numpy.random import uniform

def binomial_rv(n, p):
    count = 0
    for i in range(n):
        U = uniform()
        if U < p:
            count = count + 1    # Or count += 1
    return count

binomial_rv(10, 0.5)
```

```
8
```

Exercise 4.6.3

First, write a function that returns one realization of the following random device

1. Flip an unbiased coin 10 times.
2. If a head occurs `k` or more times consecutively within this sequence at least once, pay one dollar.
3. If not, pay nothing.

Second, write another function that does the same task except that the second rule of the above random device becomes

- If a head occurs `k` or more times within this sequence, pay one dollar.

Use no import besides `from numpy.random import uniform`.

Solution to Exercise 4.6.3

Here's a function for the first random device.

```
from numpy.random import uniform

def draw(k):  # pays if k consecutive successes in a sequence

    payoff = 0
    count = 0

    for i in range(10):
        U = uniform()
        count = count + 1 if U < 0.5 else 0
        print(count)    # print counts for clarity
        if count == k:
            payoff = 1

    return payoff

draw(3)
```

```
0
0
1
2
0
0
0
0
1
2
```

```
0
```

Here's another function for the second random device.

```
def draw_new(k):  # pays if k successes in a sequence

    payoff = 0
    count = 0

    for i in range(10):
        U = uniform()
        count = count + ( 1 if U < 0.5 else 0 )
        print(count)
        if count == k:
            payoff = 1

    return payoff

draw_new(3)
```

```
0
```

(continues on next page)

(continued from previous page)

```
0
1
2
3
3
4
4
4
4
```

```
1
```

4.7 Advanced Exercises

In the following exercises, we will write recursive functions together.

We will use more advanced syntaxes such as *list comprehensions* to test our solutions against a list of inputs.

If you are not familiar with these concepts, feel free to come back later.

Exercise 4.7.1

The Fibonacci numbers are defined by

$$x_{t+1} = x_t + x_{t-1}, \quad x_0 = 0, \; x_1 = 1 \tag{4.2}$$

The first few numbers in the sequence are $0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55$.

Write a function to recursively compute the t-th Fibonacci number for any t.

Solution to Exercise 4.7.1

Here's the standard solution

```
def x(t):
    if t == 0:
        return 0
    if t == 1:
        return 1
    else:
        return x(t-1) + x(t-2)
```

Let's test it

```
print([x(i) for i in range(10)])
```

```
[0, 1, 1, 2, 3, 5, 8, 13, 21, 34]
```

Exercise 4.7.2

For this exercise, rewrite the function `factorial(n)` in *exercise 1* using recursion.

Solution to Exercise 4.7.2

Here's the standard solution

```
def recursion_factorial(n):
   if n == 1:
       return n
   else:
       return n * recursion_factorial(n-1)
```

Here's a simplified solution

```
def recursion_factorial_simplified(n):
    return n * recursion_factorial(n-1) if n != 1 else n
```

Let's test them

```
print([recursion_factorial(i) for i in range(1, 10)])
```

```
[1, 2, 6, 24, 120, 720, 5040, 40320, 362880]
```

```
print([recursion_factorial_simplified(i) for i in range(1, 10)])
```

```
[1, 2, 6, 24, 120, 720, 5040, 40320, 362880]
```

CHAPTER

FIVE

PYTHON ESSENTIALS

Contents

5.1 Overview

We have covered a lot of material quite quickly, with a focus on examples.

Now let's cover some core features of Python in a more systematic way.

This approach is less exciting but helps clear up some details.

5.2 Data Types

Computer programs typically keep track of a range of data types.

For example, `1.5` is a floating point number, while `1` is an integer.

Programs need to distinguish between these two types for various reasons.

One is that they are stored in memory differently.

Another is that arithmetic operations are different

- For example, floating point arithmetic is implemented on most machines by a specialized Floating Point Unit (FPU).

In general, floats are more informative but arithmetic operations on integers are faster and more accurate.

Python provides numerous other built-in Python data types, some of which we've already met

- strings, lists, etc.

Let's learn a bit more about them.

5.2.1 Primitive Data Types

Boolean Values

One simple data type is **Boolean values**, which can be either `True` or `False`

```
x = True
x
```

```
True
```

We can check the type of any object in memory using the `type()` function.

```
type(x)
```

```
bool
```

In the next line of code, the interpreter evaluates the expression on the right of = and binds y to this value

```
y = 100 < 10
y
```

```
False
```

```
type(y)
```

```
bool
```

In arithmetic expressions, `True` is converted to `1` and `False` is converted `0`.

This is called **Boolean arithmetic** and is often useful in programming.

Here are some examples

```
x + y
```

```
1
```

```
x * y
```

```
0
```

```
True + True
```

```
2
```

```
bools = [True, True, False, True]  # List of Boolean values

sum(bools)
```

```
3
```

Numeric Types

Numeric types are also important primitive data types.

We have seen `integer` and `float` types before.

Complex numbers are another primitive data type in Python

```
x = complex(1, 2)
y = complex(2, 1)
print(x * y)

type(x)
```

```
5j
```

```
complex
```

5.2.2 Containers

Python has several basic types for storing collections of (possibly heterogeneous) data.

We've *already discussed lists*.

A related data type is **tuples**, which are "immutable" lists

```
x = ('a', 'b')  # Parentheses instead of the square brackets
x = 'a', 'b'    # Or no brackets --- the meaning is identical
x
```

```
('a', 'b')
```

```
type(x)
```

```
tuple
```

In Python, an object is called **immutable** if, once created, the object cannot be changed.

Conversely, an object is **mutable** if it can still be altered after creation.

Python lists are mutable

```
x = [1, 2]
x[0] = 10
x
```

```
[10, 2]
```

But tuples are not

```
x = (1, 2)
x[0] = 10
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[13], line 2
      1 x = (1, 2)
----> 2 x[0] = 10

TypeError: 'tuple' object does not support item assignment
```

We'll say more about the role of mutable and immutable data a bit later.

Tuples (and lists) can be "unpacked" as follows

```
integers = (10, 20, 30)
x, y, z = integers
x
```

```
10
```

```
y
```

```
20
```

You've actually *seen an example of this* already.

Tuple unpacking is convenient and we'll use it often.

Slice Notation

To access multiple elements of a sequence (a list, a tuple or a string), you can use Python's slice notation.

For example,

```
a = ["a", "b", "c", "d", "e"]
a[1:]
```

```
['b', 'c', 'd', 'e']
```

```
a[1:3]
```

```
['b', 'c']
```

The general rule is that `a[m:n]` returns `n - m` elements, starting at `a[m]`.

Negative numbers are also permissible

```
a[-2:]  # Last two elements of the list
```

```
['d', 'e']
```

You can also use the format `[start:end:step]` to specify the step

```
a[::2]
```

```
['a', 'c', 'e']
```

Using a negative step, you can return the sequence in a reversed order

```
a[-2::-1] # Walk backwards from the second last element to the first element
```

```
['d', 'c', 'b', 'a']
```

The same slice notation works on tuples and strings

```
s = 'foobar'
s[-3:]  # Select the last three elements
```

```
'bar'
```

Sets and Dictionaries

Two other container types we should mention before moving on are sets and dictionaries.

Dictionaries are much like lists, except that the items are named instead of numbered

```
d = {'name': 'Frodo', 'age': 33}
type(d)
```

```
dict
```

```
d['age']
```

```
33
```

The names `'name'` and `'age'` are called the *keys*.

The objects that the keys are mapped to (`'Frodo'` and `33`) are called the `values`.

Sets are unordered collections without duplicates, and set methods provide the usual set-theoretic operations

```
s1 = {'a', 'b'}
type(s1)
```

```
set
```

```
s2 = {'b', 'c'}
s1.issubset(s2)
```

```
False
```

```
s1.intersection(s2)
```

```
{'b'}
```

The `set()` function creates sets from sequences

```
s3 = set(('foo', 'bar', 'foo'))
s3
```

```
{'bar', 'foo'}
```

5.3 Input and Output

Let's briefly review reading and writing to text files, starting with writing

```
f = open('newfile.txt', 'w')    # Open 'newfile.txt' for writing
f.write('Testing\n')            # Here '\n' means new line
f.write('Testing again')
f.close()
```

Here

- The built-in function `open()` creates a file object for writing to.
- Both `write()` and `close()` are methods of file objects.

Where is this file that we've created?

Recall that Python maintains a concept of the present working directory (pwd) that can be located from with Jupyter or IPython via

```
%pwd
```

```
'/home/runner/work/lecture-python-programming.myst/lecture-python-programming.myst/
↪lectures'
```

If a path is not specified, then this is where Python writes to.

We can also use Python to read the contents of `newline.txt` as follows

```
f = open('newfile.txt', 'r')
out = f.read()
out
```

```
'Testing\nTesting again'
```

```
print(out)
```

```
Testing
Testing again
```

In fact, the recommended approach in modern Python is to use a `with` statement to ensure the files are properly acquired and released.

Containing the operations within the same block also improves the clarity of your code.

Note: This kind of block is formally referred to as a *context*.

Let's try to convert the two examples above into a `with` statement.

We change the writing example first

```
with open('newfile.txt', 'w') as f:
    f.write('Testing\n')
    f.write('Testing again')
```

Note that we do not need to call the `close()` method since the `with` block will ensure the stream is closed at the end of the block.

With slight modifications, we can also read files using `with`

```
with open('newfile.txt', 'r') as fo:
    out = fo.read()
    print(out)
```

```
Testing
Testing again
```

Now suppose that we want to read input from one file and write output to another. Here's how we could accomplish this task while correctly acquiring and returning resources to the operating system using `with` statements:

```
with open("newfile.txt", "r") as f:
    file = f.readlines()
    with open("output.txt", "w") as fo:
        for i, line in enumerate(file):
            fo.write(f'Line {i}: {line} \n')
```

The output file will be

```
with open('output.txt', 'r') as fo:
    print(fo.read())
```

```
Line 0: Testing

Line 1: Testing again
```

We can simplify the example above by grouping the two `with` statements into one line

```
with open("newfile.txt", "r") as f, open("output2.txt", "w") as fo:
        for i, line in enumerate(f):
            fo.write(f'Line {i}: {line} \n')
```

The output file will be the same

```
with open('output2.txt', 'r') as fo:
    print(fo.read())
```

```
Line 0: Testing

Line 1: Testing again
```

Suppose we want to continue to write into the existing file instead of overwriting it.

we can switch the mode to `a` which stands for append mode

```
with open('output2.txt', 'a') as fo:
    fo.write('\nThis is the end of the file')
```

```
with open('output2.txt', 'r') as fo:
    print(fo.read())
```

```
Line 0: Testing

Line 1: Testing again

This is the end of the file
```

Note: Note that we only covered `r`, `w`, and `a` mode here, which are the most commonly used modes. Python provides a variety of modes that you could experiment with.

5.3.1 Paths

Note that if `newfile.txt` is not in the present working directory then this call to `open()` fails.

In this case, you can shift the file to the pwd or specify the full path to the file

```
f = open('insert_full_path_to_file/newfile.txt', 'r')
```

5.4 Iterating

One of the most important tasks in computing is stepping through a sequence of data and performing a given action.

One of Python's strengths is its simple, flexible interface to this kind of iteration via the `for` loop.

5.4.1 Looping over Different Objects

Many Python objects are "iterable", in the sense that they can be looped over.

To give an example, let's write the file us_cities.txt, which lists US cities and their population, to the present working directory.

```
%%writefile us_cities.txt
new york: 8244910
los angeles: 3819702
chicago: 2707120
houston: 2145146
philadelphia: 1536471
phoenix: 1469471
san antonio: 1359758
san diego: 1326179
dallas: 1223229
```

```
Overwriting us_cities.txt
```

Here `%%writefile` is an IPython cell magic.

Suppose that we want to make the information more readable, by capitalizing names and adding commas to mark thousands.

The program below reads the data in and makes the conversion:

```
data_file = open('us_cities.txt', 'r')
for line in data_file:
    city, population = line.split(':')         # Tuple unpacking
    city = city.title()                        # Capitalize city names
    population = f'{int(population):,}'        # Add commas to numbers
    print(city.ljust(15) + population)
data_file.close()
```

```
New York       8,244,910
Los Angeles    3,819,702
Chicago        2,707,120
Houston        2,145,146
Philadelphia   1,536,471
Phoenix        1,469,471
San Antonio    1,359,758
San Diego      1,326,179
Dallas         1,223,229
```

Here `format()` is a string method used for inserting variables into strings.

The reformatting of each line is the result of three different string methods, the details of which can be left till later.

The interesting part of this program for us is line 2, which shows that

1. The file object `data_file` is iterable, in the sense that it can be placed to the right of `in` within a `for` loop.
2. Iteration steps through each line in the file.

This leads to the clean, convenient syntax shown in our program.

Many other kinds of objects are iterable, and we'll discuss some of them later on.

5.4.2 Looping without Indices

One thing you might have noticed is that Python tends to favor looping without explicit indexing.

For example,

```
x_values = [1, 2, 3]  # Some iterable x
for x in x_values:
    print(x * x)
```

```
1
4
9
```

is preferred to

```
for i in range(len(x_values)):
    print(x_values[i] * x_values[i])
```

```
1
4
9
```

When you compare these two alternatives, you can see why the first one is preferred.

Python provides some facilities to simplify looping without indices.

One is `zip()`, which is used for stepping through pairs from two sequences.

For example, try running the following code

```
countries = ('Japan', 'Korea', 'China')
cities = ('Tokyo', 'Seoul', 'Beijing')
for country, city in zip(countries, cities):
    print(f'The capital of {country} is {city}')
```

```
The capital of Japan is Tokyo
The capital of Korea is Seoul
The capital of China is Beijing
```

The `zip()` function is also useful for creating dictionaries — for example

```
names = ['Tom', 'John']
marks = ['E', 'F']
dict(zip(names, marks))
```

```
{'Tom': 'E', 'John': 'F'}
```

If we actually need the index from a list, one option is to use `enumerate()`.

To understand what `enumerate()` does, consider the following example

```
letter_list = ['a', 'b', 'c']
for index, letter in enumerate(letter_list):
    print(f"letter_list[{index}] = '{letter}'")
```

```
letter_list[0] = 'a'
letter_list[1] = 'b'
letter_list[2] = 'c'
```

5.4.3 List Comprehensions

We can also simplify the code for generating the list of random draws considerably by using something called a *list comprehension*.

List comprehensions are an elegant Python tool for creating lists.

Consider the following example, where the list comprehension is on the right-hand side of the second line

```
animals = ['dog', 'cat', 'bird']
plurals = [animal + 's' for animal in animals]
plurals
```

```
['dogs', 'cats', 'birds']
```

Here's another example

```
range(8)
```

```
range(0, 8)
```

```
doubles = [2 * x for x in range(8)]
doubles
```

```
[0, 2, 4, 6, 8, 10, 12, 14]
```

5.5 Comparisons and Logical Operators

5.5.1 Comparisons

Many different kinds of expressions evaluate to one of the Boolean values (i.e., `True` or `False`).

A common type is comparisons, such as

```
x, y = 1, 2
x < y
```

```
True
```

```
x > y
```

```
False
```

One of the nice features of Python is that we can *chain* inequalities

```
1 < 2 < 3
```

```
True
```

```
1 <= 2 <= 3
```

```
True
```

As we saw earlier, when testing for equality we use ==

```
x = 1    # Assignment
x == 2   # Comparison
```

```
False
```

For "not equal" use !=

```
1 != 2
```

```
True
```

Note that when testing conditions, we can use **any** valid Python expression

```
x = 'yes' if 42 else 'no'
x
```

```
'yes'
```

```
x = 'yes' if [] else 'no'
x
```

```
'no'
```

What's going on here?

The rule is:

- Expressions that evaluate to zero, empty sequences or containers (strings, lists, etc.) and `None` are all equivalent to `False`.
  - for example, `[]` and `()` are equivalent to `False` in an `if` clause
- All other values are equivalent to `True`.
  - for example, `42` is equivalent to `True` in an `if` clause

5.5.2 Combining Expressions

We can combine expressions using `and`, `or` and `not`.

These are the standard logical connectives (conjunction, disjunction and denial)

```
1 < 2 and 'f' in 'foo'
```

```
True
```

```
1 < 2 and 'g' in 'foo'
```

```
False
```

```
1 < 2 or 'g' in 'foo'
```

```
True
```

```
not True
```

```
False
```

```
not not True
```

```
True
```

Remember

- `P and Q` is `True` if both are `True`, else `False`
- `P or Q` is `False` if both are `False`, else `True`

We can also use `all()` and `any()` to test a sequence of expressions

```
all([1 <= 2 <= 3, 5 <= 6 <= 7])
```

```
True
```

```
all([1 <= 2 <= 3, "a" in "letter"])
```

```
False
```

```
any([1 <= 2 <= 3, "a" in "letter"])
```

```
True
```

Note:

- `all()` returns `True` when *all* boolean values/expressions in the sequence are `True`
- `any()` returns `True` when *any* boolean values/expressions in the sequence are `True`

5.6 Coding Style and Documentation

A consistent coding style and the use of documentation can make the code easier to understand and maintain.

5.6.1 Python Style Guidelines: PEP8

You can find Python programming philosophy by typing `import this` at the prompt.

Among other things, Python strongly favors consistency in programming style.

We've all heard the saying about consistency and little minds.

In programming, as in mathematics, the opposite is true

- A mathematical paper where the symbols $\cup$ and $\cap$ were reversed would be very hard to read, even if the author told you so on the first page.

In Python, the standard style is set out in PEP8.

(Occasionally we'll deviate from PEP8 in these lectures to better match mathematical notation)

5.6.2 Docstrings

Python has a system for adding comments to modules, classes, functions, etc. called *docstrings*.

The nice thing about docstrings is that they are available at run-time.

Try running this

```
def f(x):
    """
    This function squares its argument
    """
    return x**2
```

After running this code, the docstring is available

```
f?
```

```
Type:       function
String Form:<function f at 0x2223320>
File:       /home/john/temp/temp.py
Definition: f(x)
Docstring:  This function squares its argument
```

```
f??
```

```
Type:       function
String Form:<function f at 0x2223320>
File:       /home/john/temp/temp.py
Definition: f(x)
Source:
def f(x):
    """
    This function squares its argument
    """
    return x**2
```

With one question mark we bring up the docstring, and with two we get the source code as well.

You can find conventions for docstrings in PEP257.

5.7 Exercises

Solve the following exercises.

(For some, the built-in function `sum()` comes in handy).

Exercise 5.7.1

Part 1: Given two numeric lists or tuples `x_vals` and `y_vals` of equal length, compute their inner product using `zip()`.

Part 2: In one line, count the number of even numbers in 0,…,99.

Part 3: Given `pairs = ((2, 5), (4, 2), (9, 8), (12, 10))`, count the number of pairs `(a, b)` such that both `a` and `b` are even.

Hint: `x % 2` returns 0 if `x` is even, 1 otherwise.

Solution to Exercise 5.7.1

Part 1 Solution:

Here's one possible solution

```
x_vals = [1, 2, 3]
y_vals = [1, 1, 1]
sum([x * y for x, y in zip(x_vals, y_vals)])
```

```
6
```

This also works

```
sum(x * y for x, y in zip(x_vals, y_vals))
```

```
6
```

Part 2 Solution:

One solution is

```
sum([x % 2 == 0 for x in range(100)])
```

```
50
```

This also works:

```
sum(x % 2 == 0 for x in range(100))
```

```
50
```

Some less natural alternatives that nonetheless help to illustrate the flexibility of list comprehensions are

```
len([x for x in range(100) if x % 2 == 0])
```

```
50
```

and

```
sum([1 for x in range(100) if x % 2 == 0])
```

```
50
```

Part 3 Solution:

Here's one possibility

```
pairs = ((2, 5), (4, 2), (9, 8), (12, 10))
sum([x % 2 == 0 and y % 2 == 0 for x, y in pairs])
```

```
2
```

Exercise 5.7.2

Consider the polynomial

$$p(x) = a_0 + a_1 x + a_2 x^2 + \cdots a_n x^n = \sum_{i=0}^{n} a_i x^i \tag{5.1}$$

Write a function `p` such that `p(x, coeff)` that computes the value in (5.1) given a point `x` and a list of coefficients `coeff` $(a_1, a_2, \cdots a_n)$.

Try to use `enumerate()` in your loop.

Solution to Exercise 5.7.2

Here's a solution:

```
def p(x, coeff):
    return sum(a * x**i for i, a in enumerate(coeff))
```

```
p(1, (2, 4))
```

```
6
```

Exercise 5.7.3

Write a function that takes a string as an argument and returns the number of capital letters in the string.

Hint: `'foo'.upper()` returns `'FOO'`.

Solution to Exercise 5.7.3

Here's one solution:

```
def f(string):
    count = 0
    for letter in string:
        if letter == letter.upper() and letter.isalpha():
            count += 1
    return count

f('The Rain in Spain')
```

```
3
```

An alternative, more pythonic solution:

```
def count_uppercase_chars(s):
    return sum([c.isupper() for c in s])

count_uppercase_chars('The Rain in Spain')
```

```
3
```

Exercise 5.7.4

Write a function that takes two sequences `seq_a` and `seq_b` as arguments and returns `True` if every element in `seq_a` is also an element of `seq_b`, else `False`.

- By "sequence" we mean a list, a tuple or a string.
- Do the exercise without using sets and set methods.

Solution to Exercise 5.7.4

Here's a solution:

```
def f(seq_a, seq_b):
    for a in seq_a:
        if a not in seq_b:
            return False
    return True

# == test == #
print(f("ab", "cadb"))
print(f("ab", "cjdb"))
print(f([1, 2], [1, 2, 3]))
print(f([1, 2, 3], [1, 2]))
```

```
True
False
True
False
```

An alternative, more pythonic solution using `all()`:

```
def f(seq_a, seq_b):
  return all([i in seq_b for i in seq_a])

# == test == #
print(f("ab", "cadb"))
print(f("ab", "cjdb"))
print(f([1, 2], [1, 2, 3]))
print(f([1, 2, 3], [1, 2]))
```

```
True
False
True
False
```

Of course, if we use the `sets` data type then the solution is easier

```
def f(seq_a, seq_b):
    return set(seq_a).issubset(set(seq_b))
```

Exercise 5.7.5

When we cover the numerical libraries, we will see they include many alternatives for interpolation and function approximation.

Nevertheless, let's write our own function approximation routine as an exercise.

In particular, without using any imports, write a function `linapprox` that takes as arguments

- A function `f` mapping some interval $[a, b]$ into $\mathbb{R}$.
- Two scalars `a` and `b` providing the limits of this interval.
- An integer `n` determining the number of grid points.
- A number `x` satisfying `a <= x <= b`.

and returns the piecewise linear interpolation of `f` at `x`, based on `n` evenly spaced grid points `a = point[0] < point[1] < ... < point[n-1] = b`.

Aim for clarity, not efficiency.

Solution to Exercise 5.7.5

Here's a solution:

```
def linapprox(f, a, b, n, x):
    """
    Evaluates the piecewise linear interpolant of f at x on the interval
    [a, b], with n evenly spaced grid points.

    Parameters
    ==========
        f : function
            The function to approximate

        x, a, b : scalars (floats or integers)
            Evaluation point and endpoints, with a <= x <= b

        n : integer
            Number of grid points

    Returns
    =======
        A float. The interpolant evaluated at x

    """
    length_of_interval = b - a
    num_subintervals = n - 1
    step = length_of_interval / num_subintervals

    # === find first grid point larger than x === #
    point = a
    while point <= x:
        point += step

    # === x must lie between the gridpoints (point - step) and point === #
    u, v = point - step, point

    return f(u) + (x - u) * (f(v) - f(u)) / (v - u)
```

Exercise 5.7.6

Using list comprehension syntax, we can simplify the loop in the following code.

```
import numpy as np

n = 100
ϵ_values = []
for i in range(n):
    e = np.random.randn()
    ϵ_values.append(e)
```

Solution to Exercise 5.7.6

Here's one solution.

```
n = 100
ϵ_values = [np.random.randn() for i in range(n)]
```

CHAPTER

SIX

OOP I: OBJECTS AND NAMES

Contents

6.1 Overview

Object-oriented programming (OOP) is one of the major paradigms in programming.

The traditional programming paradigm (think Fortran, C, MATLAB, etc.) is called *procedural*.

It works as follows

- The program has a state corresponding to the values of its variables.
- Functions are called to act on these data.
- Data are passed back and forth via function calls.

In contrast, in the OOP paradigm

- data and functions are "bundled together" into "objects"

(Functions in this context are referred to as **methods**)

6.1.1 Python and OOP

Python is a pragmatic language that blends object-oriented and procedural styles, rather than taking a purist approach.

However, at a foundational level, Python *is* object-oriented.

In particular, in Python, *everything is an object*.

In this lecture, we explain what that statement means and why it matters.

6.2 Objects

In Python, an *object* is a collection of data and instructions held in computer memory that consists of

1. a type
2. a unique identity
3. data (i.e., content)
4. methods

These concepts are defined and discussed sequentially below.

6.2.1 Type

Python provides for different types of objects, to accommodate different categories of data.

For example

```
s = 'This is a string'
type(s)
```

```
str
```

```
x = 42    # Now let's create an integer
type(x)
```

```
int
```

The type of an object matters for many expressions.

For example, the addition operator between two strings means concatenation

```
'300' + 'cc'
```

```
'300cc'
```

On the other hand, between two numbers it means ordinary addition

```
300 + 400
```

```
700
```

Consider the following expression

```
'300' + 400
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[5], line 1
----> 1 '300' + 400

TypeError: can only concatenate str (not "int") to str
```

Here we are mixing types, and it's unclear to Python whether the user wants to

- convert `'300'` to an integer and then add it to `400`, or
- convert `400` to string and then concatenate it with `'300'`

Some languages might try to guess but Python is *strongly typed*

- Type is important, and implicit type conversion is rare.
- Python will respond instead by raising a `TypeError`.

To avoid the error, you need to clarify by changing the relevant type.

For example,

```
int('300') + 400   # To add as numbers, change the string to an integer
```

```
700
```

6.2.2 Identity

In Python, each object has a unique identifier, which helps Python (and us) keep track of the object.

The identity of an object can be obtained via the `id()` function

```
y = 2.5
z = 2.5
id(y)
```

```
140472214388432
```

```
id(z)
```

```
140472214388240
```

In this example, `y` and `z` happen to have the same value (i.e., `2.5`), but they are not the same object.

The identity of an object is in fact just the address of the object in memory.

6.2.3 Object Content: Data and Attributes

If we set `x = 42` then we create an object of type `int` that contains the data `42`.

In fact, it contains more, as the following example shows

```
x = 42
x
```

```
42
```

```
x.imag
```

```
0
```

```
x.__class__
```

```
int
```

When Python creates this integer object, it stores with it various auxiliary information, such as the imaginary part, and the type.

Any name following a dot is called an *attribute* of the object to the left of the dot.

- e.g.,`imag` and `__class__` are attributes of `x`.

We see from this example that objects have attributes that contain auxiliary information.

They also have attributes that act like functions, called *methods*.

These attributes are important, so let's discuss them in-depth.

6.2.4 Methods

Methods are *functions that are bundled with objects*.

Formally, methods are attributes of objects that are callable (i.e., can be called as functions)

```
x = ['foo', 'bar']
callable(x.append)
```

```
True
```

```
callable(x.__doc__)
```

```
False
```

Methods typically act on the data contained in the object they belong to, or combine that data with other data

```
x = ['a', 'b']
x.append('c')
s = 'This is a string'
s.upper()
```

```
'THIS IS A STRING'
```

```
s.lower()
```

```
'this is a string'
```

```
s.replace('This', 'That')
```

```
'That is a string'
```

A great deal of Python functionality is organized around method calls.

For example, consider the following piece of code

```
x = ['a', 'b']
x[0] = 'aa'  # Item assignment using square bracket notation
x
```

```
['aa', 'b']
```

It doesn't look like there are any methods used here, but in fact the square bracket assignment notation is just a convenient interface to a method call.

What actually happens is that Python calls the `__setitem__` method, as follows

```
x = ['a', 'b']
x.__setitem__(0, 'aa')  # Equivalent to x[0] = 'aa'
x
```

```
['aa', 'b']
```

(If you wanted to you could modify the `__setitem__` method, so that square bracket assignment does something totally different)

6.3 Names and Name Resolution

6.3.1 Variable Names in Python

Consider the Python statement

```
x = 42
```

We now know that when this statement is executed, Python creates an object of type `int` in your computer's memory, containing

- the value `42`
- some associated attributes

But what is `x` itself?

In Python, `x` is called a *name*, and the statement `x = 42` *binds* the name `x` to the integer object we have just discussed.

Under the hood, this process of binding names to objects is implemented as a dictionary—more about this in a moment.

There is no problem binding two or more names to the one object, regardless of what that object is

```
def f(string):      # Create a function called f
    print(string)   # that prints any string it's passed

g = f
id(g) == id(f)
```

```
True
```

```
g('test')
```

```
test
```

In the first step, a function object is created, and the name `f` is bound to it.

After binding the name `g` to the same object, we can use it anywhere we would use `f`.

What happens when the number of names bound to an object goes to zero?

Here's an example of this situation, where the name `x` is first bound to one object and then rebound to another

```
x = 'foo'
id(x)
```

```
140472239369648
```

```
x = 'bar'  # No names bound to the first object
```

What happens here is that the first object is garbage collected.

In other words, the memory slot that stores that object is deallocated, and returned to the operating system.

Garbage collection is actually an active research area in computer science.

You can read more on garbage collection if you are interested.

6.3.2 Namespaces

Recall from the preceding discussion that the statement

```
x = 42
```

binds the name `x` to the integer object on the right-hand side.

We also mentioned that this process of binding `x` to the correct object is implemented as a dictionary.

This dictionary is called a *namespace*.

Definition: A namespace is a symbol table that maps names to objects in memory.

Python uses multiple namespaces, creating them on the fly as necessary.

For example, every time we import a module, Python creates a namespace for that module.

To see this in action, suppose we write a script `mathfoo.py` with a single line

```
%%file mathfoo.py
pi = 'foobar'
```

```
Writing mathfoo.py
```

Now we start the Python interpreter and import it

```
import mathfoo
```

Next let's import the `math` module from the standard library

```
import math
```

Both of these modules have an attribute called `pi`

```
math.pi
```

```
3.141592653589793
```

```
mathfoo.pi
```

```
'foobar'
```

These two different bindings of `pi` exist in different namespaces, each one implemented as a dictionary.

We can look at the dictionary directly, using `module_name.__dict__`

```
import math

math.__dict__.items()
```

```
dict_items([('__name__', 'math'), ('__doc__', 'This module provides access to the␣
↪mathematical functions\ndefined by the C standard.'), ('__package__', ''), ('__
↪loader__', <_frozen_importlib_external.ExtensionFileLoader object at␣
↪0x7fc23f2bba50>), ('__spec__', ModuleSpec(name='math', loader=<_frozen_importlib_
↪external.ExtensionFileLoader object at 0x7fc23f2bba50>, origin='/usr/share/
↪miniconda3/envs/quantecon/lib/python3.11/lib-dynload/math.cpython-311-x86_64-
↪linux-gnu.so')), ('acos', <built-in function acos>), ('acosh', <built-in␣
↪function acosh>), ('asin', <built-in function asin>), ('asinh', <built-in␣
↪function asinh>), ('atan', <built-in function atan>), ('atan2', <built-in␣
↪function atan2>), ('atanh', <built-in function atanh>), ('cbrt', <built-in␣
↪function cbrt>), ('ceil', <built-in function ceil>), ('copysign', <built-in␣
```

(continues on next page)

(continued from previous page)

```
import mathfoo

mathfoo.__dict__.items()
```

```
dict_items([('__name__', 'mathfoo'), ('__doc__', None), ('__package__', ''), ('__
↪loader__', <_frozen_importlib_external.SourceFileLoader object at 0x7fc23fb7b350>
↪), ('__spec__', ModuleSpec(name='mathfoo', loader=<_frozen_importlib_external.
↪SourceFileLoader object at 0x7fc23fb7b350>, origin='/home/runner/work/lecture-
↪python-programming.myst/lecture-python-programming.myst/lectures/mathfoo.py')), (
↪'__file__', '/home/runner/work/lecture-python-programming.myst/lecture-python-
↪programming.myst/lectures/mathfoo.py'), ('__cached__', '/home/runner/work/
↪lecture-python-programming.myst/lecture-python-programming.myst/lectures/__
↪pycache__/mathfoo.cpython-311.pyc'), ('__builtins__', {'__name__': 'builtins', '_
↪_doc__': "Built-in functions, types, exceptions, and other objects.\n\nThis␣
↪module provides direct access to all 'built-in'\nidentifiers of Python; for␣
↪example, builtins.len is\nthe full name for the built-in function len().\n\nThis␣
↪module is not normally accessed explicitly by most\napplications, but can be␣
↪useful in modules that provide\nobjects with the same name as a built-in value,␣
↪but in\nwhich the built-in of that name is also needed.", '__package__': '', '__
↪loader__': <class '_frozen_importlib.BuiltinImporter'>, '__spec__':␣
↪ModuleSpec(name='builtins', loader=<class '_frozen_importlib.BuiltinImporter'>,␣
↪origin='built-in'), '__build_class__': <built-in function __build_class__>, '__
↪import__': <built-in function __import__>, 'abs': <built-in function abs>, 'all
↪': <built-in function all>, 'any': <built-in function any>, 'ascii': <built-in␣
↪function ascii>, 'bin': <built-in function bin>, 'breakpoint': <built-in␣
↪function breakpoint>, 'callable': <built-in function callable>, 'chr': <built-in␣
↪function chr>, 'compile': <built-in function compile>, 'delattr': <built-in␣
↪function delattr>, 'dir': <built-in function dir>, 'divmod': <built-in function␣
↪divmod>, 'eval': <built-in function eval>, 'exec': <built-in function exec>,
↪'format': <built-in function format>, 'getattr': <built-in function getattr>,
↪'globals': <built-in function globals>, 'hasattr': <built-in function hasattr>,
↪'hash': <built-in function hash>, 'hex': <built-in function hex>, 'id': <built-
↪in function id>, 'input': <bound method Kernel.raw_input of <ipykernel.ipkernel.
↪IPythonKernel object at 0x7fc23c5f0790>>, 'isinstance': <built-in function␣
↪isinstance>, 'issubclass': <built-in function issubclass>, 'iter': <built-in␣
↪function iter>, 'aiter': <built-in function aiter>, 'len': <built-in function␣
↪len>, 'locals': <built-in function locals>, 'max': <built-in function max>, 'min
↪': <built-in function min>, 'next': <built-in function next>, 'anext': <built-in␣
↪function anext>, 'oct': <built-in function oct>, 'ord': <built-in function ord>,
↪'pow': <built-in function pow>, 'print': <built-in function print>, 'repr':
↪<built-in function repr>, 'round': <built-in function round>, 'setattr': <built-
↪in function setattr>, 'sorted': <built-in function sorted>, 'sum': <built-in␣
↪function sum>, 'vars': <built-in function vars>, 'None': None, 'Ellipsis':␣
↪Ellipsis, 'NotImplemented': NotImplemented, 'False': False, 'True': True, 'bool
↪': <class 'bool'>, 'memoryview': <class 'memoryview'>, 'bytearray': <class
↪'bytearray'>, 'bytes': <class 'bytes'>, 'classmethod': <class 'classmethod'>,
↪'complex': <class 'complex'>, 'dict': <class 'dict'>, 'enumerate': <class
↪'enumerate'>, 'filter': <class 'filter'>, 'float': <class 'float'>, 'frozenset':
↪<class 'frozenset'>, 'property': <class 'property'>, 'int': <class 'int'>, 'list
↪': <class 'list'>, 'map': <class 'map'>, 'object': <class 'object'>, 'range':
↪<class 'range'>, 'reversed': <class 'reversed'>, 'set': <class 'set'>, 'slice':
↪<class 'slice'>, 'staticmethod': <class 'staticmethod'>, 'str': <class 'str'>,
↪'super': <class 'super'>, 'tuple': <class 'tuple'>, 'type': <class 'type'>, 'zip
↪': <class 'zip'>, '__debug__': True, 'BaseException': <class 'BaseException'>,
↪'BaseExceptionGroup': <class 'BaseExceptionGroup'>, 'Exception': <class
↪'Exception'>, 'GeneratorExit': <class 'GeneratorExit'>, 'KeyboardInterrupt':
↪<class 'KeyboardInterrupt'>, 'SystemExit': <class 'SystemExit'>, 'ArithmeticError
↪': <class 'ArithmeticError'>, 'AssertionError': <class 'AssertionError'>,
↪'AttributeError': <class 'AttributeError'>, 'BufferError': <class 'BufferError'>,
↪ 'EOFError': <class 'EOFError'>, 'ImportError': <class 'ImportError'>,
↪'LookupError': <class 'LookupError'>, 'MemoryError': <class 'MemoryError'>,
```

(continues on next page)

(continued from previous page)

```
All Rights Reserved.

Copyright (c) 2000 BeOpen.com.
All Rights Reserved.

Copyright (c) 1995-2001 Corporation for National Research Initiatives.
All Rights Reserved.

Copyright (c) 1991-1995 Stichting Mathematisch Centrum, Amsterdam.
All Rights Reserved., 'credits':     Thanks to CWI, CNRI, BeOpen.com, Zope␣
↪Corporation and a cast of thousands
    for supporting Python development.  See www.python.org for more information.,
↪'license': Type license() to see the full license text, 'help': Type help() for␣
↪interactive help, or help(object) for help about object., 'execfile': <function␣
↪execfile at 0x7fc23cb258a0>, 'runfile': <function runfile at 0x7fc23ca48e00>, '__
↪IPYTHON__': True, 'display': <function display at 0x7fc23dc2f420>, 'get_ipython
↪': <bound method InteractiveShell.get_ipython of <ipykernel.zmqshell.
↪ZMQInteractiveShell object at 0x7fc23c5f1590>>}), ('pi', 'foobar')])
```

As you know, we access elements of the namespace using the dotted attribute notation

```
math.pi
```

```
3.141592653589793
```

In fact this is entirely equivalent to `math.__dict__['pi']`

```
math.__dict__['pi'] == math.pi
```

```
True
```

6.3.3 Viewing Namespaces

As we saw above, the `math` namespace can be printed by typing `math.__dict__`.

Another way to see its contents is to type `vars(math)`

```
vars(math).items()
```

```
dict_items([('__name__', 'math'), ('__doc__', 'This module provides access to the␣
↪mathematical functions\ndefined by the C standard.'), ('__package__', ''), ('__
↪loader__', <_frozen_importlib_external.ExtensionFileLoader object at␣
↪0x7fc23f2bba50>), ('__spec__', ModuleSpec(name='math', loader=<_frozen_importlib_
↪external.ExtensionFileLoader object at 0x7fc23f2bba50>, origin='/usr/share/
↪miniconda3/envs/quantecon/lib/python3.11/lib-dynload/math.cpython-311-x86_64-
↪linux-gnu.so')), ('acos', <built-in function acos>), ('acosh', <built-in␣
↪function acosh>), ('asin', <built-in function asin>), ('asinh', <built-in␣
↪function asinh>), ('atan', <built-in function atan>), ('atan2', <built-in␣
↪function atan2>), ('atanh', <built-in function atanh>), ('cbrt', <built-in␣
↪function cbrt>), ('ceil', <built-in function ceil>), ('copysign', <built-in␣
↪function copysign>), ('cos', <built-in function cos>), ('cosh', <built-in␣
↪function cosh>), ('degrees', <built-in function degrees>), ('dist', <built-in␣
↪function dist>), ('erf', <built-in function erf>), ('erfc', <built-in function␣
↪erfc>), ('exp', <built-in function exp>), ('exp2', <built-in function exp2>), (
↪'expm1', <built-in function expm1>), ('fabs', <built-in function fabs>), (
↪'factorial', <built-in function factorial>), ('floor', <built-in function floor>
↪), ('fmod', <built-in function fmod>), ('frexp', <built-in function frexp>), (
↪'fsum', <built-in function fsum>), ('gamma', <built-in function gamma>), ('gcd',
↪<built-in function gcd>), ('hypot', <built-in function hypot>), ('isclose',
↪<built-in function isclose>), ('isfinite', <built-in function isfinite>), ('isinf
```

(continues on next page)

(continued from previous page)

If you just want to see the names, you can type

```
# Show the first 10 names
dir(math)[0:10]
```

```
['__doc__',
 '__file__',
 '__loader__',
 '__name__',
 '__package__',
 '__spec__',
 'acos',
 'acosh',
 'asin',
 'asinh']
```

Notice the special names `__doc__` and `__name__`.

These are initialized in the namespace when any module is imported

- `__doc__` is the doc string of the module
- `__name__` is the name of the module

```
print(math.__doc__)
```

```
This module provides access to the mathematical functions
defined by the C standard.
```

```
math.__name__
```

```
'math'
```

6.3.4 Interactive Sessions

In Python, **all** code executed by the interpreter runs in some module.

What about commands typed at the prompt?

These are also regarded as being executed within a module — in this case, a module called `__main__`.

To check this, we can look at the current module name via the value of `__name__` given at the prompt

```
print(__name__)
```

```
__main__
```

When we run a script using IPython's `run` command, the contents of the file are executed as part of `__main__` too.

To see this, let's create a file `mod.py` that prints its own `__name__` attribute

```
%%file mod.py
print(__name__)
```

```
Writing mod.py
```

Now let's look at two different ways of running it in IPython

```
import mod  # Standard import
```

```
mod
```

```
%run mod.py  # Run interactively
```

```
__main__
```

In the second case, the code is executed as part of __main__, so __name__ is equal to __main__.

To see the contents of the namespace of __main__ we use `vars()` rather than `vars(__main__)`.

If you do this in IPython, you will see a whole lot of variables that IPython needs, and has initialized when you started up your session.

If you prefer to see only the variables you have initialized, use `%whos`

```
x = 2
y = 3

import numpy as np

%whos
```

```
Variable   Type        Data/Info
--------------------------------
f          function    <function f at 0x7fc238477880>
g          function    <function f at 0x7fc238477880>
math       module      <module 'math' from '/usr<...>311-x86_64-linux-gnu.so'>
mathfoo    module      <module 'mathfoo' from '/<...>yst/lectures/mathfoo.py'>
mod        module      <module 'mod' from '/home<...>ng.myst/lectures/mod.py'>
np         module      <module 'numpy' from '/us<...>kages/numpy/__init__.py'>
s          str         This is a string
x          int         2
y          int         3
z          float       2.5
```

6.3.5 The Global Namespace

Python documentation often makes reference to the "global namespace".

The global namespace is *the namespace of the module currently being executed*.

For example, suppose that we start the interpreter and begin making assignments.

We are now working in the module `__main__`, and hence the namespace for `__main__` is the global namespace.

Next, we import a module called `amodule`

```
import amodule
```

At this point, the interpreter creates a namespace for the module `amodule` and starts executing commands in the module.

While this occurs, the namespace `amodule.__dict__` is the global namespace.

Once execution of the module finishes, the interpreter returns to the module from where the import statement was made.

In this case it's `__main__`, so the namespace of `__main__` again becomes the global namespace.

6.3.6 Local Namespaces

Important fact: When we call a function, the interpreter creates a *local namespace* for that function, and registers the variables in that namespace.

The reason for this will be explained in just a moment.

Variables in the local namespace are called *local variables*.

After the function returns, the namespace is deallocated and lost.

While the function is executing, we can view the contents of the local namespace with `locals()`.

For example, consider

```
def f(x):
    a = 2
    print(locals())
    return a * x
```

Now let's call the function

```
f(1)
```

```
{'x': 1, 'a': 2}
```

```
2
```

You can see the local namespace of `f` before it is destroyed.

6.3.7 The `__builtins__` Namespace

We have been using various built-in functions, such as `max()`, `dir()`, `str()`, `list()`, `len()`, `range()`, `type()`, etc.

How does access to these names work?

- These definitions are stored in a module called `__builtin__`.
- They have their own namespace called `__builtins__`.

```
# Show the first 10 names in `__main__`
dir()[0:10]
```

```
['In', 'Out', '_', '_1', '_10', '_11', '_12', '_13', '_14', '_15']
```

```
# Show the first 10 names in `__builtins__`
dir(__builtins__)[0:10]
```

```
['ArithmeticError',
 'AssertionError',
 'AttributeError',
 'BaseException',
 'BaseExceptionGroup',
 'BlockingIOError',
 'BrokenPipeError',
 'BufferError',
 'BytesWarning',
 'ChildProcessError']
```

We can access elements of the namespace as follows

```
__builtins__.max
```

```
<function max>
```

But `__builtins__` is special, because we can always access them directly as well

```
max
```

```
<function max>
```

```
__builtins__.max == max
```

```
True
```

The next section explains how this works …

6.3.8 Name Resolution

Namespaces are great because they help us organize variable names.

(Type `import this` at the prompt and look at the last item that's printed)

However, we do need to understand how the Python interpreter works with multiple namespaces.

Understanding the flow of execution will help us to check which variables are in scope and how to operate on them when writing and debugging programs.

At any point of execution, there are in fact at least two namespaces that can be accessed directly.

("Accessed directly" means without using a dot, as in `pi` rather than `math.pi`)

These namespaces are

- The global namespace (of the module being executed)
- The builtin namespace

If the interpreter is executing a function, then the directly accessible namespaces are

- The local namespace of the function
- The global namespace (of the module being executed)
- The builtin namespace

Sometimes functions are defined within other functions, like so

```
def f():
    a = 2
    def g():
        b = 4
        print(a * b)
    g()
```

Here `f` is the *enclosing function* for `g`, and each function gets its own namespaces.

Now we can give the rule for how namespace resolution works:

The order in which the interpreter searches for names is

1. the local namespace (if it exists)
2. the hierarchy of enclosing namespaces (if they exist)
3. the global namespace
4. the builtin namespace

If the name is not in any of these namespaces, the interpreter raises a `NameError`.

This is called the **LEGB rule** (local, enclosing, global, builtin).

Here's an example that helps to illustrate.

Visualizations here are created by nbtutor in a Jupyter notebook.

They can help you better understand your program when you are learning a new language.

Consider a script `test.py` that looks as follows

```
%%file test.py
def g(x):
    a = 1
    x = x + a
    return x

a = 0
y = g(10)
print("a = ", a, "y = ", y)
```

```
Writing test.py
```

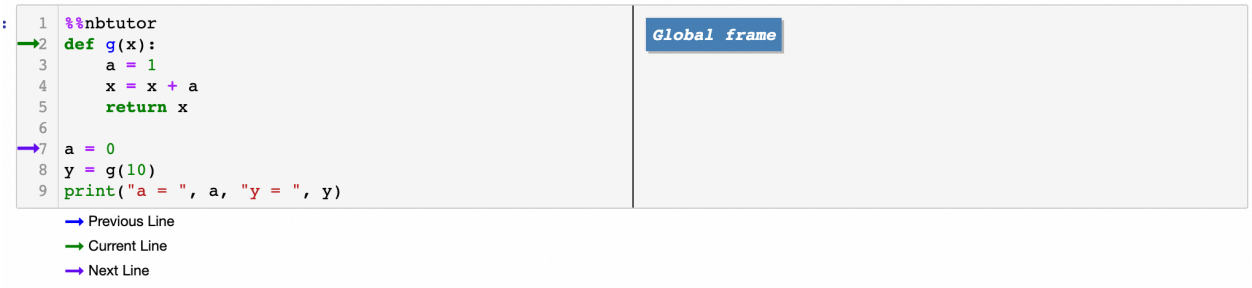
What happens when we run this script?

```
%run test.py
```

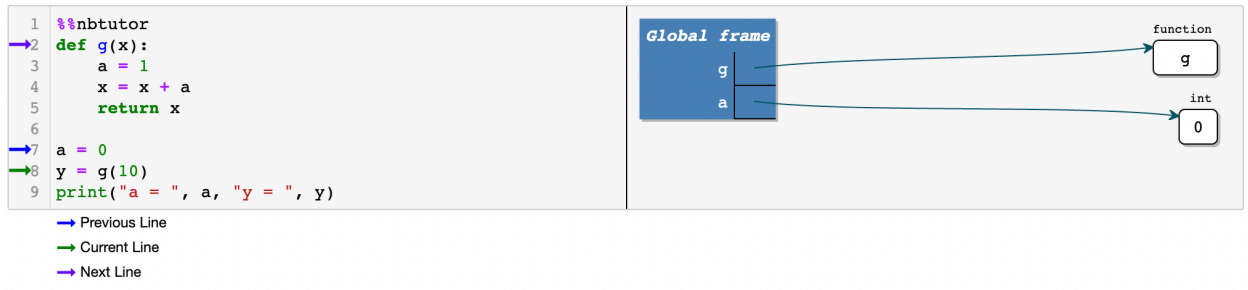
```
a =  0 y =  11
```

First,

- The global namespace `{}` is created.

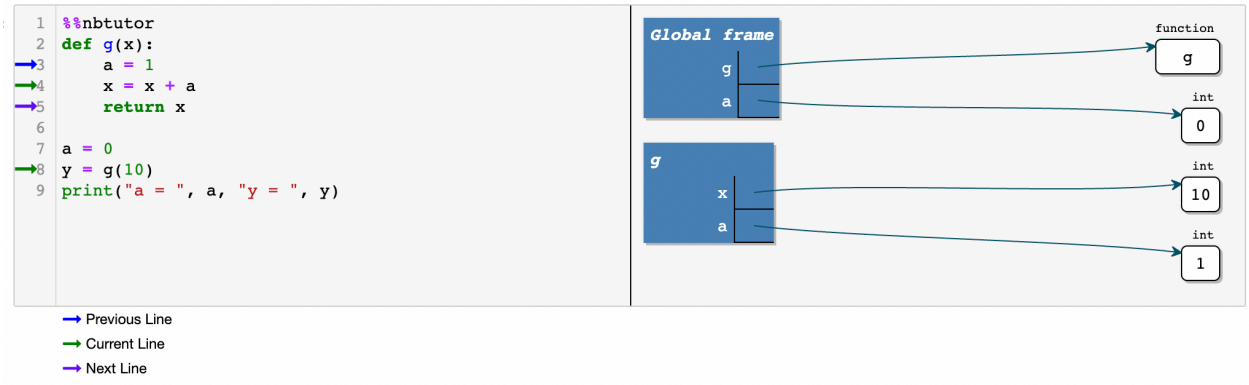


- The function object is created, and `g` is bound to it within the global namespace.
- The name `a` is bound to `0`, again in the global namespace.

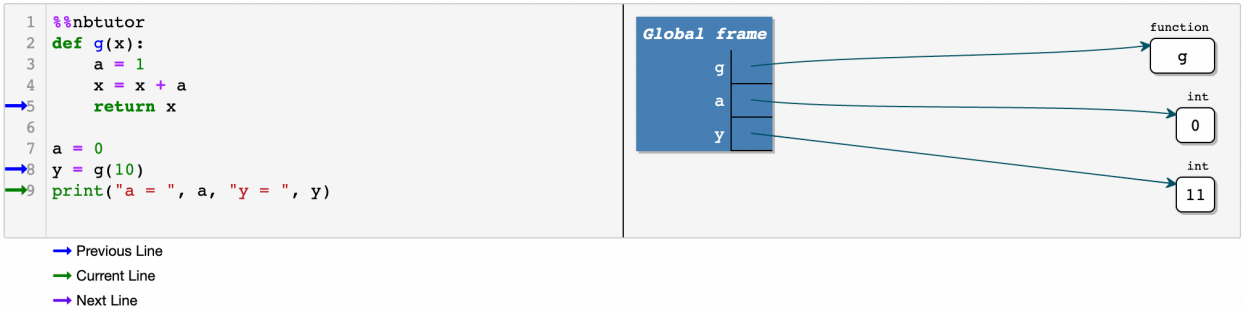


Next `g` is called via `y = g(10)`, leading to the following sequence of actions

- The local namespace for the function is created.
- Local names `x` and `a` are bound, so that the local namespace becomes `{'x': 10, 'a': 1}`.
  - Note that the global `a` was not affected by the local `a`.
- Statement `x = x + a` uses the local `a` and local `x` to compute `x + a`, and binds local name `x` to the result.



- This value is returned, and `y` is bound to it in the global namespace.
- Local `x` and `a` are discarded (and the local namespace is deallocated).



6.3.9 Mutable Versus Immutable Parameters

This is a good time to say a little more about mutable vs immutable objects.

Consider the code segment

```
def f(x):
    x = x + 1
    return x

x = 1
print(f(x), x)
```

```
2 1
```

We now understand what will happen here: The code prints `2` as the value of `f(x)` and `1` as the value of `x`.

First `f` and `x` are registered in the global namespace.

The call `f(x)` creates a local namespace and adds `x` to it, bound to `1`.

Next, this local `x` is rebound to the new integer object `2`, and this value is returned.

None of this affects the global `x`.

However, it's a different story when we use a **mutable** data type such as a list

```
def f(x):
    x[0] = x[0] + 1
    return x

x = [1]
print(f(x), x)
```

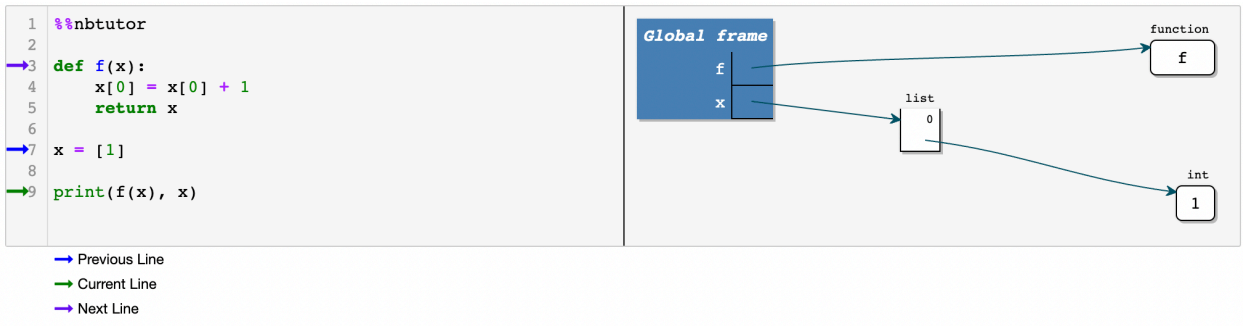
```
[2] [2]
```

This prints `[2]` as the value of `f(x)` and *same* for `x`.

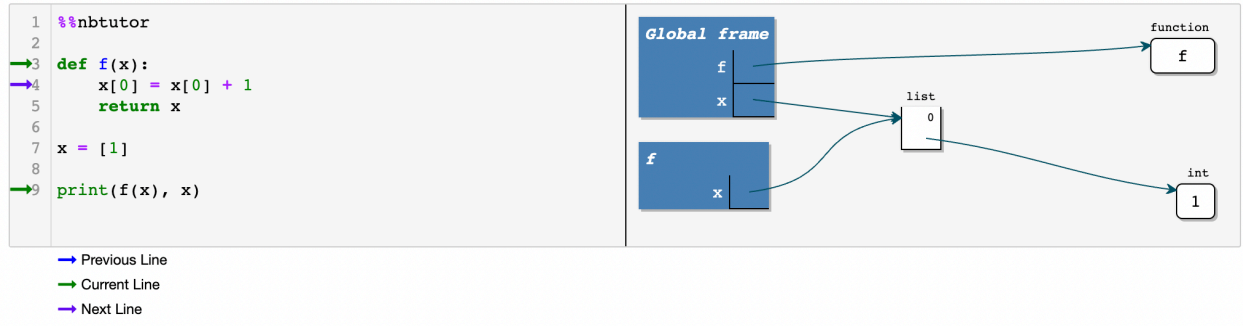
Here's what happens

- `f` is registered as a function in the global namespace

- `x` bound to `[1]` in the global namespace



- The call `f(x)`
  - Creates a local namespace
  - Adds `x` to the local namespace, bound to `[1]`



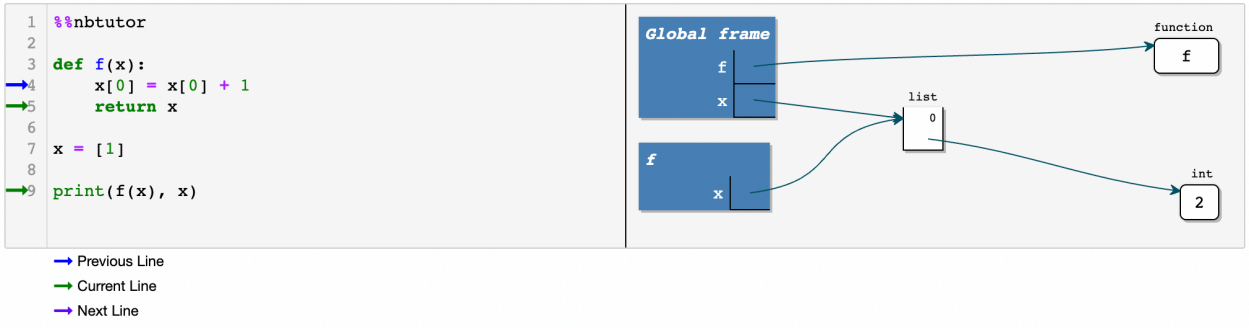
Note: The global `x` and the local `x` refer to the same `[1]`

We can see the identity of local `x` and the identity of global `x` are the same

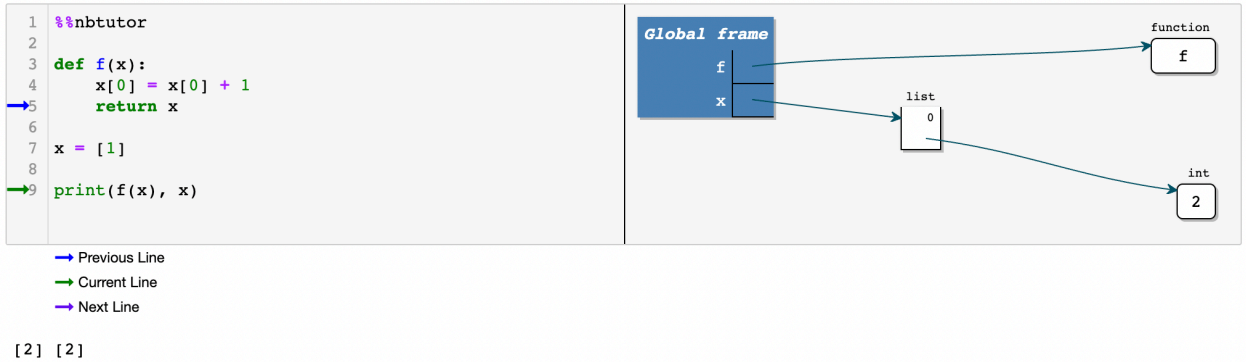
```
def f(x):
    x[0] = x[0] + 1
    print(f'the identity of local x is {id(x)}')
    return x

x = [1]
print(f'the identity of global x is {id(x)}')
print(f(x), x)
```

```
the identity of global x is 140471461499776
the identity of local x is 140471461499776
[2] [2]
```

- Within `f(x)`
  - The list `[1]` is modified to `[2]`
  - Returns the list `[2]`



- The local namespace is deallocated, and the local `x` is lost




```
[2] [2]
```

If you want to modify the local `x` and the global `x` separately, you can create a *copy* of the list and assign the copy to the local `x`.

We will leave this for you to explore.

6.4 Summary

Messages in this lecture are clear:

- In Python, *everything in memory is treated as an object*.
- Zero, one or many names can be bound to a given object.
- Every name resides within a scope defined by its namespace.

This includes not just lists, strings, etc., but also less obvious things, such as

- functions (once they have been read into memory)
- modules (ditto)
- files opened for reading or writing
- integers, etc.

Consider, for example, functions.

When Python reads a function definition, it creates a **function object** and stores it in memory.

The following code illustrates further this idea

```
#reset the current namespace
%reset
```

```
def f(x): return x**2
f
```

```
<function __main__.f(x)>
```

```
type(f)
```

```
function
```

```
id(f)
```

```
140472213439648
```

```
f.__name__
```

```
'f'
```

We can see that `f` has type, identity, attributes and so on—just like any other object.

It also has methods.

One example is the `__call__` method, which just evaluates the function

```
f.__call__(3)
```

```
9
```

Another is the `__dir__` method, which returns a list of attributes.

We can also find `f` our current namespace

```
'f' in dir()
```

```
True
```

Modules loaded into memory are also treated as objects

```
import math

id(math)
```

```
140472260240432
```

We can find `math` in our global namespace after the import

```
print(dir()[-1::-1])
```

```
['quit', 'open', 'math', 'get_ipython', 'f', 'exit', '_oh', '_iii', '_ii', '_ih',
 ↪'_i64', '_i63', '_i62', '_i61', '_i60', '_i59', '_i58', '_i57', '_i', '_dh', '__
 ↪name__', '__builtins__', '__builtin__', '___', '__', '_63', '_62', '_61', '_60',
 ↪'_59', '_58', '_57', '_', 'Out', 'In']
```

We can also find all objects associated with the `math` module in the private namespace of `math`

```
print(dir(math))
```

```
['__doc__', '__file__', '__loader__', '__name__', '__package__', '__spec__', 'acos
 ↪', 'acosh', 'asin', 'asinh', 'atan', 'atan2', 'atanh', 'cbrt', 'ceil', 'comb',
 ↪'copysign', 'cos', 'cosh', 'degrees', 'dist', 'e', 'erf', 'erfc', 'exp', 'exp2',
 ↪'expm1', 'fabs', 'factorial', 'floor', 'fmod', 'frexp', 'fsum', 'gamma', 'gcd',
 ↪'hypot', 'inf', 'isclose', 'isfinite', 'isinf', 'isnan', 'isqrt', 'lcm', 'ldexp',
 ↪ 'lgamma', 'log', 'log10', 'log1p', 'log2', 'modf', 'nan', 'nextafter', 'perm',
 ↪'pi', 'pow', 'prod', 'radians', 'remainder', 'sin', 'sinh', 'sqrt', 'tan', 'tanh
 ↪', 'tau', 'trunc', 'ulp']
```

We can also directly import objects to our current namespace using `from ... import ...`

```
from math import log, pi, sqrt

print(dir()[-1::-1])
```

```
['sqrt', 'quit', 'pi', 'open', 'math', 'log', 'get_ipython', 'f', 'exit', '_oh', '_
 ↪iii', '_ii', '_ih', '_i66', '_i65', '_i64', '_i63', '_i62', '_i61', '_i60', '_i59
 ↪', '_i58', '_i57', '_i', '_dh', '__name__', '__builtins__', '__builtin__', '___',
 ↪ '__', '_63', '_62', '_61', '_60', '_59', '_58', '_57', '_', 'Out', 'In']
```

We can find these names appear in the current namespace now.

This uniform treatment of data in Python (everything is an object) helps keep the language simple and consistent.

6.5 Exercises

Exercise 6.5.1

We have met the *boolean data type* previously. Using what we have learnt in this lecture, print a list of methods of boolean objects.

Hint: You can use `callable()` to test whether an attribute of an object can be called as a function

Solution to Exercise 6.5.1

Firstly, we need to find all attributes of a boolean object.

You can use one of the following ways:

1. You can call the `.__dir__()` method

```
print(sorted(True.__dir__()))
```

```
['__abs__', '__add__', '__and__', '__bool__', '__ceil__', '__class__', '__delattr__
 ↪', '__dir__', '__divmod__', '__doc__', '__eq__', '__float__', '__floor__', '__
 ↪floordiv__', '__format__', '__ge__', '__getattribute__', '__getnewargs__', '__
 ↪getstate__', '__gt__', '__hash__', '__index__', '__init__', '__init_subclass__',
 ↪'__int__', '__invert__', '__le__', '__lshift__', '__lt__', '__mod__', '__mul__',
 ↪'__ne__', '__neg__', '__new__', '__or__', '__pos__', '__pow__', '__radd__', '__
 ↪rand__', '__rdivmod__', '__reduce__', '__reduce_ex__', '__repr__', '__rfloordiv__
 ↪', '__rlshift__', '__rmod__', '__rmul__', '__ror__', '__round__', '__rpow__', '__
 ↪rrshift__', '__rshift__', '__rsub__', '__rtruediv__', '__rxor__', '__setattr__',
 ↪'__sizeof__', '__str__', '__sub__', '__subclasshook__', '__truediv__', '__trunc__
 ↪', '__xor__', 'as_integer_ratio', 'bit_count', 'bit_length', 'conjugate',
 ↪'denominator', 'from_bytes', 'imag', 'numerator', 'real', 'to_bytes']
```

2. You can use the built-in function `dir()`

```
print(sorted(dir(True)))
```

```
['__abs__', '__add__', '__and__', '__bool__', '__ceil__', '__class__', '__delattr__
 ↪', '__dir__', '__divmod__', '__doc__', '__eq__', '__float__', '__floor__', '__
 ↪floordiv__', '__format__', '__ge__', '__getattribute__', '__getnewargs__', '__
 ↪getstate__', '__gt__', '__hash__', '__index__', '__init__', '__init_subclass__',
 ↪'__int__', '__invert__', '__le__', '__lshift__', '__lt__', '__mod__', '__mul__',
 ↪'__ne__', '__neg__', '__new__', '__or__', '__pos__', '__pow__', '__radd__', '__
 ↪rand__', '__rdivmod__', '__reduce__', '__reduce_ex__', '__repr__', '__rfloordiv__
 ↪', '__rlshift__', '__rmod__', '__rmul__', '__ror__', '__round__', '__rpow__', '__
 ↪rrshift__', '__rshift__', '__rsub__', '__rtruediv__', '__rxor__', '__setattr__',
 ↪'__sizeof__', '__str__', '__sub__', '__subclasshook__', '__truediv__', '__trunc__
 ↪', '__xor__', 'as_integer_ratio', 'bit_count', 'bit_length', 'conjugate',
 ↪'denominator', 'from_bytes', 'imag', 'numerator', 'real', 'to_bytes']
```

3. Since the boolean data type is a primitive type, you can also find it in the built-in namespace

```
print(dir(__builtins__.bool))
```

```
['__abs__', '__add__', '__and__', '__bool__', '__ceil__', '__class__', '__delattr__
 ↪', '__dir__', '__divmod__', '__doc__', '__eq__', '__float__', '__floor__', '__
 ↪floordiv__', '__format__', '__ge__', '__getattribute__', '__getnewargs__', '__
 ↪getstate__', '__gt__', '__hash__', '__index__', '__init__', '__init_subclass__',
 ↪'__int__', '__invert__', '__le__', '__lshift__', '__lt__', '__mod__', '__mul__',
 ↪'__ne__', '__neg__', '__new__', '__or__', '__pos__', '__pow__', '__radd__', '__
 ↪rand__', '__rdivmod__', '__reduce__', '__reduce_ex__', '__repr__', '__rfloordiv__
 ↪', '__rlshift__', '__rmod__', '__rmul__', '__ror__', '__round__', '__rpow__', '__
 ↪rrshift__', '__rshift__', '__rsub__', '__rtruediv__', '__rxor__', '__setattr__',
 ↪'__sizeof__', '__str__', '__sub__', '__subclasshook__', '__truediv__', '__trunc__
 ↪', '__xor__', 'as_integer_ratio', 'bit_count', 'bit_length', 'conjugate',
 ↪'denominator', 'from_bytes', 'imag', 'numerator', 'real', 'to_bytes']
```

Next, we can use a `for` loop to filter out attributes that are callable

```
attrls = dir(__builtins__.bool)
callablels = list()

for i in attrls:
  # Use eval() to evaluate a string as an expression
  if callable(eval(f'True.{i}')):
    callablels.append(i)
print(callablels)
```

```
['__abs__', '__add__', '__and__', '__bool__', '__ceil__', '__class__', '__delattr__
 ↪', '__dir__', '__divmod__', '__eq__', '__float__', '__floor__', '__floordiv__',
 ↪'__format__', '__ge__', '__getattribute__', '__getnewargs__', '__getstate__', '__
 ↪gt__', '__hash__', '__index__', '__init__', '__init_subclass__', '__int__', '__
 ↪invert__', '__le__', '__lshift__', '__lt__', '__mod__', '__mul__', '__ne__', '__
 ↪neg__', '__new__', '__or__', '__pos__', '__pow__', '__radd__', '__rand__', '__
 ↪rdivmod__', '__reduce__', '__reduce_ex__', '__repr__', '__rfloordiv__', '__
 ↪rlshift__', '__rmod__', '__rmul__', '__ror__', '__round__', '__rpow__', '__
 ↪rrshift__', '__rshift__', '__rsub__', '__rtruediv__', '__rxor__', '__setattr__',
 ↪'__sizeof__', '__str__', '__sub__', '__subclasshook__', '__truediv__', '__trunc__
 ↪', '__xor__', 'as_integer_ratio', 'bit_count', 'bit_length', 'conjugate', 'from_
 ↪bytes', 'to_bytes']
```

Here is a one-line solution

```
print([i for i in attrls if callable(eval(f'True.{i}'))])
```

```
['__abs__', '__add__', '__and__', '__bool__', '__ceil__', '__class__', '__delattr__
 ↪', '__dir__', '__divmod__', '__eq__', '__float__', '__floor__', '__floordiv__',
 ↪'__format__', '__ge__', '__getattribute__', '__getnewargs__', '__getstate__', '__
 ↪gt__', '__hash__', '__index__', '__init__', '__init_subclass__', '__int__', '__
 ↪invert__', '__le__', '__lshift__', '__lt__', '__mod__', '__mul__', '__ne__', '__
 ↪neg__', '__new__', '__or__', '__pos__', '__pow__', '__radd__', '__rand__', '__
 ↪rdivmod__', '__reduce__', '__reduce_ex__', '__repr__', '__rfloordiv__', '__
 ↪rlshift__', '__rmod__', '__rmul__', '__ror__', '__round__', '__rpow__', '__
 ↪rrshift__', '__rshift__', '__rsub__', '__rtruediv__', '__rxor__', '__setattr__',
 ↪'__sizeof__', '__str__', '__sub__', '__subclasshook__', '__truediv__', '__trunc__
 ↪', '__xor__', 'as_integer_ratio', 'bit_count', 'bit_length', 'conjugate', 'from_
 ↪bytes', 'to_bytes']
```

(continues on next page)

(continued from previous page)

You can explore these methods and see what they are used for.

CHAPTER

SEVEN

OOP II: BUILDING CLASSES

Contents

7.1 Overview

In an *earlier lecture*, we learned some foundations of object-oriented programming.

The objectives of this lecture are

- cover OOP in more depth
- learn how to build our own objects, specialized to our needs

For example, you already know how to

- create lists, strings and other Python objects
- use their methods to modify their contents

So imagine now you want to write a program with consumers, who can

- hold and spend cash
- consume goods
- work and earn cash

A natural solution in Python would be to create consumers as objects with

- data, such as cash on hand
- methods, such as `buy` or `work` that affect this data

Python makes it easy to do this, by providing you with **class definitions**.

Classes are blueprints that help you build objects according to your own specifications.

It takes a little while to get used to the syntax so we'll provide plenty of examples.

We'll use the following imports:

```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

7.2 OOP Review

OOP is supported in many languages:

- JAVA and Ruby are relatively pure OOP.
- Python supports both procedural and object-oriented programming.
- Fortran and MATLAB are mainly procedural, some OOP recently tacked on.
- C is a procedural language, while C++ is C with OOP added on top.

Let's cover general OOP concepts before we specialize to Python.

7.2.1 Key Concepts

As discussed an *earlier lecture*, in the OOP paradigm, data and functions are **bundled together** into "objects".

An example is a Python list, which not only stores data but also knows how to sort itself, etc.

```
x = [1, 5, 4]
x.sort()
x
```

```
[1, 4, 5]
```

As we now know, `sort` is a function that is "part of" the list object — and hence called a *method*.

If we want to make our own types of objects we need to use class definitions.

A *class definition* is a blueprint for a particular class of objects (e.g., lists, strings or complex numbers).

It describes

- What kind of data the class stores
- What methods it has for acting on these data

An *object* or *instance* is a realization of the class, created from the blueprint

- Each instance has its own unique data.
- Methods set out in the class definition act on this (and other) data.

In Python, the data and methods of an object are collectively referred to as *attributes*.

Attributes are accessed via "dotted attribute notation"

- `object_name.data`
- `object_name.method_name()`

In the example

```
x = [1, 5, 4]
x.sort()
x.__class__
```

```
list
```

- `x` is an object or instance, created from the definition for Python lists, but with its own particular data.
- `x.sort()` and `x.__class__` are two attributes of `x`.
- `dir(x)` can be used to view all the attributes of `x`.

7.2.2 Why is OOP Useful?

OOP is useful for the same reason that abstraction is useful: for recognizing and exploiting the common structure.

For example,

- *a Markov chain* consists of a set of states, an initial probability distribution over states, and a collection of probabilities of moving across states
- *a general equilibrium theory* consists of a commodity space, preferences, technologies, and an equilibrium definition
- *a game* consists of a list of players, lists of actions available to each player, each player's payoffs as functions of all other players' actions, and a timing protocol

These are all abstractions that collect together "objects" of the same "type".

Recognizing common structure allows us to employ common tools.

In economic theory, this might be a proposition that applies to all games of a certain type.

In Python, this might be a method that's useful for all Markov chains (e.g., `simulate`).

When we use OOP, the `simulate` method is conveniently bundled together with the Markov chain object.

7.3 Defining Your Own Classes

Let's build some simple classes to start off.

Before we do so, in order to indicate some of the power of Classes, we'll define two functions that we'll call `earn` and `spend`.

```
def earn(w,y):
    "Consumer with inital wealth w earns y"
    return w+y

def spend(w,x):
    "consumer with initial wealth w spends x"
    new_wealth = w -x
    if new_wealth < 0:
        print("Insufficient funds")
    else:
        return new_wealth
```

The `earn` function takes a consumer's initial wealth w and adds to it her current earnings y.

The `spend` function takes a consumer's initial wealth w and deducts from it her current spending x.

We can use these two functions to keep track of a consumer's wealth as she earns and spends.

For example

```
w0=100
w1=earn(w0,10)
w2=spend(w1,20)
w3=earn(w2,10)
w4=spend(w3,20)
print("w0,w1,w2,w3,w4 = ", w0,w1,w2,w3,w4)
```

```
w0,w1,w2,w3,w4 =  100 110 90 100 80
```

A *Class* bundles a set of data tied to a particular *instance* together with a collection of functions that operate on the data.

In our example, an *instance* will be the name of particular *person* whose *instance data* consist solely of its wealth.

(In other examples *instance data* will consist of a vector of data.)

In our example, two functions `earn` and `spend` can be applied to the current instance data.

Taken together, the instance data and functions are called *methods*.

These can be readily accessed in ways that we shall describe now.

7.3.1 Example: A Consumer Class

We'll build a `Consumer` class with

- a `wealth` attribute that stores the consumer's wealth (data)
- an `earn` method, where `earn(y)` increments the consumer's wealth by `y`
- a `spend` method, where `spend(x)` either decreases wealth by `x` or returns an error if insufficient funds exist

Admittedly a little contrived, this example of a class helps us internalize some peculiar syntax.

Here how we set up our Consumer class.

```
class Consumer:

    def __init__(self, w):
        "Initialize consumer with w dollars of wealth"
        self.wealth = w

    def earn(self, y):
        "The consumer earns y dollars"
        self.wealth += y

    def spend(self, x):
        "The consumer spends x dollars if feasible"
        new_wealth = self.wealth - x
        if new_wealth < 0:
            print("Insufficent funds")
        else:
            self.wealth = new_wealth
```

There's some special syntax here so let's step through carefully

- The `class` keyword indicates that we are building a class.

The `Consumer` class defines instance data `wealth` and three methods: `__init__`, `earn` and `spend`

- `wealth` is *instance data* because each consumer we create (each instance of the `Consumer` class) will have its own wealth data.

The `earn` and `spend` methods deploy the functions we described earlier and that can potentially be applied to the `wealth` instance data.

The `__init__` method is a *constructor method*.

Whenever we create an instance of the class, the `__init_` method will be called automatically.

Calling `__init__` sets up a "namespace" to hold the instance data — more on this soon.

We'll also discuss the role of the peculiar `self` bookkeeping device in detail below.

Usage

Here's an example in which we use the class `Consumer` to create an instance of a consumer whom we affectionately name $c1$.

After we create consumer $c1$ and endow it with initial wealth 10, we'll apply the `spend` method.

```
c1 = Consumer(10)  # Create instance with initial wealth 10
c1.spend(5)
c1.wealth
```

```
5
```

```
c1.earn(15)
c1.spend(100)
```

```
Insufficent funds
```

We can of course create multiple instances, i.e., multiple consumers, each with its own name and data

```
c1 = Consumer(10)
c2 = Consumer(12)
c2.spend(4)
c2.wealth
```

```
8
```

```
c1.wealth
```

```
10
```

Each instance, i.e., each consumer, stores its data in a separate namespace dictionary

```
c1.__dict__
```

```
{'wealth': 10}
```

```
c2.__dict__
```

```
{'wealth': 8}
```

When we access or set attributes we're actually just modifying the dictionary maintained by the instance.

Self

If you look at the `Consumer` class definition again you'll see the word self throughout the code.

The rules for using `self` in creating a Class are that

- Any instance data should be prepended with `self`
  - e.g., the `earn` method uses `self.wealth` rather than just `wealth`
- A method defined within the code that defines the class should have `self` as its first argument
  - e.g., `def earn(self, y)` rather than just `def earn(y)`
- Any method referenced within the class should be called as `self.method_name`

There are no examples of the last rule in the preceding code but we will see some shortly.

Details

In this section, we look at some more formal details related to classes and `self`

- You might wish to skip to *the next section* the first time you read this lecture.
- You can return to these details after you've familiarized yourself with more examples.

Methods actually live inside a class object formed when the interpreter reads the class definition

```
print(Consumer.__dict__)  # Show __dict__ attribute of class object
```

```
{'__module__': '__main__', '__init__': <function Consumer.__init__ at␣
↪0x7fbe7c09cea0>, 'earn': <function Consumer.earn at 0x7fbe7c09ce00>, 'spend':
↪<function Consumer.spend at 0x7fbe7c09cfe0>, '__dict__': <attribute '__dict__'␣
↪of 'Consumer' objects>, '__weakref__': <attribute '__weakref__' of 'Consumer'␣
↪objects>, '__doc__': None}
```

Note how the three methods `__init__`, `earn` and `spend` are stored in the class object.

Consider the following code

```
c1 = Consumer(10)
c1.earn(10)
c1.wealth
```

```
20
```

When you call `earn` via `c1.earn(10)` the interpreter passes the instance `c1` and the argument `10` to `Consumer.earn`.

In fact, the following are equivalent

- `c1.earn(10)`
- `Consumer.earn(c1, 10)`

In the function call `Consumer.earn(c1, 10)` note that `c1` is the first argument.

Recall that in the definition of the `earn` method, `self` is the first parameter

```
def earn(self, y):
    "The consumer earns y dollars"
    self.wealth += y
```

The end result is that `self` is bound to the instance `c1` inside the function call.

That's why the statement `self.wealth += y` inside `earn` ends up modifying `c1.wealth`.

7.3.2 Example: The Solow Growth Model

For our next example, let's write a simple class to implement the Solow growth model.

The Solow growth model is a neoclassical growth model in which the per capita capital stock k_t evolves according to the rule

$$k_{t+1} = \frac{sz k_t^\alpha + (1-\delta)k_t}{1+n} \tag{7.1}$$

Here

- s is an exogenously given saving rate
- z is a productivity parameter
- α is capital's share of income
- n is the population growth rate
- δ is the depreciation rate

A **steady state** of the model is a k that solves (7.1) when $k_{t+1} = k_t = k$.

Here's a class that implements this model.

Some points of interest in the code are

- An instance maintains a record of its current capital stock in the variable `self.k`.
- The `h` method implements the right-hand side of (7.1).
- The `update` method uses `h` to update capital as per (7.1).
  - Notice how inside `update` the reference to the local method `h` is `self.h`.

The methods `steady_state` and `generate_sequence` are fairly self-explanatory

```
class Solow:
    r"""
    Implements the Solow growth model with the update rule
```

(continues on next page)

(continued from previous page)

```
        k_{t+1} = [(s z k^α_t) + (1 - δ)k_t] /(1 + n)

    """
    def __init__(self, n=0.05,  # population growth rate
                       s=0.25,  # savings rate
                       δ=0.1,   # depreciation rate
                       α=0.3,   # share of labor
                       z=2.0,   # productivity
                       k=1.0):  # current capital stock

        self.n, self.s, self.δ, self.α, self.z = n, s, δ, α, z
        self.k = k

    def h(self):
        "Evaluate the h function"
        # Unpack parameters (get rid of self to simplify notation)
        n, s, δ, α, z = self.n, self.s, self.δ, self.α, self.z
        # Apply the update rule
        return (s * z * self.k**α + (1 - δ) * self.k) / (1 + n)

    def update(self):
        "Update the current state (i.e., the capital stock)."
        self.k =  self.h()

    def steady_state(self):
        "Compute the steady state value of capital."
        # Unpack parameters (get rid of self to simplify notation)
        n, s, δ, α, z = self.n, self.s, self.δ, self.α, self.z
        # Compute and return steady state
        return ((s * z) / (n + δ))**(1 / (1 - α))

    def generate_sequence(self, t):
        "Generate and return a time series of length t"
        path = []
        for i in range(t):
            path.append(self.k)
            self.update()
        return path
```

Here's a little program that uses the class to compute time series from two different initial conditions.

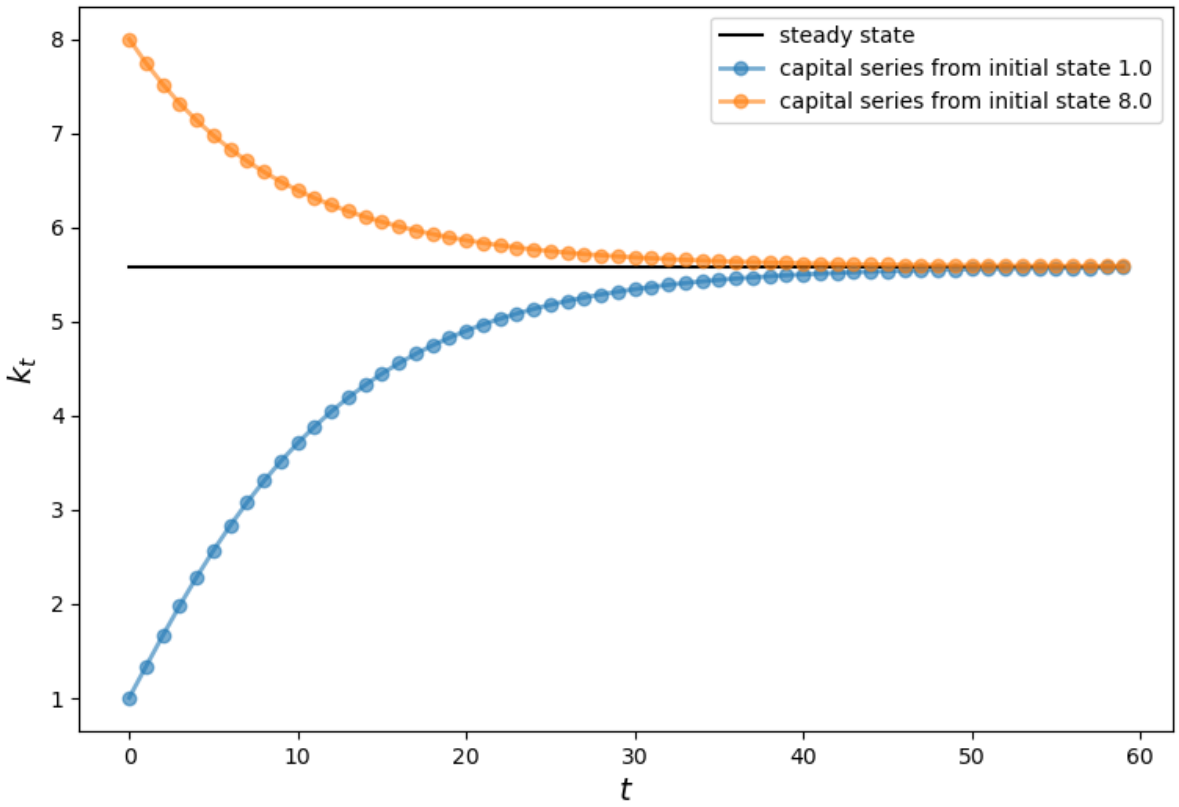
The common steady state is also plotted for comparison

```
s1 = Solow()
s2 = Solow(k=8.0)

T = 60
fig, ax = plt.subplots(figsize=(9, 6))

# Plot the common steady state value of capital
ax.plot([s1.steady_state()]*T, 'k-', label='steady state')

# Plot time series for each economy
for s in s1, s2:
    lb = f'capital series from initial state {s.k}'
    ax.plot(s.generate_sequence(T), 'o-', lw=2, alpha=0.6, label=lb)
```

(continues on next page)

(continued from previous page)

```
ax.set_xlabel('$t$', fontsize=14)
ax.set_ylabel('$k_t$', fontsize=14)
ax.legend()
plt.show()
```



7.3.3 Example: A Market

Next, let's write a class for competitive market in which buyers and sellers are both price takers.

The market consists of the following objects:

- A linear demand curve $Q = a_d - b_d p$
- A linear supply curve $Q = a_z + b_z(p - t)$

Here

- p is price paid by the buyer, Q is quantity and t is a per-unit tax.
- Other symbols are demand and supply parameters.

The class provides methods to compute various values of interest, including competitive equilibrium price and quantity, tax revenue raised, consumer surplus and producer surplus.

Here's our implementation.

(It uses a function from SciPy called quad for numerical integration—a topic we will say more about later on.)

```
from scipy.integrate import quad

class Market:

    def __init__(self, ad, bd, az, bz, tax):
        """
        Set up market parameters.  All parameters are scalars.  See
        https://lectures.quantecon.org/py/python_oop.html for interpretation.

        """
        self.ad, self.bd, self.az, self.bz, self.tax = ad, bd, az, bz, tax
        if ad < az:
            raise ValueError('Insufficient demand.')

    def price(self):
        "Compute equilibrium price"
        return  (self.ad - self.az + self.bz * self.tax) / (self.bd + self.bz)

    def quantity(self):
        "Compute equilibrium quantity"
        return  self.ad - self.bd * self.price()

    def consumer_surp(self):
        "Compute consumer surplus"
        # == Compute area under inverse demand function == #
        integrand = lambda x: (self.ad / self.bd) - (1 / self.bd) * x
        area, error = quad(integrand, 0, self.quantity())
        return area - self.price() * self.quantity()

    def producer_surp(self):
        "Compute producer surplus"
        #  == Compute area above inverse supply curve, excluding tax == #
        integrand = lambda x: -(self.az / self.bz) + (1 / self.bz) * x
        area, error = quad(integrand, 0, self.quantity())
        return (self.price() - self.tax) * self.quantity() - area

    def taxrev(self):
        "Compute tax revenue"
        return self.tax * self.quantity()

    def inverse_demand(self, x):
        "Compute inverse demand"
        return self.ad / self.bd - (1 / self.bd)* x

    def inverse_supply(self, x):
        "Compute inverse supply curve"
        return -(self.az / self.bz) + (1 / self.bz) * x + self.tax

    def inverse_supply_no_tax(self, x):
        "Compute inverse supply curve without tax"
        return -(self.az / self.bz) + (1 / self.bz) * x
```

Here's a sample of usage

```
baseline_params = 15, .5, -2, .5, 3
m = Market(*baseline_params)
print("equilibrium price = ", m.price())
```

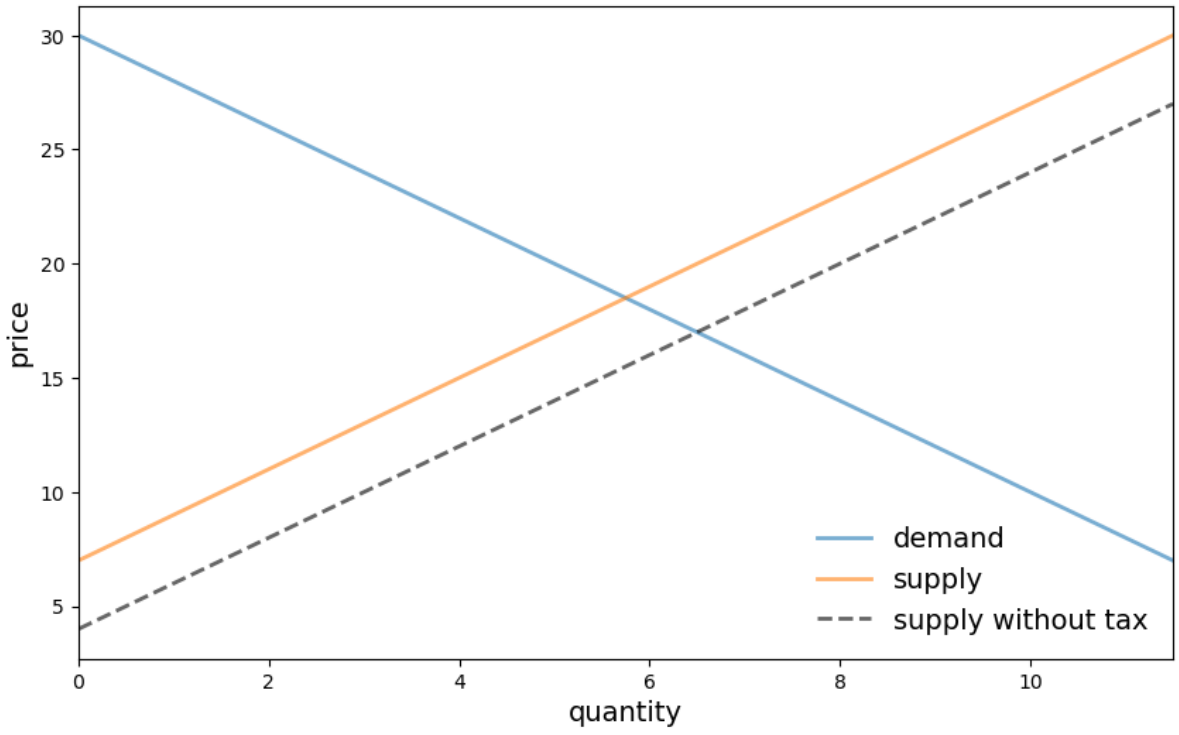
```
equilibrium price =  18.5
```

```
print("consumer surplus = ", m.consumer_surp())
```

```
consumer surplus =  33.0625
```

Here's a short program that uses this class to plot an inverse demand curve together with inverse supply curves with and without taxes

```
# Baseline ad, bd, az, bz, tax
baseline_params = 15, .5, -2, .5, 3
m = Market(*baseline_params)

q_max = m.quantity() * 2
q_grid = np.linspace(0.0, q_max, 100)
pd = m.inverse_demand(q_grid)
ps = m.inverse_supply(q_grid)
psno = m.inverse_supply_no_tax(q_grid)

fig, ax = plt.subplots()
ax.plot(q_grid, pd, lw=2, alpha=0.6, label='demand')
ax.plot(q_grid, ps, lw=2, alpha=0.6, label='supply')
ax.plot(q_grid, psno, '--k', lw=2, alpha=0.6, label='supply without tax')
ax.set_xlabel('quantity', fontsize=14)
ax.set_xlim(0, q_max)
ax.set_ylabel('price', fontsize=14)
ax.legend(loc='lower right', frameon=False, fontsize=14)
plt.show()
```



The next program provides a function that

- takes an instance of `Market` as a parameter
- computes dead weight loss from the imposition of the tax

```
def deadw(m):
    "Computes deadweight loss for market m."
    # == Create analogous market with no tax == #
    m_no_tax = Market(m.ad, m.bd, m.az, m.bz, 0)
    # == Compare surplus, return difference == #
    surp1 = m_no_tax.consumer_surp() + m_no_tax.producer_surp()
    surp2 = m.consumer_surp() + m.producer_surp() + m.taxrev()
    return surp1 - surp2
```

Here's an example of usage

```
baseline_params = 15, .5, -2, .5, 3
m = Market(*baseline_params)
deadw(m)  # Show deadweight loss
```

```
1.125
```

7.3.4 Example: Chaos

Let's look at one more example, related to chaotic dynamics in nonlinear systems.

A simple transition rule that can generate erratic time paths is the logistic map

$$x_{t+1} = r x_t (1 - x_t), \quad x_0 \in [0, 1], \quad r \in [0, 4] \tag{7.2}$$

Let's write a class for generating time series from this model.

Here's one implementation

```
class Chaos:
  """
  Models the dynamical system :math:`x_{t+1} = r x_t (1 - x_t)`
  """
  def __init__(self, x0, r):
      """
      Initialize with state x0 and parameter r
      """
      self.x, self.r = x0, r

  def update(self):
      "Apply the map to update state."
      self.x =  self.r * self.x *(1 - self.x)

  def generate_sequence(self, n):
      "Generate and return a sequence of length n."
      path = []
      for i in range(n):
          path.append(self.x)
          self.update()
      return path
```

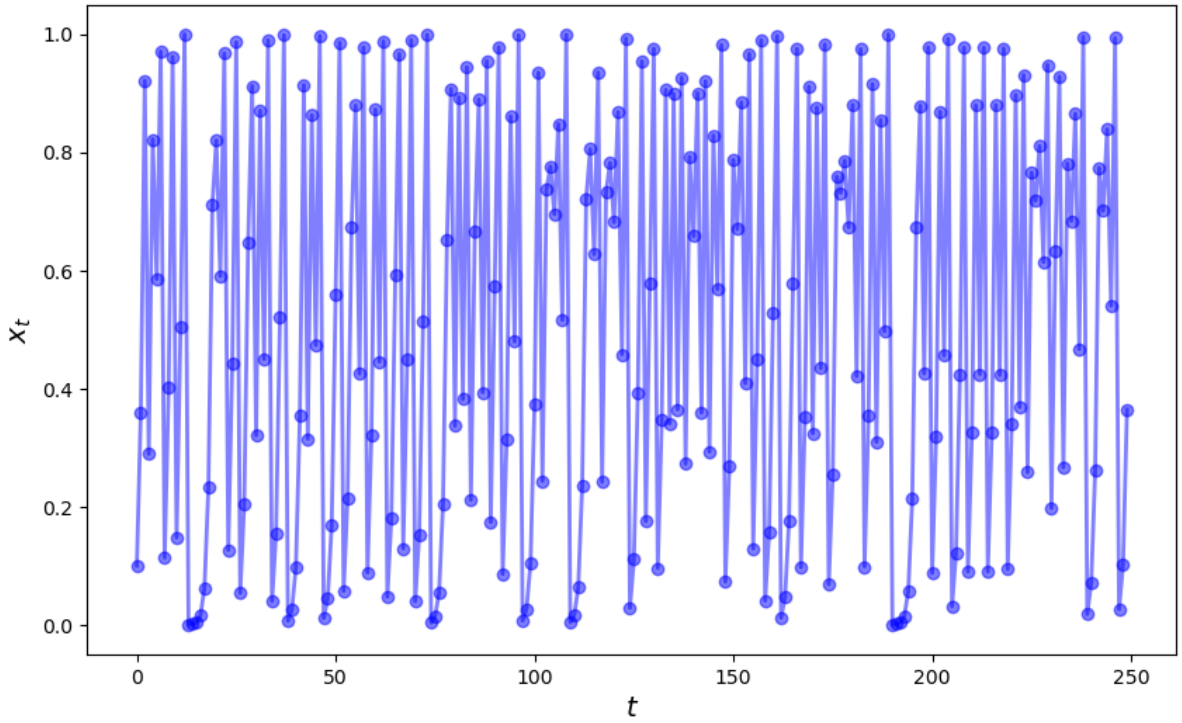
Here's an example of usage

```
ch = Chaos(0.1, 4.0)      # x0 = 0.1 and r = 0.4
ch.generate_sequence(5)   # First 5 iterates
```

```
[0.1, 0.36000000000000004, 0.9216, 0.28901376000000006, 0.8219392261226498]
```

This piece of code plots a longer trajectory

```
ch = Chaos(0.1, 4.0)
ts_length = 250

fig, ax = plt.subplots()
ax.set_xlabel('$t$', fontsize=14)
ax.set_ylabel('$x_t$', fontsize=14)
x = ch.generate_sequence(ts_length)
ax.plot(range(ts_length), x, 'bo-', alpha=0.5, lw=2, label='$x_t$')
plt.show()
```



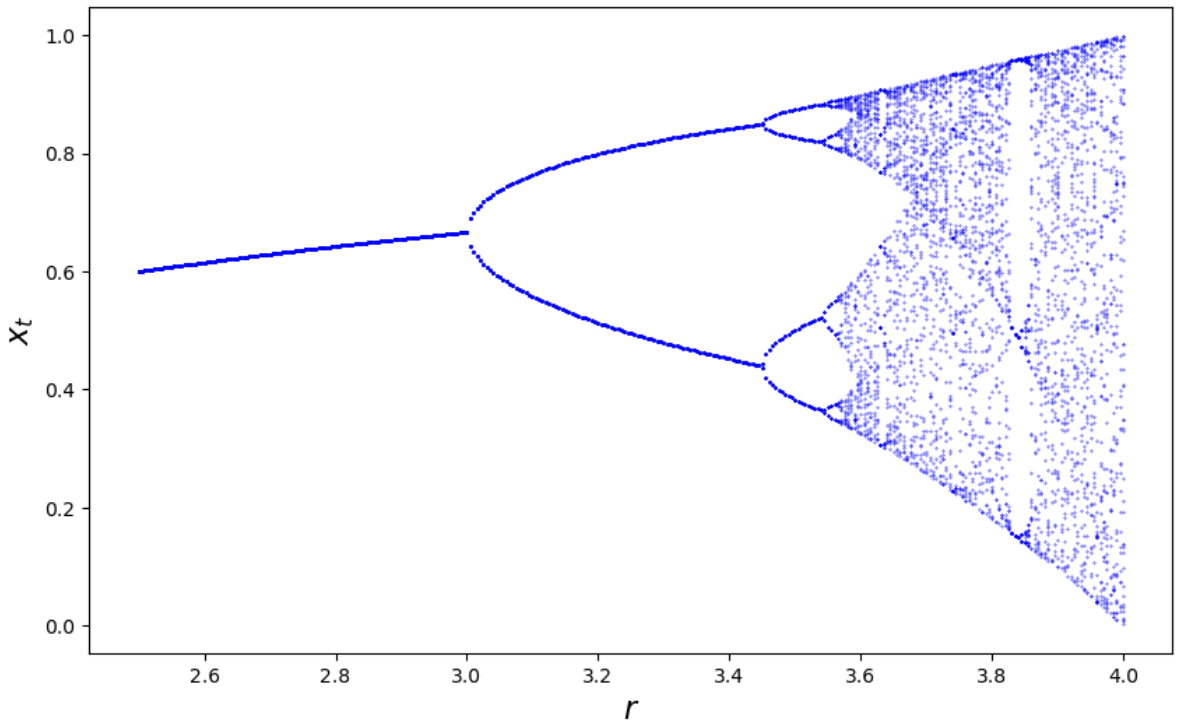
The next piece of code provides a bifurcation diagram

```
fig, ax = plt.subplots()
ch = Chaos(0.1, 4)
r = 2.5
while r < 4:
    ch.r = r
    t = ch.generate_sequence(1000)[950:]
    ax.plot([r] * len(t), t, 'b.', ms=0.6)
    r = r + 0.005

ax.set_xlabel('$r$', fontsize=16)
```

(continues on next page)

(continued from previous page)

```
ax.set_ylabel('$x_t$', fontsize=16)
plt.show()
```



On the horizontal axis is the parameter r in (7.2).

The vertical axis is the state space $[0, 1]$.

For each r we compute a long time series and then plot the tail (the last 50 points).

The tail of the sequence shows us where the trajectory concentrates after settling down to some kind of steady state, if a steady state exists.

Whether it settles down, and the character of the steady state to which it does settle down, depend on the value of r.

For r between about 2.5 and 3, the time series settles into a single fixed point plotted on the vertical axis.

For r between about 3 and 3.45, the time series settles down to oscillating between the two values plotted on the vertical axis.

For r a little bit higher than 3.45, the time series settles down to oscillating among the four values plotted on the vertical axis.

Notice that there is no value of r that leads to a steady state oscillating among three values.

7.4 Special Methods

Python provides special methods that come in handy.

For example, recall that lists and tuples have a notion of length and that this length can be queried via the `len` function

```
x = (10, 20)
len(x)
```

```
2
```

If you want to provide a return value for the `len` function when applied to your user-defined object, use the `__len__` special method

```
class Foo:

    def __len__(self):
        return 42
```

Now we get

```
f = Foo()
len(f)
```

```
42
```

A special method we will use regularly is the `__call__` method.

This method can be used to make your instances callable, just like functions

```
class Foo:

    def __call__(self, x):
        return x + 42
```

After running we get

```
f = Foo()
f(8)  # Exactly equivalent to f.__call__(8)
```

```
50
```

Exercise 1 provides a more useful example.

7.5 Exercises

Exercise 7.5.1

The empirical cumulative distribution function (ecdf) corresponding to a sample $\{X_i\}_{i=1}^n$ is defined as

$$F_n(x) := \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}\{X_i \leq x\} \qquad (x \in \mathbb{R}) \tag{7.3}$$

Here $\mathbf{1}\{X_i \leq x\}$ is an indicator function (one if $X_i \leq x$ and zero otherwise) and hence $F_n(x)$ is the fraction of the sample that falls below x.

The Glivenko–Cantelli Theorem states that, provided that the sample is IID, the ecdf F_n converges to the true distribution function F.

Implement F_n as a class called `ECDF`, where

- A given sample $\{X_i\}_{i=1}^n$ are the instance data, stored as `self.observations`.
- The class implements a `__call__` method that returns $F_n(x)$ for any x.

Your code should work as follows (modulo randomness)

```
from random import uniform

samples = [uniform(0, 1) for i in range(10)]
F = ECDF(samples)
F(0.5)  # Evaluate ecdf at x = 0.5
```

```
F.observations = [uniform(0, 1) for i in range(1000)]
F(0.5)
```

Aim for clarity, not efficiency.

Solution to Exercise 7.5.1

```
class ECDF:

    def __init__(self, observations):
        self.observations = observations

    def __call__(self, x):
        counter = 0.0
        for obs in self.observations:
            if obs <= x:
                counter += 1
        return counter / len(self.observations)
```

```
# == test == #

from random import uniform

samples = [uniform(0, 1) for i in range(10)]
F = ECDF(samples)
```

(continues on next page)

(continued from previous page)

```
print(F(0.5))  # Evaluate ecdf at x = 0.5

F.observations = [uniform(0, 1) for i in range(1000)]

print(F(0.5))
```

```
0.5
0.491
```

Exercise 7.5.2

In an *earlier exercise*, you wrote a function for evaluating polynomials.

This exercise is an extension, where the task is to build a simple class called `Polynomial` for representing and manipulating polynomial functions such as

$$p(x) = a_0 + a_1 x + a_2 x^2 + \cdots a_N x^N = \sum_{n=0}^{N} a_n x^n \qquad (x \in \mathbb{R}) \tag{7.4}$$

The instance data for the class `Polynomial` will be the coefficients (in the case of (7.4), the numbers $a_0, \ldots, a_N$).

Provide methods that

1. Evaluate the polynomial (7.4), returning $p(x)$ for any x.
2. Differentiate the polynomial, replacing the original coefficients with those of its derivative p'.

Avoid using any `import` statements.

Solution to Exercise 7.5.2

```
class Polynomial:

    def __init__(self, coefficients):
        """
        Creates an instance of the Polynomial class representing

            p(x) = a_0 x^0 + ... + a_N x^N,

        where a_i = coefficients[i].
        """
        self.coefficients = coefficients

    def __call__(self, x):
        "Evaluate the polynomial at x."
        y = 0
        for i, a in enumerate(self.coefficients):
            y += a * x**i
        return y

    def differentiate(self):
        "Reset self.coefficients to those of p' instead of p."
```

(continues on next page)

(continued from previous page)

```
        new_coefficients = []
        for i, a in enumerate(self.coefficients):
            new_coefficients.append(i * a)
        # Remove the first element, which is zero
        del new_coefficients[0]
        # And reset coefficients data to new values
        self.coefficients = new_coefficients
        return new_coefficients
```

CHAPTER

EIGHT

WRITING LONGER PROGRAMS

Contents

8.1 Overview

So far, we have explored the use of Jupyter Notebooks in writing and executing Python code.

While they are efficient and adaptable when working with short pieces of code, Notebooks are not the best choice for longer programs and scripts.

Jupyter Notebooks are well suited to interactive computing (i.e. data science workflows) and can help execute chunks of code one at a time.

Text files and scripts allow for long pieces of code to be written and executed in a single go.

We will explore the use of Python scripts as an alternative.

The Jupyter Lab and Visual Studio Code (VS Code) development environments are then introduced along with a primer on version control (Git).

In this lecture, you will learn to

- work with Python scripts
- set up various development environments
- get started with GitHub

Note: Going forward, it is assumed that you have an Anaconda environment up and running.

You may want to create a new conda environment if you haven't done so already.

8.2 Working with Python files

Python files are used when writing long, reusable blocks of code - by convention, they have a `.py` suffix.

Let us begin by working with the following example.

Listing 8.1: sine_wave.py

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

x = np.linspace(0, 10, 100)
y = np.sin(x)

plt.plot(x, y)
plt.xlabel('x')
plt.ylabel('y')
plt.title('Sine Wave')
plt.show()
```

The code is first saved locally on the computer before it is executed.

As there are various ways to execute the code, we will explore them in the context of different development environments.

One major advantage of using Python scripts lies in the fact that you can "import" functionality from other scripts into your current script or Jupyter Notebook.

Let's rewrite the earlier code into a function.

Listing 8.2: sine_wave.py

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

# Define the plot_wave function.
def plot_wave(title : str = 'Sine Wave'):
  x = np.linspace(0, 10, 100)
  y = np.sin(x)

  plt.plot(x, y)
  plt.xlabel('x')
  plt.ylabel('y')
  plt.title(title)
  plt.show()
```

Listing 8.3: second_script.py

```
import sine_wave # Import the sine_wave script

# Call the plot_wave function.
sine_wave.plot_wave("Sine Wave - Called from the Second Script")
```

This allows you to split your code into chunks and structure your codebase better.

Look into the use of modules and packages for more information on importing functionality.

8.3 Development environments

A development environment is a one stop workspace where you can

- edit and run your code
- test and debug
- manage project files

This lecture takes you through the workings of two development environments.

8.4 A step forward from Jupyter Notebooks: JupyterLab

JupyterLab is a browser based development environment for Jupyter Notebooks, code scripts, and data files.

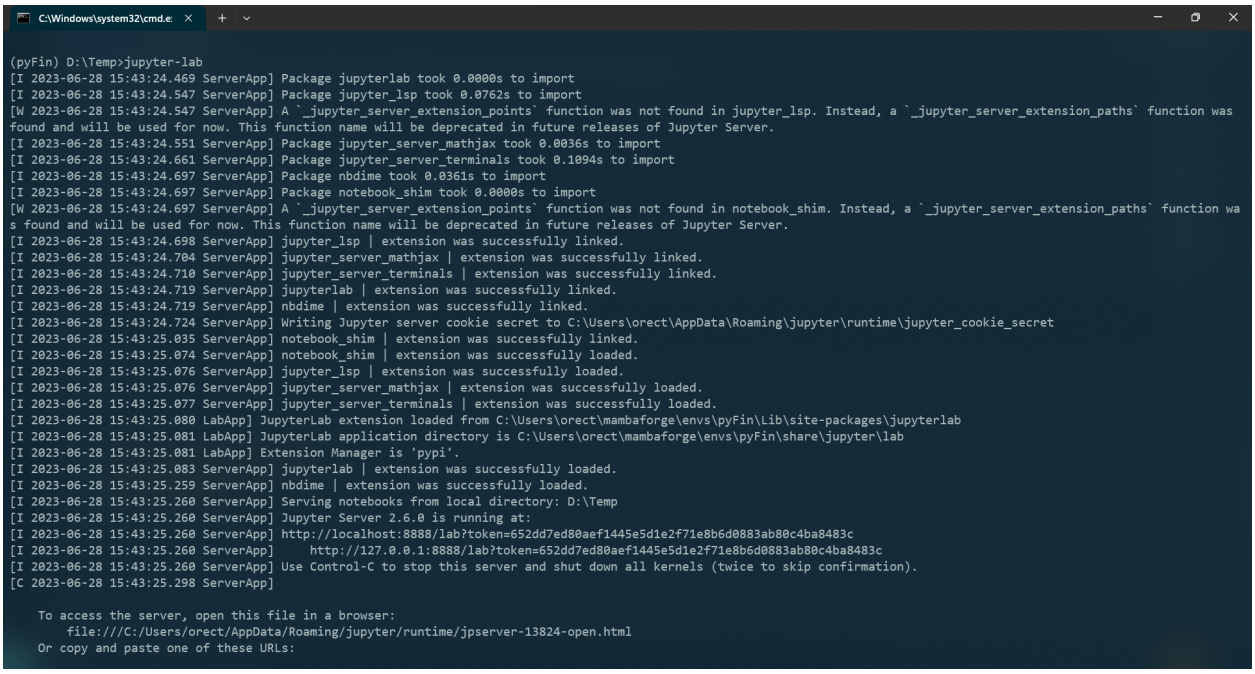
You can try JupyterLab in the browser if you want to test it out before installing it locally.

You can install JupyterLab using pip

```
> pip install jupyterlab
```

and launch it in the browser, similar to Jupyter Notebooks.

```
> jupyter-lab
```

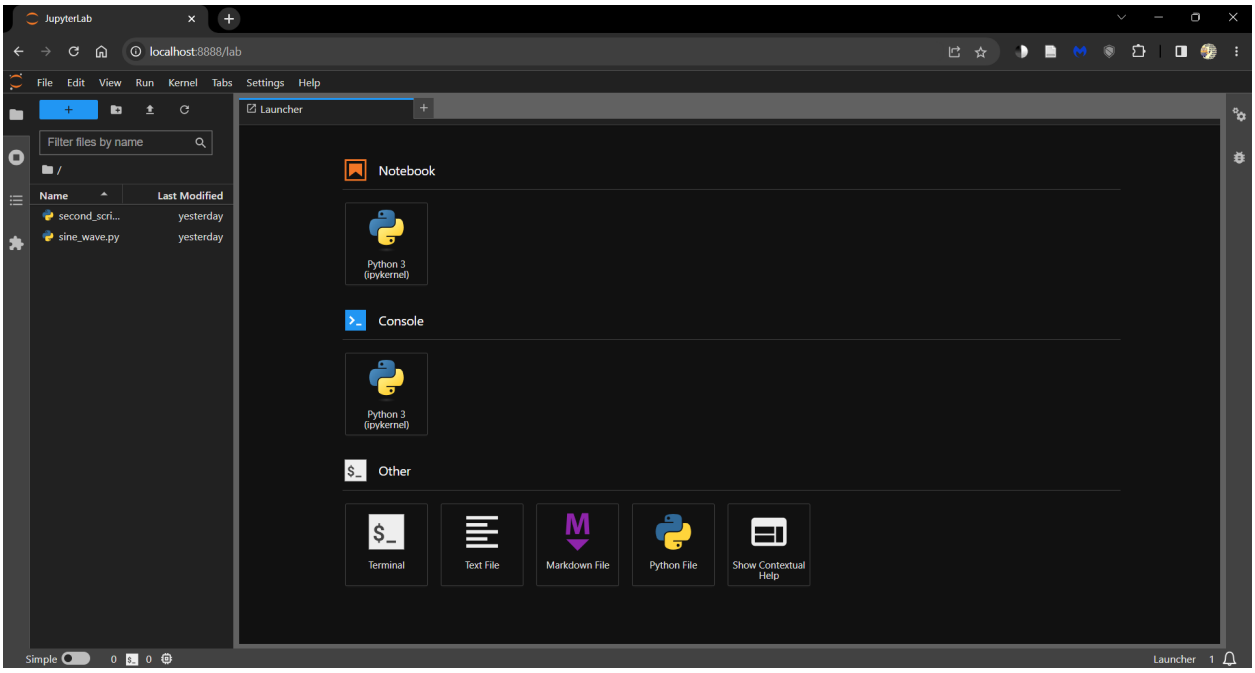


You can see that the Jupyter Server is running on port 8888 on the localhost.

The following interface should open up on your default browser automatically - if not, CTRL + Click the server URL.

Click on

- the Python 3 (ipykernel) button under Notebooks to open a new Jupyter Notebook

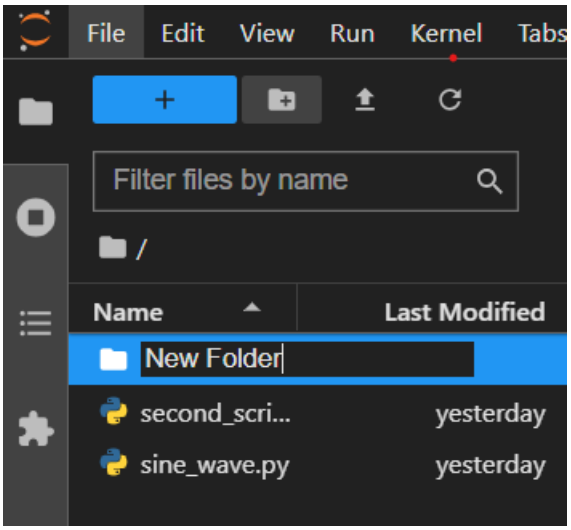


- the Python File button to open a new Python script (.py)

You can always open this launcher tab by clicking the '+' button on the top.

All the files and folders in your working directory can be found in the File Browser (tab on the left).

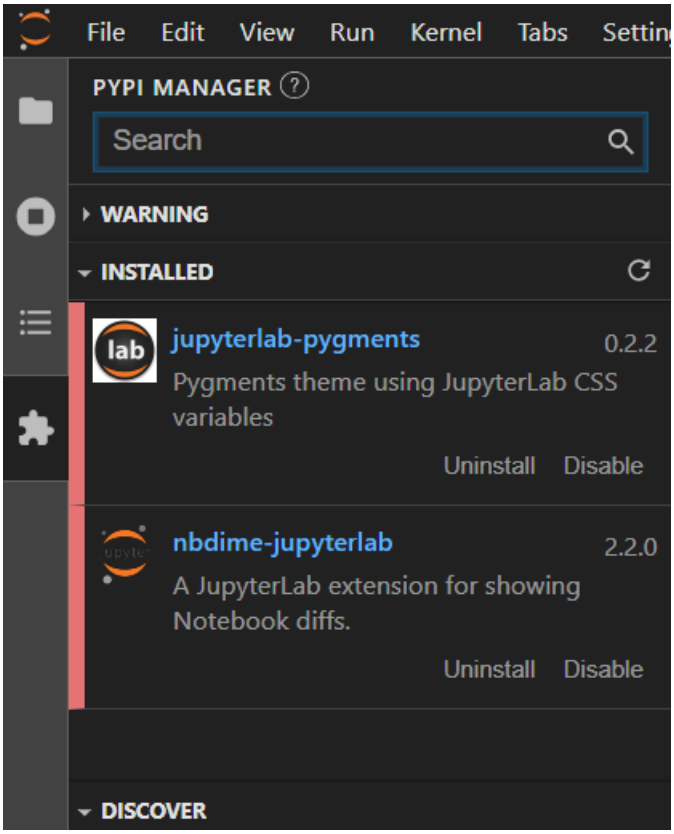
You can create new files and folders using the buttons available at the top of the File Browser tab.



You can install extensions that increase the functionality of JupyterLab by visiting the Extensions tab.

Coming back to the example scripts from earlier, there are two ways to work with them in JupyterLab.

- Using magic commands
- Using the terminal



8.4.1 Using magic commands

Jupyter Notebooks and JupyterLab support the use of magic commands - commands that extend the capabilities of a standard Jupyter Notebook.

The `%run` magic command allows you to run a Python script from within a Notebook.

This is a convenient way to run scripts that you are working on in the same directory as your Notebook and present the outputs within the Notebook.

8.4.2 Using the terminal

However, if you are looking into just running the `.py` file, it is sometimes easier to use the terminal.

Open a terminal from the launcher and run the following command.

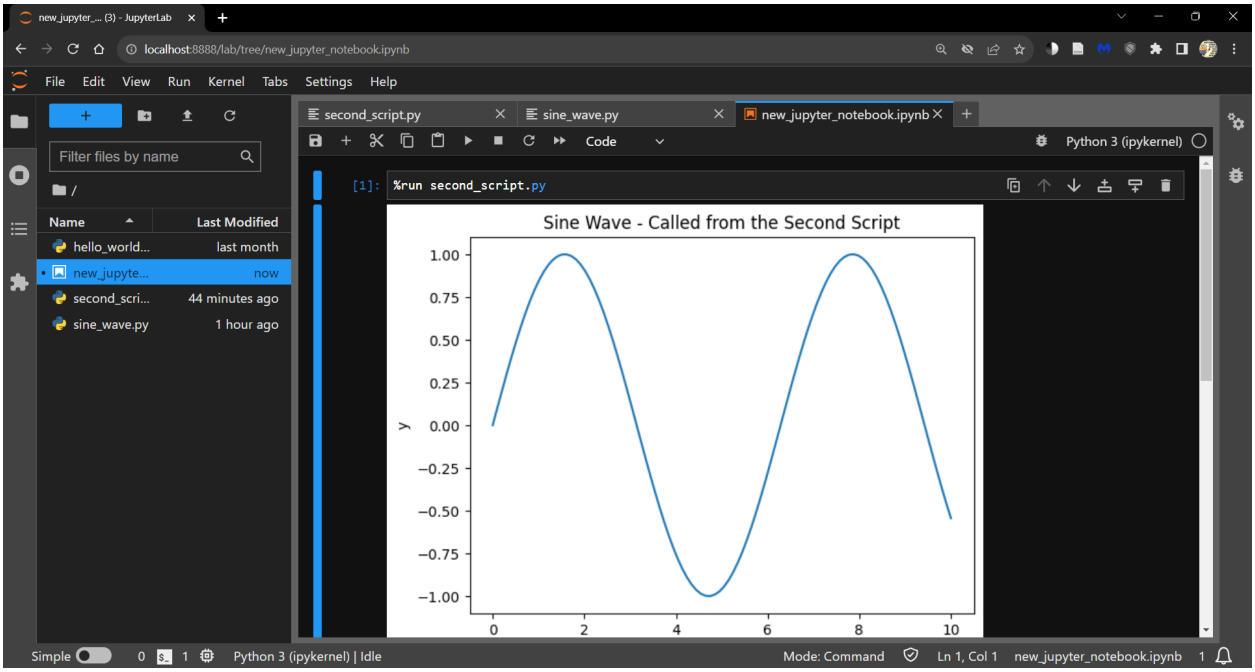
```
> python <path to file.py>
```

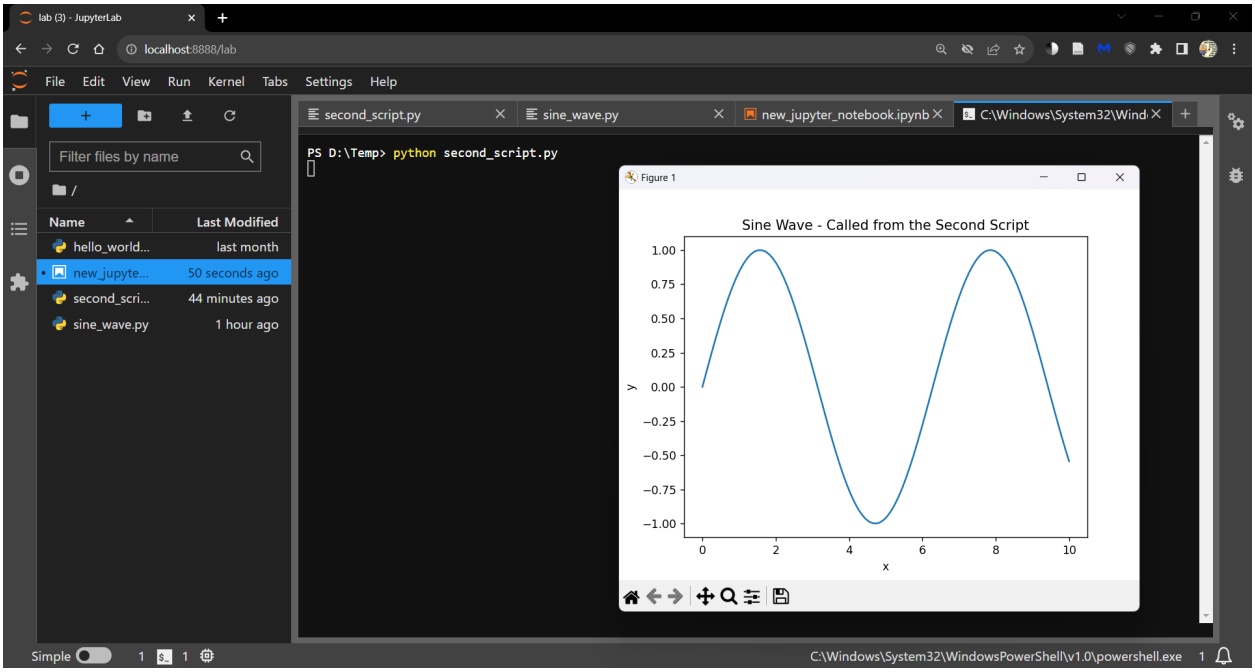
Note: You can also run the script line by line by opening an ipykernel console either

- from the launcher
- by right clicking within the Notebook and selecting Create Console for Editor

Use Shift + Enter to run a line of code.

More on ipykernel consoles here.


new_jupyter_... (3) - JupyterLab
localhost:8888/lab/tree/new_jupyter_notebook.ipynb
File Edit View Run Kernel Tabs Settings Help
Filter files by name
Name
Last Modified
hello_world...
last month
new_jupyte...
now
second_scri...
44 minutes ago
sine_wave.py
1 hour ago
second_script.py
sine_wave.py
new_jupyter_notebook.ipynb
Code
Python 3 (ipykernel)
[1]:
%run second_script.py
Sine Wave - Called from the Second Script
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
y
0
2
4
6
8
10
Simple
Python 3 (ipykernel) | Idle
Mode: Command
Ln 1, Col 1
new_jupyter_notebook.ipynb


lab (3) - JupyterLab
localhost:8888/lab
File Edit View Run Kernel Tabs Settings Help
Filter files by name
Name
Last Modified
hello_world...
last month
new_jupyte...
50 seconds ago
second_scri...
44 minutes ago
sine_wave.py
1 hour ago
second_script.py
sine_wave.py
new_jupyter_notebook.ipynb
C:\Windows\System32\Wind
PS D:\Temp> python second_script.py
Figure 1
Sine Wave - Called from the Second Script
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
y
0
2
4
6
8
10
x
Simple
C:\Windows\System32\WindowsPowerShell\v1.0\powershell.exe

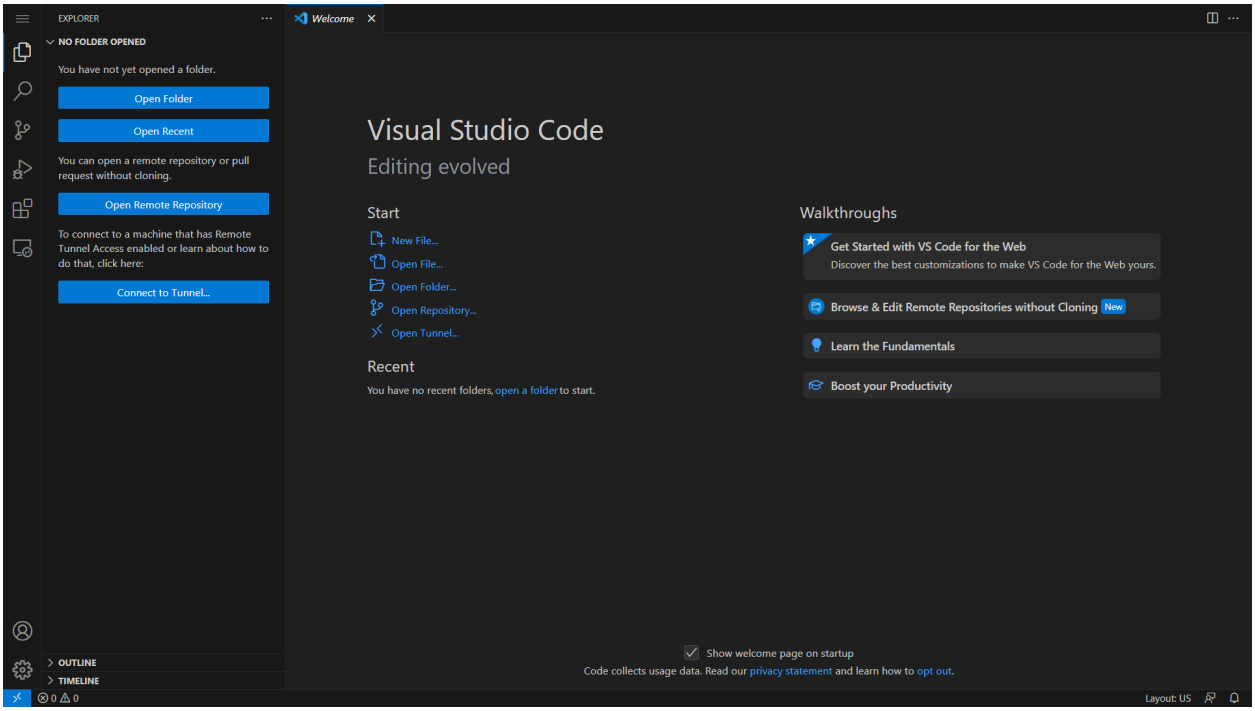
8.5 A walk through Visual Studio Code

Visual Studio Code (VS Code) is a code editor and development workspace that can run

- in the browser.
- as a local installation.

Both interfaces are identical.

When you launch VS Code, you will see the following interface.



Explore how to customize VS Code to your liking through the guided walkthroughs.

When presented with the following prompt, go ahead an install all recommended extensions.

You can also install extensions from the Extensions tab.

Jupyter Notebooks (`.ipynb` files) can be worked on in VS Code.

Make sure to install the Jupyter extension from the Extensions tab before you try to open a Jupyter Notebook.

Create a new file (in the file Explorer tab) and save it with the `.ipynb` extension.

Choose a kernel/environment to run the Notebook in by clicking on the Select Kernel button on the top right corner of the editor.

VS Code also has excellent version control functionality through the Source Control tab.

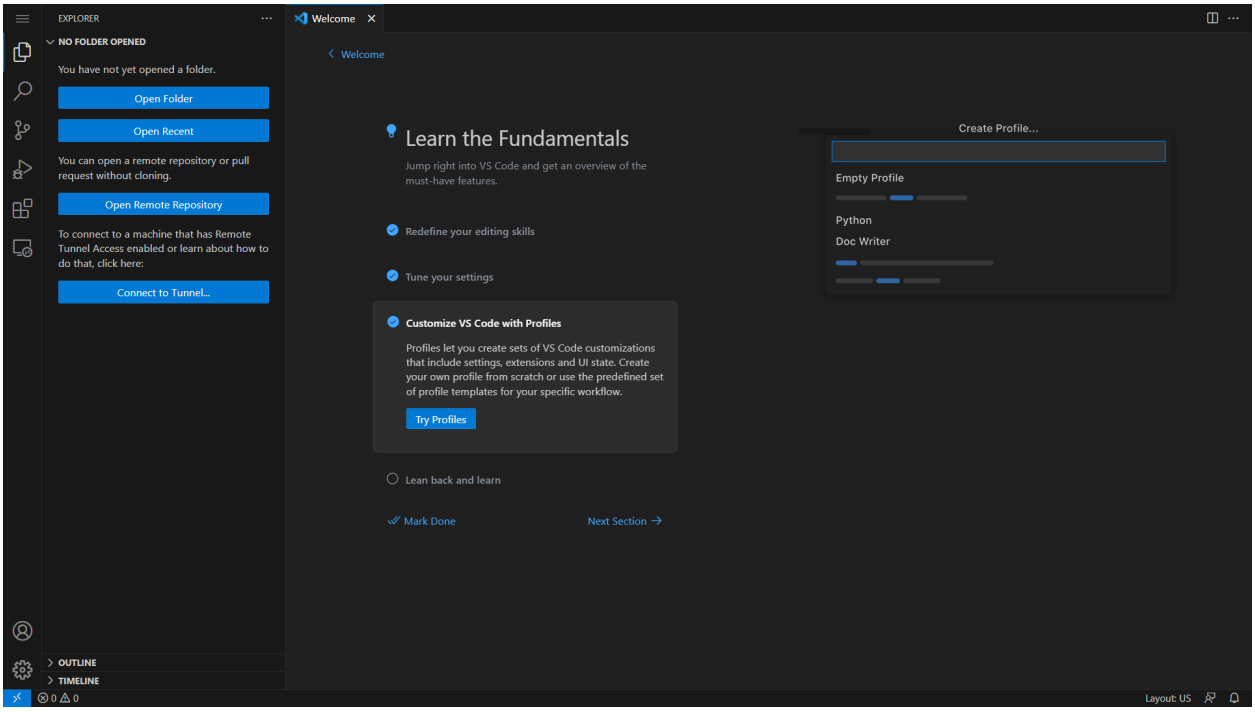
Link your GitHub account to VS Code to push and pull changes to and from your repositories.

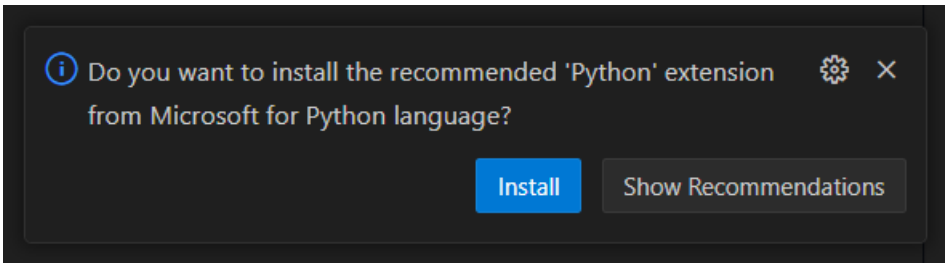
Further discussions about version control can be found in the next section.

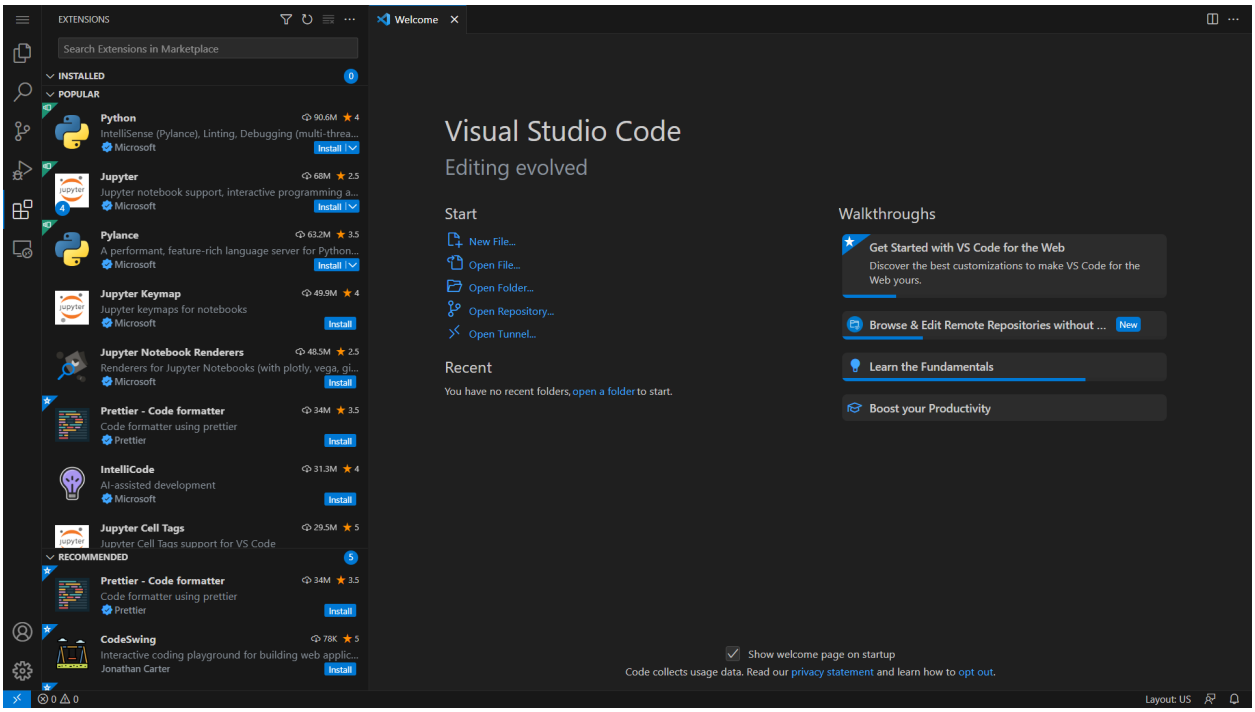
To open a new Terminal in VS Code, click on the Terminal tab and select New Terminal.

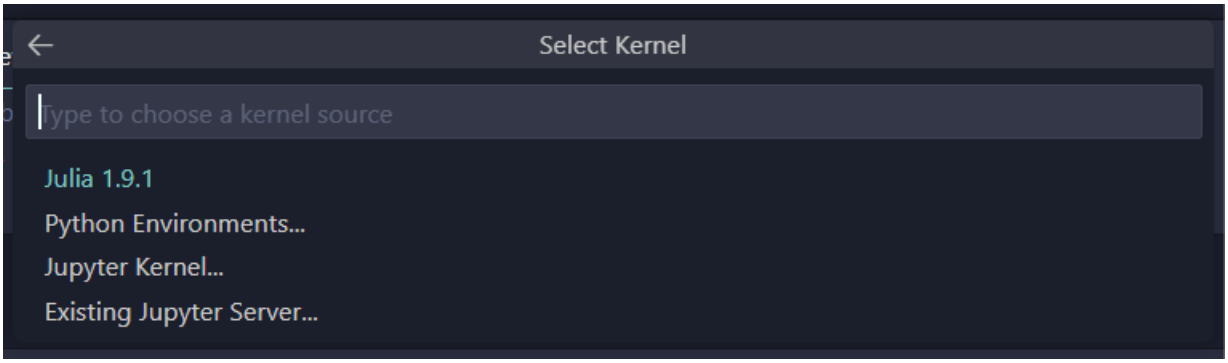
VS Code opens a new Terminal in the same directory you are working in - a PowerShell in Windows and a Bash in Linux.

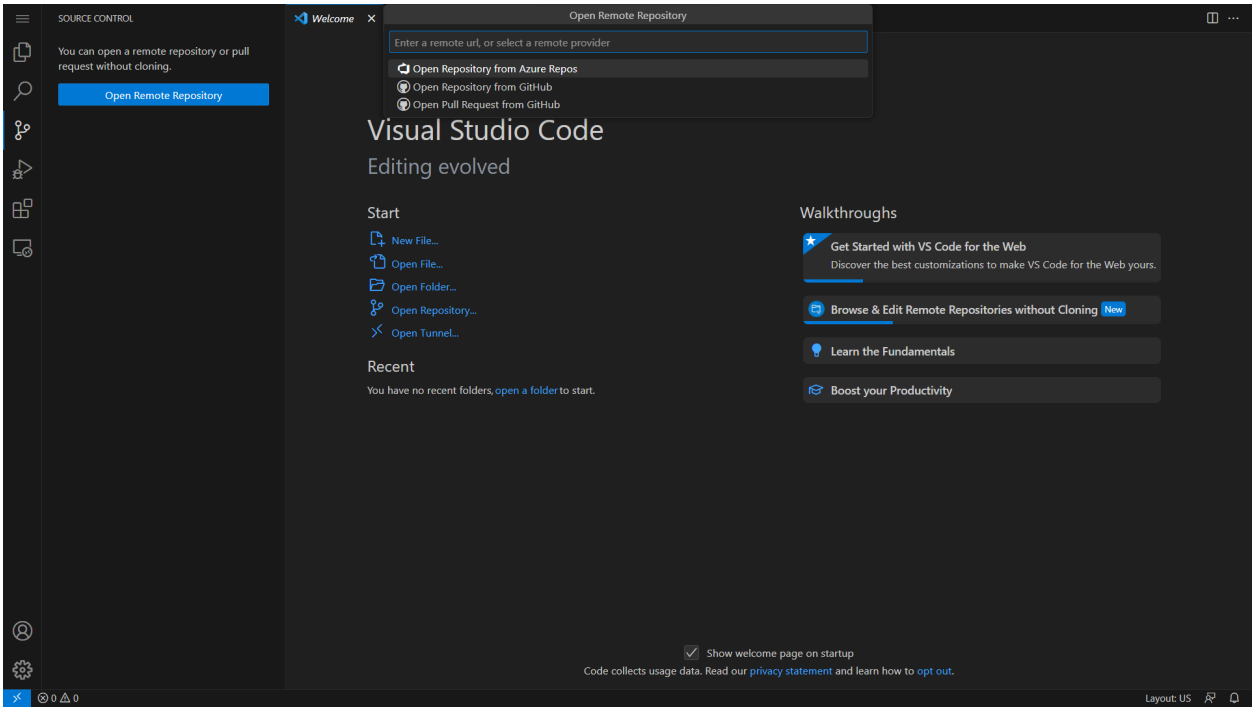
You can change the shell or open a new instance through the dropdown menu on the right end of the terminal tab.

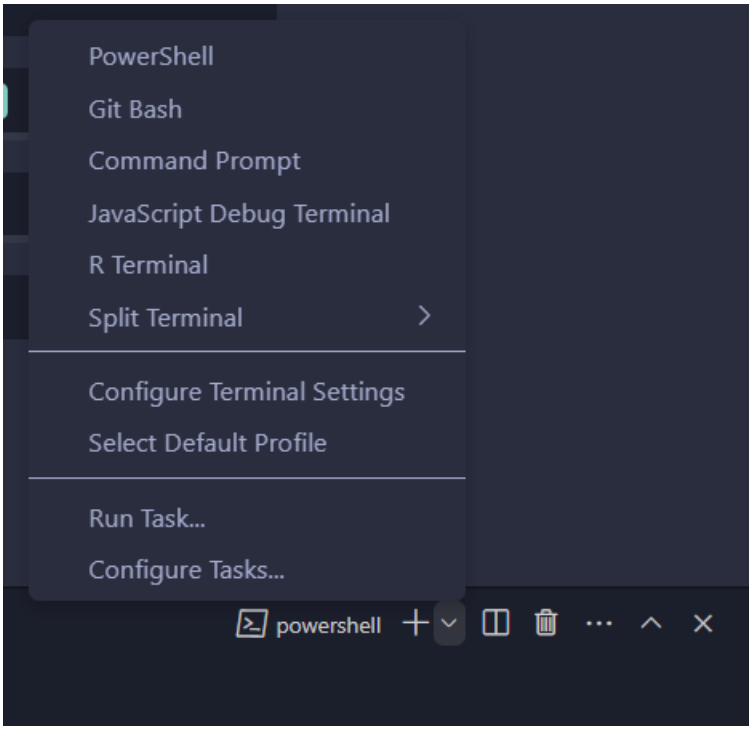

EXPLORER
NO FOLDER OPENED
You have not yet opened a folder.
Open Folder
Open Recent
You can open a remote repository or pull request without cloning.
Open Remote Repository
To connect to a machine that has Remote Tunnel Access enabled or learn about how to do that, click here:
Connect to Tunnel...
OUTLINE
TIMELINE
Welcome
Welcome
Learn the Fundamentals
Jump right into VS Code and get an overview of the must-have features.
Redefine your editing skills
Tune your settings
Customize VS Code with Profiles
Profiles let you create sets of VS Code customizations that include settings, extensions and UI state. Create your own profile from scratch or use the predefined set of profile templates for your specific workflow.
Try Profiles
Lean back and learn
Mark Done
Next Section
Create Profile...
Empty Profile
Python
Doc Writer
Layout: US


Do you want to install the recommended 'Python' extension from Microsoft for Python language?
Install
Show Recommendations


EXTENSIONS
Search Extensions in Marketplace
INSTALLED
POPULAR
Python
IntelliSense (Pylance), Linting, Debugging (multi-threa...
Microsoft
Jupyter
Jupyter notebook support, interactive programming a...
Microsoft
Pylance
A performant, feature-rich language server for Python...
Microsoft
Jupyter Keymap
Jupyter keymaps for notebooks
Microsoft
Jupyter Notebook Renderers
Renderers for Jupyter Notebooks (with plotly, vega, gi...
Microsoft
Prettier - Code formatter
Code formatter using prettier
Prettier
IntelliCode
AI-assisted development
Microsoft
Jupyter Cell Tags
Jupyter Cell Tags support for VS Code
RECOMMENDED
Prettier - Code formatter
Code formatter using prettier
Prettier
CodeSwing
Interactive coding playground for building web applic...
Jonathan Carter
Welcome
Visual Studio Code
Editing evolved
Start
New File...
Open File...
Open Folder...
Open Repository...
Open Tunnel...
Recent
You have no recent folders, open a folder to start.
Walkthroughs
Get Started with VS Code for the Web
Discover the best customizations to make VS Code for the Web yours.
Browse & Edit Remote Repositories without ...
New
Learn the Fundamentals
Boost your Productivity
Show welcome page on startup
Code collects usage data. Read our privacy statement and learn how to opt out.
Layout: US


Select Kernel
Type to choose a kernel source
Julia 1.9.1
Python Environments...
Jupyter Kernel...
Existing Jupyter Server...


SOURCE CONTROL
You can open a remote repository or pull request without cloning.
Open Remote Repository
Welcome
Open Remote Repository
Enter a remote url, or select a remote provider
Open Repository from Azure Repos
Open Repository from GitHub
Open Pull Request from GitHub
Visual Studio Code
Editing evolved
Start
New File...
Open File...
Open Folder...
Open Repository...
Open Tunnel...
Recent
You have no recent folders, open a folder to start.
Walkthroughs
Get Started with VS Code for the Web
Discover the best customizations to make VS Code for the Web yours.
Browse & Edit Remote Repositories without Cloning New
Learn the Fundamentals
Boost your Productivity
Show welcome page on startup
Code collects usage data. Read our privacy statement and learn how to opt out.
Layout: US



VS Code helps you manage conda environments without using the command line.

Open the Command Palette (CTRL + SHIFT + P or from the dropdown menu under View tab) and search for `Python: Select Interpreter`.

This loads existing environments.

You can also create new environments using `Python: Create Environment` in the Command Palette.

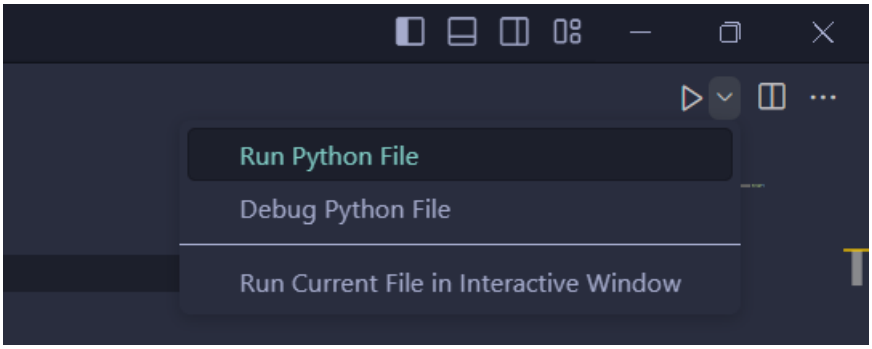
A new environment (.conda folder) is created in the the current working directory.

Coming to the example scripts from earlier, there are again two ways to work with them in VS Code.

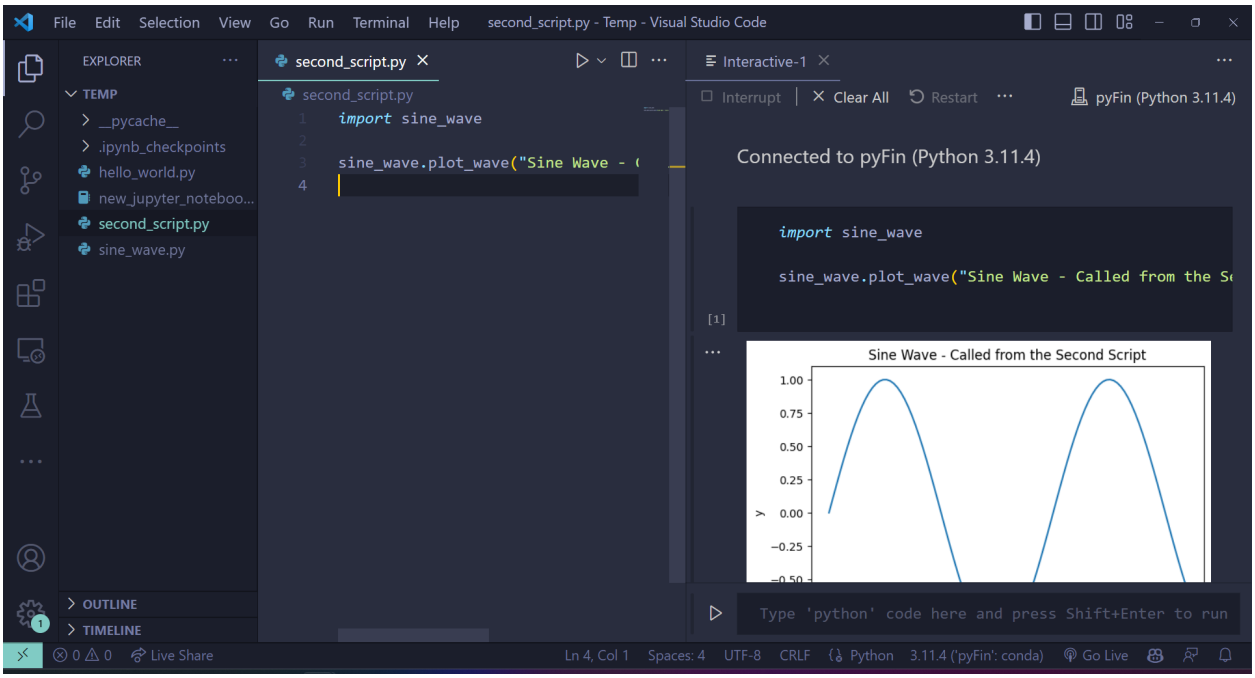
- Using the run button
- Using the terminal

8.5.1 Using the run button

You can run the script by clicking on the run button on the top right corner of the editor.



You can also run the script interactively by selecting the **Run Current File in Interactive Window** option from the dropdown.



This creates an ipykernel console and runs the script.

8.5.2 Using the terminal

The command `python <path to file.py>` is executed on the console of your choice.

If you are using a Windows machine, you can either use the Anaconda Prompt or the Command Prompt - but, generally not the PowerShell.

Here's an execution of the earlier code.

Note: If you would like to develop packages and build tools using Python, you may want to look into the use of Docker containers and VS Code.

However, this is outside the focus of these lectures.

8.6 Git your hands dirty

This section will familiarize you with git and GitHub.

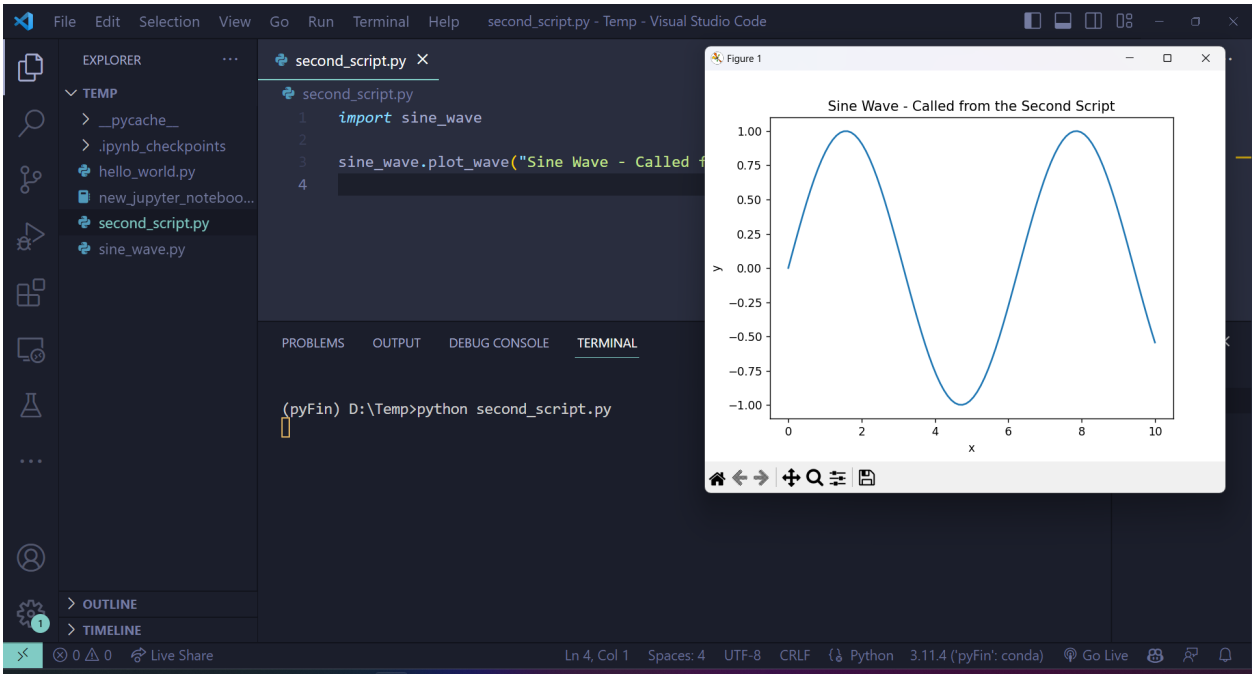
Git is a *version control system* — a piece of software used to manage digital projects such as code libraries.

In many cases, the associated collections of files — called *repositories* — are stored on GitHub.

GitHub is a wonderland of collaborative coding projects.

For example, it hosts many of the scientific libraries we'll be using later on, such as this one.

Git is the underlying software used to manage these projects.



Git is an extremely powerful tool for distributed collaboration — for example, we use it to share and synchronize all the source files for these lectures.

There are two main flavors of Git

1. the plain vanilla command line Git version
2. the various point-and-click GUI versions
    - See, for example, the GitHub version or Git GUI integrated into your IDE.

In case you already haven't, try

1. Installing Git.
2. Getting a copy of QuantEcon.py using Git.

For example, if you've installed the command line version, open up a terminal and enter.

```
git clone https://github.com/QuantEcon/QuantEcon.py
```

(This is just `git clone` in front of the URL for the repository)

This command will download all necessary components to rebuild the lecture you are reading now.

As the 2nd task,

1. Sign up to GitHub.
2. Look into 'forking' GitHub repositories (forking means making your own copy of a GitHub repository, stored on GitHub).
3. Fork QuantEcon.py.
4. Clone your fork to some local directory, make edits, commit them, and push them back up to your forked GitHub repo.
5. If you made a valuable improvement, send us a pull request!

For reading on these and other topics, try

- The official Git documentation.
- Reading through the docs on GitHub.
- Pro Git Book by Scott Chacon and Ben Straub.
- One of the thousands of Git tutorials on the Net.

Part II

The Scientific Libraries

CHAPTER

NINE

PYTHON FOR SCIENTIFIC COMPUTING

Contents

> "We should forget about small efficiencies, say about 97% of the time: premature optimization is the root of all evil." – Donald Knuth

9.1 Overview

Python is extremely popular for scientific computing, due to such factors as

- the accessible and flexible nature of the language itself,
- the huge range of high quality scientific libraries now available,
- the fact that the language and libraries are open source,
- the popular Anaconda Python distribution, which simplifies installation and management of those libraries, and
- the recent surge of interest in using Python for machine learning and artificial intelligence.

In this lecture we give a short overview of scientific computing in Python, addressing the following questions:

- What are the relative strengths and weaknesses of Python for these tasks?
- What are the main elements of the scientific Python ecosystem?
- How is the situation changing over time?

In addition to what's in Anaconda, this lecture will need

```
!pip install quantecon
```

9.2 Scientific Libraries

Let's briefly review Python's scientific libraries, starting with why we need them.

9.2.1 The Role of Scientific Libraries

One obvious reason we use scientific libraries is because they implement routines we want to use.

For example, it's almost always better to use an existing routine for root finding than to write a new one from scratch.

(For standard algorithms, efficiency is maximized if the community can coordinate on a common set of implementations, written by experts and tuned by users to be as fast and robust as possible.)

But this is not the only reason that we use Python's scientific libraries.

Another is that pure Python, while flexible and elegant, is not fast.

So we need libraries that are designed to accelerate execution of Python code.

As we'll see below, there are now Python libraries that can do this extremely well.

9.2.2 Python's Scientific Ecosystem

In terms of popularity, the big four in the world of scientific Python libraries are

- NumPy
- SciPy
- Matplotlib
- Pandas

For us, there's another (relatively new) library that will also be essential for numerical computing:

- Numba

Over the next few lectures we'll see how to use these libraries.

But first, let's quickly review how they fit together.

- NumPy forms the foundations by providing a basic array data type (think of vectors and matrices) and functions for acting on these arrays (e.g., matrix multiplication).
- SciPy builds on NumPy by adding the kinds of numerical methods that are routinely used in science (interpolation, optimization, root finding, etc.).
- Matplotlib is used to generate figures, with a focus on plotting data stored in NumPy arrays.
- Pandas provides types and functions for empirical work (e.g., manipulating data).
- Numba accelerates execution via JIT compilation — we'll learn about this soon.

9.3 The Need for Speed

Now let's discuss execution speed.

Higher-level languages like Python are optimized for humans.

This means that the programmer can leave many details to the runtime environment

- specifying variable types
- memory allocation/deallocation, etc.

The upside is that, compared to low-level languages, Python is typically faster to write, less error-prone and easier to debug.

The downside is that Python is harder to optimize — that is, turn into fast machine code — than languages like C or Fortran.

Indeed, the standard implementation of Python (called CPython) cannot match the speed of compiled languages such as C or Fortran.

Does that mean that we should just switch to C or Fortran for everything?

The answer is: No, no and one hundred times no!

(This is what you should say to the senior professor insisting that the model needs to be rewritten in Fortran or C++.)

There are two reasons why:

First, for any given program, relatively few lines are ever going to be time-critical.

Hence it is far more efficient to write most of our code in a high productivity language like Python.

Second, even for those lines of code that *are* time-critical, we can now achieve the same speed as C or Fortran using Python's scientific libraries.

9.3.1 Where are the Bottlenecks?

Before we learn how to do this, let's try to understand why plain vanilla Python is slower than C or Fortran.

This will, in turn, help us figure out how to speed things up.

Dynamic Typing

Consider this Python operation

```
a, b = 10, 10
a + b
```

```
20
```

Even for this simple operation, the Python interpreter has a fair bit of work to do.

For example, in the statement `a + b`, the interpreter has to know which operation to invoke.

If `a` and `b` are strings, then `a + b` requires string concatenation

```
a, b = 'foo', 'bar'
a + b
```

```
'foobar'
```

If `a` and `b` are lists, then `a + b` requires list concatenation

```
a, b = ['foo'], ['bar']
a + b
```

```
['foo', 'bar']
```

(We say that the operator + is *overloaded* — its action depends on the type of the objects on which it acts)

As a result, Python must check the type of the objects and then call the correct operation.

This involves substantial overheads.

Static Types

Compiled languages avoid these overheads with explicit, static types.

For example, consider the following C code, which sums the integers from 1 to 10

```
#include <stdio.h>

int main(void) {
    int i;
    int sum = 0;
    for (i = 1; i <= 10; i++) {
        sum = sum + i;
    }
    printf("sum = %d\n", sum);
    return 0;
}
```

The variables `i` and `sum` are explicitly declared to be integers.

Hence, the meaning of addition here is completely unambiguous.

9.3.2 Data Access

Another drag on speed for high-level languages is data access.

To illustrate, let's consider the problem of summing some data — say, a collection of integers.

Summing with Compiled Code

In C or Fortran, these integers would typically be stored in an array, which is a simple data structure for storing homogeneous data.

Such an array is stored in a single contiguous block of memory

- In modern computers, memory addresses are allocated to each byte (one byte = 8 bits).
- For example, a 64 bit integer is stored in 8 bytes of memory.
- An array of n such integers occupies $8n$ **consecutive** memory slots.

Moreover, the compiler is made aware of the data type by the programmer.

- In this case 64 bit integers

Hence, each successive data point can be accessed by shifting forward in memory space by a known and fixed amount.

- In this case 8 bytes

Summing in Pure Python

Python tries to replicate these ideas to some degree.

For example, in the standard Python implementation (CPython), list elements are placed in memory locations that are in a sense contiguous.

However, these list elements are more like pointers to data rather than actual data.

Hence, there is still overhead involved in accessing the data values themselves.

This is a considerable drag on speed.

In fact, it's generally true that memory traffic is a major culprit when it comes to slow execution.

Let's look at some ways around these problems.

9.4 Vectorization

There is a clever method called **vectorization** that can be used to speed up high level languages in numerical applications.

The key idea is to send array processing operations in batch to pre-compiled and efficient native machine code.

The machine code itself is typically compiled from carefully optimized C or Fortran.

For example, when working in a high level language, the operation of inverting a large matrix can be subcontracted to efficient machine code that is pre-compiled for this purpose and supplied to users as part of a package.

This clever idea dates back to MATLAB, which uses vectorization extensively.

Vectorization can greatly accelerate many numerical computations (but not all, as we shall see).

Let's see how vectorization works in Python, using NumPy.

9.4.1 Operations on Arrays

First, let's run some imports

```
import random
import numpy as np
import quantecon as qe
```

Next let's try some non-vectorized code, which uses a native Python loop to generate, square and then sum a large number of random variables:

```
n = 1_000_000
```

```
%%time

y = 0      # Will accumulate and store sum
for i in range(n):
    x = random.uniform(0, 1)
    y += x**2
```

```
CPU times: user 237 ms, sys: 370 µs, total: 237 ms
Wall time: 237 ms
```

The following vectorized code achieves the same thing.

```
%%time

x = np.random.uniform(0, 1, n)
y = np.sum(x**2)
```

```
CPU times: user 9.08 ms, sys: 272 µs, total: 9.36 ms
Wall time: 9.12 ms
```

As you can see, the second code block runs much faster. Why?

The second code block breaks the loop down into three basic operations

1. draw `n` uniforms
2. square them
3. sum them

These are sent as batch operators to optimized machine code.

Apart from minor overheads associated with sending data back and forth, the result is C or Fortran-like speed.

When we run batch operations on arrays like this, we say that the code is *vectorized*.

Vectorized code is typically fast and efficient.

It is also surprisingly flexible, in the sense that many operations can be vectorized.

The next section illustrates this point.

9.4.2 Universal Functions

Many functions provided by NumPy are so-called *universal functions* — also called ufuncs.

This means that they

- map scalars into scalars, as expected
- map arrays into arrays, acting element-wise

For example, `np.cos` is a ufunc:

```
np.cos(1.0)
```

```
0.5403023058681398
```

```
np.cos(np.linspace(0, 1, 3))
```

```
array([1.        , 0.87758256, 0.54030231])
```

By exploiting ufuncs, many operations can be vectorized.

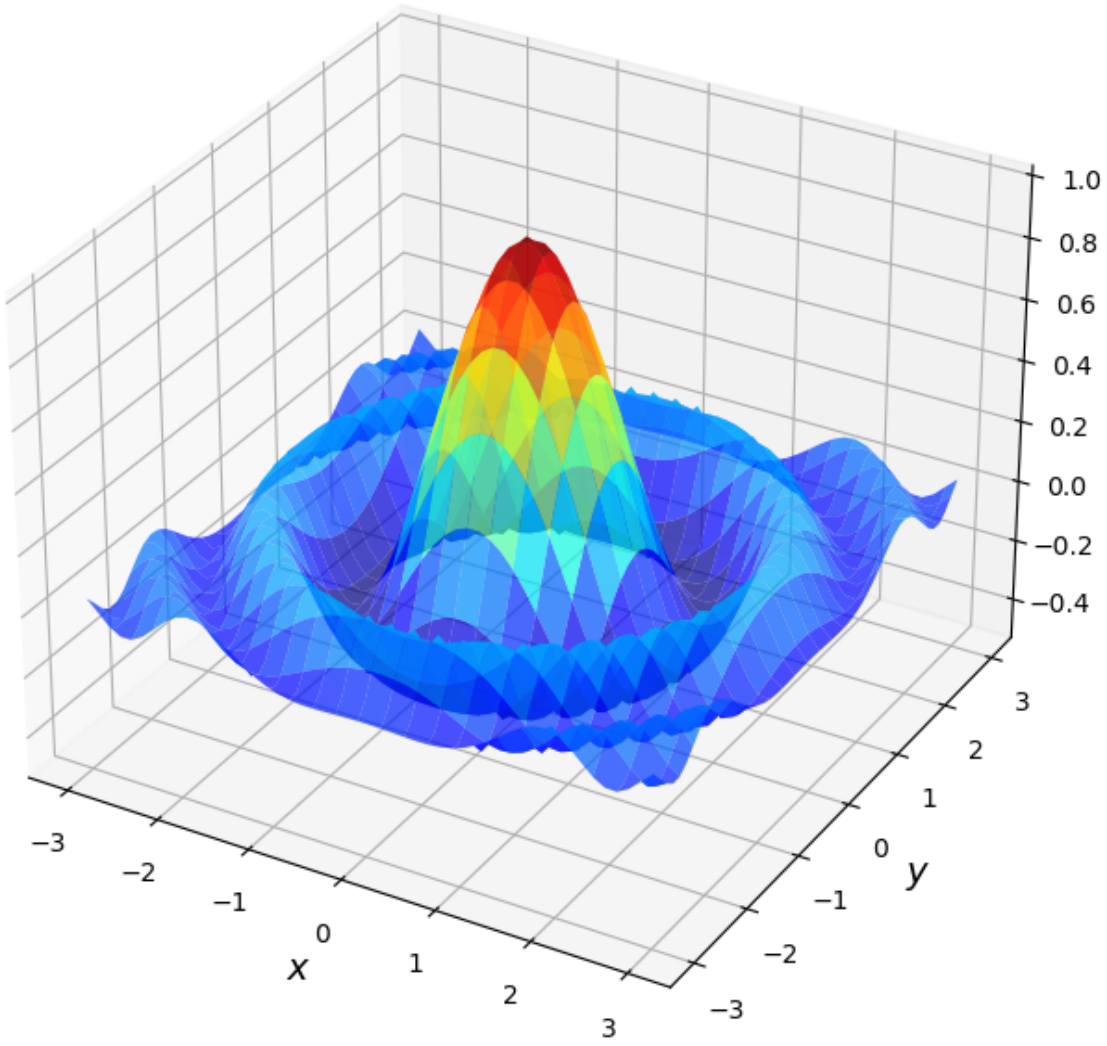
For example, consider the problem of maximizing a function f of two variables (x, y) over the square $[-a, a] \times [-a, a]$.

For f and a let's choose

$$f(x, y) = \frac{\cos(x^2 + y^2)}{1 + x^2 + y^2} \quad \text{and} \quad a = 3$$

Here's a plot of f

```
import matplotlib.pyplot as plt
%matplotlib inline
from mpl_toolkits.mplot3d.axes3d import Axes3D
from matplotlib import cm

def f(x, y):
    return np.cos(x**2 + y**2) / (1 + x**2 + y**2)

xgrid = np.linspace(-3, 3, 50)
ygrid = xgrid
x, y = np.meshgrid(xgrid, ygrid)

fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')
ax.plot_surface(x,
                y,
                f(x, y),
                rstride=2, cstride=2,
                cmap=cm.jet,
                alpha=0.7,
                linewidth=0.25)
ax.set_zlim(-0.5, 1.0)
ax.set_xlabel('$x$', fontsize=14)
ax.set_ylabel('$y$', fontsize=14)
plt.show()
```



To maximize it, we're going to use a naive grid search:

1. Evaluate f for all (x, y) in a grid on the square.
2. Return the maximum of observed values.

The grid will be

```
grid = np.linspace(-3, 3, 1000)
```

Here's a non-vectorized version that uses Python loops.

```
%%time

m = -np.inf

for x in grid:
```

(continues on next page)

(continued from previous page)

```
    for y in grid:
        z = f(x, y)
        if z > m:
            m = z
```

```
CPU times: user 1.48 s, sys: 4.97 ms, total: 1.48 s
Wall time: 1.39 s
```

And here's a vectorized version

```
%%time

x, y = np.meshgrid(grid, grid)
np.max(f(x, y))
```

```
CPU times: user 13.5 ms, sys: 8.24 ms, total: 21.8 ms
Wall time: 21.6 ms
```

```
0.9999819641085747
```

In the vectorized version, all the looping takes place in compiled code.

As you can see, the second version is **much** faster.

(We'll make it even faster again later on, using more scientific programming tricks.)

9.5 Beyond Vectorization

At its best, vectorization yields fast, simple code.

However, it's not without disadvantages.

One issue is that it can be highly memory-intensive.

For example, the vectorized maximization routine above is far more memory intensive than the non-vectorized version that preceded it.

This is because vectorization tends to create many intermediate arrays before producing the final calculation.

Another issue is that not all algorithms can be vectorized.

In these kinds of settings, we need to go back to loops.

Fortunately, there are alternative ways to speed up Python loops that work in almost any setting.

For example, in the last few years, a new Python library called Numba has appeared that solves the main problems with vectorization listed above.

It does so through something called **just in time (JIT) compilation**, which can generate extremely fast and efficient code.

We'll learn how to use Numba *soon*.

CHAPTER

TEN

NUMPY

Contents

> "Let's be clear: the work of science has nothing whatever to do with consensus. Consensus is the business of politics. Science, on the contrary, requires only one investigator who happens to be right, which means that he or she has results that are verifiable by reference to the real world. In science consensus is irrelevant. What is relevant is reproducible results." – Michael Crichton

10.1 Overview

NumPy is a first-rate library for numerical programming

- Widely used in academia, finance and industry.
- Mature, fast, stable and under continuous development.

We have already seen some code involving NumPy in the preceding lectures.

In this lecture, we will start a more systematic discussion of both

- NumPy arrays and
- the fundamental array processing operations provided by NumPy.

10.1.1 References

- The official NumPy documentation.

10.2 NumPy Arrays

The essential problem that NumPy solves is fast array processing.

The most important structure that NumPy defines is an array data type formally called a numpy.ndarray.

NumPy arrays power a large proportion of the scientific Python ecosystem.

Let's first import the library.

```
import numpy as np
```

To create a NumPy array containing only zeros we use np.zeros

```
a = np.zeros(3)
a
```

```
array([0., 0., 0.])
```

```
type(a)
```

```
numpy.ndarray
```

NumPy arrays are somewhat like native Python lists, except that

- Data *must be homogeneous* (all elements of the same type).
- These types must be one of the data types (`dtypes`) provided by NumPy.

The most important of these dtypes are:

- float64: 64 bit floating-point number
- int64: 64 bit integer
- bool: 8 bit True or False

There are also dtypes to represent complex numbers, unsigned integers, etc.

On modern machines, the default dtype for arrays is `float64`

```
a = np.zeros(3)
type(a[0])
```

```
numpy.float64
```

If we want to use integers we can specify as follows:

```
a = np.zeros(3, dtype=int)
type(a[0])
```

```
numpy.int64
```

10.2.1 Shape and Dimension

Consider the following assignment

```
z = np.zeros(10)
```

Here `z` is a *flat* array with no dimension — neither row nor column vector.

The dimension is recorded in the `shape` attribute, which is a tuple

```
z.shape
```

```
(10,)
```

Here the shape tuple has only one element, which is the length of the array (tuples with one element end with a comma).

To give it dimension, we can change the `shape` attribute

```
z.shape = (10, 1)
z
```

```
array([[0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [0.],
       [0.]])
```

```
z = np.zeros(4)
z.shape = (2, 2)
z
```

```
array([[0., 0.],
       [0., 0.]])
```

In the last case, to make the 2 by 2 array, we could also pass a tuple to the `zeros()` function, as in `z = np.zeros((2, 2))`.

10.2.2 Creating Arrays

As we've seen, the `np.zeros` function creates an array of zeros.

You can probably guess what `np.ones` creates.

Related is `np.empty`, which creates arrays in memory that can later be populated with data

```
z = np.empty(3)
z
```

```
array([0., 0., 0.])
```

The numbers you see here are garbage values.

(Python allocates 3 contiguous 64 bit pieces of memory, and the existing contents of those memory slots are interpreted as `float64` values)

To set up a grid of evenly spaced numbers use `np.linspace`

```
z = np.linspace(2, 4, 5)  # From 2 to 4, with 5 elements
```

To create an identity matrix use either `np.identity` or `np.eye`

```
z = np.identity(2)
z
```

```
array([[1., 0.],
       [0., 1.]])
```

In addition, NumPy arrays can be created from Python lists, tuples, etc. using `np.array`

```
z = np.array([10, 20])                # ndarray from Python list
z
```

```
array([10, 20])
```

```
type(z)
```

```
numpy.ndarray
```

```
z = np.array((10, 20), dtype=float)    # Here 'float' is equivalent to 'np.float64'
z
```

```
array([10., 20.])
```

```
z = np.array([[1, 2], [3, 4]])         # 2D array from a list of lists
z
```

```
array([[1, 2],
       [3, 4]])
```

See also `np.asarray`, which performs a similar function, but does not make a distinct copy of data already in a NumPy array.

```
na = np.linspace(10, 20, 2)
na is np.asarray(na)   # Does not copy NumPy arrays
```

```
True
```

```
na is np.array(na)     # Does make a new copy --- perhaps unnecessarily
```

```
False
```

To read in the array data from a text file containing numeric data use `np.loadtxt` or `np.genfromtxt`—see the documentation for details.

10.2.3 Array Indexing

For a flat array, indexing is the same as Python sequences:

```
z = np.linspace(1, 2, 5)
z
```

```
array([1.  , 1.25, 1.5 , 1.75, 2.  ])
```

```
z[0]
```

```
1.0
```

```
z[0:2]  # Two elements, starting at element 0
```

```
array([1.  , 1.25])
```

```
z[-1]
```

```
2.0
```

For 2D arrays the index syntax is as follows:

```
z = np.array([[1, 2], [3, 4]])
z
```

```
array([[1, 2],
       [3, 4]])
```

```
z[0, 0]
```

```
1
```

```
z[0, 1]
```

```
2
```

And so on.

Note that indices are still zero-based, to maintain compatibility with Python sequences.

Columns and rows can be extracted as follows

```
z[0, :]
```

```
array([1, 2])
```

```
z[:, 1]
```

```
array([2, 4])
```

NumPy arrays of integers can also be used to extract elements

```
z = np.linspace(2, 4, 5)
z
```

```
array([2. , 2.5, 3. , 3.5, 4. ])
```

```
indices = np.array((0, 2, 3))
z[indices]
```

```
array([2. , 3. , 3.5])
```

Finally, an array of `dtype bool` can be used to extract elements

```
z
```

```
array([2. , 2.5, 3. , 3.5, 4. ])
```

```
d = np.array([0, 1, 1, 0, 0], dtype=bool)
d
```

```
array([False,  True,  True, False, False])
```

```
z[d]
```

```
array([2.5, 3. ])
```

We'll see why this is useful below.

An aside: all elements of an array can be set equal to one number using slice notation

```
z = np.empty(3)
z
```

```
array([2. , 3. , 3.5])
```

```
z[:] = 42
z
```

```
array([42., 42., 42.])
```

10.2.4 Array Methods

Arrays have useful methods, all of which are carefully optimized

```
a = np.array((4, 3, 2, 1))
a
```

```
array([4, 3, 2, 1])
```

```
a.sort()              # Sorts a in place
a
```

```
array([1, 2, 3, 4])
```

```
a.sum()               # Sum
```

```
10
```

```
a.mean()              # Mean
```

```
2.5
```

```
a.max()               # Max
```

```
4
```

```
a.argmax()            # Returns the index of the maximal element
```

```
3
```

```
a.cumsum()              # Cumulative sum of the elements of a
```

```
array([ 1,  3,  6, 10])
```

```
a.cumprod()             # Cumulative product of the elements of a
```

```
array([ 1,  2,  6, 24])
```

```
a.var()                 # Variance
```

```
1.25
```

```
a.std()                 # Standard deviation
```

```
1.1180339887498895
```

```
a.shape = (2, 2)
a.T                     # Equivalent to a.transpose()
```

```
array([[1, 3],
       [2, 4]])
```

Another method worth knowing is `searchsorted()`.

If `z` is a nondecreasing array, then `z.searchsorted(a)` returns the index of the first element of `z` that is `>= a`

```
z = np.linspace(2, 4, 5)
z
```

```
array([2. , 2.5, 3. , 3.5, 4. ])
```

```
z.searchsorted(2.2)
```

```
1
```

Many of the methods discussed above have equivalent functions in the NumPy namespace

```
a = np.array((4, 3, 2, 1))
```

```
np.sum(a)
```

```
10
```

```
np.mean(a)
```

```
2.5
```

10.3 Arithmetic Operations

The operators +, −, *, / and ** all act *elementwise* on arrays

```
a = np.array([1, 2, 3, 4])
b = np.array([5, 6, 7, 8])
a + b
```

```
array([ 6,  8, 10, 12])
```

```
a * b
```

```
array([ 5, 12, 21, 32])
```

We can add a scalar to each element as follows

```
a + 10
```

```
array([11, 12, 13, 14])
```

Scalar multiplication is similar

```
a * 10
```

```
array([10, 20, 30, 40])
```

The two-dimensional arrays follow the same general rules

```
A = np.ones((2, 2))
B = np.ones((2, 2))
A + B
```

```
array([[2., 2.],
       [2., 2.]])
```

```
A + 10
```

```
array([[11., 11.],
       [11., 11.]])
```

```
A * B
```

```
array([[1., 1.],
       [1., 1.]])
```

In particular, `A * B` is *not* the matrix product, it is an element-wise product.

10.4 Matrix Multiplication

With Anaconda's scientific Python package based around Python 3.5 and above, one can use the `@` symbol for matrix multiplication, as follows:

```
A = np.ones((2, 2))
B = np.ones((2, 2))
A @ B
```

```
array([[2., 2.],
       [2., 2.]])
```

(For older versions of Python and NumPy you need to use the np.dot function)

We can also use `@` to take the inner product of two flat arrays

```
A = np.array((1, 2))
B = np.array((10, 20))
A @ B
```

```
50
```

In fact, we can use `@` when one element is a Python list or tuple

```
A = np.array(((1, 2), (3, 4)))
A
```

```
array([[1, 2],
       [3, 4]])
```

```
A @ (0, 1)
```

```
array([2, 4])
```

Since we are post-multiplying, the tuple is treated as a column vector.

10.5 Broadcasting

(This section extends an excellent discussion of broadcasting provided by Jake VanderPlas.)

Note: Broadcasting is a very important aspect of NumPy. At the same time, advanced broadcasting is relatively complex and some of the details below can be skimmed on first pass.

In element-wise operations, arrays may not have the same shape.

When this happens, NumPy will automatically expand arrays to the same shape whenever possible.

This useful (but sometimes confusing) feature in NumPy is called **broadcasting**.

The value of broadcasting is that

- `for` loops can be avoided, which helps numerical code run fast and
- broadcasting can allow us to implement operations on arrays without actually creating some dimensions of these arrays in memory, which can be important when arrays are large.

For example, suppose `a` is a 3×3 array (`a -> (3, 3)`), while `b` is a flat array with three elements (`b -> (3,)`).

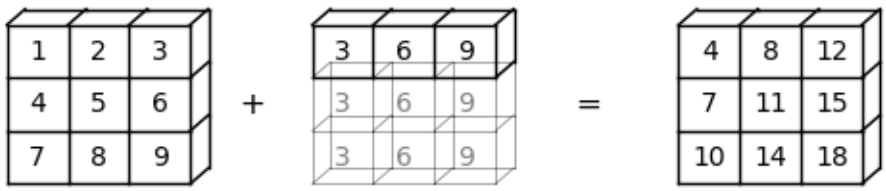
When adding them together, NumPy will automatically expand `b -> (3,)` to `b -> (3, 3)`.

The element-wise addition will result in a 3×3 array

```
a = np.array(
        [[1, 2, 3],
         [4, 5, 6],
         [7, 8, 9]])
b = np.array([3, 6, 9])

a + b
```

```
array([[ 4,  8, 12],
       [ 7, 11, 15],
       [10, 14, 18]])
```

Here is a visual representation of this broadcasting operation:



How about `b -> (3, 1)`?

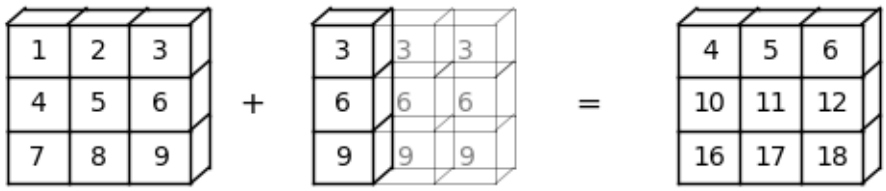
In this case, NumPy will automatically expand `b -> (3, 1)` to `b -> (3, 3)`.

Element-wise addition will then result in a 3×3 matrix

```
b.shape = (3, 1)

a + b
```

```
array([[ 4,  5,  6],
       [10, 11, 12],
       [16, 17, 18]])
```

Here is a visual representation of this broadcasting operation:



The previous broadcasting operation is equivalent to the following `for` loop

```
row, column = a.shape
result = np.empty((3, 3))
for i in range(row):
    for j in range(column):
        result[i, j] = a[i, j] + b[i]

result
```

```
array([[ 4.,  5.,  6.],
       [10., 11., 12.],
       [16., 17., 18.]])
```

In some cases, both operands will be expanded.

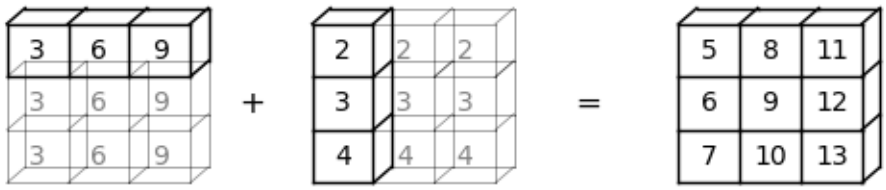
When we have `a -> (3,)` and `b -> (3, 1)`, `a` will be expanded to `a -> (3, 3)`, and `b` will be expanded to `b -> (3, 3)`.

In this case, element-wise addition will result in a 3×3 matrix

```
a = np.array([3, 6, 9])
b = np.array([2, 3, 4])
b.shape = (3, 1)

a + b
```

```
array([[ 5,  8, 11],
       [ 6,  9, 12],
       [ 7, 10, 13]])
```

Here is a visual representation of this broadcasting operation:



While broadcasting is very useful, it can sometimes seem confusing.

For example, let's try adding `a -> (3, 2)` and `b -> (3,)`.

```
a = np.array(
      [[1, 2],
```

(continues on next page)

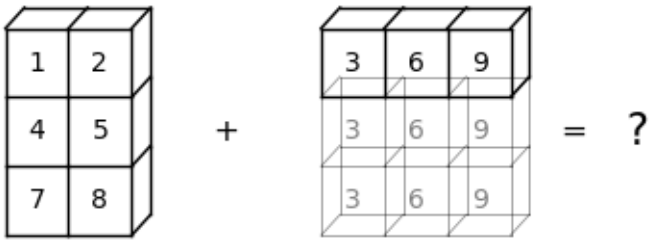
(continued from previous page)

```
       [4, 5],
       [7, 8]])
b = np.array([3, 6, 9])

a + b
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[69], line 7
      1 a = np.array(
      2       [[1, 2],
      3        [4, 5],
      4        [7, 8]])
      5 b = np.array([3, 6, 9])
----> 7 a + b

ValueError: operands could not be broadcast together with shapes (3,2) (3,)
```

The `ValueError` tells us that operands could not be broadcast together.

Here is a visual representation to show why this broadcasting cannot be executed:



We can see that NumPy cannot expand the arrays to the same size.

It is because, when `b` is expanded from `b -> (3,)` to `b -> (3, 3)`, NumPy cannot match `b` with `a -> (3, 2)`.

Things get even trickier when we move to higher dimensions.

To help us, we can use the following list of rules:

- *Step 1:* When the dimensions of two arrays do not match, NumPy will expand the one with fewer dimensions by adding dimension(s) on the left of the existing dimensions.
  - For example, if `a -> (3, 3)` and `b -> (3,)`, then broadcasting will add a dimension to the left so that `b -> (1, 3)`;
  - If `a -> (2, 2, 2)` and `b -> (2, 2)`, then broadcasting will add a dimension to the left so that `b -> (1, 2, 2)`;
  - If `a -> (3, 2, 2)` and `b -> (2,)`, then broadcasting will add two dimensions to the left so that `b -> (1, 1, 2)` (you can also see this process as going through *Step 1* twice).
- *Step 2:* When the two arrays have the same dimension but different shapes, NumPy will try to expand dimensions where the shape index is 1.
  - For example, if `a -> (1, 3)` and `b -> (3, 1)`, then broadcasting will expand dimensions with shape 1 in both `a` and `b` so that `a -> (3, 3)` and `b -> (3, 3)`;

- If `a -> (2, 2, 2)` and `b -> (1, 2, 2)`, then broadcasting will expand the first dimension of `b` so that `b -> (2, 2, 2)`;
- If `a -> (3, 2, 2)` and `b -> (1, 1, 2)`, then broadcasting will expand `b` on all dimensions with shape 1 so that `b -> (3, 2, 2)`.

Here are code examples for broadcasting higher dimensional arrays

```
# a -> (2, 2, 2) and  b -> (1, 2, 2)

a = np.array(
    [[[1, 2],
      [2, 3]],

     [[2, 3],
      [3, 4]]])
print(f'the shape of array a is {a.shape}')

b = np.array(
    [[1,7],
     [7,1]])
print(f'the shape of array b is {b.shape}')

a + b
```

```
the shape of array a is (2, 2, 2)
the shape of array b is (2, 2)
```

```
array([[[ 2,  9],
        [ 9,  4]],

       [[ 3, 10],
        [10,  5]]])
```

```
# a -> (3, 2, 2) and b -> (2,)

a = np.array(
    [[[1, 2],
      [3, 4]],

     [[4, 5],
      [6, 7]],

     [[7, 8],
      [9, 10]]])
print(f'the shape of array a is {a.shape}')

b = np.array([3, 6])
print(f'the shape of array b is {b.shape}')

a + b
```

```
the shape of array a is (3, 2, 2)
the shape of array b is (2,)
```

```
array([[[ 4,  8],
        [ 6, 10]],

       [[ 7, 11],
        [ 9, 13]],

       [[10, 14],
        [12, 16]]])
```

- *Step 3:* After Step 1 and 2, if the two arrays still do not match, a `ValueError` will be raised. For example, suppose `a -> (2, 2, 3)` and `b -> (2, 2)`
  - By *Step 1*, `b` will be expanded to `b -> (1, 2, 2)`;
  - By *Step 2*, `b` will be expanded to `b -> (2, 2, 2)`;
  - We can see that they do not match each other after the first two steps. Thus, a `ValueError` will be raised

```
a = np.array(
    [[[1, 2, 3],
      [2, 3, 4]],

     [[2, 3, 4],
      [3, 4, 5]]])
print(f'the shape of array a is {a.shape}')

b = np.array(
    [[1,7],
     [7,1]])
print(f'the shape of array b is {b.shape}')

a + b
```

```
the shape of array a is (2, 2, 3)
the shape of array b is (2, 2)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[73], line 14
      9 b = np.array(
     10     [[1,7],
     11      [7,1]])
     12 print(f'the shape of array b is {b.shape}')
---> 14 a + b

ValueError: operands could not be broadcast together with shapes (2,2,3) (2,2)
```

10.6 Mutability and Copying Arrays

NumPy arrays are mutable data types, like Python lists.

In other words, their contents can be altered (mutated) in memory after initialization.

We already saw examples above.

Here's another example:

```
a = np.array([42, 44])
a
```

```
array([42, 44])
```

```
a[-1] = 0  # Change last element to 0
a
```

```
array([42,  0])
```

Mutability leads to the following behavior (which can be shocking to MATLAB programmers…)

```
a = np.random.randn(3)
a
```

```
array([-0.54890232, -0.63618665, -0.94948789])
```

```
b = a
b[0] = 0.0
a
```

```
array([ 0.        , -0.63618665, -0.94948789])
```

What's happened is that we have changed `a` by changing `b`.

The name `b` is bound to `a` and becomes just another reference to the array (the Python assignment model is described in more detail *later in the course*).

Hence, it has equal rights to make changes to that array.

This is in fact the most sensible default behavior!

It means that we pass around only pointers to data, rather than making copies.

Making copies is expensive in terms of both speed and memory.

10.6.1 Making Copies

It is of course possible to make `b` an independent copy of `a` when required.

This can be done using `np.copy`

```
a = np.random.randn(3)
a
```

```
array([-0.17144282,  1.25599012,  0.94965095])
```

```
b = np.copy(a)
b
```

```
array([-0.17144282,  1.25599012,  0.94965095])
```

Now `b` is an independent copy (called a *deep copy*)

```
b[:] = 1
b
```

```
array([1., 1., 1.])
```

```
a
```

```
array([-0.17144282,  1.25599012,  0.94965095])
```

Note that the change to `b` has not affected `a`.

10.7 Additional Functionality

Let's look at some other useful things we can do with NumPy.

10.7.1 Vectorized Functions

NumPy provides versions of the standard functions `log`, `exp`, `sin`, etc. that act *element-wise* on arrays

```
z = np.array([1, 2, 3])
np.sin(z)
```

```
array([0.84147098, 0.90929743, 0.14112001])
```

This eliminates the need for explicit element-by-element loops such as

```
n = len(z)
y = np.empty(n)
for i in range(n):
    y[i] = np.sin(z[i])
```

Because they act element-wise on arrays, these functions are called *vectorized functions*.

In NumPy-speak, they are also called *ufuncs*, which stands for "universal functions".

As we saw above, the usual arithmetic operations (+, *, etc.) also work element-wise, and combining these with the ufuncs gives a very large set of fast element-wise functions.

```
z
```

```
array([1, 2, 3])
```

```
(1 / np.sqrt(2 * np.pi)) * np.exp(- 0.5 * z**2)
```

```
array([0.24197072, 0.05399097, 0.00443185])
```

Not all user-defined functions will act element-wise.

For example, passing the function `f` defined below a NumPy array causes a `ValueError`

```
def f(x):
    return 1 if x > 0 else 0
```

The NumPy function `np.where` provides a vectorized alternative:

```
x = np.random.randn(4)
x
```

```
array([-1.4410515 , -0.65186216, -0.64465183,  0.8134109 ])
```

```
np.where(x > 0, 1, 0)  # Insert 1 if x > 0 true, otherwise 0
```

```
array([0, 0, 0, 1])
```

You can also use `np.vectorize` to vectorize a given function

```
f = np.vectorize(f)
f(x)                # Passing the same vector x as in the previous example
```

```
array([0, 0, 0, 1])
```

However, this approach doesn't always obtain the same speed as a more carefully crafted vectorized function.

10.7.2 Comparisons

As a rule, comparisons on arrays are done element-wise

```
z = np.array([2, 3])
y = np.array([2, 3])
z == y
```

```
array([ True,  True])
```

```
y[0] = 5
z == y
```

```
array([False,  True])
```

```
z != y
```

```
array([ True, False])
```

The situation is similar for >, <, >= and <=.

We can also do comparisons against scalars

```
z = np.linspace(0, 10, 5)
z
```

```
array([ 0. ,  2.5,  5. ,  7.5, 10. ])
```

```
z > 3
```

```
array([False, False,  True,  True,  True])
```

This is particularly useful for *conditional extraction*

```
b = z > 3
b
```

```
array([False, False,  True,  True,  True])
```

```
z[b]
```

```
array([ 5. ,  7.5, 10. ])
```

Of course we can—and frequently do—perform this in one step

```
z[z > 3]
```

```
array([ 5. ,  7.5, 10. ])
```

10.7.3 Sub-packages

NumPy provides some additional functionality related to scientific programming through its sub-packages.

We've already seen how we can generate random variables using np.random

```
z = np.random.randn(10000)  # Generate standard normals
y = np.random.binomial(10, 0.5, size=1000)    # 1,000 draws from Bin(10, 0.5)
y.mean()
```

```
5.045
```

Another commonly used subpackage is np.linalg

```
A = np.array([[1, 2], [3, 4]])

np.linalg.det(A)           # Compute the determinant
```

```
-2.0000000000000004
```

```
np.linalg.inv(A)           # Compute the inverse
```

```
array([[-2. ,  1. ],
       [ 1.5, -0.5]])
```

Much of this functionality is also available in SciPy, a collection of modules that are built on top of NumPy.

We'll cover the SciPy versions in more detail *soon*.

For a comprehensive list of what's available in NumPy see this documentation.

10.8 Exercises

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

Exercise 10.8.1

Consider the polynomial expression

$$p(x) = a_0 + a_1 x + a_2 x^2 + \cdots a_N x^N = \sum_{n=0}^{N} a_n x^n \tag{10.1}$$

Earlier, you wrote a simple function `p(x, coeff)` to evaluate (10.1) without considering efficiency.

Now write a new function that does the same job, but uses NumPy arrays and array operations for its computations, rather than any form of Python loop.

(Such functionality is already implemented as `np.poly1d`, but for the sake of the exercise don't use this class)

Hint: Use `np.cumprod()`

Solution to Exercise 10.8.1

This code does the job

```
def p(x, coef):
    X = np.ones_like(coef)
    X[1:] = x
    y = np.cumprod(X)   # y = [1, x, x**2,...]
    return coef @ y
```

Let's test it

```
x = 2
coef = np.linspace(2, 4, 3)
print(coef)
print(p(x, coef))
# For comparison
q = np.poly1d(np.flip(coef))
print(q(x))
```

```
[2. 3. 4.]
24.0
24.0
```

Exercise 10.8.2

Let `q` be a NumPy array of length `n` with `q.sum() == 1`.

Suppose that `q` represents a probability mass function.

We wish to generate a discrete random variable x such that $\mathbb{P}\{x = i\} = q_i$.

In other words, `x` takes values in `range(len(q))` and `x = i` with probability `q[i]`.

The standard (inverse transform) algorithm is as follows:

- Divide the unit interval $[0, 1]$ into n subintervals $I_0, I_1, \ldots, I_{n-1}$ such that the length of I_i is q_i.
- Draw a uniform random variable U on $[0, 1]$ and return the i such that $U \in I_i$.

The probability of drawing i is the length of I_i, which is equal to q_i.

We can implement the algorithm as follows

```
from random import uniform

def sample(q):
    a = 0.0
    U = uniform(0, 1)
    for i in range(len(q)):
```

(continues on next page)

(continued from previous page)

```
        if a < U <= a + q[i]:
            return i
        a = a + q[i]
```

If you can't see how this works, try thinking through the flow for a simple example, such as `q = [0.25, 0.75]` It helps to sketch the intervals on paper.

Your exercise is to speed it up using NumPy, avoiding explicit loops

---

Hint: Use `np.searchsorted` and `np.cumsum`

If you can, implement the functionality as a class called `DiscreteRV`, where

- the data for an instance of the class is the vector of probabilities `q`
- the class has a `draw()` method, which returns one draw according to the algorithm described above

If you can, write the method so that `draw(k)` returns `k` draws from `q`.

Solution to Exercise 10.8.2

Here's our first pass at a solution:

```
from numpy import cumsum
from numpy.random import uniform

class DiscreteRV:
    """
    Generates an array of draws from a discrete random variable with vector of
    probabilities given by q.
    """

    def __init__(self, q):
        """
        The argument q is a NumPy array, or array like, nonnegative and sums
        to 1
        """
        self.q = q
        self.Q = cumsum(q)

    def draw(self, k=1):
        """
        Returns k draws from q. For each such draw, the value i is returned
        with probability q[i].
        """
        return self.Q.searchsorted(uniform(0, 1, size=k))
```

The logic is not obvious, but if you take your time and read it slowly, you will understand.

There is a problem here, however.

Suppose that `q` is altered after an instance of `discreteRV` is created, for example by

```
q = (0.1, 0.9)
d = DiscreteRV(q)
d.q = (0.5, 0.5)
```

The problem is that `Q` does not change accordingly, and `Q` is the data used in the `draw` method.

To deal with this, one option is to compute `Q` every time the draw method is called.

But this is inefficient relative to computing `Q` once-off.

A better option is to use descriptors.

A solution from the quantecon library using descriptors that behaves as we desire can be found here.

Exercise 10.8.3

Recall our *earlier discussion* of the empirical cumulative distribution function.

Your task is to

1. Make the `__call__` method more efficient using NumPy.
2. Add a method that plots the ECDF over $[a, b]$, where a and b are method parameters.

Solution to Exercise 10.8.3

An example solution is given below.

In essence, we've just taken this code from QuantEcon and added in a plot method

```
"""
Modifies ecdf.py from QuantEcon to add in a plot method

"""

class ECDF:
    """
    One-dimensional empirical distribution function given a vector of
    observations.

    Parameters
    ----------
    observations : array_like
        An array of observations

    Attributes
    ----------
    observations : array_like
        An array of observations

    """

    def __init__(self, observations):
        self.observations = np.asarray(observations)

    def __call__(self, x):
        """
```

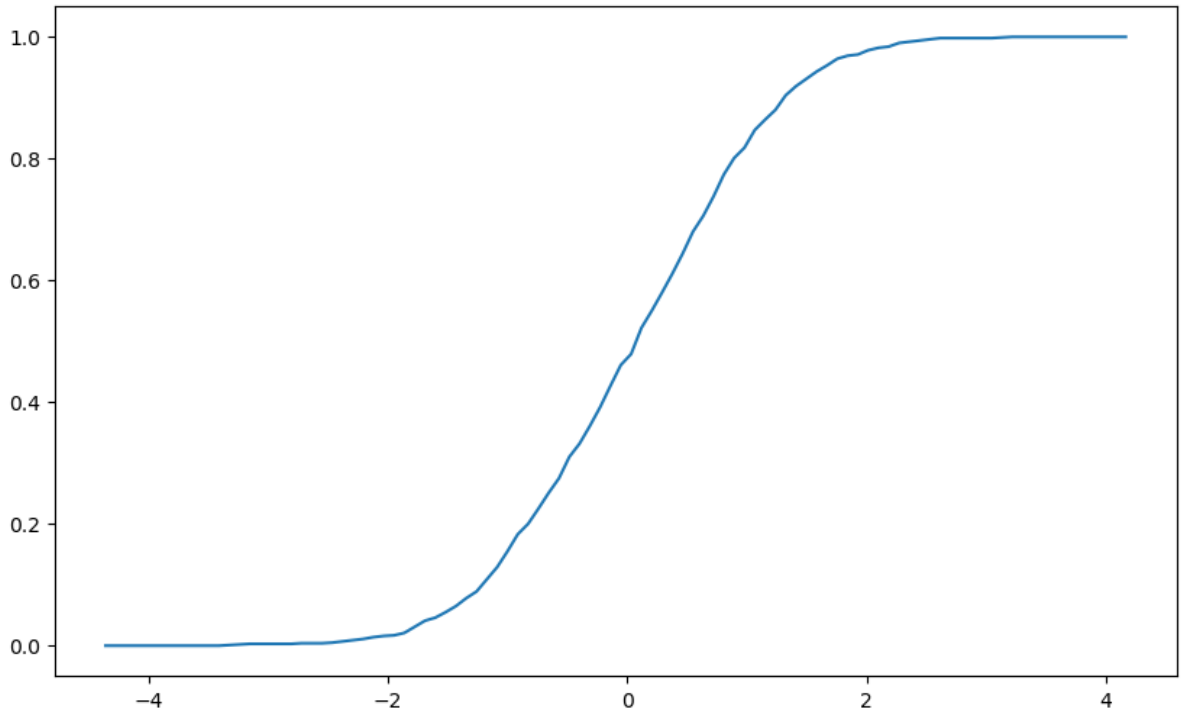
(continues on next page)

(continued from previous page)

```
        Evaluates the ecdf at x

        Parameters
        ----------
        x : scalar(float)
            The x at which the ecdf is evaluated

        Returns
        -------
        scalar(float)
            Fraction of the sample less than x

        """
        return np.mean(self.observations <= x)

    def plot(self, ax, a=None, b=None):
        """
        Plot the ecdf on the interval [a, b].

        Parameters
        ----------
        a : scalar(float), optional(default=None)
            Lower endpoint of the plot interval
        b : scalar(float), optional(default=None)
            Upper endpoint of the plot interval

        """

        # === choose reasonable interval if [a, b] not specified === #
        if a is None:
            a = self.observations.min() - self.observations.std()
        if b is None:
            b = self.observations.max() + self.observations.std()

        # === generate plot === #
        x_vals = np.linspace(a, b, num=100)
        f = np.vectorize(self.__call__)
        ax.plot(x_vals, f(x_vals))
        plt.show()
```

Here's an example of usage

```
fig, ax = plt.subplots()
X = np.random.randn(1000)
F = ECDF(X)
F.plot(ax)
```



Exercise 10.8.4

Recall that *broadcasting* in Numpy can help us conduct element-wise operations on arrays with different number of dimensions without using `for` loops.

In this exercise, try to use `for` loops to replicate the result of the following broadcasting operations.

Part1: Try to replicate this simple example using `for` loops and compare your results with the broadcasting operation below.

```
np.random.seed(123)
x = np.random.randn(4, 4)
y = np.random.randn(4)
A = x / y
```

Here is the output

```
print(A)
```

Part2: Move on to replicate the result of the following broadcasting operation. Meanwhile, compare the speeds of broadcasting and the `for` loop you implement.

```
import quantecon as qe

np.random.seed(123)
x = np.random.randn(1000, 100, 100)
y = np.random.randn(100)

qe.tic()
```

(continues on next page)

(continued from previous page)

```
B = x / y
qe.toc()
```

```
TOC: Elapsed: 0:00:0.01
```

```
0.012936592102050781
```

Here is the output

```
print(B)
```

Solution to Exercise 10.8.4

Part 1 Solution

```
np.random.seed(123)
x = np.random.randn(4, 4)
y = np.random.randn(4)

C = np.empty_like(x)
n = len(x)
for i in range(n):
    for j in range(n):
        C[i, j] = x[i, j] / y[j]
```

Compare the results to check your answer

```
print(C)
```

You can also use `array_equal()` to check your answer

```
print(np.array_equal(A, C))
```

```
True
```

Part 2 Solution

```
np.random.seed(123)
x = np.random.randn(1000, 100, 100)
y = np.random.randn(100)

qe.tic()
D = np.empty_like(x)
d1, d2, d3 = x.shape
for i in range(d1):
    for j in range(d2):
        for k in range(d3):
            D[i, j, k] = x[i, j, k] / y[k]
qe.toc()
```

```
TOC: Elapsed: 0:00:3.59
```

```
3.5994060039520264
```

Note that the `for` loop takes much longer than the broadcasting operation.

Compare the results to check your answer

```
print(D)
```

```
print(np.array_equal(B, D))
```

```
True
```

CHAPTER

ELEVEN

MATPLOTLIB

Contents

11.1 Overview

We've already generated quite a few figures in these lectures using Matplotlib.

Matplotlib is an outstanding graphics library, designed for scientific computing, with

- high-quality 2D and 3D plots
- output in all the usual formats (PDF, PNG, etc.)
- LaTeX integration
- fine-grained control over all aspects of presentation
- animation, etc.

11.1.1 Matplotlib's Split Personality

Matplotlib is unusual in that it offers two different interfaces to plotting.

One is a simple MATLAB-style API (Application Programming Interface) that was written to help MATLAB refugees find a ready home.

The other is a more "Pythonic" object-oriented API.

For reasons described below, we recommend that you use the second API.

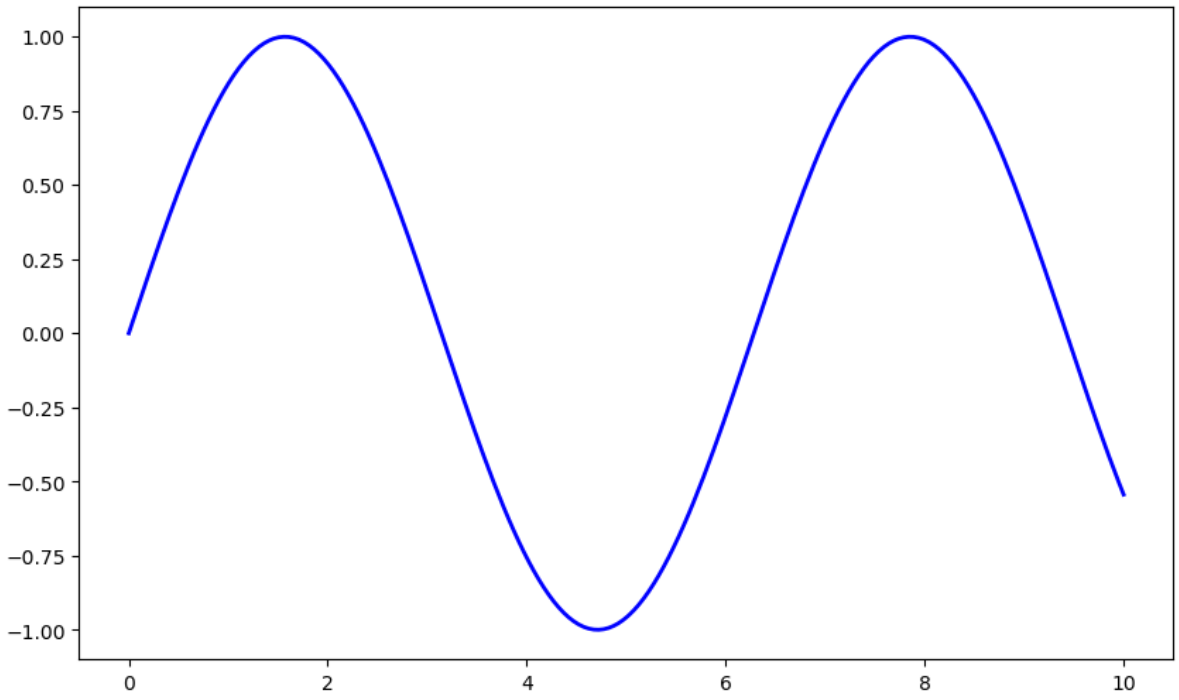
But first, let's discuss the difference.

11.2 The APIs

11.2.1 The MATLAB-style API

Here's the kind of easy example you might find in introductory treatments

```
%matplotlib inline
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = (10, 6) #set default figure size
import numpy as np

x = np.linspace(0, 10, 200)
y = np.sin(x)

plt.plot(x, y, 'b-', linewidth=2)
plt.show()
```



This is simple and convenient, but also somewhat limited and un-Pythonic.

For example, in the function calls, a lot of objects get created and passed around without making themselves known to the programmer.

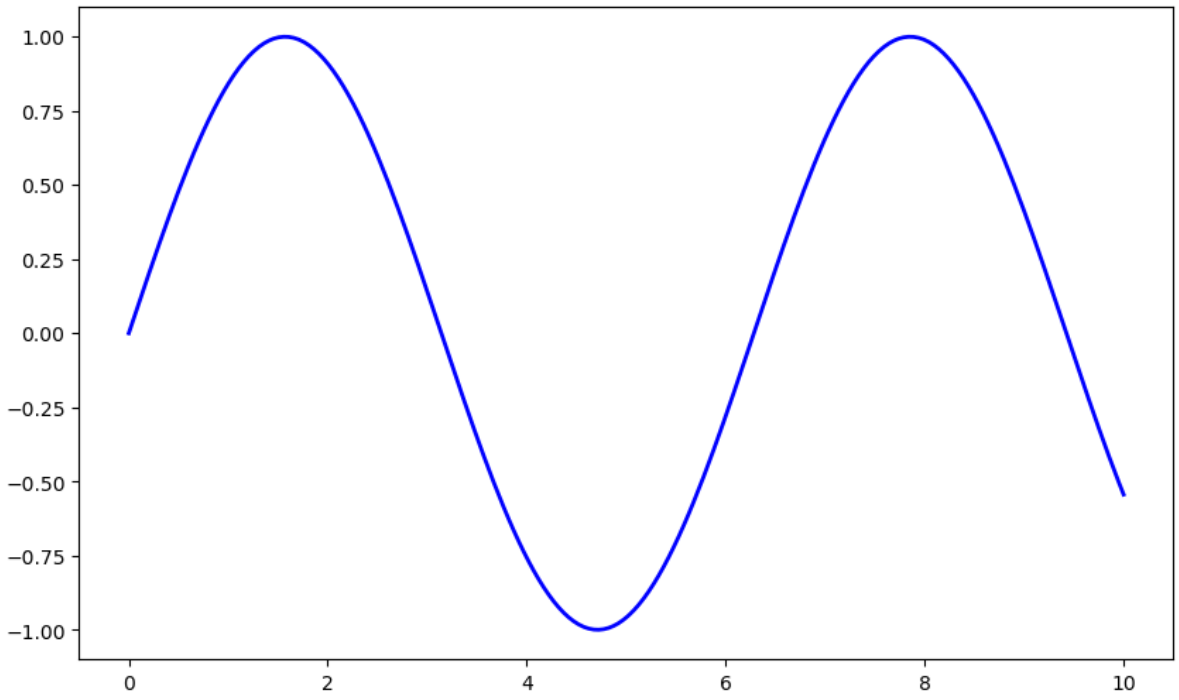
Python programmers tend to prefer a more explicit style of programming (run `import this` in a code block and look at the second line).

This leads us to the alternative, object-oriented Matplotlib API.

11.2.2 The Object-Oriented API

Here's the code corresponding to the preceding figure using the object-oriented API

```
fig, ax = plt.subplots()
ax.plot(x, y, 'b-', linewidth=2)
plt.show()
```



Here the call `fig, ax = plt.subplots()` returns a pair, where

- `fig` is a `Figure` instance—like a blank canvas.
- `ax` is an `AxesSubplot` instance—think of a frame for plotting in.

The `plot()` function is actually a method of `ax`.

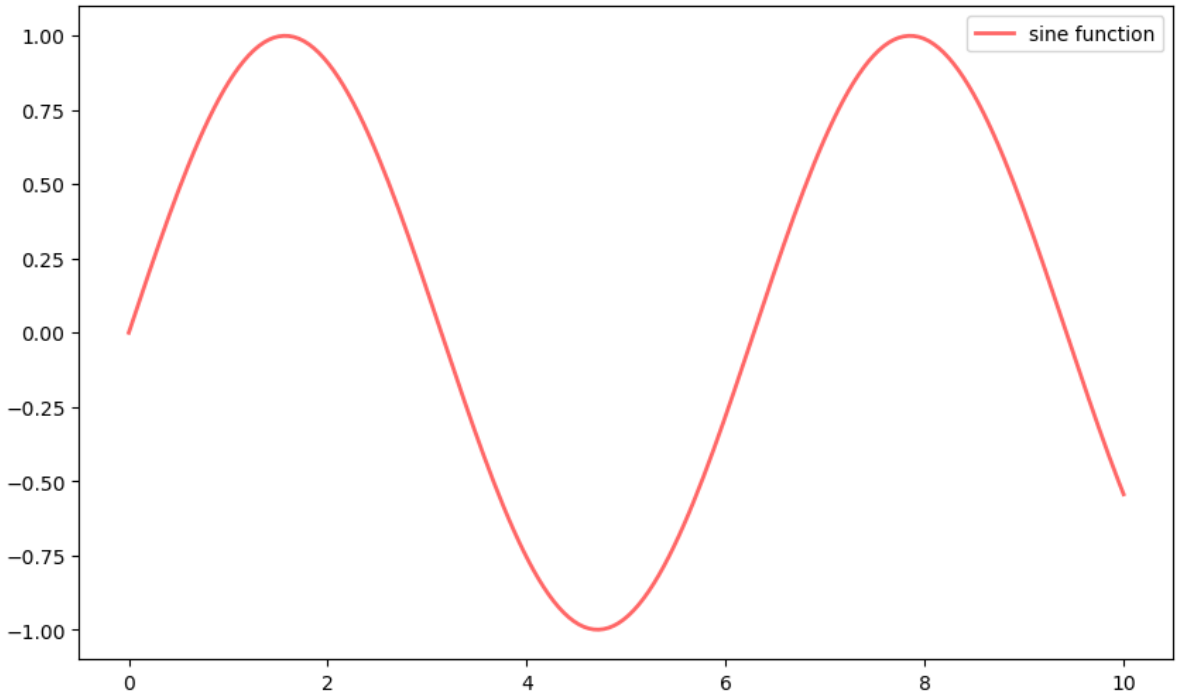
While there's a bit more typing, the more explicit use of objects gives us better control.

This will become more clear as we go along.

11.2.3 Tweaks

Here we've changed the line to red and added a legend

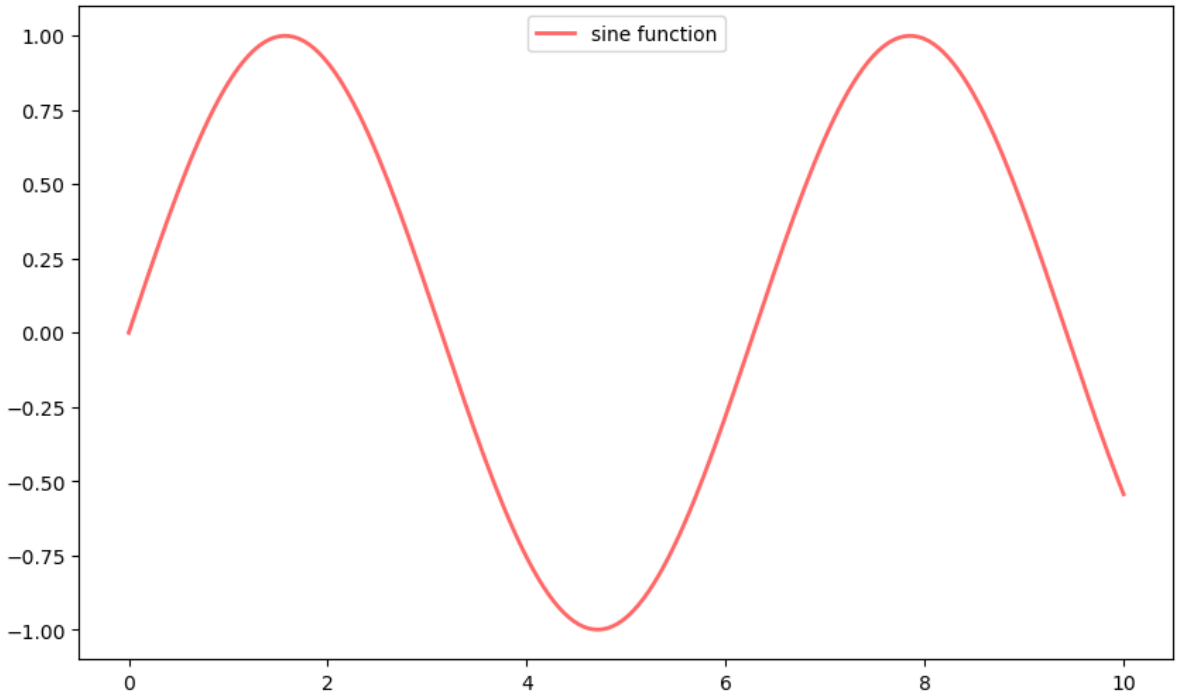
```
fig, ax = plt.subplots()
ax.plot(x, y, 'r-', linewidth=2, label='sine function', alpha=0.6)
ax.legend()
plt.show()
```



We've also used `alpha` to make the line slightly transparent—which makes it look smoother.

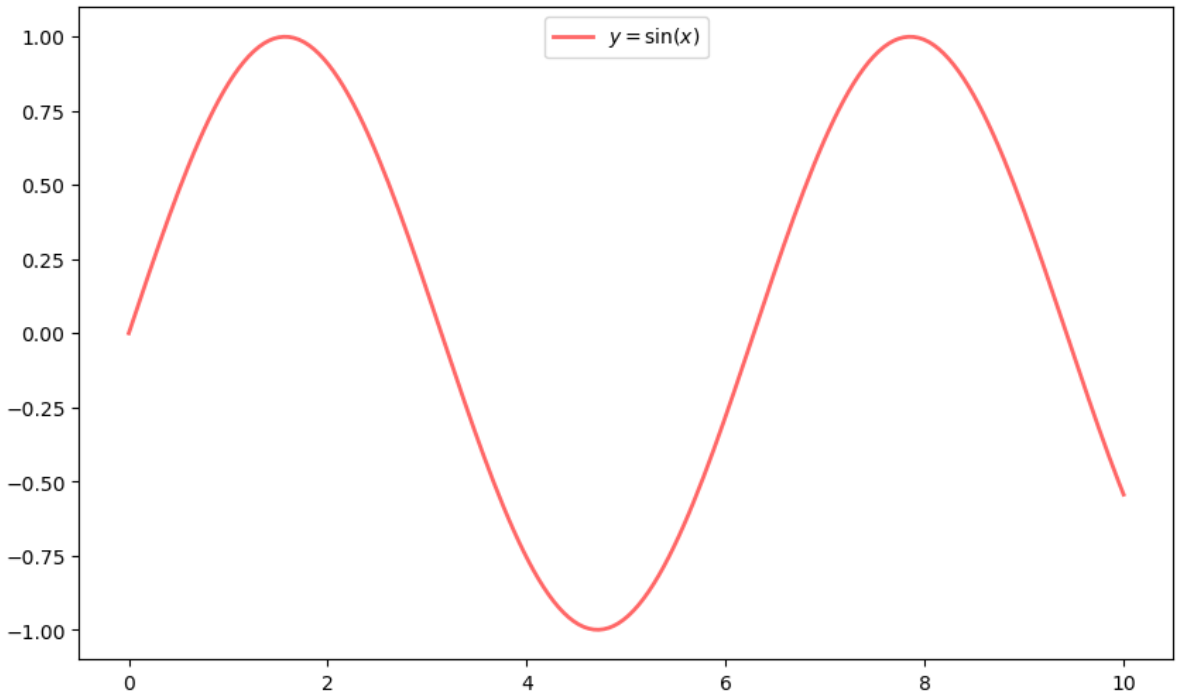
The location of the legend can be changed by replacing `ax.legend()` with `ax.legend(loc='upper center')`.

```
fig, ax = plt.subplots()
ax.plot(x, y, 'r-', linewidth=2, label='sine function', alpha=0.6)
ax.legend(loc='upper center')
plt.show()
```



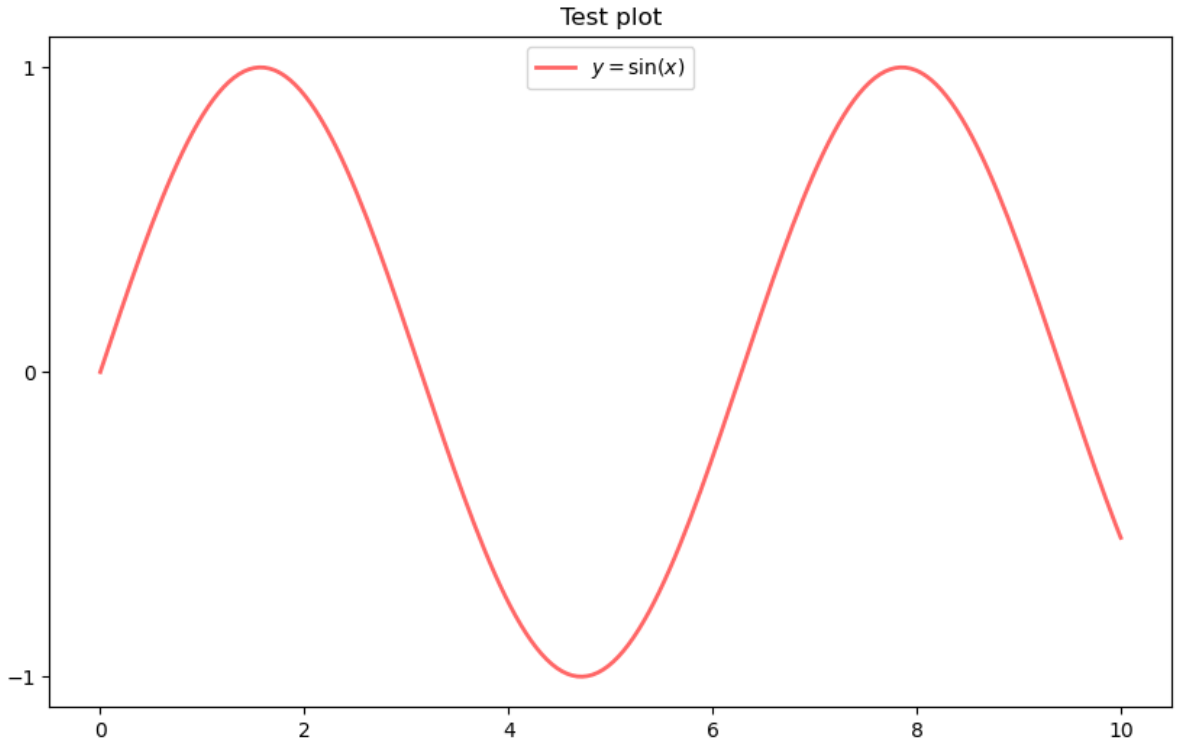
If everything is properly configured, then adding LaTeX is trivial

```
fig, ax = plt.subplots()
ax.plot(x, y, 'r-', linewidth=2, label='$y=\sin(x)$', alpha=0.6)
ax.legend(loc='upper center')
plt.show()
```



Controlling the ticks, adding titles and so on is also straightforward

```
fig, ax = plt.subplots()
ax.plot(x, y, 'r-', linewidth=2, label='$y=\sin(x)$', alpha=0.6)
ax.legend(loc='upper center')
ax.set_yticks([-1, 0, 1])
ax.set_title('Test plot')
plt.show()
```



11.3 More Features

Matplotlib has a huge array of functions and features, which you can discover over time as you have need for them.

We mention just a few.

11.3.1 Multiple Plots on One Axis

It's straightforward to generate multiple plots on the same axes.

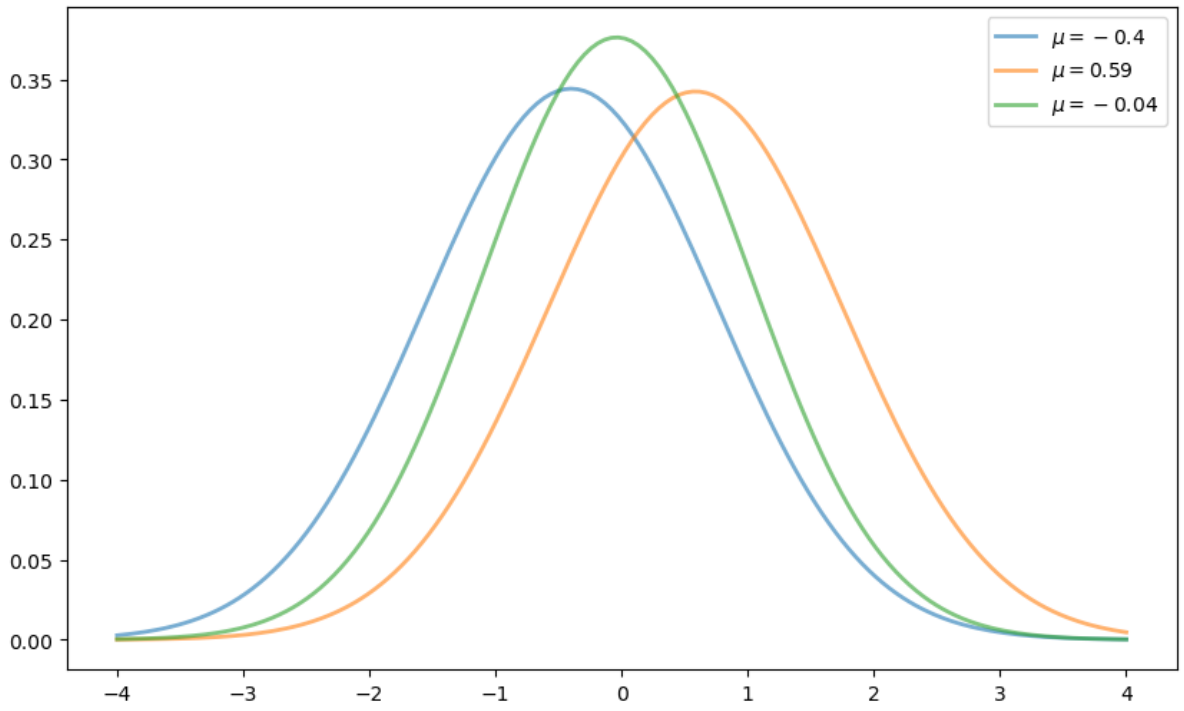
Here's an example that randomly generates three normal densities and adds a label with their mean

```
from scipy.stats import norm
from random import uniform

fig, ax = plt.subplots()
x = np.linspace(-4, 4, 150)
for i in range(3):
    m, s = uniform(-1, 1), uniform(1, 2)
    y = norm.pdf(x, loc=m, scale=s)
```

(continues on next page)

(continued from previous page)

```
    current_label = f'$\mu = {m:.2}$'
    ax.plot(x, y, linewidth=2, alpha=0.6, label=current_label)
ax.legend()
plt.show()
```

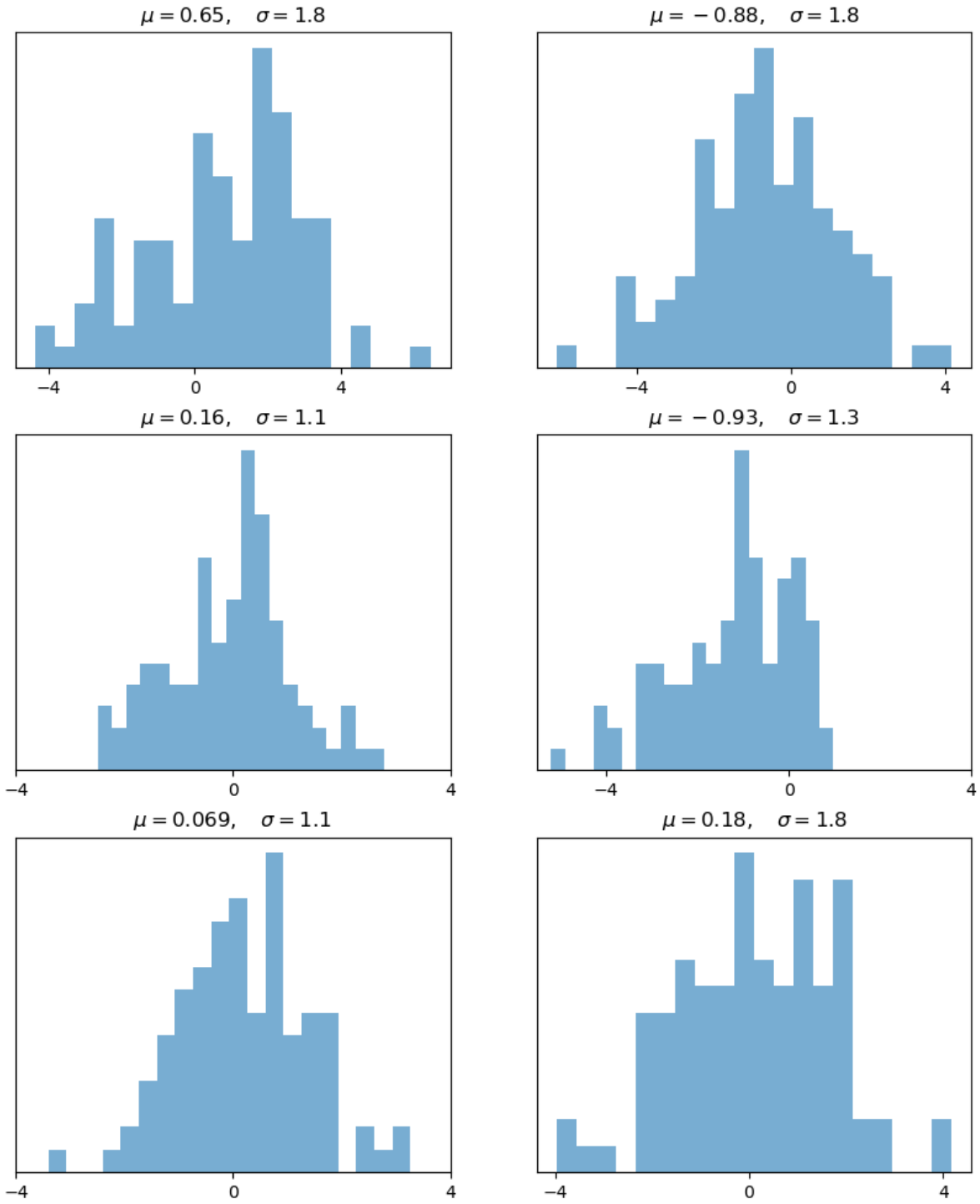


11.3.2 Multiple Subplots

Sometimes we want multiple subplots in one figure.

Here's an example that generates 6 histograms

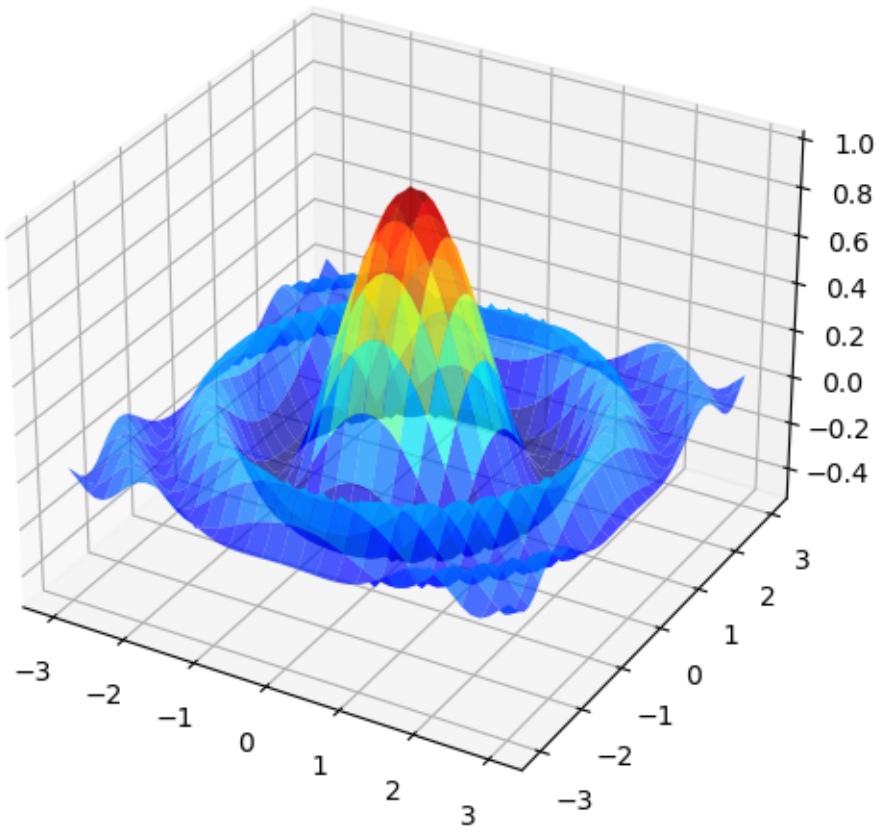
```
num_rows, num_cols = 3, 2
fig, axes = plt.subplots(num_rows, num_cols, figsize=(10, 12))
for i in range(num_rows):
    for j in range(num_cols):
        m, s = uniform(-1, 1), uniform(1, 2)
        x = norm.rvs(loc=m, scale=s, size=100)
        axes[i, j].hist(x, alpha=0.6, bins=20)
        t = f'$\mu = {m:.2}, \quad \sigma = {s:.2}$'
        axes[i, j].set(title=t, xticks=[-4, 0, 4], yticks=[])
plt.show()
```


$\mu = 0.65, \quad \sigma = 1.8$
$\mu = -0.88, \quad \sigma = 1.8$
$\mu = 0.16, \quad \sigma = 1.1$
$\mu = -0.93, \quad \sigma = 1.3$
$\mu = 0.069, \quad \sigma = 1.1$
$\mu = 0.18, \quad \sigma = 1.8$
−4
0
4

11.3.3 3D Plots

Matplotlib does a nice job of 3D plots — here is one example

```
from mpl_toolkits.mplot3d.axes3d import Axes3D
from matplotlib import cm


def f(x, y):
    return np.cos(x**2 + y**2) / (1 + x**2 + y**2)

xgrid = np.linspace(-3, 3, 50)
ygrid = xgrid
x, y = np.meshgrid(xgrid, ygrid)

fig = plt.figure(figsize=(10, 6))
ax = fig.add_subplot(111, projection='3d')
ax.plot_surface(x,
                y,
                f(x, y),
                rstride=2, cstride=2,
                cmap=cm.jet,
                alpha=0.7,
                linewidth=0.25)
ax.set_zlim(-0.5, 1.0)
plt.show()
```



11.3.4 A Customizing Function

Perhaps you will find a set of customizations that you regularly use.

Suppose we usually prefer our axes to go through the origin, and to have a grid.

Here's a nice example from Matthew Doty of how the object-oriented API can be used to build a custom `subplots` function that implements these changes.

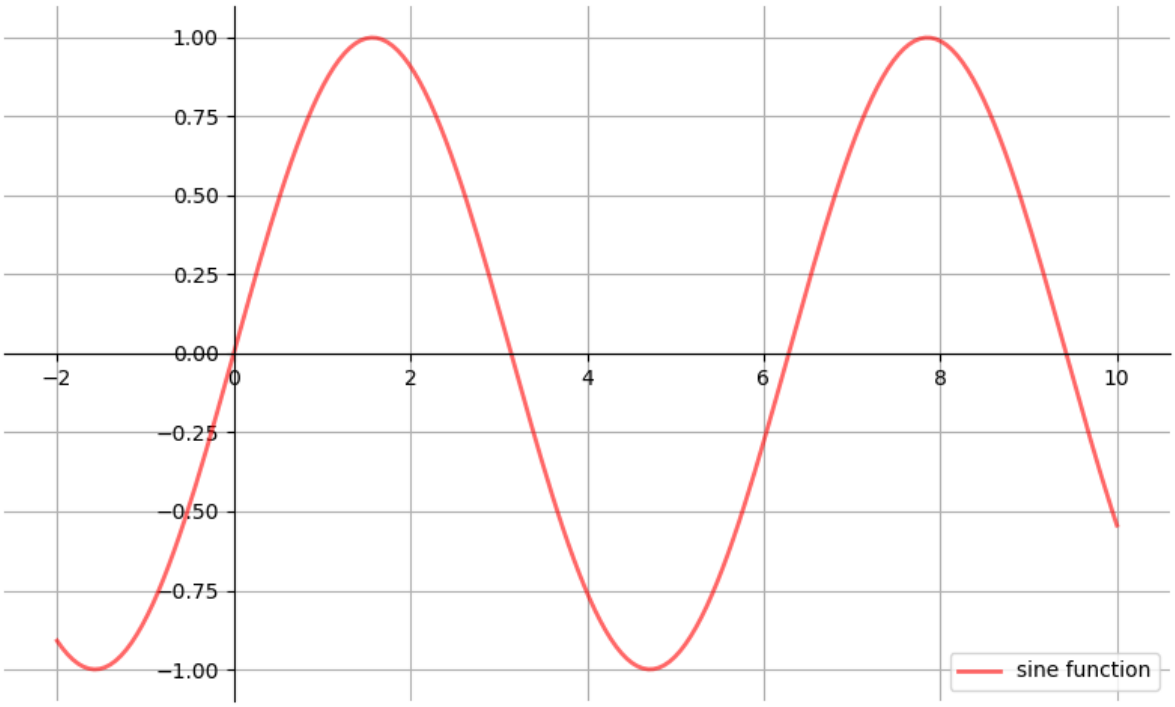
Read carefully through the code and see if you can follow what's going on

```
def subplots():
    "Custom subplots with axes through the origin"
    fig, ax = plt.subplots()

    # Set the axes through the origin
    for spine in ['left', 'bottom']:
        ax.spines[spine].set_position('zero')
    for spine in ['right', 'top']:
        ax.spines[spine].set_color('none')

    ax.grid()
    return fig, ax
```

(continues on next page)

(continued from previous page)

```
fig, ax = subplots()  # Call the local version, not plt.subplots()
x = np.linspace(-2, 10, 200)
y = np.sin(x)
ax.plot(x, y, 'r-', linewidth=2, label='sine function', alpha=0.6)
ax.legend(loc='lower right')
plt.show()
```



The custom `subplots` function

1. calls the standard `plt.subplots` function internally to generate the `fig, ax` pair,
2. makes the desired customizations to `ax`, and
3. passes the `fig, ax` pair back to the calling code.

11.3.5 Style Sheets

Another useful feature in Matplotlib is style sheets.

We can use style sheets to create plots with uniform styles.

We can find a list of available styles by printing the attribute `plt.style.available`

```
print(plt.style.available)
```

```
['Solarize_Light2', '_classic_test_patch', '_mpl-gallery', '_mpl-gallery-nogrid',
 ↪'bmh', 'classic', 'dark_background', 'fast', 'fivethirtyeight', 'ggplot',
 ↪'grayscale', 'seaborn-v0_8', 'seaborn-v0_8-bright', 'seaborn-v0_8-colorblind',
 ↪'seaborn-v0_8-dark', 'seaborn-v0_8-dark-palette', 'seaborn-v0_8-darkgrid',
 ↪'seaborn-v0_8-deep', 'seaborn-v0_8-muted', 'seaborn-v0_8-notebook', 'seaborn-v0_
 ↪8-paper', 'seaborn-v0_8-pastel', 'seaborn-v0_8-poster', 'seaborn-v0_8-talk',
 ↪'seaborn-v0_8-ticks', 'seaborn-v0_8-white', 'seaborn-v0_8-whitegrid', 'tableau-
 ↪colorblind10']
```

(continues on next page)

(continued from previous page)

We can now use the `plt.style.use()` method to set the style sheet.

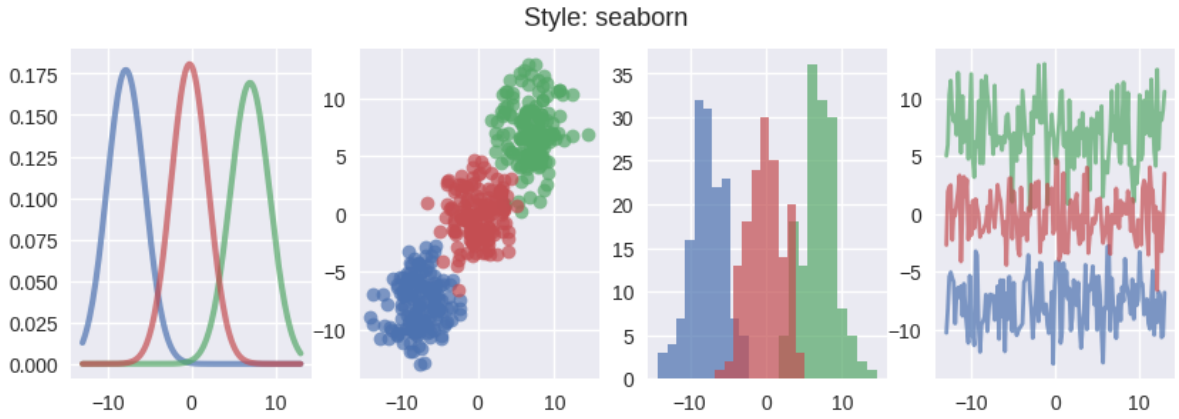
Let's write a function that takes the name of a style sheet and draws different plots with the style

```
def draw_graphs(style='default'):

    # Setting a style sheet
    plt.style.use(style)

    fig, axes = plt.subplots(nrows=1, ncols=4, figsize=(10, 3))
    x = np.linspace(-13, 13, 150)

    # Set seed values to replicate results of random draws
    np.random.seed(9)

    for i in range(3):

        # Draw mean and standard deviation from uniform distributions
        m, s = np.random.uniform(-8, 8), np.random.uniform(2, 2.5)

        # Generate a normal density plot
        y = norm.pdf(x, loc=m, scale=s)
        axes[0].plot(x, y, linewidth=3, alpha=0.7)

        # Create a scatter plot with random X and Y values
        # from normal distributions
        rnormX = norm.rvs(loc=m, scale=s, size=150)
        rnormY = norm.rvs(loc=m, scale=s, size=150)
        axes[1].plot(rnormX, rnormY, ls='none', marker='o', alpha=0.7)

        # Create a histogram with random X values
        axes[2].hist(rnormX, alpha=0.7)

        # and a line graph with random Y values
        axes[3].plot(x, rnormY, linewidth=2, alpha=0.7)

    style_name = style.split('-')[0]
    plt.suptitle(f'Style: {style_name}', fontsize=13)
    plt.show()
```

Let's see what some of the styles look like.

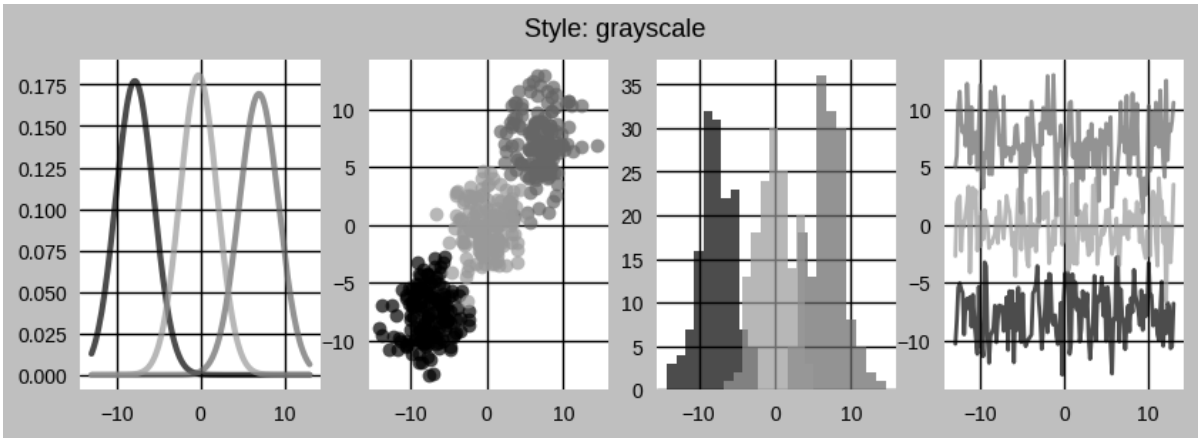
First, we draw graphs with the style sheet `seaborn`

```
draw_graphs(style='seaborn-v0_8')
```



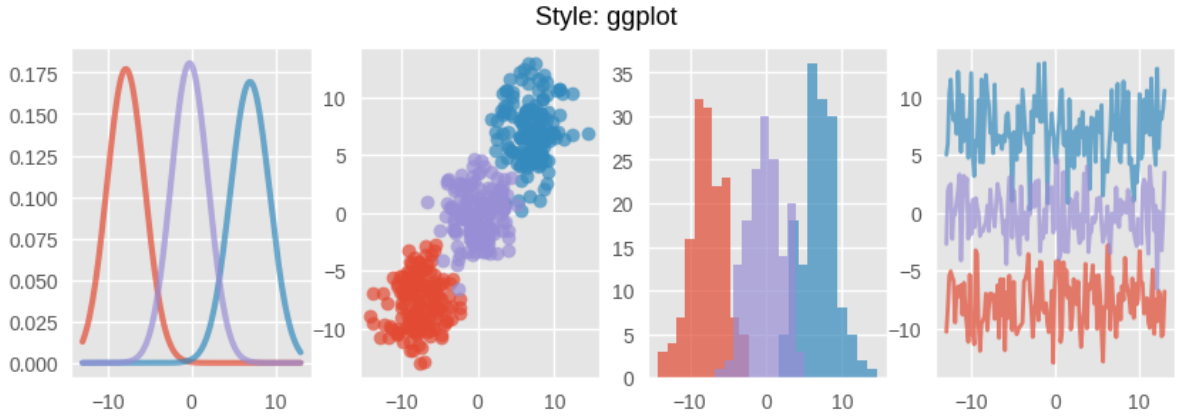
We can use `grayscale` to remove colors in plots

```
draw_graphs(style='grayscale')
```



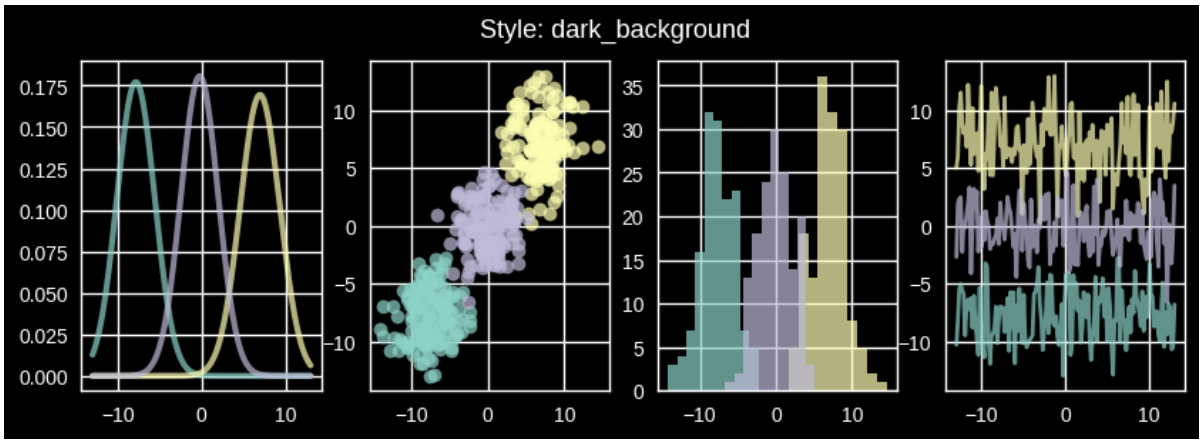
Here is what `ggplot` looks like

```
draw_graphs(style='ggplot')
```



We can also use the style `dark_background`

```
draw_graphs(style='dark_background')
```



You can use the function to experiment with other styles in the list.

If you are interested, you can even create your own style sheets.

Parameters for your style sheets are stored in a dictionary-like variable `plt.rcParams`

```
print(plt.rcParams.keys())
```

There are many parameters you could set for your style sheets.

Set parameters for your style sheet by:

1. creating your own `matplotlibrc` file, or
2. updating values stored in the dictionary-like variable `plt.rcParams`

Let's change the style of our overlaid density lines using the second method

```
from cycler import cycler

# set to the default style sheet
plt.style.use('default')

# You can update single values using keys:

# Set the font style to italic
plt.rcParams['font.style'] = 'italic'

# Update linewidth
plt.rcParams['lines.linewidth'] = 2


# You can also update many values at once using the update() method:

parameters = {

    # Change default figure size
    'figure.figsize': (5, 4),

    # Add horizontal grid lines
    'axes.grid': True,
```

(continues on next page)

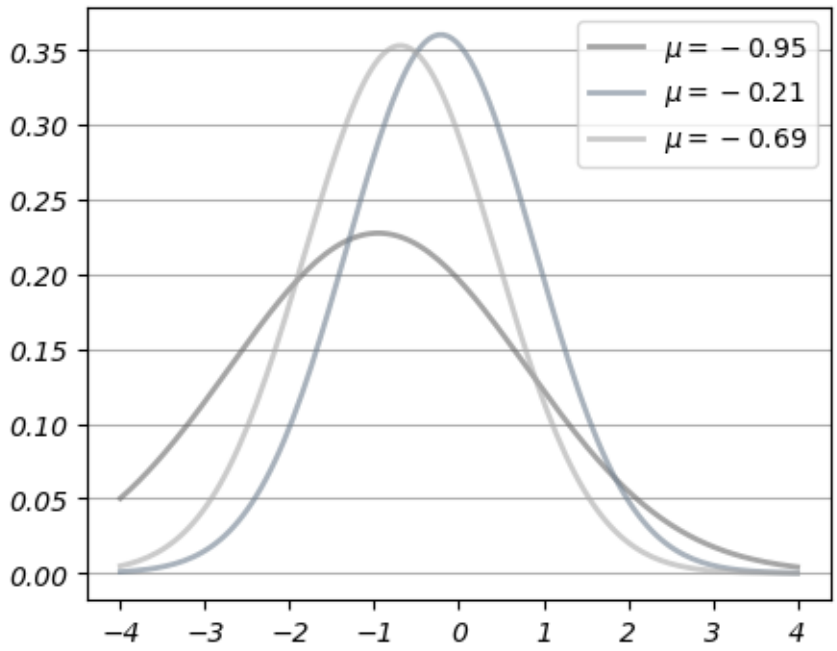
(continued from previous page)

```
    'axes.grid.axis': 'y',

    # Update colors for density lines
    'axes.prop_cycle': cycler('color',
                              ['dimgray', 'slategrey', 'darkgray'])
}

plt.rcParams.update(parameters)
```

Note: These settings are `global`.

Any plot generated after changing parameters in `.rcParams` will be affected by the setting.

```
fig, ax = plt.subplots()
x = np.linspace(-4, 4, 150)
for i in range(3):
    m, s = uniform(-1, 1), uniform(1, 2)
    y = norm.pdf(x, loc=m, scale=s)
    current_label = f'$\mu = {m:.2}$'
    ax.plot(x, y, linewidth=2, alpha=0.6, label=current_label)
ax.legend()
plt.show()
```



Apply the `default` style sheet again to change your style back to default

```
plt.style.use('default')

# Reset default figure size
plt.rcParams['figure.figsize'] = (10, 6)
```

Here are more examples on how to change these parameters.

11.4 Further Reading

- The Matplotlib gallery provides many examples.
- A nice Matplotlib tutorial by Nicolas Rougier, Mike Muller and Gael Varoquaux.
- mpltools allows easy switching between plot styles.
- Seaborn facilitates common statistics plots in Matplotlib.

11.5 Exercises

Exercise 11.5.1

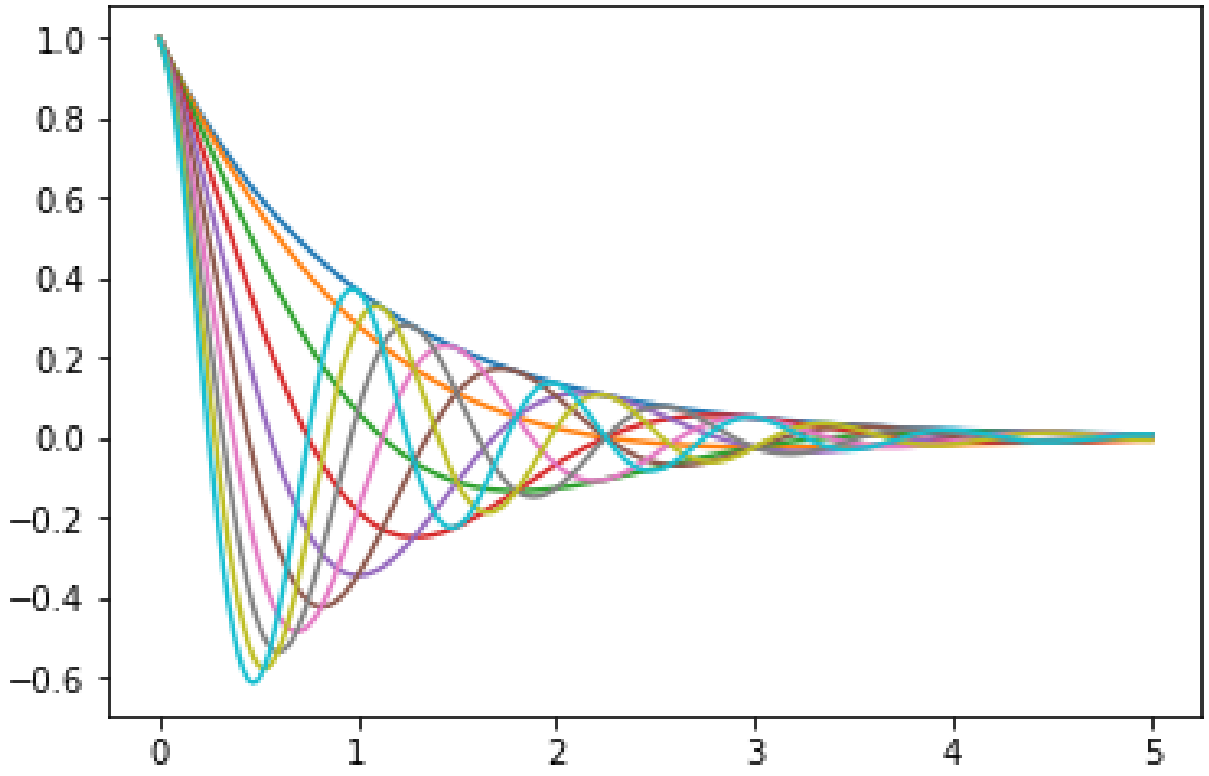
Plot the function

$$f(x) = \cos(\pi\theta x)\exp(-x)$$

over the interval $[0, 5]$ for each θ in `np.linspace(0, 2, 10)`.

Place all the curves in the same figure.

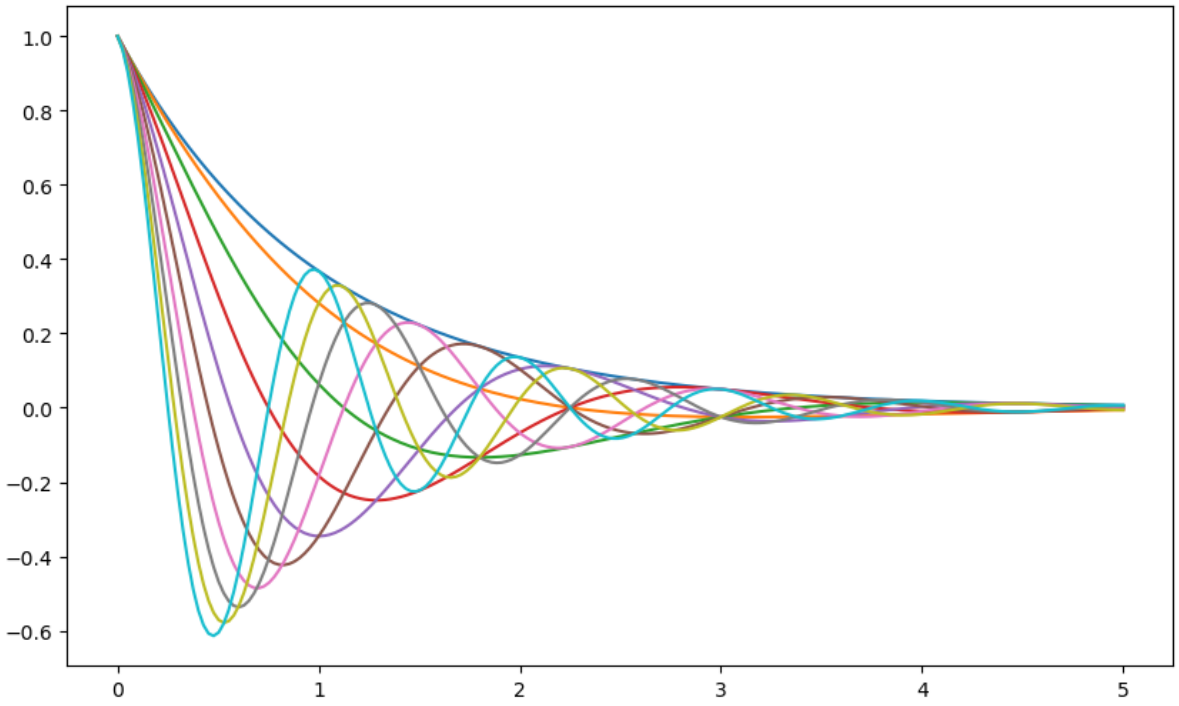
The output should look like this



Solution to Exercise 11.5.1

Here's one solution

```
def f(x, θ):
    return np.cos(np.pi * θ * x ) * np.exp(- x)

θ_vals = np.linspace(0, 2, 10)
x = np.linspace(0, 5, 200)
fig, ax = plt.subplots()

for θ in θ_vals:
    ax.plot(x, f(x, θ))

plt.show()
```



CHAPTER

TWELVE

SCIPY

Contents

12.1 Overview

SciPy builds on top of NumPy to provide common tools for scientific programming such as

- linear algebra
- numerical integration
- interpolation
- optimization
- distributions and random number generation
- signal processing
- etc., etc

Like NumPy, SciPy is stable, mature and widely used.

Many SciPy routines are thin wrappers around industry-standard Fortran libraries such as LAPACK, BLAS, etc.

It's not really necessary to "learn" SciPy as a whole.

A more common approach is to get some idea of what's in the library and then look up documentation as required.

In this lecture, we aim only to highlight some useful parts of the package.

12.2 SciPy versus NumPy

SciPy is a package that contains various tools that are built on top of NumPy, using its array data type and related functionality.

In fact, when we import SciPy we also get NumPy, as can be seen from this excerpt the SciPy initialization file:

```
# Import numpy symbols to scipy namespace
from numpy import *
from numpy.random import rand, randn
from numpy.fft import fft, ifft
from numpy.lib.scimath import *
```

However, it's more common and better practice to use NumPy functionality explicitly.

```
import numpy as np

a = np.identity(3)
```

What is useful in SciPy is the functionality in its sub-packages

- `scipy.optimize`, `scipy.integrate`, `scipy.stats`, etc.

Let's explore some of the major sub-packages.

12.3 Statistics

The `scipy.stats` subpackage supplies

- numerous random variable objects (densities, cumulative distributions, random sampling, etc.)
- some estimation procedures
- some statistical tests

12.3.1 Random Variables and Distributions

Recall that `numpy.random` provides functions for generating random variables

```
np.random.beta(5, 5, size=3)
```

```
array([0.28365394, 0.30195851, 0.83421157])
```

This generates a draw from the distribution with the density function below when `a, b = 5, 5`

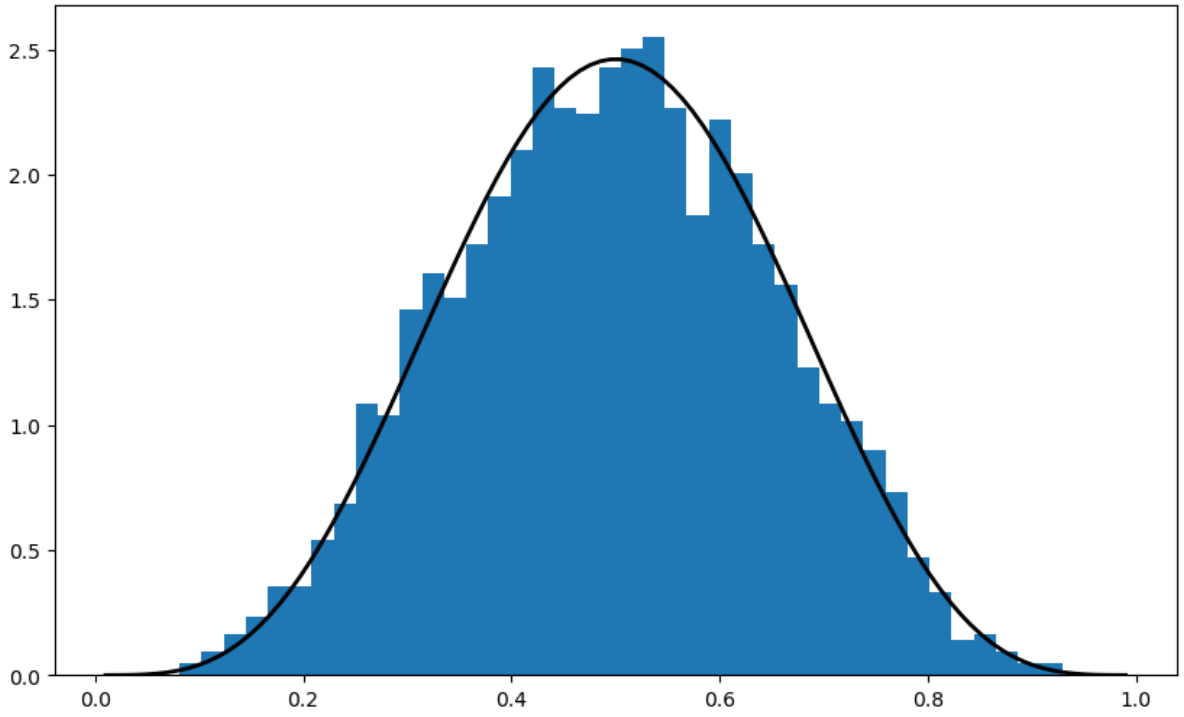
$$f(x; a, b) = \frac{x^{(a-1)}(1-x)^{(b-1)}}{\int_0^1 u^{(a-1)}(1-u)^{(b-1)}du} \qquad (0 \leq x \leq 1) \tag{12.1}$$

Sometimes we need access to the density itself, or the cdf, the quantiles, etc.

For this, we can use `scipy.stats`, which provides all of this functionality as well as random number generation in a single consistent interface.

Here's an example of usage

```
%matplotlib inline
from scipy.stats import beta
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)

q = beta(5, 5)       # Beta(a, b), with a = b = 5
obs = q.rvs(2000)    # 2000 observations
grid = np.linspace(0.01, 0.99, 100)

fig, ax = plt.subplots()
ax.hist(obs, bins=40, density=True)
ax.plot(grid, q.pdf(grid), 'k-', linewidth=2)
plt.show()
```



The object `q` that represents the distribution has additional useful methods, including

```
q.cdf(0.4)      # Cumulative distribution function
```

```
0.26656768000000003
```

```
q.ppf(0.8)      # Quantile (inverse cdf) function
```

```
0.6339134834642708
```

```
q.mean()
```

```
0.5
```

The general syntax for creating these objects that represent distributions (of type `rv_frozen`) is

```
name = scipy.stats.distribution_name(shape_parameters, loc=c, scale=d)
```

Here `distribution_name` is one of the distribution names in scipy.stats.

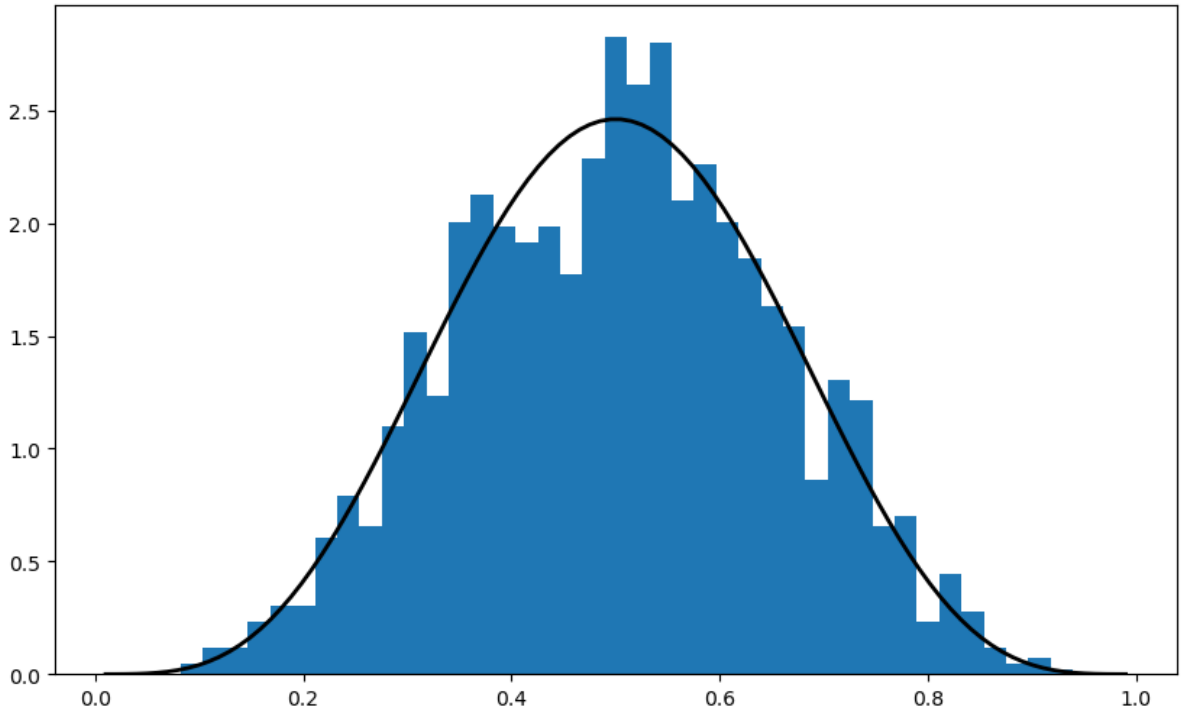
The `loc` and `scale` parameters transform the original random variable X into $Y = c + dX$.

12.3.2 Alternative Syntax

There is an alternative way of calling the methods described above.

For example, the code that generates the figure above can be replaced by

```
obs = beta.rvs(5, 5, size=2000)
grid = np.linspace(0.01, 0.99, 100)

fig, ax = plt.subplots()
ax.hist(obs, bins=40, density=True)
ax.plot(grid, beta.pdf(grid, 5, 5), 'k-', linewidth=2)
plt.show()
```



12.3.3 Other Goodies in scipy.stats

There are a variety of statistical functions in `scipy.stats`.

For example, `scipy.stats.linregress` implements simple linear regression

```
from scipy.stats import linregress

x = np.random.randn(200)
y = 2 * x + 0.1 * np.random.randn(200)
gradient, intercept, r_value, p_value, std_err = linregress(x, y)
gradient, intercept
```

```
(1.995172323965754, 0.011553895772083343)
```

To see the full list, consult the documentation.

12.4 Roots and Fixed Points

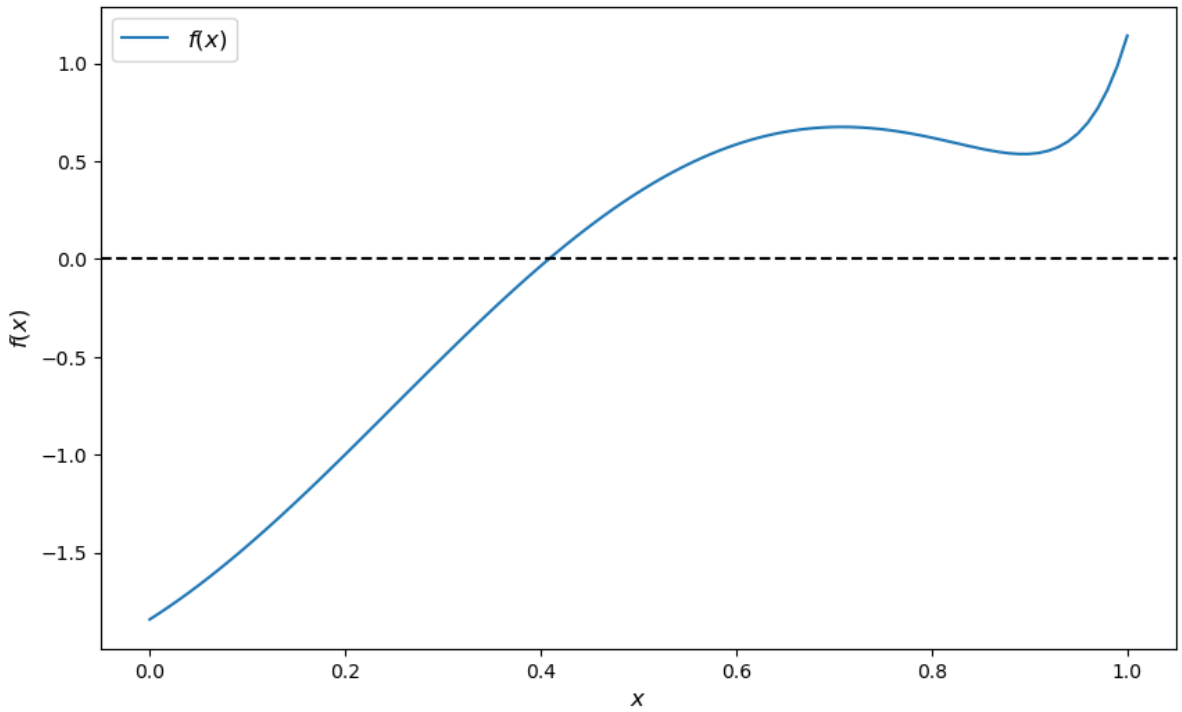
A **root** or **zero** of a real function f on $[a, b]$ is an $x \in [a, b]$ such that $f(x) = 0$.

For example, if we plot the function

$$f(x) = \sin(4(x - 1/4)) + x + x^{20} - 1 \tag{12.2}$$

with $x \in [0, 1]$ we get

```
f = lambda x: np.sin(4 * (x - 1/4)) + x + x**20 - 1
x = np.linspace(0, 1, 100)

fig, ax = plt.subplots()
ax.plot(x, f(x), label='$f(x)$')
ax.axhline(ls='--', c='k')
ax.set_xlabel('$x$', fontsize=12)
ax.set_ylabel('$f(x)$', fontsize=12)
ax.legend(fontsize=12)
plt.show()
```



The unique root is approximately 0.408.

Let's consider some numerical techniques for finding roots.

12.4.1 Bisection

One of the most common algorithms for numerical root-finding is *bisection*.

To understand the idea, recall the well-known game where

- Player A thinks of a secret number between 1 and 100
- Player B asks if it's less than 50
  - If yes, B asks if it's less than 25
  - If no, B asks if it's less than 75

And so on.

This is bisection.

Here's a simplistic implementation of the algorithm in Python.

It works for all sufficiently well behaved increasing continuous functions with $f(a) < 0 < f(b)$

```
def bisect(f, a, b, tol=10e-5):
    """
    Implements the bisection root finding algorithm, assuming that f is a
    real-valued function on [a, b] satisfying f(a) < 0 < f(b).
    """
    lower, upper = a, b

    while upper - lower > tol:
```

(continues on next page)

(continued from previous page)

```
        middle = 0.5 * (upper + lower)
        if f(middle) > 0:   # root is between lower and middle
            lower, upper = lower, middle
        else:               # root is between middle and upper
            lower, upper = middle, upper

    return 0.5 * (upper + lower)
```

Let's test it using the function f defined in (12.2)

```
bisect(f, 0, 1)
```

```
0.408294677734375
```

Not surprisingly, SciPy provides its own bisection function.

Let's test it using the same function f defined in (12.2)

```
from scipy.optimize import bisect

bisect(f, 0, 1)
```

```
0.4082935042806639
```

12.4.2 The Newton-Raphson Method

Another very common root-finding algorithm is the Newton-Raphson method.

In SciPy this algorithm is implemented by `scipy.optimize.newton`.

Unlike bisection, the Newton-Raphson method uses local slope information in an attempt to increase the speed of convergence.

Let's investigate this using the same function f defined above.

With a suitable initial condition for the search we get convergence:

```
from scipy.optimize import newton

newton(f, 0.2)   # Start the search at initial condition x = 0.2
```

```
0.40829350427935673
```

But other initial conditions lead to failure of convergence:

```
newton(f, 0.7)   # Start the search at x = 0.7 instead
```

```
0.7001700000000279
```

12.4.3 Hybrid Methods

A general principle of numerical methods is as follows:

- If you have specific knowledge about a given problem, you might be able to exploit it to generate efficiency.
- If not, then the choice of algorithm involves a trade-off between speed and robustness.

In practice, most default algorithms for root-finding, optimization and fixed points use *hybrid* methods.

These methods typically combine a fast method with a robust method in the following manner:

1. Attempt to use a fast method
2. Check diagnostics
3. If diagnostics are bad, then switch to a more robust algorithm

In `scipy.optimize`, the function `brentq` is such a hybrid method and a good default

```
from scipy.optimize import brentq

brentq(f, 0, 1)
```

```
0.40829350427936706
```

Here the correct solution is found and the speed is better than bisection:

```
%timeit brentq(f, 0, 1)
```

```
20.1 µs ± 170 ns per loop (mean ± std. dev. of 7 runs, 10,000 loops each)
```

```
%timeit bisect(f, 0, 1)
```

```
80.6 µs ± 322 ns per loop (mean ± std. dev. of 7 runs, 10,000 loops each)
```

12.4.4 Multivariate Root-Finding

Use `scipy.optimize.fsolve`, a wrapper for a hybrid method in MINPACK.

See the documentation for details.

12.4.5 Fixed Points

A **fixed point** of a real function f on $[a, b]$ is an $x \in [a, b]$ such that $f(x) = x$.

SciPy has a function for finding (scalar) fixed points too

```
from scipy.optimize import fixed_point

fixed_point(lambda x: x**2, 10.0)  # 10.0 is an initial guess
```

```
array(1.)
```

If you don't get good results, you can always switch back to the `brentq` root finder, since the fixed point of a function f is the root of $g(x) := x - f(x)$.

12.5 Optimization

Most numerical packages provide only functions for *minimization*.

Maximization can be performed by recalling that the maximizer of a function f on domain D is the minimizer of $-f$ on D.

Minimization is closely related to root-finding: For smooth functions, interior optima correspond to roots of the first derivative.

The speed/robustness trade-off described above is present with numerical optimization too.

Unless you have some prior information you can exploit, it's usually best to use hybrid methods.

For constrained, univariate (i.e., scalar) minimization, a good hybrid option is `fminbound`

```
from scipy.optimize import fminbound

fminbound(lambda x: x**2, -1, 2)  # Search in [-1, 2]
```

```
0.0
```

12.5.1 Multivariate Optimization

Multivariate local optimizers include `minimize`, `fmin`, `fmin_powell`, `fmin_cg`, `fmin_bfgs`, and `fmin_ncg`.

Constrained multivariate local optimizers include `fmin_l_bfgs_b`, `fmin_tnc`, `fmin_cobyla`.

See the documentation for details.

12.6 Integration

Most numerical integration methods work by computing the integral of an approximating polynomial.

The resulting error depends on how well the polynomial fits the integrand, which in turn depends on how "regular" the integrand is.

In SciPy, the relevant module for numerical integration is `scipy.integrate`.

A good default for univariate integration is `quad`

```
from scipy.integrate import quad

integral, error = quad(lambda x: x**2, 0, 1)
integral
```

```
0.33333333333333337
```

In fact, `quad` is an interface to a very standard numerical integration routine in the Fortran library QUADPACK.

It uses Clenshaw-Curtis quadrature, based on expansion in terms of Chebychev polynomials.

There are other options for univariate integration—a useful one is `fixed_quad`, which is fast and hence works well inside `for` loops.

There are also functions for multivariate integration.

See the documentation for more details.

12.7 Linear Algebra

We saw that NumPy provides a module for linear algebra called `linalg`.

SciPy also provides a module for linear algebra with the same name.

The latter is not an exact superset of the former, but overall it has more functionality.

We leave you to investigate the set of available routines.

12.8 Exercises

The first few exercises concern pricing a European call option under the assumption of risk neutrality. The price satisfies

$$P = \beta^n \mathbb{E} \max\{S_n - K, 0\}$$

where

1. β is a discount factor,
2. n is the expiry date,
3. K is the strike price and
4. $\{S_t\}$ is the price of the underlying asset at each time t.

For example, if the call option is to buy stock in Amazon at strike price K, the owner has the right (but not the obligation) to buy 1 share in Amazon at price K after n days.

The payoff is therefore $\max\{S_n - K, 0\}$

The price is the expectation of the payoff, discounted to current value.

Exercise 12.8.1

Suppose that S_n has the log-normal distribution with parameters μ and σ. Let f denote the density of this distribution. Then

$$P = \beta^n \int_0^\infty \max\{x - K, 0\} f(x) dx$$

Plot the function

$$g(x) = \beta^n \max\{x - K, 0\} f(x)$$

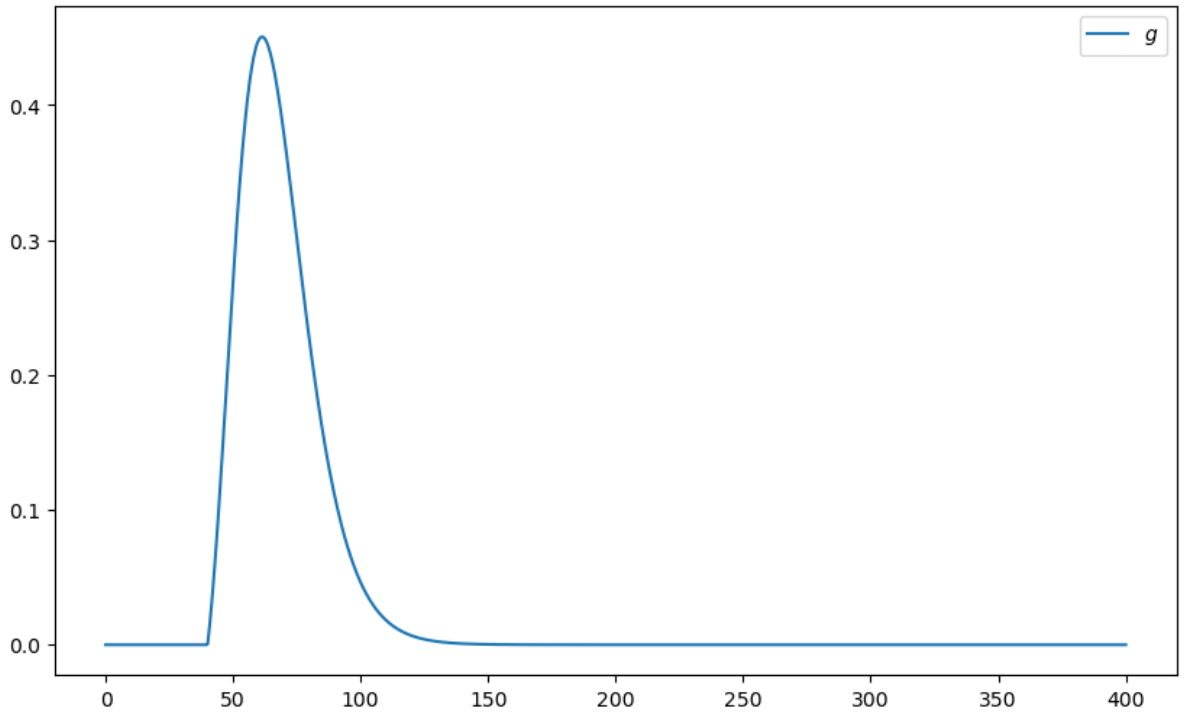
over the interval $[0, 400]$ when `μ, σ, β, n, K = 4, 0.25, 0.99, 10, 40`.

Hint: From `scipy.stats` you can import `lognorm` and then use `lognorm(x, σ, scale=np.exp(μ)` to get the density f.

Solution to Exercise 12.8.1

Here's one possible solution

```
from scipy.integrate import quad
from scipy.stats import lognorm

μ, σ, β, n, K = 4, 0.25, 0.99, 10, 40

def g(x):
    return β**n * np.maximum(x - K, 0) * lognorm.pdf(x, σ, scale=np.exp(μ))

x_grid = np.linspace(0, 400, 1000)
y_grid = g(x_grid)

fig, ax = plt.subplots()
ax.plot(x_grid, y_grid, label="$g$")
ax.legend()
plt.show()
```



Exercise 12.8.2

In order to get the option price, compute the integral of this function numerically using `quad` from `scipy.optimize`.

Solution to Exercise 12.8.2

```
P, error = quad(g, 0, 1_000)
print(f"The numerical integration based option price is {P:.3f}")
```

```
The numerical integration based option price is 15.188
```

Exercise 12.8.3

Try to get a similar result using Monte Carlo to compute the expectation term in the option price, rather than `quad`.

In particular, use the fact that if $S_n^1, \ldots, S_n^M$ are independent draws from the lognormal distribution specified above, then, by the law of large numbers,

$$\mathbb{E} \max\{S_n - K, 0\} \approx \frac{1}{M} \sum_{m=1}^{M} \max\{S_n^m - K, 0\}$$

Set `M = 10_000_000`

Solution to Exercise 12.8.3

Here is one solution:

```
M = 10_000_000
S = np.exp(μ + σ * np.random.randn(M))
return_draws = np.maximum(S - K, 0)
P = β**n * np.mean(return_draws)
print(f"The Monte Carlo option price is {P:3f}")
```

```
The Monte Carlo option price is 15.182483
```

Exercise 12.8.4

In *this lecture*, we discussed the concept of *recursive function calls*.

Try to write a recursive implementation of the homemade bisection function *described above*.

Test it on the function (12.2).

Solution to Exercise 12.8.4

Here's a reasonable solution:

```
def bisect(f, a, b, tol=10e-5):
    """
    Implements the bisection root-finding algorithm, assuming that f is a
    real-valued function on [a, b] satisfying f(a) < 0 < f(b).
    """
```

(continues on next page)

(continued from previous page)

```
    lower, upper = a, b
    if upper - lower < tol:
        return 0.5 * (upper + lower)
    else:
        middle = 0.5 * (upper + lower)
        print(f'Current mid point = {middle}')
        if f(middle) > 0:   # Implies root is between lower and middle
            return bisect(f, lower, middle)
        else:               # Implies root is between middle and upper
            return bisect(f, middle, upper)
```

We can test it as follows

```
f = lambda x: np.sin(4 * (x - 0.25)) + x + x**20 - 1
bisect(f, 0, 1)
```

```
Current mid point = 0.5
Current mid point = 0.25
Current mid point = 0.375
Current mid point = 0.4375
Current mid point = 0.40625
Current mid point = 0.421875
Current mid point = 0.4140625
Current mid point = 0.41015625
Current mid point = 0.408203125
Current mid point = 0.4091796875
Current mid point = 0.40869140625
Current mid point = 0.408447265625
Current mid point = 0.4083251953125
Current mid point = 0.40826416015625
```

```
0.408294677734375
```

CHAPTER

THIRTEEN

PANDAS

Contents

In addition to what's in Anaconda, this lecture will need the following libraries:

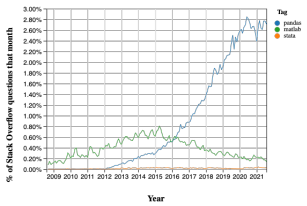
```
!pip install --upgrade pandas-datareader
!pip install --upgrade yfinance
```

13.1 Overview

Pandas is a package of fast, efficient data analysis tools for Python.

Its popularity has surged in recent years, coincident with the rise of fields such as data science and machine learning.

Here's a popularity comparison over time against Matlab and STATA courtesy of Stack Overflow Trends



Just as NumPy provides the basic array data type plus core array operations, pandas

1. defines fundamental structures for working with data and
2. endows them with methods that facilitate operations such as
   - reading in data

- adjusting indices
- working with dates and time series
- sorting, grouping, re-ordering and general data munging[1]
- dealing with missing values, etc., etc.

More sophisticated statistical functionality is left to other packages, such as statsmodels and scikit-learn, which are built on top of pandas.

This lecture will provide a basic introduction to pandas.

Throughout the lecture, we will assume that the following imports have taken place

```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"] = [10,8]  # Set default figure size
import requests
```

Two important data types defined by pandas are `Series` and `DataFrame`.

You can think of a `Series` as a "column" of data, such as a collection of observations on a single variable.

A `DataFrame` is a two-dimensional object for storing related columns of data.

13.2 Series

Let's start with Series.

We begin by creating a series of four random observations

```
s = pd.Series(np.random.randn(4), name='daily returns')
s
```

```
0   -0.720017
1   -0.210659
2   -0.262305
3    0.848900
Name: daily returns, dtype: float64
```

Here you can imagine the indices `0, 1, 2, 3` as indexing four listed companies, and the values being daily returns on their shares.

Pandas `Series` are built on top of NumPy arrays and support many similar operations

```
s * 100
```

```
0   -72.001671
1   -21.065885
2   -26.230458
3    84.889974
Name: daily returns, dtype: float64
```

[1] Wikipedia defines munging as cleaning data from one raw form into a structured, purged one.

```
np.abs(s)
```

```
0    0.720017
1    0.210659
2    0.262305
3    0.848900
Name: daily returns, dtype: float64
```

But `Series` provide more than NumPy arrays.

Not only do they have some additional (statistically oriented) methods

```
s.describe()
```

```
count    4.000000
mean    -0.086020
std      0.663987
min     -0.720017
25%     -0.376733
50%     -0.236482
75%      0.054231
max      0.848900
Name: daily returns, dtype: float64
```

But their indices are more flexible

```
s.index = ['AMZN', 'AAPL', 'MSFT', 'GOOG']
s
```

```
AMZN   -0.720017
AAPL   -0.210659
MSFT   -0.262305
GOOG    0.848900
Name: daily returns, dtype: float64
```

Viewed in this way, `Series` are like fast, efficient Python dictionaries (with the restriction that the items in the dictionary all have the same type—in this case, floats).

In fact, you can use much of the same syntax as Python dictionaries

```
s['AMZN']
```

```
-0.7200167069505793
```

```
s['AMZN'] = 0
s
```

```
AMZN    0.000000
AAPL   -0.210659
MSFT   -0.262305
GOOG    0.848900
Name: daily returns, dtype: float64
```

```
'AAPL' in s
```

```
True
```

13.3 DataFrames

While a `Series` is a single column of data, a `DataFrame` is several columns, one for each variable.

In essence, a `DataFrame` in pandas is analogous to a (highly optimized) Excel spreadsheet.

Thus, it is a powerful tool for representing and analyzing data that are naturally organized into rows and columns, often with descriptive indexes for individual rows and individual columns.

Let's look at an example that reads data from the CSV file `pandas/data/test_pwt.csv`, which is taken from the Penn World Tables.

The dataset contains the following indicators

Variable Name	Description
POP	Population (in thousands)
XRAT	Exchange Rate to US Dollar
tcgdp	Total PPP Converted GDP (in million international dollar)
cc	Consumption Share of PPP Converted GDP Per Capita (%)
cg	Government Consumption Share of PPP Converted GDP Per Capita (%)

We'll read this in from a URL using the `pandas` function `read_csv`.

```
df = pd.read_csv('https://raw.githubusercontent.com/QuantEcon/lecture-python-
↪programming/master/source/_static/lecture_specific/pandas/data/test_pwt.csv')
type(df)
```

```
pandas.core.frame.DataFrame
```

Here's the content of `test_pwt.csv`

```
df
```

```
         country country isocode  year          POP        XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653    0.999500  2.950722e+05
1      Australia             AUS  2000    19053.186    1.724830  5.418047e+05
2          India             IND  2000  1006300.297   44.941600  1.728144e+06
3         Israel             ISR  2000     6114.570    4.077330  1.292539e+05
4         Malawi             MWI  2000    11801.505   59.543808  5.026222e+03
5   South Africa             ZAF  2000    45064.098    6.939830  2.272424e+05
6  United States             USA  2000   282171.957    1.000000  9.898700e+06
7        Uruguay             URY  2000     3219.793   12.099592  2.525596e+04

          cc         cg
0  75.716805   5.578804
1  67.759026   6.720098
2  64.575551  14.072206
```

(continues on next page)

(continued from previous page)

```
3  64.436451  10.266688
4  74.707624  11.658954
5  72.718710   5.726546
6  72.347054   6.032454
7  78.978740   5.108068
```

13.3.1 Select Data by Position

In practice, one thing that we do all the time is to find, select and work with a subset of the data of our interests.

We can select particular rows using standard Python array slicing notation

```
df[2:5]
```

```
  country country isocode  year          POP       XRAT         tcgdp  \
2   India             IND  2000  1006300.297  44.941600  1.728144e+06
3  Israel             ISR  2000     6114.570   4.077330  1.292539e+05
4  Malawi             MWI  2000    11801.505  59.543808  5.026222e+03

          cc         cg
2  64.575551  14.072206
3  64.436451  10.266688
4  74.707624  11.658954
```

To select columns, we can pass a list containing the names of the desired columns represented as strings

```
df[['country', 'tcgdp']]
```

```
         country         tcgdp
0      Argentina  2.950722e+05
1      Australia  5.418047e+05
2          India  1.728144e+06
3         Israel  1.292539e+05
4         Malawi  5.026222e+03
5   South Africa  2.272424e+05
6  United States  9.898700e+06
7        Uruguay  2.525596e+04
```

To select both rows and columns using integers, the `iloc` attribute should be used with the format `.iloc[rows, columns]`.

```
df.iloc[2:5, 0:4]
```

```
  country country isocode  year          POP
2   India             IND  2000  1006300.297
3  Israel             ISR  2000     6114.570
4  Malawi             MWI  2000    11801.505
```

To select rows and columns using a mixture of integers and labels, the `loc` attribute can be used in a similar way

```
df.loc[df.index[2:5], ['country', 'tcgdp']]
```

```
  country         tcgdp
2   India  1.728144e+06
3  Israel  1.292539e+05
4  Malawi  5.026222e+03
```

13.3.2 Select Data by Conditions

Instead of indexing rows and columns using integers and names, we can also obtain a sub-dataframe of our interests that satisfies certain (potentially complicated) conditions.

This section demonstrates various ways to do that.

The most straightforward way is with the `[]` operator.

```
df[df.POP >= 20000]
```

```
         country country isocode  year          POP      XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653   0.99950  2.950722e+05
2          India             IND  2000  1006300.297  44.94160  1.728144e+06
5   South Africa             ZAF  2000    45064.098   6.93983  2.272424e+05
6  United States             USA  2000   282171.957   1.00000  9.898700e+06

           cc         cg
0  75.716805   5.578804
2  64.575551  14.072206
5  72.718710   5.726546
6  72.347054   6.032454
```

To understand what is going on here, notice that `df.POP >= 20000` returns a series of boolean values.

```
df.POP >= 20000
```

```
0     True
1    False
2     True
3    False
4    False
5     True
6     True
7    False
Name: POP, dtype: bool
```

In this case, `df[____]` takes a series of boolean values and only returns rows with the `True` values.

Take one more example,

```
df[(df.country.isin(['Argentina', 'India', 'South Africa'])) & (df.POP > 40000)]
```

```
        country country isocode  year          POP      XRAT         tcgdp  \
2         India             IND  2000  1006300.297  44.94160  1.728144e+06
5  South Africa             ZAF  2000    45064.098   6.93983  2.272424e+05

           cc         cg
```

(continues on next page)

(continued from previous page)

```
2  64.575551  14.072206
5  72.718710   5.726546
```

However, there is another way of doing the same thing, which can be slightly faster for large dataframes, with more natural syntax.

```
# the above is equivalent to
df.query("POP >= 20000")
```

```
         country country isocode  year          POP      XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653   0.99950  2.950722e+05
2          India             IND  2000  1006300.297  44.94160  1.728144e+06
5   South Africa             ZAF  2000    45064.098   6.93983  2.272424e+05
6  United States             USA  2000   282171.957   1.00000  9.898700e+06

          cc         cg
0  75.716805   5.578804
2  64.575551  14.072206
5  72.718710   5.726546
6  72.347054   6.032454
```

```
df.query("country in ['Argentina', 'India', 'South Africa'] and POP > 40000")
```

```
        country country isocode  year          POP      XRAT         tcgdp  \
2         India             IND  2000  1006300.297  44.94160  1.728144e+06
5  South Africa             ZAF  2000    45064.098   6.93983  2.272424e+05

          cc         cg
2  64.575551  14.072206
5  72.718710   5.726546
```

We can also allow arithmetic operations between different columns.

```
df[(df.cc + df.cg >= 80) & (df.POP <= 20000)]
```

```
   country country isocode  year        POP       XRAT         tcgdp  \
4   Malawi             MWI  2000  11801.505  59.543808   5026.221784
7  Uruguay             URY  2000   3219.793  12.099592  25255.961693

          cc         cg
4  74.707624  11.658954
7  78.978740   5.108068
```

```
# the above is equivalent to
df.query("cc + cg >= 80 & POP <= 20000")
```

```
   country country isocode  year        POP       XRAT         tcgdp  \
4   Malawi             MWI  2000  11801.505  59.543808   5026.221784
7  Uruguay             URY  2000   3219.793  12.099592  25255.961693

          cc         cg
```

(continues on next page)

(continued from previous page)

```
4  74.707624  11.658954
7  78.978740   5.108068
```

For example, we can use the conditioning to select the country with the largest household consumption - gdp share `cc`.

```
df.loc[df.cc == max(df.cc)]
```

```
   country country isocode  year       POP       XRAT         tcgdp        cc  \
7  Uruguay             URY  2000  3219.793  12.099592  25255.961693  78.97874

         cg
7  5.108068
```

When we only want to look at certain columns of a selected sub-dataframe, we can use the above conditions with the `.loc[__ , __]` command.

The first argument takes the condition, while the second argument takes a list of columns we want to return.

```
df.loc[(df.cc + df.cg >= 80) & (df.POP <= 20000), ['country', 'year', 'POP']]
```

```
   country  year        POP
4   Malawi  2000  11801.505
7  Uruguay  2000   3219.793
```

Application: Subsetting Dataframe

Real-world datasets can be enormous.

It is sometimes desirable to work with a subset of data to enhance computational efficiency and reduce redundancy.

Let's imagine that we're only interested in the population (`POP`) and total GDP (`tcgdp`).

One way to strip the data frame `df` down to only these variables is to overwrite the dataframe using the selection method described above

```
df_subset = df[['country', 'POP', 'tcgdp']]
df_subset
```

```
         country          POP         tcgdp
0      Argentina    37335.653  2.950722e+05
1      Australia    19053.186  5.418047e+05
2          India  1006300.297  1.728144e+06
3         Israel     6114.570  1.292539e+05
4         Malawi    11801.505  5.026222e+03
5   South Africa    45064.098  2.272424e+05
6  United States   282171.957  9.898700e+06
7        Uruguay     3219.793  2.525596e+04
```

We can then save the smaller dataset for further analysis.

```
df_subset.to_csv('pwt_subset.csv', index=False)
```

13.3.3 Apply Method

Another widely used Pandas method is `df.apply()`.

It applies a function to each row/column and returns a series.

This function can be some built-in functions like the `max` function, a `lambda` function, or a user-defined function.

Here is an example using the `max` function

```
df[['year', 'POP', 'XRAT', 'tcgdp', 'cc', 'cg']].apply(max)
```

```
year     2.000000e+03
POP      1.006300e+06
XRAT     5.954381e+01
tcgdp    9.898700e+06
cc       7.897874e+01
cg       1.407221e+01
dtype: float64
```

This line of code applies the `max` function to all selected columns.

`lambda` function is often used with `df.apply()` method

A trivial example is to return itself for each row in the dataframe

```
df.apply(lambda row: row, axis=1)
```

```
         country country isocode  year          POP       XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653   0.999500  2.950722e+05
1      Australia             AUS  2000    19053.186   1.724830  5.418047e+05
2          India             IND  2000  1006300.297  44.941600  1.728144e+06
3         Israel             ISR  2000     6114.570   4.077330  1.292539e+05
4         Malawi             MWI  2000    11801.505  59.543808  5.026222e+03
5   South Africa             ZAF  2000    45064.098   6.939830  2.272424e+05
6  United States             USA  2000   282171.957   1.000000  9.898700e+06
7        Uruguay             URY  2000     3219.793  12.099592  2.525596e+04

          cc         cg
0  75.716805   5.578804
1  67.759026   6.720098
2  64.575551  14.072206
3  64.436451  10.266688
4  74.707624  11.658954
5  72.718710   5.726546
6  72.347054   6.032454
7  78.978740   5.108068
```

Note: For the `.apply()` method

- axis = 0 – apply function to each column (variables)
- axis = 1 – apply function to each row (observations)
- axis = 0 is the default parameter

We can use it together with `.loc[]` to do some more advanced selection.

```
complexCondition = df.apply(
    lambda row: row.POP > 40000 if row.country in ['Argentina', 'India', 'South Africa
↪'] else row.POP < 20000,
    axis=1), ['country', 'year', 'POP', 'XRAT', 'tcgdp']
```

`df.apply()` here returns a series of boolean values rows that satisfies the condition specified in the if-else statement.

In addition, it also defines a subset of variables of interest.

```
complexCondition
```

```
(0    False
 1     True
 2     True
 3     True
 4     True
 5     True
 6    False
 7     True
 dtype: bool,
 ['country', 'year', 'POP', 'XRAT', 'tcgdp'])
```

When we apply this condition to the dataframe, the result will be

```
df.loc[complexCondition]
```

	country	year	POP	XRAT	tcgdp
1	Australia	2000	19053.186	1.724830	5.418047e+05
2	India	2000	1006300.297	44.941600	1.728144e+06
3	Israel	2000	6114.570	4.077330	1.292539e+05
4	Malawi	2000	11801.505	59.543808	5.026222e+03
5	South Africa	2000	45064.098	6.939830	2.272424e+05
7	Uruguay	2000	3219.793	12.099592	2.525596e+04

13.3.4 Make Changes in DataFrames

The ability to make changes in dataframes is important to generate a clean dataset for future analysis.

1. We can use `df.where()` conveniently to "keep" the rows we have selected and replace the rest rows with any other values

```
df.where(df.POP >= 20000, False)
```

	country	country isocode	year	POP	XRAT	tcgdp	\
0	Argentina	ARG	2000	37335.653	0.9995	295072.21869	
1	False	False	False	False	False	False	
2	India	IND	2000	1006300.297	44.9416	1728144.3748	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
5	South Africa	ZAF	2000	45064.098	6.93983	227242.36949	
6	United States	USA	2000	282171.957	1.0	9898700.0	
7	False	False	False	False	False	False	

(continues on next page)

(continued from previous page)

```
          cc         cg
0  75.716805   5.578804
1      False      False
2  64.575551  14.072206
3      False      False
4      False      False
5   72.71871   5.726546
6  72.347054   6.032454
7      False      False
```

2. We can simply use `.loc[]` to specify the column that we want to modify, and assign values

```
df.loc[df.cg == max(df.cg), 'cg'] = np.nan
df
```

```
         country country isocode  year          POP       XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653   0.999500  2.950722e+05
1      Australia             AUS  2000    19053.186   1.724830  5.418047e+05
2          India             IND  2000  1006300.297  44.941600  1.728144e+06
3         Israel             ISR  2000     6114.570   4.077330  1.292539e+05
4         Malawi             MWI  2000    11801.505  59.543808  5.026222e+03
5   South Africa             ZAF  2000    45064.098   6.939830  2.272424e+05
6  United States             USA  2000   282171.957   1.000000  9.898700e+06
7        Uruguay             URY  2000     3219.793  12.099592  2.525596e+04

          cc         cg
0  75.716805   5.578804
1  67.759026   6.720098
2  64.575551        NaN
3  64.436451  10.266688
4  74.707624  11.658954
5  72.718710   5.726546
6  72.347054   6.032454
7  78.978740   5.108068
```

3. We can use the `.apply()` method to modify *rows/columns as a whole*

```
def update_row(row):
    # modify POP
    row.POP = np.nan if row.POP<= 10000 else row.POP

    # modify XRAT
    row.XRAT = row.XRAT / 10
    return row

df.apply(update_row, axis=1)
```

```
         country country isocode  year          POP      XRAT         tcgdp  \
0      Argentina             ARG  2000    37335.653  0.099950  2.950722e+05
1      Australia             AUS  2000    19053.186  0.172483  5.418047e+05
2          India             IND  2000  1006300.297  4.494160  1.728144e+06
3         Israel             ISR  2000          NaN  0.407733  1.292539e+05
4         Malawi             MWI  2000    11801.505  5.954381  5.026222e+03
```

(continues on next page)

(continued from previous page)

```
5   South Africa             ZAF  2000    45064.098  0.693983  2.272424e+05
6  United States             USA  2000   282171.957  0.100000  9.898700e+06
7        Uruguay             URY  2000          NaN  1.209959  2.525596e+04

          cc         cg
0  75.716805   5.578804
1  67.759026   6.720098
2  64.575551        NaN
3  64.436451  10.266688
4  74.707624  11.658954
5  72.718710   5.726546
6  72.347054   6.032454
7  78.978740   5.108068
```

4. We can use the `.applymap()` method to modify all *individual entries* in the dataframe altogether.

```
# Round all decimal numbers to 2 decimal places
df.applymap(lambda x : round(x,2) if type(x)!=str else x)
```

```
         country country isocode  year         POP   XRAT       tcgdp     cc  \
0      Argentina             ARG  2000    37335.65   1.00   295072.22  75.72
1      Australia             AUS  2000    19053.19   1.72   541804.65  67.76
2          India             IND  2000  1006300.30  44.94  1728144.37  64.58
3         Israel             ISR  2000     6114.57   4.08   129253.89  64.44
4         Malawi             MWI  2000    11801.50  59.54     5026.22  74.71
5   South Africa             ZAF  2000    45064.10   6.94   227242.37  72.72
6  United States             USA  2000   282171.96   1.00  9898700.00  72.35
7        Uruguay             URY  2000     3219.79  12.10    25255.96  78.98

      cg
0   5.58
1   6.72
2    NaN
3  10.27
4  11.66
5   5.73
6   6.03
7   5.11
```

Application: Missing Value Imputation

Replacing missing values is an important step in data munging.

Let's randomly insert some NaN values

```
for idx in list(zip([0, 3, 5, 6], [3, 4, 6, 2])):
    df.iloc[idx] = np.nan

df
```

```
         country country isocode    year          POP       XRAT  \
0      Argentina             ARG  2000.0          NaN   0.999500
1      Australia             AUS  2000.0    19053.186   1.724830
2          India             IND  2000.0  1006300.297  44.941600
3         Israel             ISR  2000.0     6114.570        NaN
```

(continues on next page)

(continued from previous page)

```
4         Malawi             MWI  2000.0    11801.505  59.543808
5   South Africa             ZAF  2000.0    45064.098   6.939830
6  United States             USA     NaN   282171.957   1.000000
7        Uruguay             URY  2000.0     3219.793  12.099592

          tcgdp         cc         cg
0  2.950722e+05  75.716805   5.578804
1  5.418047e+05  67.759026   6.720098
2  1.728144e+06  64.575551        NaN
3  1.292539e+05  64.436451  10.266688
4  5.026222e+03  74.707624  11.658954
5  2.272424e+05        NaN   5.726546
6  9.898700e+06  72.347054   6.032454
7  2.525596e+04  78.978740   5.108068
```

The `zip()` function here creates pairs of values from the two lists (i.e. [0,3], [3,4] …)

We can use the `.applymap()` method again to replace all missing values with 0

```
# replace all NaN values by 0
def replace_nan(x):
    if type(x)!=str:
        return  0 if np.isnan(x) else x
    else:
        return x

df.applymap(replace_nan)
```

```
         country country isocode    year          POP       XRAT  \
0      Argentina             ARG  2000.0        0.000   0.999500
1      Australia             AUS  2000.0    19053.186   1.724830
2          India             IND  2000.0  1006300.297  44.941600
3         Israel             ISR  2000.0     6114.570   0.000000
4         Malawi             MWI  2000.0    11801.505  59.543808
5   South Africa             ZAF  2000.0    45064.098   6.939830
6  United States             USA     0.0   282171.957   1.000000
7        Uruguay             URY  2000.0     3219.793  12.099592

          tcgdp         cc         cg
0  2.950722e+05  75.716805   5.578804
1  5.418047e+05  67.759026   6.720098
2  1.728144e+06  64.575551   0.000000
3  1.292539e+05  64.436451  10.266688
4  5.026222e+03  74.707624  11.658954
5  2.272424e+05   0.000000   5.726546
6  9.898700e+06  72.347054   6.032454
7  2.525596e+04  78.978740   5.108068
```

Pandas also provides us with convenient methods to replace missing values.

For example, single imputation using variable means can be easily done in pandas

```
df = df.fillna(df.iloc[:,2:8].mean())
df
```

```
         country country isocode    year           POP       XRAT  \
0      Argentina             ARG  2000.0  1.962465e+05   0.999500
1      Australia             AUS  2000.0  1.905319e+04   1.724830
2          India             IND  2000.0  1.006300e+06  44.941600
3         Israel             ISR  2000.0  6.114570e+03  18.178451
4         Malawi             MWI  2000.0  1.180150e+04  59.543808
5   South Africa             ZAF  2000.0  4.506410e+04   6.939830
6  United States             USA  2000.0  2.821720e+05   1.000000
7        Uruguay             URY  2000.0  3.219793e+03  12.099592

          tcgdp         cc         cg
0  2.950722e+05  75.716805   5.578804
1  5.418047e+05  67.759026   6.720098
2  1.728144e+06  64.575551   7.298802
3  1.292539e+05  64.436451  10.266688
4  5.026222e+03  74.707624  11.658954
5  2.272424e+05  71.217322   5.726546
6  9.898700e+06  72.347054   6.032454
7  2.525596e+04  78.978740   5.108068
```

Missing value imputation is a big area in data science involving various machine learning techniques.

There are also more advanced tools in python to impute missing values.

13.3.5 Standardization and Visualization

Let's imagine that we're only interested in the population (`POP`) and total GDP (`tcgdp`).

One way to strip the data frame `df` down to only these variables is to overwrite the dataframe using the selection method described above

```
df = df[['country', 'POP', 'tcgdp']]
df
```

```
         country           POP         tcgdp
0      Argentina  1.962465e+05  2.950722e+05
1      Australia  1.905319e+04  5.418047e+05
2          India  1.006300e+06  1.728144e+06
3         Israel  6.114570e+03  1.292539e+05
4         Malawi  1.180150e+04  5.026222e+03
5   South Africa  4.506410e+04  2.272424e+05
6  United States  2.821720e+05  9.898700e+06
7        Uruguay  3.219793e+03  2.525596e+04
```

Here the index `0, 1,..., 7` is redundant because we can use the country names as an index.

To do this, we set the index to be the `country` variable in the dataframe

```
df = df.set_index('country')
df
```

```
                         POP         tcgdp
country
Argentina      1.962465e+05  2.950722e+05
```

(continues on next page)

(continued from previous page)

```
Australia      1.905319e+04  5.418047e+05
India          1.006300e+06  1.728144e+06
Israel         6.114570e+03  1.292539e+05
Malawi         1.180150e+04  5.026222e+03
South Africa   4.506410e+04  2.272424e+05
United States  2.821720e+05  9.898700e+06
Uruguay        3.219793e+03  2.525596e+04
```

Let's give the columns slightly better names

```
df.columns = 'population', 'total GDP'
df
```

```
                population     total GDP
country
Argentina      1.962465e+05  2.950722e+05
Australia      1.905319e+04  5.418047e+05
India          1.006300e+06  1.728144e+06
Israel         6.114570e+03  1.292539e+05
Malawi         1.180150e+04  5.026222e+03
South Africa   4.506410e+04  2.272424e+05
United States  2.821720e+05  9.898700e+06
Uruguay        3.219793e+03  2.525596e+04
```

The `population` variable is in thousands, let's revert to single units

```
df['population'] = df['population'] * 1e3
df
```

```
                population     total GDP
country
Argentina      1.962465e+08  2.950722e+05
Australia      1.905319e+07  5.418047e+05
India          1.006300e+09  1.728144e+06
Israel         6.114570e+06  1.292539e+05
Malawi         1.180150e+07  5.026222e+03
South Africa   4.506410e+07  2.272424e+05
United States  2.821720e+08  9.898700e+06
Uruguay        3.219793e+06  2.525596e+04
```

Next, we're going to add a column showing real GDP per capita, multiplying by 1,000,000 as we go because total GDP is in millions

```
df['GDP percap'] = df['total GDP'] * 1e6 / df['population']
df
```

```
                population     total GDP    GDP percap
country
Argentina      1.962465e+08  2.950722e+05   1503.579625
Australia      1.905319e+07  5.418047e+05  28436.433261
India          1.006300e+09  1.728144e+06   1717.324719
Israel         6.114570e+06  1.292539e+05  21138.672749
Malawi         1.180150e+07  5.026222e+03    425.896679
```

(continues on next page)

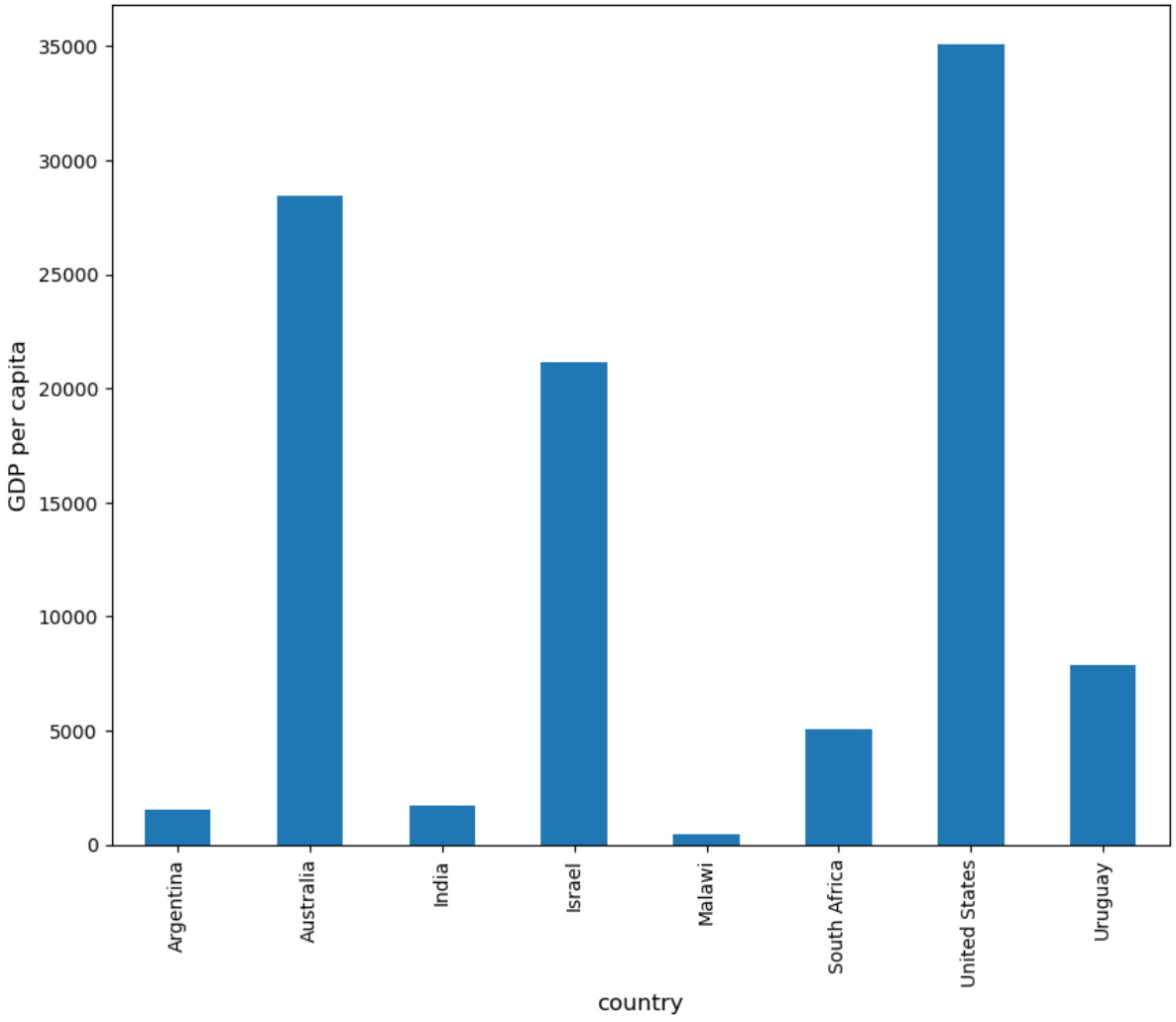
(continued from previous page)

```
South Africa    4.506410e+07  2.272424e+05   5042.647686
United States   2.821720e+08  9.898700e+06  35080.381854
Uruguay         3.219793e+06  2.525596e+04   7843.970620
```

One of the nice things about pandas `DataFrame` and `Series` objects is that they have methods for plotting and visualization that work through Matplotlib.

For example, we can easily generate a bar plot of GDP per capita

```
ax = df['GDP percap'].plot(kind='bar')
ax.set_xlabel('country', fontsize=12)
ax.set_ylabel('GDP per capita', fontsize=12)
plt.show()
```



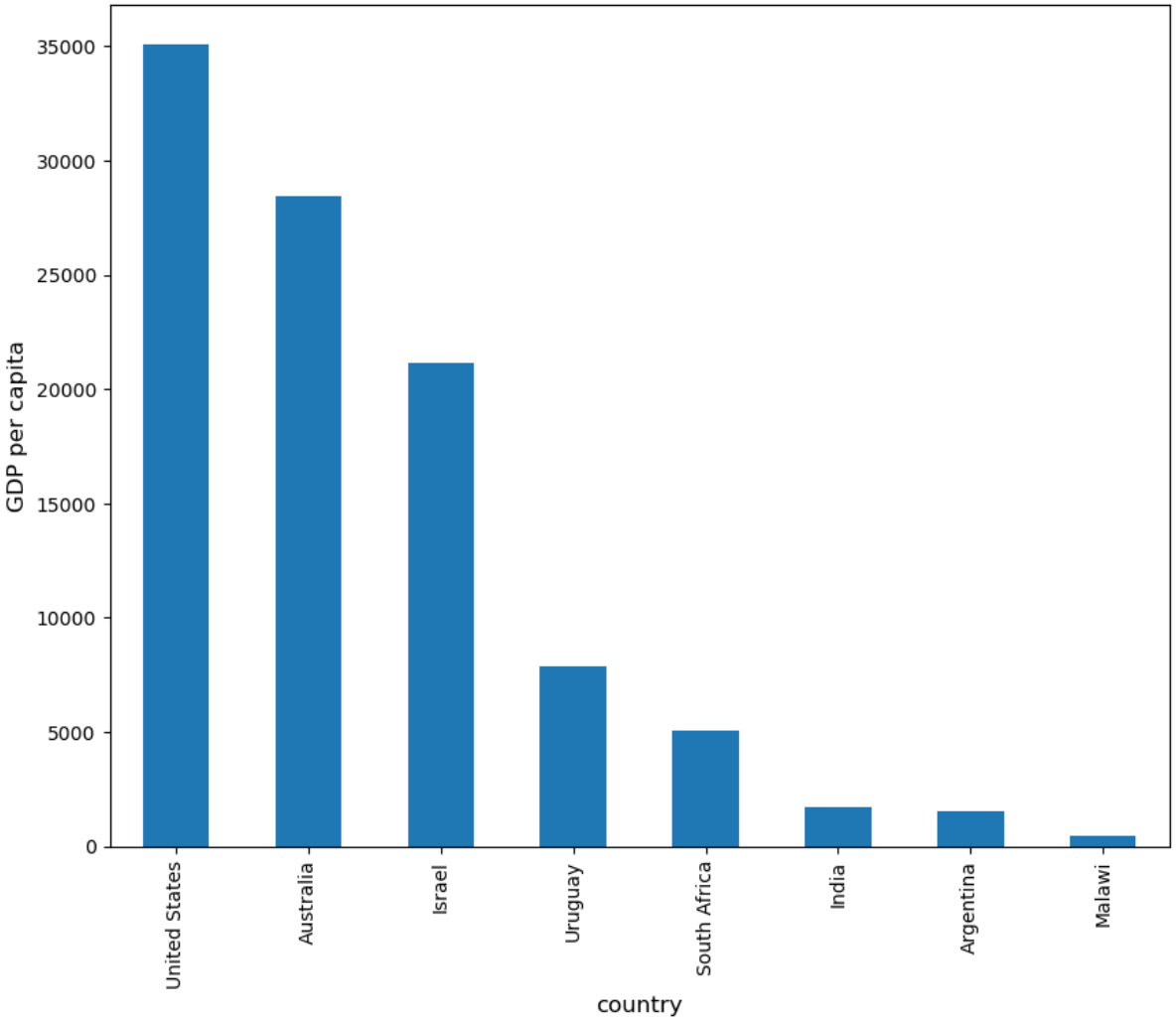
At the moment the data frame is ordered alphabetically on the countries—let's change it to GDP per capita

```
df = df.sort_values(by='GDP percap', ascending=False)
df
```

```
                population     total GDP    GDP percap
country
United States  2.821720e+08  9.898700e+06  35080.381854
Australia      1.905319e+07  5.418047e+05  28436.433261
Israel         6.114570e+06  1.292539e+05  21138.672749
Uruguay        3.219793e+06  2.525596e+04   7843.970620
South Africa   4.506410e+07  2.272424e+05   5042.647686
India          1.006300e+09  1.728144e+06   1717.324719
Argentina      1.962465e+08  2.950722e+05   1503.579625
Malawi         1.180150e+07  5.026222e+03    425.896679
```

Plotting as before now yields

```
ax = df['GDP percap'].plot(kind='bar')
ax.set_xlabel('country', fontsize=12)
ax.set_ylabel('GDP per capita', fontsize=12)
plt.show()
```



13.4 On-Line Data Sources

Python makes it straightforward to query online databases programmatically.

An important database for economists is FRED — a vast collection of time series data maintained by the St. Louis Fed.

For example, suppose that we are interested in the unemployment rate.

Via FRED, the entire series for the US civilian unemployment rate can be downloaded directly by entering this URL into your browser (note that this requires an internet connection)

```
https://research.stlouisfed.org/fred2/series/UNRATE/downloaddata/UNRATE.csv
```

(Equivalently, click here: https://research.stlouisfed.org/fred2/series/UNRATE/downloaddata/UNRATE.csv)

This request returns a CSV file, which will be handled by your default application for this class of files.

Alternatively, we can access the CSV file from within a Python program.

This can be done with a variety of methods.

We start with a relatively low-level method and then return to pandas.

13.4.1 Accessing Data with requests

One option is to use requests, a standard Python library for requesting data over the Internet.

To begin, try the following code on your computer

```
r = requests.get('http://research.stlouisfed.org/fred2/series/UNRATE/downloaddata/
↪UNRATE.csv')
```

If there's no error message, then the call has succeeded.

If you do get an error, then there are two likely causes

1. You are not connected to the Internet — hopefully, this isn't the case.
2. Your machine is accessing the Internet through a proxy server, and Python isn't aware of this.

In the second case, you can either

- switch to another machine
- solve your proxy problem by reading the documentation

Assuming that all is working, you can now proceed to use the `source` object returned by the call `requests.get('http://research.stlouisfed.org/fred2/series/UNRATE/downloaddata/UNRATE.csv')`

```
url = 'http://research.stlouisfed.org/fred2/series/UNRATE/downloaddata/UNRATE.csv'
source = requests.get(url).content.decode().split("\n")
source[0]
```

```
'DATE,VALUE\r'
```

```
source[1]
```

```
'1948-01-01,3.4\r'
```

```
source[2]
```

```
'1948-02-01,3.8\r'
```

We could now write some additional code to parse this text and store it as an array.

But this is unnecessary — pandas' `read_csv` function can handle the task for us.

We use `parse_dates=True` so that pandas recognizes our dates column, allowing for simple date filtering

```
data = pd.read_csv(url, index_col=0, parse_dates=True)
```

The data has been read into a pandas DataFrame called `data` that we can now manipulate in the usual way

```
type(data)
```

```
pandas.core.frame.DataFrame
```

```
data.head()  # A useful method to get a quick look at a data frame
```

```
            VALUE
DATE
1948-01-01    3.4
1948-02-01    3.8
1948-03-01    4.0
1948-04-01    3.9
1948-05-01    3.5
```

```
pd.set_option('display.precision', 1)
data.describe()  # Your output might differ slightly
```

```
       VALUE
count  911.0
mean     5.7
std      1.7
min      2.5
25%      4.4
50%      5.5
75%      6.7
max     14.7
```

We can also plot the unemployment rate from 2006 to 2012 as follows

```
ax = data['2006':'2012'].plot(title='US Unemployment Rate', legend=False)
ax.set_xlabel('year', fontsize=12)
ax.set_ylabel('%', fontsize=12)
plt.show()
```

Note that pandas offers many other file type alternatives.

Pandas has a wide variety of top-level methods that we can use to read, excel, json, parquet or plug straight into a database server.

13.4.2 Using pandas_datareader and yfinance to Access Data

The maker of pandas has also authored a library called pandas_datareader that gives programmatic access to many data sources straight from the Jupyter notebook.

While some sources require an access key, many of the most important (e.g., FRED, OECD, EUROSTAT and the World Bank) are free to use.

We will also use yfinance to fetch data from Yahoo finance in the exercises.

For now let's work through one example of downloading and plotting data — this time from the World Bank.

Note: There are also other python libraries available for working with world bank data such as wbgapi

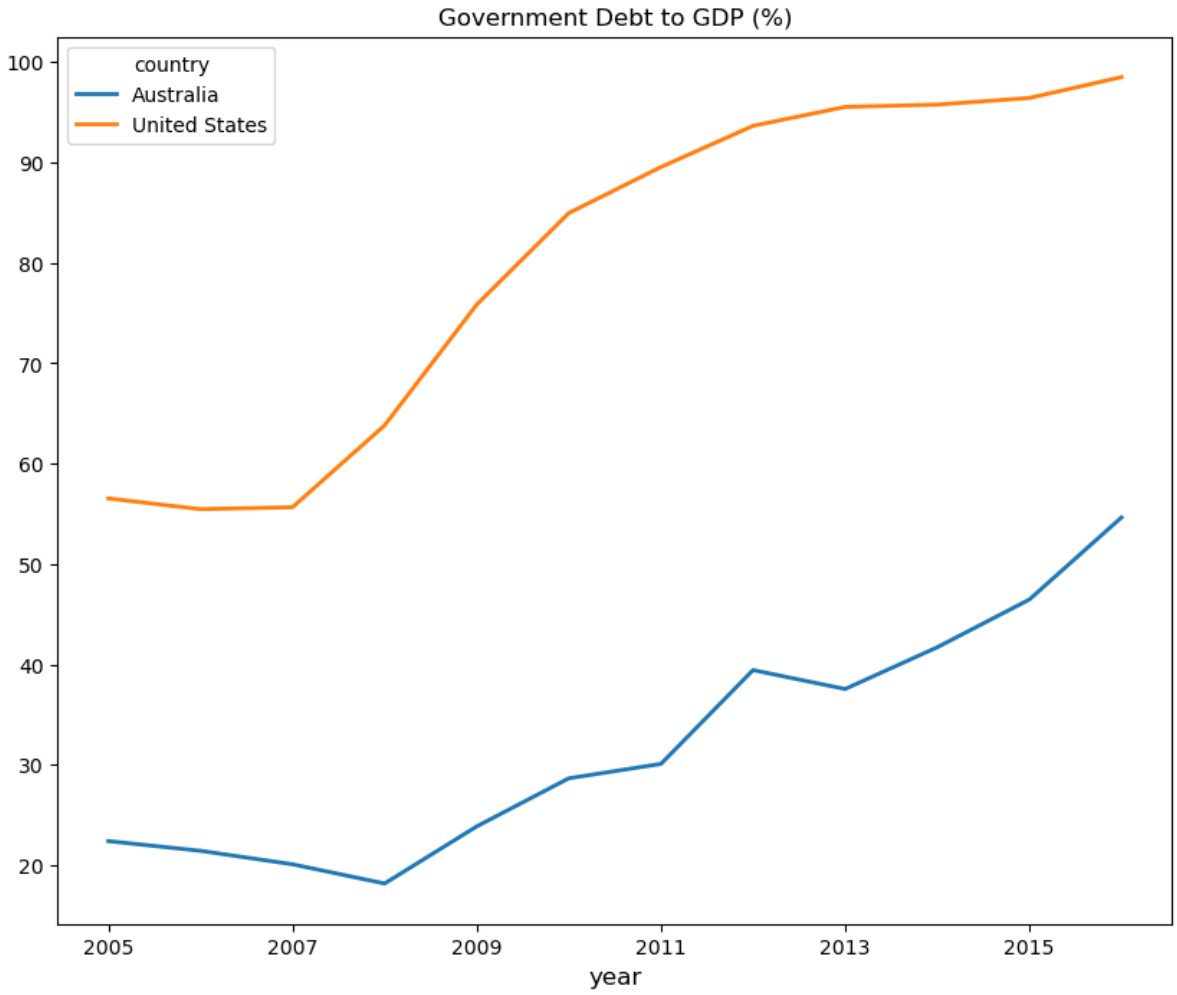
---

The World Bank collects and organizes data on a huge range of indicators.

For example, here's some data on government debt as a ratio to GDP.

The next code example fetches the data for you and plots time series for the US and Australia

```
from pandas_datareader import wb

govt_debt = wb.download(indicator='GC.DOD.TOTL.GD.ZS', country=['US', 'AU'],␣
↪start=2005, end=2016).stack().unstack(0)
ind = govt_debt.index.droplevel(-1)
govt_debt.index = ind
ax = govt_debt.plot(lw=2)
ax.set_xlabel('year', fontsize=12)
plt.title("Government Debt to GDP (%)")
plt.show()
```



The documentation provides more details on how to access various data sources.

13.5 Exercises

Exercise 13.5.1

With these imports:

```
import datetime as dt
import yfinance as yf
```

Write a program to calculate the percentage price change over 2021 for the following shares:

```
ticker_list = {'INTC': 'Intel',
               'MSFT': 'Microsoft',
               'IBM': 'IBM',
               'BHP': 'BHP',
               'TM': 'Toyota',
               'AAPL': 'Apple',
               'AMZN': 'Amazon',
               'C': 'Citigroup',
               'QCOM': 'Qualcomm',
               'KO': 'Coca-Cola',
               'GOOG': 'Google'}
```

Here's the first part of the program

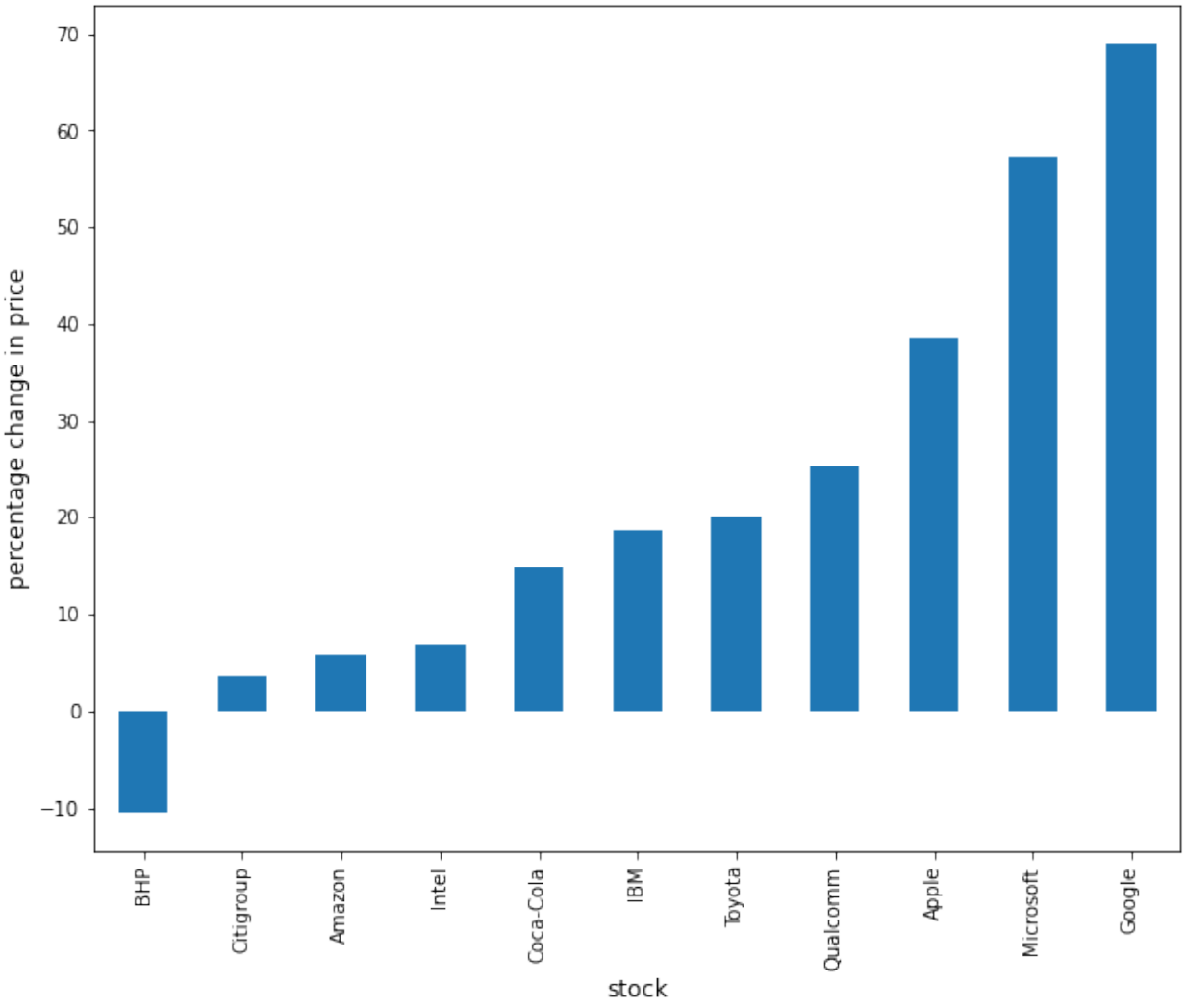
```
def read_data(ticker_list,
          start=dt.datetime(2021, 1, 1),
          end=dt.datetime(2021, 12, 31)):
    """
    This function reads in closing price data from Yahoo
    for each tick in the ticker_list.
    """
    ticker = pd.DataFrame()

    for tick in ticker_list:
        stock = yf.Ticker(tick)
        prices = stock.history(start=start, end=end)

        # Change the index to date-only
        prices.index = pd.to_datetime(prices.index.date)

        closing_prices = prices['Close']
        ticker[tick] = closing_prices

    return ticker

ticker = read_data(ticker_list)
```

Complete the program to plot the result as a bar graph like this one:

Solution to Exercise 13.5.1

There are a few ways to approach this problem using Pandas to calculate the percentage change.

First, you can extract the data and perform the calculation such as:


70
60
50
40
30
20
10
0
−10
percentage change in price
BHP
Citigroup
Amazon
Intel
Coca-Cola
IBM
Toyota
Qualcomm
Apple
Microsoft
Google
stock

```
p1 = ticker.iloc[0]    #Get the first set of prices as a Series
p2 = ticker.iloc[-1]   #Get the last set of prices as a Series
price_change = (p2 - p1) / p1 * 100
price_change
```

```
INTC     6.9
MSFT    57.2
IBM     18.7
BHP    -10.5
TM      20.1
AAPL    38.6
AMZN     5.8
C        3.6
QCOM    25.3
KO      14.9
GOOG    69.0
dtype: float64
```

Alternatively you can use an inbuilt method `pct_change` and configure it to perform the correct calculation using `periods` argument.

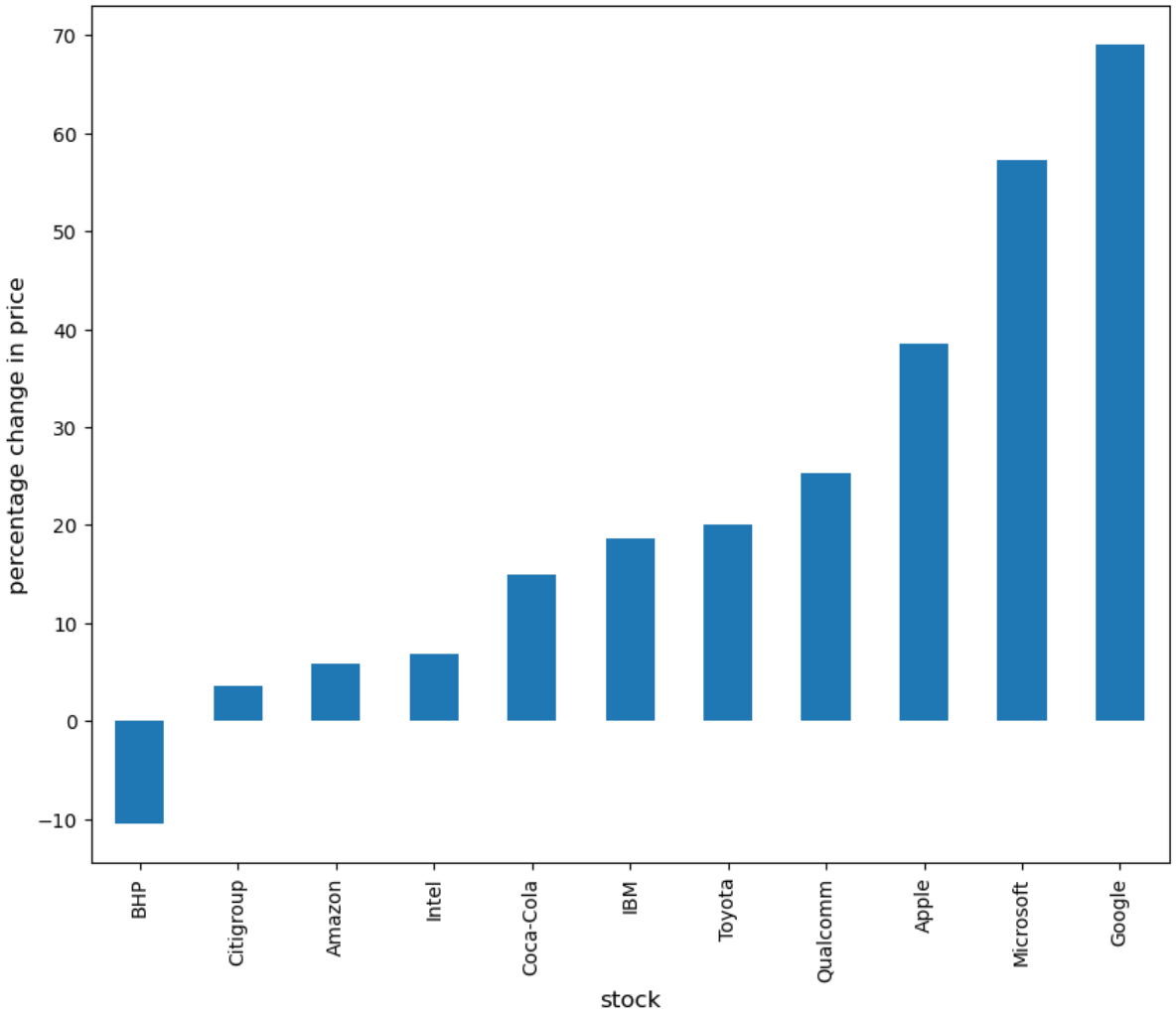
```
change = ticker.pct_change(periods=len(ticker)-1, axis='rows')*100
price_change = change.iloc[-1]
price_change
```

```
INTC     6.9
MSFT    57.2
IBM     18.7
BHP    -10.5
TM      20.1
AAPL    38.6
AMZN     5.8
C        3.6
QCOM    25.3
KO      14.9
GOOG    69.0
Name: 2021-12-30 00:00:00, dtype: float64
```

Then to plot the chart

```
price_change.sort_values(inplace=True)
price_change = price_change.rename(index=ticker_list)
fig, ax = plt.subplots(figsize=(10,8))
ax.set_xlabel('stock', fontsize=12)
ax.set_ylabel('percentage change in price', fontsize=12)
price_change.plot(kind='bar', ax=ax)
plt.show()
```

```
/tmp/ipykernel_2259/232489783.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/
↪user_guide/indexing.html#returning-a-view-versus-a-copy
  price_change.sort_values(inplace=True)
```



Exercise 13.5.2

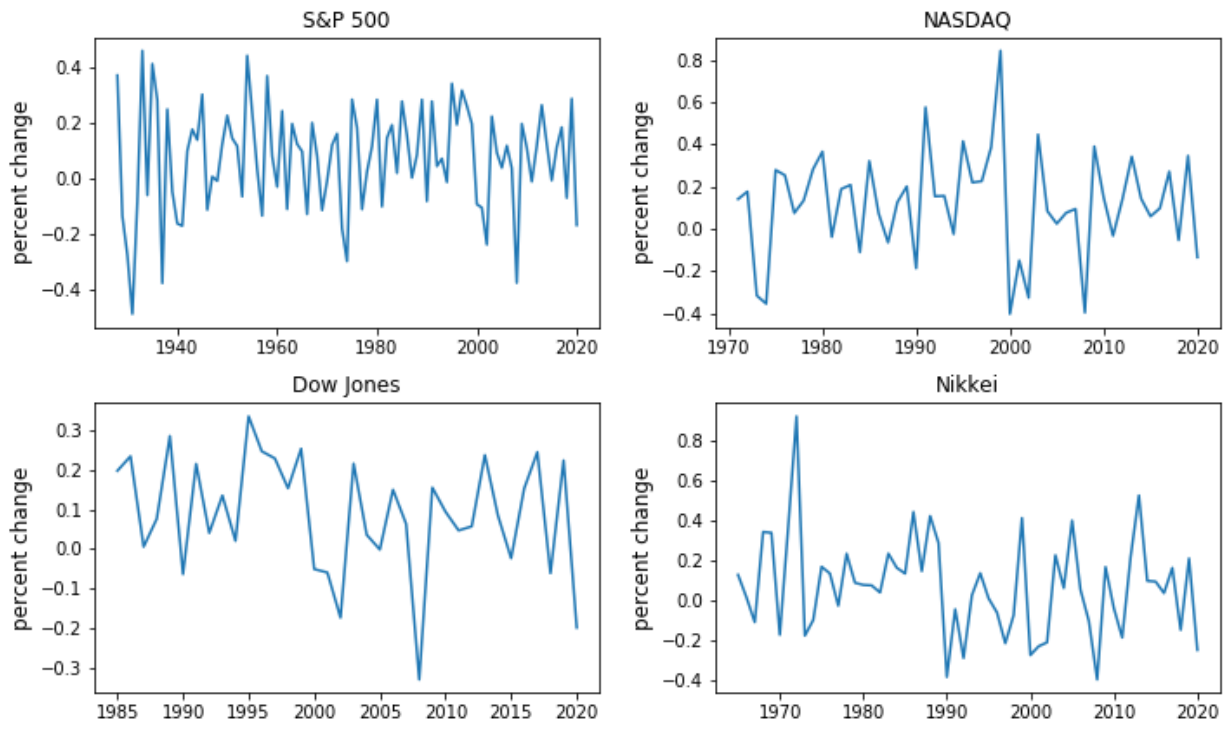
Using the method `read_data` introduced in Exercise 13.5.1, write a program to obtain year-on-year percentage change for the following indices:

```
indices_list = {'^GSPC': 'S&P 500',
                '^IXIC': 'NASDAQ',
                '^DJI': 'Dow Jones',
                '^N225': 'Nikkei'}
```

Complete the program to show summary statistics and plot the result as a time series graph like this one:

Solution to Exercise 13.5.2

Following the work you did in Exercise 13.5.1, you can query the data using `read_data` by updating the start and end dates accordingly.




```
indices_data = read_data(
        indices_list,
        start=dt.datetime(1971, 1, 1),  #Common Start Date
        end=dt.datetime(2021, 12, 31)
)
```

Then, extract the first and last set of prices per year as DataFrames and calculate the yearly returns such as:

```
yearly_returns = pd.DataFrame()

for index, name in indices_list.items():
    p1 = indices_data.groupby(indices_data.index.year)[index].first()  # Get the␣
 ↪first set of returns as a DataFrame
    p2 = indices_data.groupby(indices_data.index.year)[index].last()  # Get the last␣
 ↪set of returns as a DataFrame
    returns = (p2 - p1) / p1
    yearly_returns[name] = returns

yearly_returns
```

```
      S&P 500   NASDAQ  Dow Jones   Nikkei
1971  1.2e-01  1.4e-01        NaN  3.6e-01
1972  1.6e-01  1.8e-01        NaN  9.2e-01
1973 -1.8e-01 -3.2e-01        NaN -1.8e-01
1974 -3.0e-01 -3.5e-01        NaN -9.9e-02
1975  2.8e-01  2.8e-01        NaN  1.7e-01
1976  1.8e-01  2.5e-01        NaN  1.3e-01
1977 -1.1e-01  7.5e-02        NaN -2.7e-02
```

(continues on next page)

(continued from previous page)

```
1978  2.4e-02  1.3e-01        NaN  2.3e-01
1979  1.2e-01  2.8e-01        NaN  8.7e-02
1980  2.8e-01  3.7e-01        NaN  7.7e-02
1981 -1.0e-01 -3.8e-02        NaN  7.4e-02
1982  1.5e-01  1.9e-01        NaN  3.9e-02
1983  1.9e-01  2.1e-01        NaN  2.3e-01
1984  2.0e-02 -1.1e-01        NaN  1.6e-01
1985  2.8e-01  3.2e-01        NaN  1.3e-01
1986  1.6e-01  7.3e-02        NaN  4.4e-01
1987  2.6e-03 -6.4e-02        NaN  1.5e-01
1988  8.5e-02  1.3e-01        NaN  4.2e-01
1989  2.8e-01  2.0e-01        NaN  2.9e-01
1990 -8.2e-02 -1.9e-01        NaN -3.8e-01
1991  2.8e-01  5.8e-01        NaN -4.5e-02
1992  4.4e-02  1.5e-01    4.1e-02 -2.9e-01
1993  7.1e-02  1.6e-01    1.3e-01  2.5e-02
1994 -1.3e-02 -2.4e-02    2.1e-02  1.4e-01
1995  3.4e-01  4.1e-01    3.3e-01  9.4e-03
1996  1.9e-01  2.2e-01    2.5e-01 -6.1e-02
1997  3.2e-01  2.3e-01    2.3e-01 -2.2e-01
1998  2.6e-01  3.9e-01    1.5e-01 -7.5e-02
1999  2.0e-01  8.4e-01    2.5e-01  4.1e-01
2000 -9.3e-02 -4.0e-01   -5.0e-02 -2.7e-01
2001 -1.1e-01 -1.5e-01   -5.9e-02 -2.3e-01
2002 -2.4e-01 -3.3e-01   -1.7e-01 -2.1e-01
2003  2.2e-01  4.5e-01    2.1e-01  2.3e-01
2004  9.3e-02  8.4e-02    3.6e-02  6.1e-02
2005  3.8e-02  2.5e-02   -1.1e-03  4.0e-01
2006  1.2e-01  7.6e-02    1.5e-01  5.3e-02
2007  3.7e-02  9.5e-02    6.3e-02 -1.2e-01
2008 -3.8e-01 -4.0e-01   -3.3e-01 -4.0e-01
2009  2.0e-01  3.9e-01    1.5e-01  1.7e-01
2010  1.1e-01  1.5e-01    9.4e-02 -4.0e-02
2011 -1.1e-02 -3.2e-02    4.7e-02 -1.9e-01
2012  1.2e-01  1.4e-01    5.7e-02  2.1e-01
2013  2.6e-01  3.4e-01    2.4e-01  5.2e-01
2014  1.2e-01  1.4e-01    8.4e-02  9.7e-02
2015 -6.9e-03  5.9e-02   -2.3e-02  9.3e-02
2016  1.1e-01  9.8e-02    1.5e-01  3.6e-02
2017  1.8e-01  2.7e-01    2.4e-01  1.6e-01
2018 -7.0e-02 -5.3e-02   -6.0e-02 -1.5e-01
2019  2.9e-01  3.5e-01    2.2e-01  2.1e-01
2020  1.5e-01  4.2e-01    6.0e-02  1.8e-01
2021  2.9e-01  2.4e-01    2.0e-01  5.6e-02
```

Next, you can obtain summary statistics by using the method `describe`.

```
yearly_returns.describe()
```

```
       S&P 500   NASDAQ  Dow Jones   Nikkei
count  5.1e+01  5.1e+01    3.0e+01  5.1e+01
mean   9.2e-02  1.3e-01    9.1e-02  7.9e-02
std    1.6e-01  2.5e-01    1.4e-01  2.4e-01
min   -3.8e-01 -4.0e-01   -3.3e-01 -4.0e-01
25%   -2.2e-03  1.6e-04    2.5e-02 -6.8e-02
```

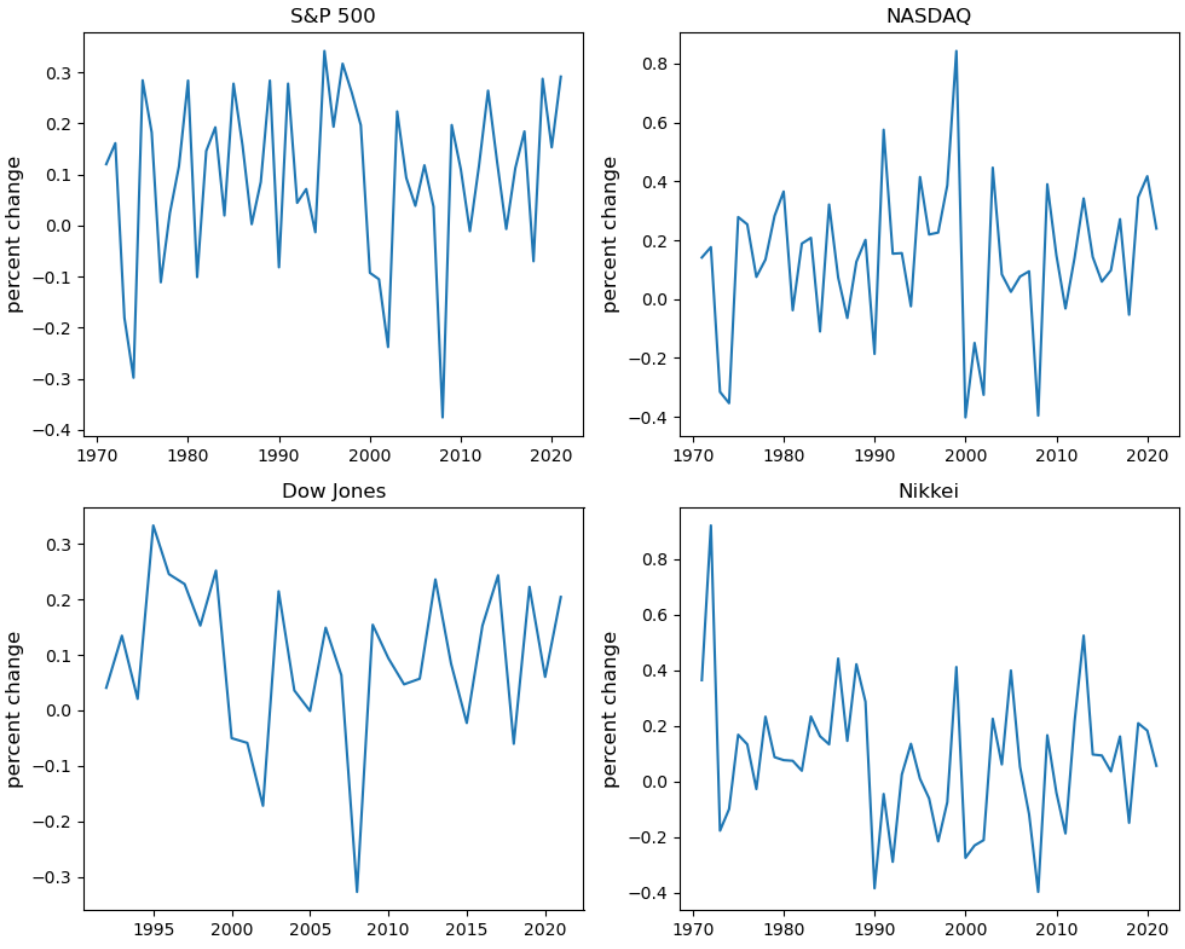
(continues on next page)

(continued from previous page)

```
50%     1.2e-01   1.4e-01     8.9e-02   7.7e-02
75%     2.0e-01   2.8e-01     2.1e-01   2.0e-01
max     3.4e-01   8.4e-01     3.3e-01   9.2e-01
```

Then, to plot the chart

```
fig, axes = plt.subplots(2, 2, figsize=(10, 8))

for iter_, ax in enumerate(axes.flatten()):             # Flatten 2-D array to 1-D␣
↪array
    index_name = yearly_returns.columns[iter_]          # Get index name per iteration
    ax.plot(yearly_returns[index_name])                 # Plot pct change of yearly␣
↪returns per index
    ax.set_ylabel("percent change", fontsize = 12)
    ax.set_title(index_name)

plt.tight_layout()
```



CHAPTER

FOURTEEN

SYMPY

Contents

14.1 Overview

Unlike numerical libraries that deal with values, SymPy focuses on manipulating mathematical symbols and expressions directly.

SymPy provides a wide range of features including

- symbolic expression
- equation solving
- simplification
- calculus
- matrices
- discrete math, etc.

These functions make SymPy a popular open-source alternative to other proprietary symbolic computational software such as Mathematica.

In this lecture, we will explore some of the functionality of SymPy and demonstrate how to use basic SymPy functions to solve economic models.

14.2 Getting Started

Let's first import the library and initialize the printer for symbolic output

```
from sympy import *
from sympy.plotting import plot, plot3d_parametric_line, plot3d
from sympy.solvers.inequalities import reduce_rational_inequalities
from sympy.stats import Poisson, Exponential, Binomial, density, moment, E, cdf

import numpy as np
import matplotlib.pyplot as plt

# Enable the mathjax printer
init_printing(use_latex='mathjax')
```

14.3 Symbolic algebra

14.3.1 Symbols

First we initialize some symbols to work with

```
x, y, z = symbols('x y z')
```

Symbols are the basic units for symbolic computation in SymPy.

14.3.2 Expressions

We can now use symbols `x`, `y`, and `z` to build expressions and equations.

Here we build a simple expression first

```
expr = (x+y) ** 2
expr
```

$$(x + y)^2$$

We can expand this expression with the `expand` function

```
expand_expr = expand(expr)
expand_expr
```

$$x^2 + 2xy + y^2$$

and factorize it back to the factored form with the `factor` function

```
factor(expand_expr)
```

$$(x + y)^2$$

We can solve this expression

```
solve(expr)
```

$$[\{x : -y\}]$$

Note this is equivalent to solving the following equation for x

$$(x + y)^2 = 0$$

Note: Solvers is an important module with tools to solve different types of equations.

There are a variety of solvers available in SymPy depending on the nature of the problem.

14.3.3 Equations

SymPy provides several functions to manipulate equations.

Let's develop an equation with the expression we defined before

```
eq = Eq(expr, 0)
eq
```

$$(x + y)^2 = 0$$

Solving this equation with respect to x gives the same output as solving the expression directly

```
solve(eq, x)
```

$$[-y]$$

SymPy can handle equations with multiple solutions

```
eq = Eq(expr, 1)
solve(eq, x)
```

$$[1 - y, \ -y - 1]$$

`solve` function can also combine multiple equations together and solve a system of equations

```
eq2 = Eq(x, y)
eq2
```

$$x = y$$

```
solve([eq, eq2], [x, y])
```

$$\left[\left(-\frac{1}{2}, -\frac{1}{2}\right), \left(\frac{1}{2}, \frac{1}{2}\right)\right]$$

We can also solve for the value of y by simply substituting x with y

```
expr_sub = expr.subs(x, y)
expr_sub
```

$$4y^2$$

```
solve(Eq(expr_sub, 1))
```

$$\left[-\frac{1}{2}, \frac{1}{2}\right]$$

Below is another example equation with the symbol `x` and functions `sin`, `cos`, and `tan` using the `Eq` function

```
# Create an equation
eq = Eq(cos(x) / (tan(x)/sin(x)), 0)
eq
```

$$\frac{\sin(x)\cos(x)}{\tan(x)} = 0$$

Now we simplify this equation using the `simplify` function

```
# Simplify an expression
simplified_expr = simplify(eq)
simplified_expr
```

$$\cos^2(x) = 0$$

Again, we use the `solve` function to solve this equation

```
# Solve the equation
sol = solve(eq, x)
sol
```

$$\left[\frac{\pi}{2}, \frac{3\pi}{2}\right]$$

SymPy can also handle more complex equations involving trigonometry and complex numbers.

We demonstrate this using Euler's formula

```
# 'I' represents the imaginary number i
euler = cos(x) + I*sin(x)
euler
```

$$i \sin(x) + \cos(x)$$

```
simplify(euler)
```

$$e^{ix}$$

If you are interested, we encourage you to read the lecture on trigonometry and complex numbers.

Example: fixed point computation

Fixed point computation is frequently used in economics and finance.

Here we solve the fixed point of the Solow-Swan growth dynamics:

$$k_{t+1} = sf(k_t) + (1-\delta)k_t, \quad t = 0, 1, ...$$

where k_t is the capital stock, f is a production function, δ is a rate of depreciation.

We are interested in calculating the fixed point of this dynamics, i.e., the value of k such that $k_{t+1} = k_t$.

With $f(k) = Ak^\alpha$, we can show the unique fixed point of the dynamics k^* using pen and paper:

$$k^* := \left(\frac{sA}{\delta}\right)^{1/(1-\alpha)}$$

This can be easily computed in SymPy

```
A, s, k, α, δ = symbols('A s k^* α δ')
```

Now we solve for the fixed point k^*

$$k^* = sA(k^*)^\alpha + (1-\delta)k^*$$

```
# Define Solow-Swan growth dynamics
solow = Eq(s*A*k**α + (1-δ)*k, k)
solow
```

$$A\left(k^*\right)^{\alpha} s + k^* \left(1 - \delta\right) = k^*$$

```
solve(solow, k)
```

$$\left[\left(\frac{As}{\delta}\right)^{-\frac{1}{\alpha-1}}\right]$$

14.3.4 Inequalities and logic

SymPy also allows users to define inequalities and set operators and provides a wide range of operations.

```
reduce_inequalities([2*x + 5*y <= 30, 4*x + 2*y <= 20], [x])
```

$$x \leq 5 - \frac{y}{2} \wedge x \leq 15 - \frac{5y}{2} \wedge -\infty < x$$

```
And(2*x + 5*y <= 30, x > 0)
```

$$2x + 5y \leq 30 \wedge x > 0$$

14.3.5 Series

Series are widely used in economics and statistics, from asset pricing to the expectation of discrete random variables.

We can construct a simple series of summations using `Sum` function and `Indexed` symbols

```
x, y, i, j = symbols("x y i j")
sum_xy = Sum(Indexed('x', i)*Indexed('y', j),
             (i, 0, 3),
             (j, 0, 3))
sum_xy
```

$$\sum_{\substack{0 \leq i \leq 3 \\ 0 \leq j \leq 3}} x_i y_j$$

To evaluate the sum, we can `lambdify` the formula.

The lambdified expression can take numeric values as input for x and y and compute the result

```
sum_xy = lambdify([x, y], sum_xy)
grid = np.arange(0, 4, 1)
sum_xy(grid, grid)
```

```
36
```

Example: bank deposits

Imagine a bank with D_0 as the deposit at time t.

It loans $(1-r)$ of its deposits and keeps a fraction r as cash reserves.

Its deposits over an infinite time horizon can be written as

$$\sum_{i=0}^{\infty}(1-r)^i D_0$$

Let's compute the deposits at time t

```
D = symbols('D_0')
r = Symbol('r', positive=True)
Dt = Sum('(1 - r)^i * D_0', (i, 0, oo))
Dt
```

$$\sum_{i=0}^{\infty} D_0 \left(1-r\right)^{i}$$

We can call the `doit` method to evaluate the series

```
Dt.doit()
```

$$D_0 \left(\begin{cases} \frac{1}{r} & \text{for } |r-1|<1 \\ \sum_{i=0}^{\infty}\left(1-r\right)^{i} & \text{otherwise} \end{cases}\right)$$

Simplifying the expression above gives

```
simplify(Dt.doit())
```

$$\begin{cases} \frac{D_0}{r} & \text{for } r>0 \wedge r<2 \\ D_0 \sum_{i=0}^{\infty}\left(1-r\right)^{i} & \text{otherwise} \end{cases}$$

This is consistent with the solution in the lecture on geometric series.

Example: discrete random variable

In the following example, we compute the expectation of a discrete random variable.

Let's define a discrete random variable X following a Poisson distribution:

$$f(x) = \frac{\lambda^x e^{-\lambda}}{x!}, \quad x = 0, 1, 2, ...$$

```
λ = symbols('lambda')

# We refine the symbol x to positive integers
x = Symbol('x', integer=True, positive=True)
pmf = λ**x * exp(-λ) / factorial(x)
pmf
```

$$\frac{\lambda^x e^{-\lambda}}{x!}$$

We can verify if the sum of probabilities for all possible values equals 1:

$$\sum_{x=0}^{\infty} f(x) = 1$$

```
sum_pmf = Sum(pmf, (x, 0, oo))
sum_pmf.doit()
```

$$1$$

The expectation of the distribution is:

$$E(X) = \sum_{x=0}^{\infty} x f(x)$$

```
fx = Sum(x*pmf, (x, 0, oo))
fx.doit()
```

$$\lambda$$

SymPy includes a statistics submodule called `Stats`.

`Stats` offers built-in distributions and functions on probability distributions.

The computation above can also be condensed into one line using the expectation function `E` in the `Stats` module

```
λ = Symbol("λ", positive = True)

# Using sympy.stats.Poisson() method
X = Poisson("x", λ)
E(X)
```

$$\lambda$$

14.4 Symbolic Calculus

SymPy allows us to perform various calculus operations, such as limits, differentiation, and integration.

14.4.1 Limits

We can compute limits for a given expression using the `limit` function

```
# Define an expression
f = x**2 / (x-1)

# Compute the limit
lim = limit(f, x, 0)
lim
```

$$0$$

14.4.2 Derivatives

We can differentiate any SymPy expression using the `diff` function

```
# Differentiate a function with respect to x
df = diff(f, x)
df
```

$$-\frac{x^2}{(x-1)^2} + \frac{2x}{x-1}$$

14.4.3 Integrals

We can compute definite and indefinite integrals using the `integrate` function

```
# Calculate the indefinite integral
indef_int = integrate(df, x)
indef_int
```

$$x + \frac{1}{x-1}$$

Let's use this function to compute the moment-generating function of exponential distribution with the probability density function:

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0$$

```
λ = Symbol('lambda', positive=True)
x = Symbol('x', positive=True)
pdf = λ * exp(-λ*x)
pdf
```

$$\lambda e^{-\lambda x}$$

```
t = Symbol('t', positive=True)
moment_t = integrate(exp(t*x) * pdf, (x, 0, oo))
simplify(moment_t)
```

$$\begin{cases} \frac{\lambda}{\lambda - t} & \text{for } \lambda > t \wedge \frac{\lambda}{t} \neq 1 \\ \lambda \int_0^\infty e^{x(-\lambda+t)}\, dx & \text{otherwise} \end{cases}$$

Note that we can also use `Stats` module to compute the moment

```
X = Exponential(x, λ)
```

```
moment(X, 1)
```

$$\frac{1}{\lambda}$$

```
E(X**t)
```

$$\lambda^{-t}\Gamma\left(t+1\right)$$

Using the `integrate` function, we can derive the cumulative density function of the exponential distribution with $\lambda = 0.5$

```
λ_pdf = pdf.subs(λ, 1/2)
λ_pdf
```

$$0.5e^{-0.5x}$$

```
integrate(λ_pdf, (x, 0, 4))
```

$$0.864664716763387$$

Using `cdf` in `Stats` module gives the same solution

```
cdf(X, 1/2)
```

$$\left(z \mapsto \begin{cases} 1 - e^{-z\lambda} & \text{for } z \geq 0 \\ 0 & \text{otherwise} \end{cases}\right)$$

```
# Plug in a value for z
λ_cdf = cdf(X, 1/2)(4)
λ_cdf
```

$$1 - e^{-4\lambda}$$

```
# Substitute λ
λ_cdf.subs({λ: 1/2})
```

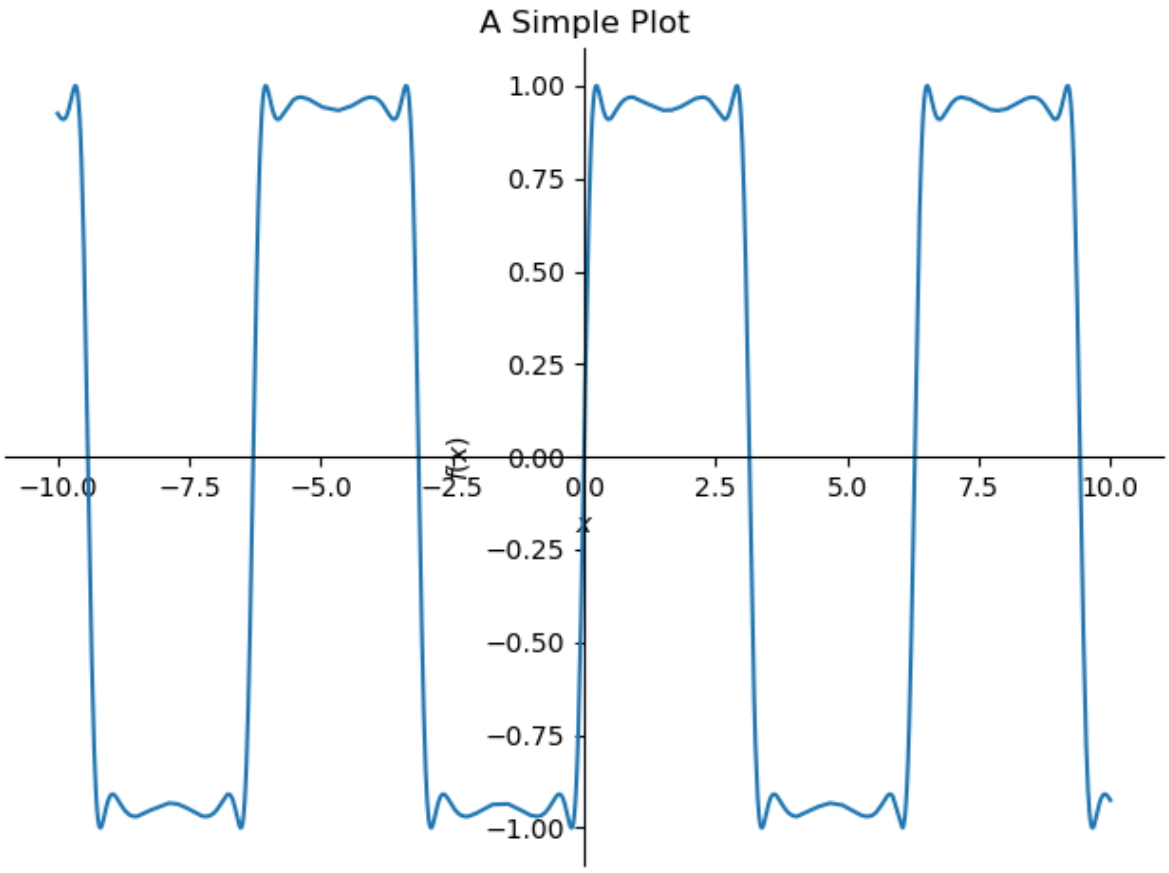
$$0.864664716763387$$

14.5 Plotting

SymPy provides a powerful plotting feature.

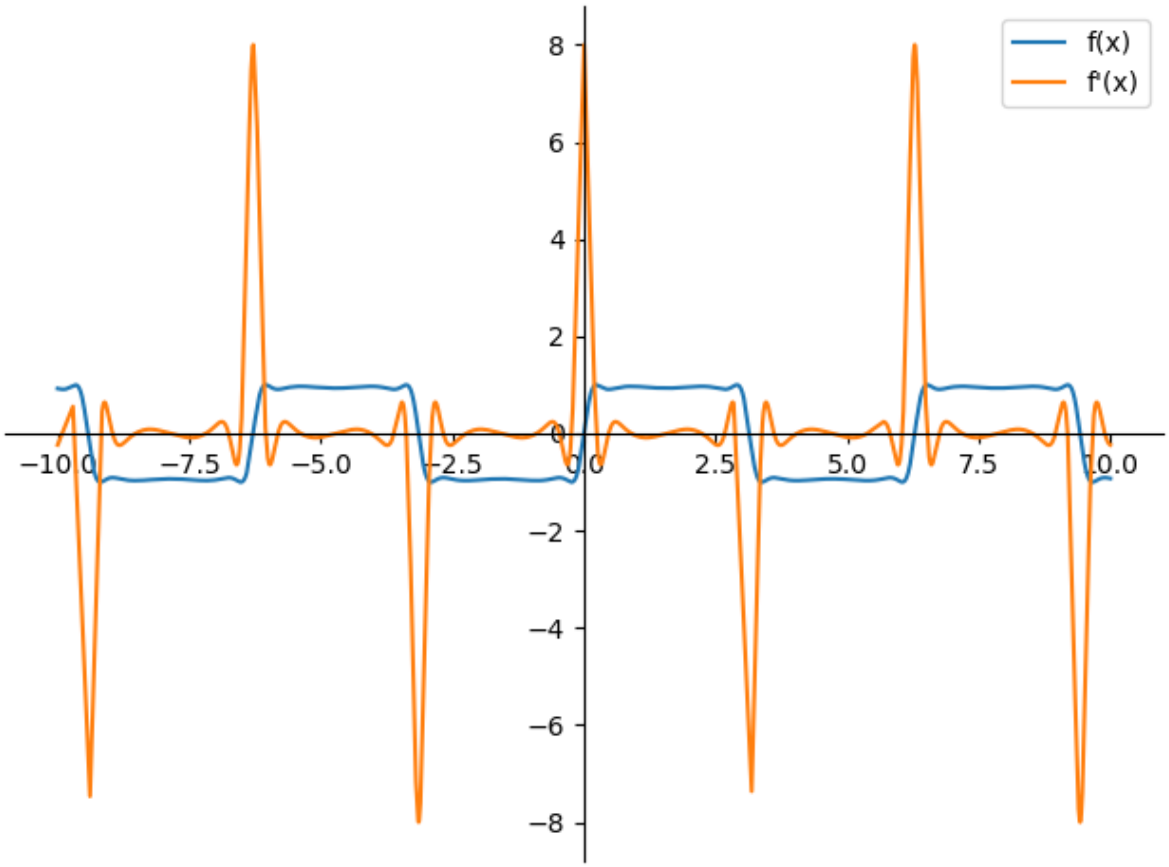
First we plot a simple function using the `plot` function

```
f = sin(2 * sin(2 * sin(2 * sin(x))))
p = plot(f, (x, -10, 10), show=False)
p.title = 'A Simple Plot'
p.show()
```



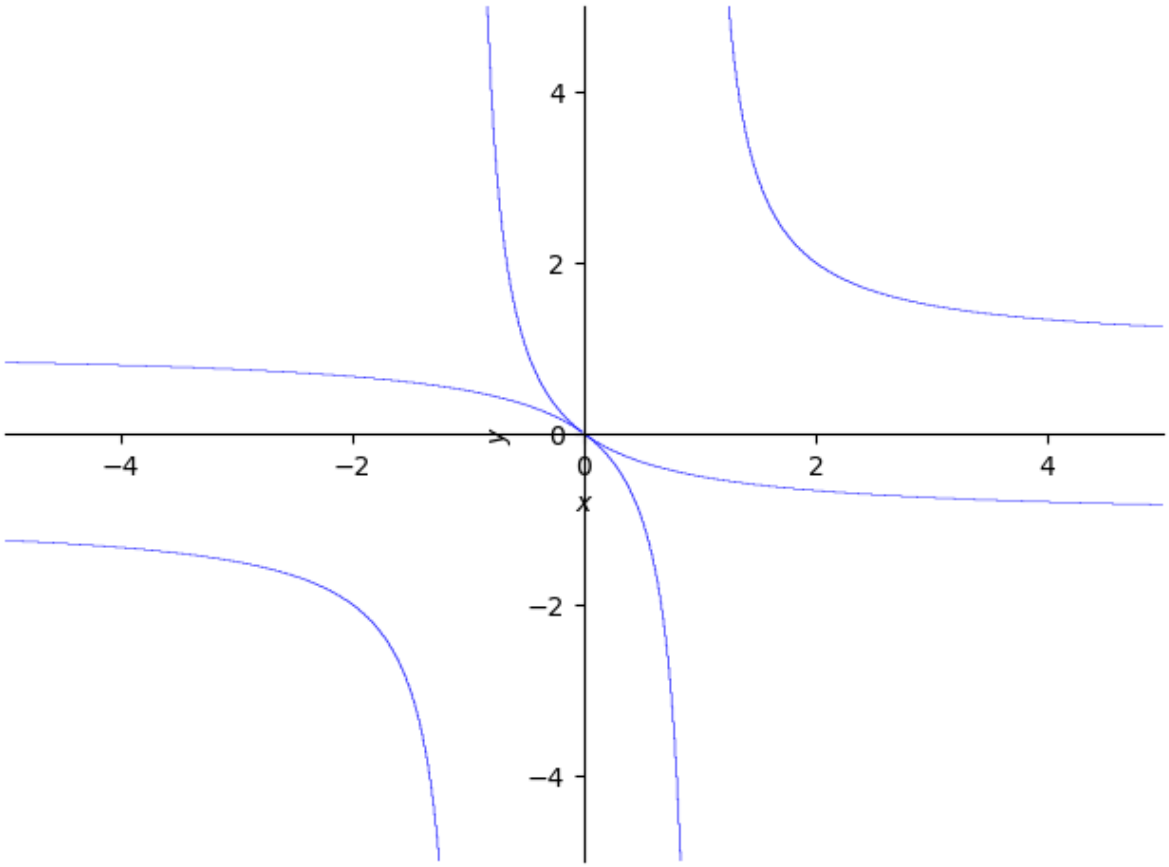
Similar to Matplotlib, SymPy provides an interface to customize the graph

```
plot_f = plot(f, (x, -10, 10),
              xlabel='', ylabel='',
              legend = True, show = False)
plot_f[0].label = 'f(x)'
df = diff(f)
plot_df = plot(df, (x, -10, 10),
            legend = True, show = False)
plot_df[0].label = 'f\'(x)'
plot_f.append(plot_df[0])
plot_f.show()
```

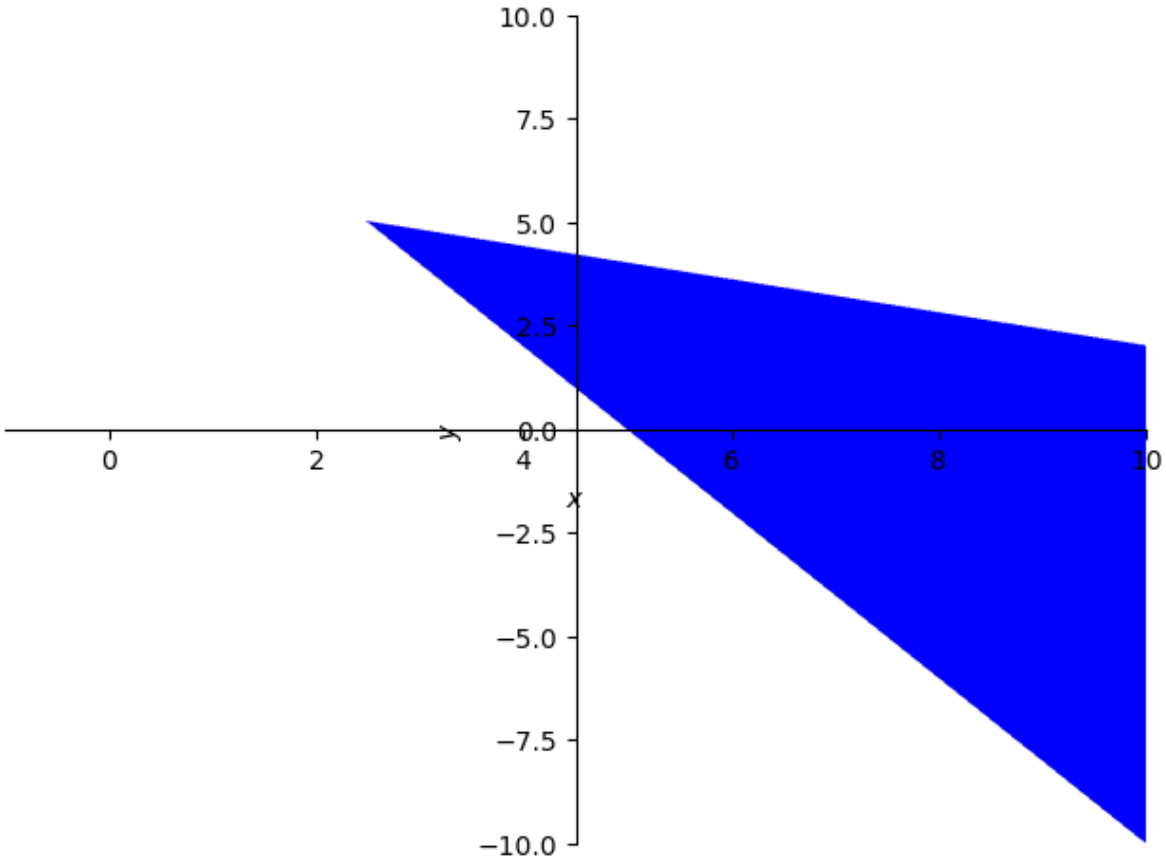


It also supports plotting implicit functions and visualizing inequalities

```
p = plot_implicit(Eq((1/x + 1/y)**2, 1))
```

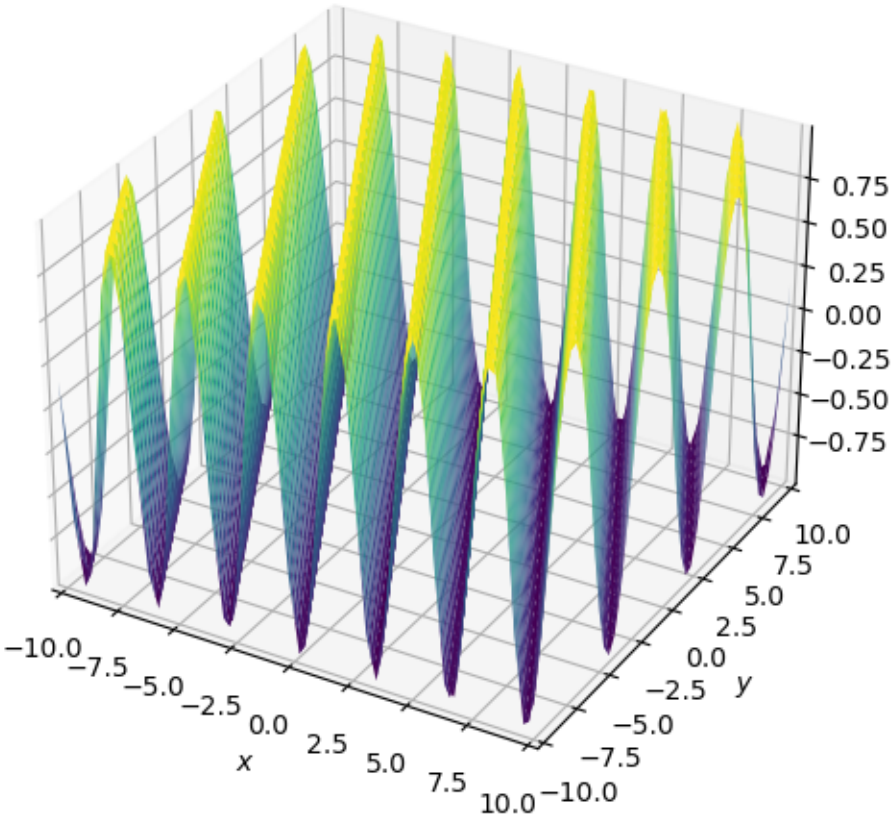



```
p = plot_implicit(And(2*x + 5*y <= 30, 4*x + 2*y >= 20),
                      (x, -1, 10), (y, -10, 10))
```



and visualizations in three-dimensional space

```
p = plot3d(cos(2*x + y), zlabel='')
```



14.6 Application: Two-person Exchange Economy

Imagine a pure exchange economy with two people (a and b) and two goods recorded as proportions (x and y).

They can trade goods with each other according to their preferences.

Assume that the utility functions of the consumers are given by

$$u_a(x, y) = x^{\alpha} y^{1-\alpha}$$

$$u_b(x, y) = (1-x)^{\beta}(1-y)^{1-\beta}$$

where $\alpha, \beta \in (0, 1)$.

First we define the symbols and utility functions

```
# Define symbols and utility functions
x, y, α, β = symbols('x, y, α, β')
u_a = x**α * y**(1-α)
u_b = (1 - x)**β * (1 - y)**(1 - β)
```

```
u_a
```

$$x^{\alpha}y^{1-\alpha}$$

```
u_b
```

$$(1-x)^{\beta}(1-y)^{1-\beta}$$

We are interested in the Pareto optimal allocation of goods x and y.

Note that a point is Pareto efficient when the allocation is optimal for one person given the allocation for the other person.

In terms of marginal utility:

$$\frac{\frac{\partial u_a}{\partial x}}{\frac{\partial u_a}{\partial y}} = \frac{\frac{\partial u_b}{\partial x}}{\frac{\partial u_b}{\partial y}}$$

```
# A point is Pareto efficient when the allocation is optimal
# for one person given the allocation for the other person

pareto = Eq(diff(u_a, x)/diff(u_a, y),
            diff(u_b, x)/diff(u_b, y))
pareto
```

$$\frac{yy^{1-\alpha}y^{\alpha-1}\alpha}{x(1-\alpha)} = -\frac{\beta(1-y)(1-y)^{1-\beta}(1-y)^{\beta-1}}{(1-x)(\beta-1)}$$

```
# Solve the equation
sol = solve(pareto, y)[0]
sol
```

$$\frac{x\beta(\alpha-1)}{x\alpha - x\beta + \alpha\beta - \alpha}$$

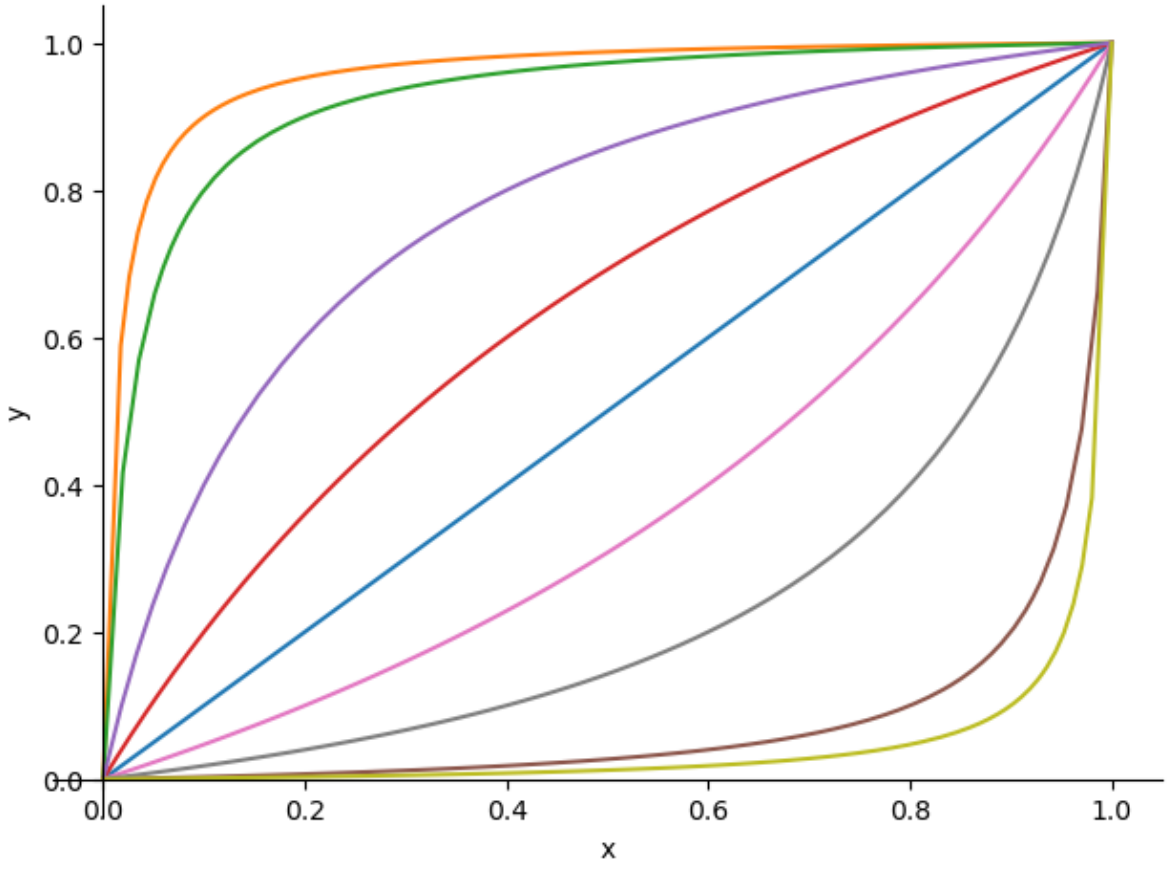
Let's compute the Pareto optimal allocations of the economy (contract curves) with $\alpha = \beta = 0.5$ using SymPy

```
# Substitute α = 0.5 and β = 0.5
sol.subs({α: 0.5, β: 0.5})
```

$$1.0x$$

We can use this result to visualize more contract curves under different parameters

```
# Plot a range of αs and βs
params = [{α: 0.5, β: 0.5},
          {α: 0.1, β: 0.9},
          {α: 0.1, β: 0.8},
          {α: 0.8, β: 0.9},
          {α: 0.4, β: 0.8},
          {α: 0.8, β: 0.1},
          {α: 0.9, β: 0.8},
          {α: 0.8, β: 0.4},
          {α: 0.9, β: 0.1}]

p = plot(xlabel='x', ylabel='y', show=False)

for param in params:
    p_add = plot(sol.subs(param), (x, 0, 1),
                 show=False)
    p.append(p_add[0])
p.show()
```



We invite you to play with the parameters and see how the contract curves change and think about the following two questions:

- Can you think of a way to draw the same graph using `numpy`?
- How difficult will it be to write a `numpy` implementation?

14.7 Exercises

Exercise 14.7.1

L'Hôpital's rule states that for two functions $f(x)$ and $g(x)$, if $\lim_{x \to a} f(x) = \lim_{x \to a} g(x) = 0$ or $\pm\infty$, then

$$\lim_{x \to a} \frac{f(x)}{g(x)} = \lim_{x \to a} \frac{f'(x)}{g'(x)}$$

Use SymPy to verify L'Hôpital's rule for the following functions

$$f(x) = \frac{y^x - 1}{x}$$

as x approaches to 0

Solution to Exercise 14.7.1

Let's define the function first

```
f_upper = y**x - 1
f_lower = x
f = f_upper/f_lower
f
```

$$\frac{y^x - 1}{x}$$

Sympy is smart enough to solve this limit

```
lim = limit(f, x, 0)
lim
```

$$\log(y)$$

We compare the result suggested by L'Hôpital's rule

```
lim = limit(diff(f_upper, x)/
            diff(f_lower, x), x, 0)
lim
```

$$\log(y)$$

Exercise 14.7.2

Maximum likelihood estimation (MLE) is a method to estimate the parameters of a statistical model.

It usually involves maximizing a log-likelihood function and solving the first-order derivative.

The binomial distribution is given by

$$f(x; n, \theta) = \frac{n!}{x!(n-x)!}\theta^x(1-\theta)^{n-x}$$

where n is the number of trials and x is the number of successes.

Assume we observed a series of binary outcomes with x successes out of n trials.

Compute the MLE of θ using SymPy

Solution to Exercise 14.7.2

First, we define the binomial distribution

```
n, x, θ = symbols('n x θ')

binomial_factor = (factorial(n)) / (factorial(x)*factorial(n-r))
binomial_factor
```

$$\frac{n!}{x!\,(n-r)!}$$

```
bino_dist = binomial_factor * ((θ**x)*(1-θ)**(n-x))
bino_dist
```

$$\frac{\theta^x\,(1-\theta)^{n-x}\,n!}{x!\,(n-r)!}$$

Now we compute the log-likelihood function and solve for the result

```
log_bino_dist = log(bino_dist)
```

```
log_bino_diff = simplify(diff(log_bino_dist, θ))
log_bino_diff
```

$$\frac{n\theta - x}{\theta\,(\theta-1)}$$

```
solve(Eq(log_bino_diff, 0), θ)[0]
```

$$\frac{x}{n}$$

Part III

High Performance Computing

CHAPTER

FIFTEEN

NUMBA

Contents

In addition to what's in Anaconda, this lecture will need the following libraries:

```
!pip install quantecon
```

Please also make sure that you have the latest version of Anaconda, since old versions are a *common source of errors*.

Let's start with some imports:

```
%matplotlib inline
import numpy as np
import quantecon as qe
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

15.1 Overview

In an *earlier lecture* we learned about vectorization, which is one method to improve speed and efficiency in numerical work.

Vectorization involves sending array processing operations in batch to efficient low-level code.

However, as *discussed previously*, vectorization has several weaknesses.

One is that it is highly memory-intensive when working with large amounts of data.

Another is that the set of algorithms that can be entirely vectorized is not universal.

In fact, for some algorithms, vectorization is ineffective.

Fortunately, a new Python library called Numba solves many of these problems.

It does so through something called **just in time (JIT) compilation**.

The key idea is to compile functions to native machine code instructions on the fly.

When it succeeds, the compiled code is extremely fast.

Numba is specifically designed for numerical work and can also do other tricks such as multithreading.

Numba will be a key part of our lectures — especially those lectures involving dynamic programming.

This lecture introduces the main ideas.

15.2 Compiling Functions

As stated above, Numba's primary use is compiling functions to fast native machine code during runtime.

15.2.1 An Example

Let's consider a problem that is difficult to vectorize: generating the trajectory of a difference equation given an initial condition.

We will take the difference equation to be the quadratic map

$$x_{t+1} = \alpha x_t (1 - x_t)$$

In what follows we set

```
α = 4.0
```

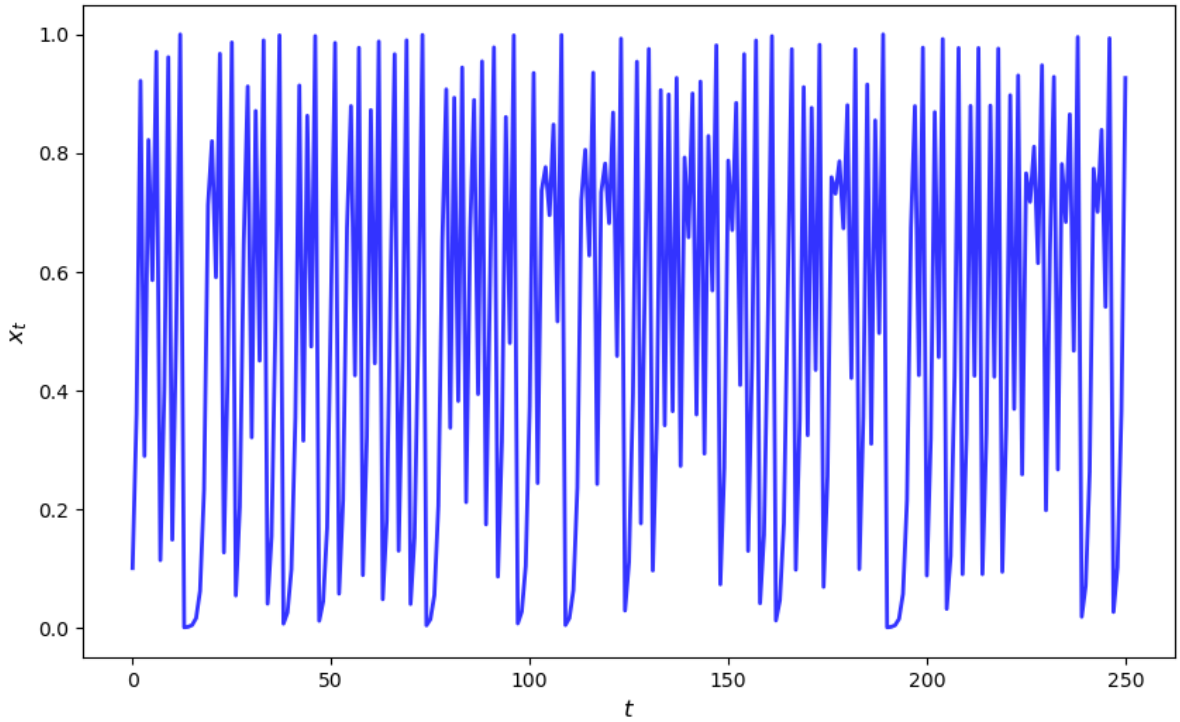
Here's the plot of a typical trajectory, starting from $x_0 = 0.1$, with t on the x-axis

```
def qm(x0, n):
    x = np.empty(n+1)
    x[0] = x0
    for t in range(n):
      x[t+1] = α * x[t] * (1 - x[t])
    return x

x = qm(0.1, 250)
fig, ax = plt.subplots()
```

(continues on next page)

(continued from previous page)

```
ax.plot(x, 'b-', lw=2, alpha=0.8)
ax.set_xlabel('$t$', fontsize=12)
ax.set_ylabel('$x_{t}$', fontsize = 12)
plt.show()
```



To speed the function `qm` up using Numba, our first step is

```
from numba import njit

qm_numba = njit(qm)
```

The function `qm_numba` is a version of `qm` that is "targeted" for JIT-compilation.

We will explain what this means momentarily.

Let's time and compare identical function calls across these two versions, starting with the original function `qm`:

```
n = 10_000_000

qe.tic()
qm(0.1, int(n))
time1 = qe.toc()
```

```
TOC: Elapsed: 0:00:3.29
```

Now let's try qm_numba

```
qe.tic()
qm_numba(0.1, int(n))
```

(continues on next page)

(continued from previous page)

```
time2 = qe.toc()
```

```
TOC: Elapsed: 0:00:0.20
```

This is already a massive speed gain.

In fact, the next time and all subsequent times it runs even faster as the function has been compiled and is in memory:

```
qe.tic()
qm_numba(0.1, int(n))
time3 = qe.toc()
```

```
TOC: Elapsed: 0:00:0.02
```

```
time1 / time3  # Calculate speed gain
```

```
128.11253329868106
```

This kind of speed gain is huge relative to how simple and clear the implementation is.

15.2.2 How and When it Works

Numba attempts to generate fast machine code using the infrastructure provided by the LLVM Project.

It does this by inferring type information on the fly.

(See our *earlier lecture* on scientific computing for a discussion of types.)

The basic idea is this:

- Python is very flexible and hence we could call the function qm with many types.
  - e.g., `x0` could be a NumPy array or a list, `n` could be an integer or a float, etc.
- This makes it hard to *pre*-compile the function.
- However, when we do actually call the function, say by executing `qm(0.5, 10)`, the types of `x0` and `n` become clear.
- Moreover, the types of other variables in `qm` can be inferred once the input is known.
- So the strategy of Numba and other JIT compilers is to wait until this moment, and *then* compile the function.

That's why it is called "just-in-time" compilation.

Note that, if you make the call `qm(0.5, 10)` and then follow it with `qm(0.9, 20)`, compilation only takes place on the first call.

The compiled code is then cached and recycled as required.

15.3 Decorator Notation

In the code above we created a JIT compiled version of `qm` via the call

```
qm_numba = njit(qm)
```

In practice this would typically be done using an alternative *decorator* syntax.

(We will explain all about decorators in a *later lecture* but you can skip the details at this stage.)

Let's see how this is done.

To target a function for JIT compilation we can put `@njit` before the function definition.

Here's what this looks like for `qm`

```
@njit
def qm(x0, n):
    x = np.empty(n+1)
    x[0] = x0
    for t in range(n):
        x[t+1] = α * x[t] * (1 - x[t])
    return x
```

This is equivalent to `qm = njit(qm)`.

The following now uses the jitted version:

```
%%time

qm(0.1, 100_000)
```

```
CPU times: user 65.9 ms, sys: 4.11 ms, total: 70 ms
Wall time: 69.7 ms
```

```
array([0.1       , 0.36      , 0.9216    , ..., 0.98112405, 0.07407858,
       0.27436377])
```

Numba provides several arguments for decorators to accelerate computation and cache functions here.

In the *following lecture on parallelization*, we will discuss how to use the `parallel` argument to achieve automatic parallelization.

15.4 Type Inference

Clearly type inference is a key part of JIT compilation.

As you can imagine, inferring types is easier for simple Python objects (e.g., simple scalar data types such as floats and integers).

Numba also plays well with NumPy arrays.

In an ideal setting, Numba can infer all necessary type information.

This allows it to generate native machine code, without having to call the Python runtime environment.

In such a setting, Numba will be on par with machine code from low-level languages.

When Numba cannot infer all type information, it will raise an error.

For example, in the case below, Numba is unable to determine the type of function `mean` when compiling the function `bootstrap`

```
@njit
def bootstrap(data, statistics, n):
    bootstrap_stat = np.empty(n)
    n = len(data)
    for i in range(n_resamples):
        resample = np.random.choice(data, size=n, replace=True)
        bootstrap_stat[i] = statistics(resample)
    return bootstrap_stat

def mean(data):
    return np.mean(data)

data = np.array([2.3, 3.1, 4.3, 5.9, 2.1, 3.8, 2.2])
n_resamples = 10

print('Type of function:', type(mean))

#Error
try:
    bootstrap(data, mean, n_resamples)
except Exception as e:
    print(e)
```

```
Type of function: <class 'function'>
```

```
Failed in nopython mode pipeline (step: nopython frontend)
non-precise type pyobject
During: typing of argument at /tmp/ipykernel_2182/2092422549.py (1)

File "../../../../../../tmp/ipykernel_2182/2092422549.py", line 1:
<source missing, REPL/exec in use?>

This error may have been caused by the following argument(s):
- argument 1: Cannot determine Numba type of <class 'function'>
```

But Numba recognizes JIT-compiled functions

```
@njit
def mean(data):
    return np.mean(data)

print('Type of function:', type(mean))

%time bootstrap(data, mean, n_resamples)
```

```
Type of function: <class 'numba.core.registry.CPUDispatcher'>
```

```
CPU times: user 277 ms, sys: 55.9 ms, total: 333 ms
Wall time: 333 ms
```

```
array([3.54285714, 3.74285714, 3.57142857, 2.45714286, 3.15714286,
       3.57142857, 3.61428571, 3.6       , 3.62857143, 3.94285714])
```

We can check the signature of the JIT-compiled function

```
bootstrap.signatures
```

```
[(Array(float64, 1, 'C', False, aligned=True),
  type(CPUDispatcher(<function mean at 0x7fbccc96d620>)),
  int64)]
```

The function `bootstrap` takes one `float64` floating point array, one function called `mean` and an `int64` integer.

Now let's see what happens when we change the inputs.

Running it again with a larger integer for `n` and a different set of data does not change the signature of the function.

```
data = np.array([4.1, 1.1, 2.3, 1.9, 0.1, 2.8, 1.2])
%time bootstrap(data, mean, 100)
bootstrap.signatures
```

```
CPU times: user 41 µs, sys: 3 µs, total: 44 µs
Wall time: 47.2 µs
```

```
[(Array(float64, 1, 'C', False, aligned=True),
  type(CPUDispatcher(<function mean at 0x7fbccc96d620>)),
  int64)]
```

As expected, the second run is much faster.

Let's try to change the data again and use an integer array as data

```
data = np.array([1, 2, 3, 4, 5], dtype=np.int64)
%time bootstrap(data, mean, 100)
bootstrap.signatures
```

```
CPU times: user 623 ms, sys: 39.7 ms, total: 662 ms
Wall time: 663 ms
```

```
[(Array(float64, 1, 'C', False, aligned=True),
  type(CPUDispatcher(<function mean at 0x7fbccc96d620>)),
  int64),
 (Array(int64, 1, 'C', False, aligned=True),
  type(CPUDispatcher(<function mean at 0x7fbccc96d620>)),
  int64)]
```

Note that a second signature is added.

It also takes longer to run, suggesting that Numba recompiles this function as the type changes.

Overall, type inference helps Numba to achieve its performance, but it also limits what Numba supports and sometimes requires careful type checks.

You can refer to the list of supported Python and Numpy features here.

15.5 Compiling Classes

As mentioned above, at present Numba can only compile a subset of Python.

However, that subset is ever expanding.

For example, Numba is now quite effective at compiling classes.

If a class is successfully compiled, then its methods act as JIT-compiled functions.

To give one example, let's consider the class for analyzing the Solow growth model we created in *this lecture*.

To compile this class we use the `@jitclass` decorator:

```
from numba import float64
from numba.experimental import jitclass
```

Notice that we also imported something called `float64`.

This is a data type representing standard floating point numbers.

We are importing it here because Numba needs a bit of extra help with types when it tries to deal with classes.

Here's our code:

```
solow_data = [
    ('n', float64),
    ('s', float64),
    ('δ', float64),
    ('α', float64),
    ('z', float64),
    ('k', float64)
]

@jitclass(solow_data)
class Solow:
    r"""
    Implements the Solow growth model with the update rule

        k_{t+1} = [(s z k^α_t) + (1 - δ)k_t] /(1 + n)

    """
    def __init__(self, n=0.05,  # population growth rate
                       s=0.25,  # savings rate
                       δ=0.1,   # depreciation rate
                       α=0.3,   # share of labor
                       z=2.0,   # productivity
                       k=1.0):  # current capital stock

        self.n, self.s, self.δ, self.α, self.z = n, s, δ, α, z
        self.k = k

    def h(self):
        "Evaluate the h function"
        # Unpack parameters (get rid of self to simplify notation)
        n, s, δ, α, z = self.n, self.s, self.δ, self.α, self.z
        # Apply the update rule
        return (s * z * self.k**α + (1 - δ) * self.k) / (1 + n)
```

(continues on next page)

(continued from previous page)

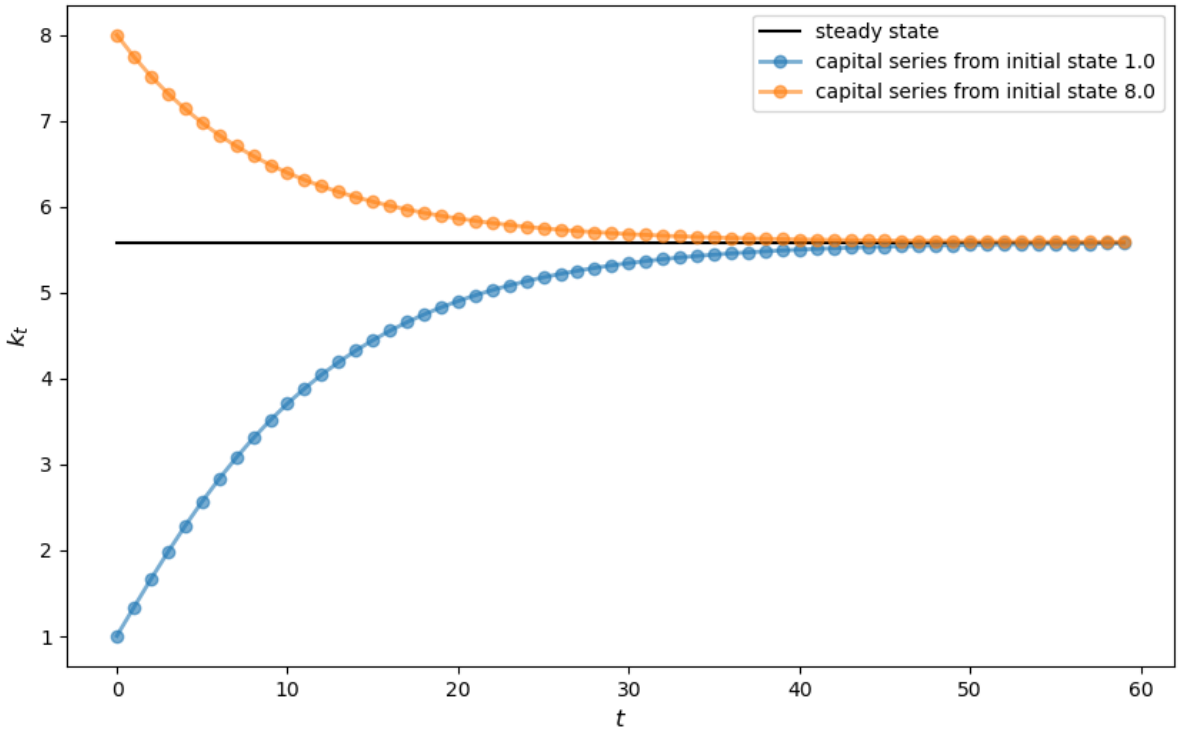
```
    def update(self):
        "Update the current state (i.e., the capital stock)."
        self.k =  self.h()

    def steady_state(self):
        "Compute the steady state value of capital."
        # Unpack parameters (get rid of self to simplify notation)
        n, s, δ, α, z = self.n, self.s, self.δ, self.α, self.z
        # Compute and return steady state
        return ((s * z) / (n + δ))**(1 / (1 - α))

    def generate_sequence(self, t):
        "Generate and return a time series of length t"
        path = []
        for i in range(t):
            path.append(self.k)
            self.update()
        return path
```

First we specified the types of the instance data for the class in `solow_data`.

After that, targeting the class for JIT compilation only requires adding `@jitclass(solow_data)` before the class definition.

When we call the methods in the class, the methods are compiled just like functions.

```
s1 = Solow()
s2 = Solow(k=8.0)

T = 60
fig, ax = plt.subplots()

# Plot the common steady state value of capital
ax.plot([s1.steady_state()]*T, 'k-', label='steady state')

# Plot time series for each economy
for s in s1, s2:
    lb = f'capital series from initial state {s.k}'
    ax.plot(s.generate_sequence(T), 'o-', lw=2, alpha=0.6, label=lb)
ax.set_ylabel('$k_{t}$', fontsize=12)
ax.set_xlabel('$t$', fontsize=12)
ax.legend()
plt.show()
```



15.6 Alternatives to Numba

There are additional options for accelerating Python loops.

Here we quickly review them.

However, we do so only for interest and completeness.

If you prefer, you can safely skip this section.

15.6.1 Cython

Like *Numba*, Cython provides an approach to generating fast compiled code that can be used from Python.

As was the case with Numba, a key problem is the fact that Python is dynamically typed.

As you'll recall, Numba solves this problem (where possible) by inferring type.

Cython's approach is different — programmers add type definitions directly to their "Python" code.

As such, the Cython language can be thought of as Python with type definitions.

In addition to a language specification, Cython is also a language translator, transforming Cython code into optimized C and C++ code.

Cython also takes care of building language extensions — the wrapper code that interfaces between the resulting compiled code and Python.

While Cython has certain advantages, we generally find it both slower and more cumbersome than Numba.

15.6.2 Interfacing with Fortran via F2Py

If you are comfortable writing Fortran you will find it very easy to create extension modules from Fortran code using F2Py.

F2Py is a Fortran-to-Python interface generator that is particularly simple to use.

Robert Johansson provides a nice introduction to F2Py, among other things.

Recently, a Jupyter cell magic for Fortran has been developed — you might want to give it a try.

15.7 Summary and Comments

Let's review the above and add some cautionary notes.

15.7.1 Limitations

As we've seen, Numba needs to infer type information on all variables to generate fast machine-level instructions.

For simple routines, Numba infers types very well.

For larger ones, or for routines using external libraries, it can easily fail.

Hence, it's prudent when using Numba to focus on speeding up small, time-critical snippets of code.

This will give you much better performance than blanketing your Python programs with `@njit` statements.

15.7.2 A Gotcha: Global Variables

Here's another thing to be careful about when using Numba.

Consider the following example

```
a = 1

@njit
def add_a(x):
    return a + x

print(add_a(10))
```

```
11
```

```
a = 2

print(add_a(10))
```

```
11
```

Notice that changing the global had no effect on the value returned by the function.

When Numba compiles machine code for functions, it treats global variables as constants to ensure type stability.

15.8 Exercises

Exercise 15.8.1

Previously we considered how to approximate π by Monte Carlo.

Use the same idea here, but make the code efficient using Numba.

Compare speed with and without Numba when the sample size is large.

Solution to Exercise 15.8.1

Here is one solution:

```
from random import uniform

@njit
def calculate_pi(n=1_000_000):
    count = 0
    for i in range(n):
        u, v = uniform(0, 1), uniform(0, 1)
        d = np.sqrt((u - 0.5)**2 + (v - 0.5)**2)
        if d < 0.5:
            count += 1

    area_estimate = count / n
    return area_estimate * 4  # dividing by radius**2
```

Now let's see how fast it runs:

```
%time calculate_pi()
```

```
CPU times: user 148 ms, sys: 3.99 ms, total: 152 ms
Wall time: 152 ms
```

```
3.138976
```

```
%time calculate_pi()
```

```
CPU times: user 10.9 ms, sys: 0 ns, total: 10.9 ms
Wall time: 10.8 ms
```

```
3.142884
```

If we switch off JIT compilation by removing `@njit`, the code takes around 150 times as long on our machine.

So we get a speed gain of 2 orders of magnitude–which is huge–by adding four characters.

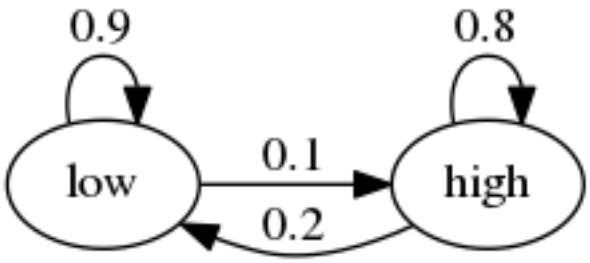
Exercise 15.8.2

In the Introduction to Quantitative Economics with Python lecture series you can learn all about finite-state Markov chains.

For now, let's just concentrate on simulating a very simple example of such a chain.

Suppose that the volatility of returns on an asset can be in one of two regimes — high or low.

The transition probabilities across states are as follows



For example, let the period length be one day, and suppose the current state is high.

We see from the graph that the state tomorrow will be

- high with probability 0.8
- low with probability 0.2

Your task is to simulate a sequence of daily volatility states according to this rule.

Set the length of the sequence to `n = 1_000_000` and start in the high state.

Implement a pure Python version and a Numba version, and compare speeds.

To test your code, evaluate the fraction of time that the chain spends in the low state.

If your code is correct, it should be about 2/3.

Hint:

- Represent the low state as 0 and the high state as 1.
- If you want to store integers in a NumPy array and then apply JIT compilation, use `x = np.empty(n, dtype=np.int_)`.

Solution to Exercise 15.8.2

We let

- 0 represent "low"
- 1 represent "high"

```
p, q = 0.1, 0.2  # Prob of leaving low and high state respectively
```

Here's a pure Python version of the function

```
def compute_series(n):
    x = np.empty(n, dtype=np.int_)
    x[0] = 1  # Start in state 1
    U = np.random.uniform(0, 1, size=n)
    for t in range(1, n):
```

(continues on next page)

(continued from previous page)

```
        current_x = x[t-1]
        if current_x == 0:
            x[t] = U[t] < p
        else:
            x[t] = U[t] > q
    return x
```

Let's run this code and check that the fraction of time spent in the low state is about 0.666

```
n = 1_000_000
x = compute_series(n)
print(np.mean(x == 0))  # Fraction of time x is in state 0
```

```
0.668802
```

This is (approximately) the right output.

Now let's time it:

```
qe.tic()
compute_series(n)
qe.toc()
```

```
TOC: Elapsed: 0:00:0.39
```

```
0.39469242095947266
```

Next let's implement a Numba version, which is easy

```
compute_series_numba = njit(compute_series)
```

Let's check we still get the right numbers

```
x = compute_series_numba(n)
print(np.mean(x == 0))
```

```
0.667323
```

Let's see the time

```
qe.tic()
compute_series_numba(n)
qe.toc()
```

```
TOC: Elapsed: 0:00:0.00
```

```
0.007478237152099609
```

This is a nice speed improvement for one line of code!

CHAPTER

SIXTEEN

PARALLELIZATION

Contents

In addition to what's in Anaconda, this lecture will need the following libraries:

```
!pip install quantecon
```

16.1 Overview

The growth of CPU clock speed (i.e., the speed at which a single chain of logic can be run) has slowed dramatically in recent years.

This is unlikely to change in the near future, due to inherent physical limitations on the construction of chips and circuit boards.

Chip designers and computer programmers have responded to the slowdown by seeking a different path to fast execution: parallelization.

Hardware makers have increased the number of cores (physical CPUs) embedded in each machine.

For programmers, the challenge has been to exploit these multiple CPUs by running many processes in parallel (i.e., simultaneously).

This is particularly important in scientific programming, which requires handling

- large amounts of data and
- CPU intensive simulations and other calculations.

In this lecture we discuss parallelization for scientific computing, with a focus on

1. the best tools for parallelization in Python and
2. how these tools can be applied to quantitative economic problems.

Let's start with some imports:

```
%matplotlib inline
import numpy as np
import quantecon as qe
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

16.2 Types of Parallelization

Large textbooks have been written on different approaches to parallelization but we will keep a tight focus on what's most useful to us.

We will briefly review the two main kinds of parallelization commonly used in scientific computing and discuss their pros and cons.

16.2.1 Multiprocessing

Multiprocessing means concurrent execution of multiple processes using more than one processor.

In this context, a **process** is a chain of instructions (i.e., a program).

Multiprocessing can be carried out on one machine with multiple CPUs or on a collection of machines connected by a network.

In the latter case, the collection of machines is usually called a **cluster**.

With multiprocessing, each process has its own memory space, although the physical memory chip might be shared.

16.2.2 Multithreading

Multithreading is similar to multiprocessing, except that, during execution, the threads all share the same memory space.

Native Python struggles to implement multithreading due to some legacy design features.

But this is not a restriction for scientific libraries like NumPy and Numba.

Functions imported from these libraries and JIT-compiled code run in low level execution environments where Python's legacy restrictions don't apply.

16.2.3 Advantages and Disadvantages

Multithreading is more lightweight because most system and memory resources are shared by the threads.

In addition, the fact that multiple threads all access a shared pool of memory is extremely convenient for numerical programming.

On the other hand, multiprocessing is more flexible and can be distributed across clusters.

For the great majority of what we do in these lectures, multithreading will suffice.

16.3 Implicit Multithreading in NumPy

Actually, you have already been using multithreading in your Python code, although you might not have realized it.

(We are, as usual, assuming that you are running the latest version of Anaconda Python.)

This is because NumPy cleverly implements multithreading in a lot of its compiled code.

Let's look at some examples to see this in action.

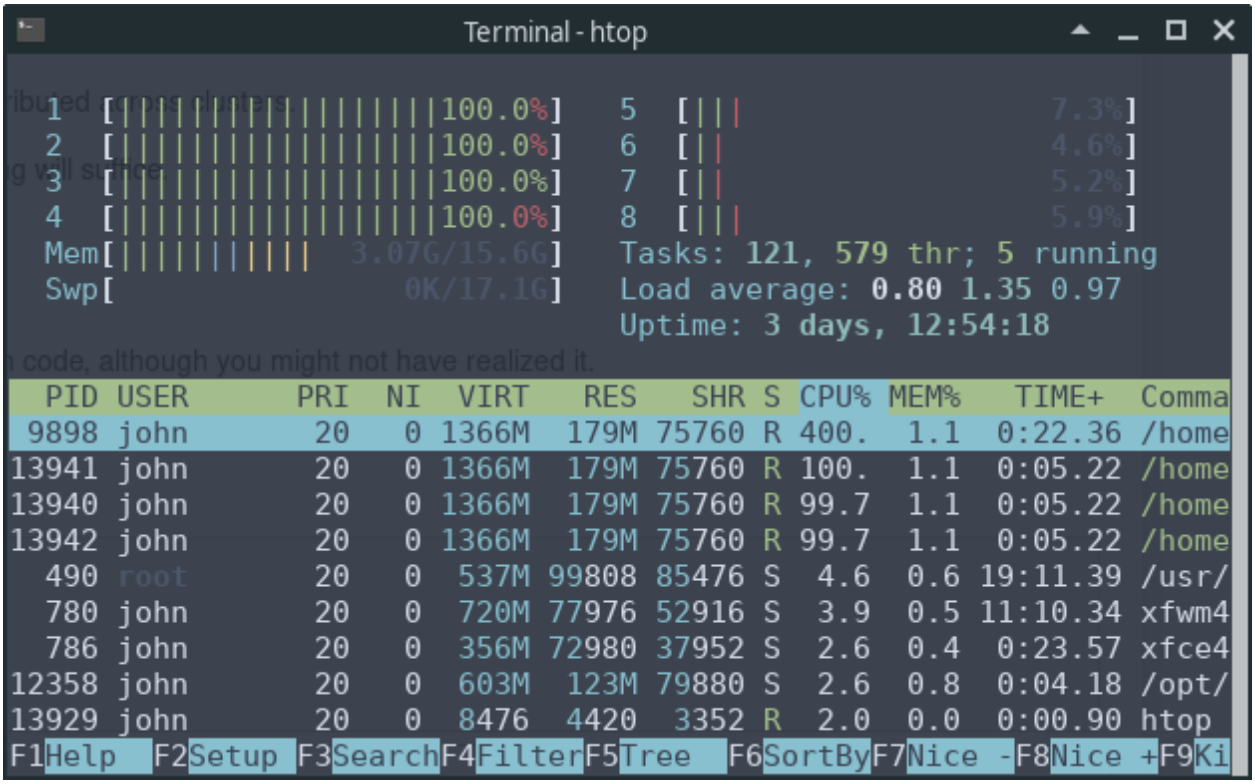
16.3.1 A Matrix Operation

The next piece of code computes the eigenvalues of a large number of randomly generated matrices.

It takes a few seconds to run.

```
n = 20
m = 1000
for i in range(n):
    X = np.random.randn(m, m)
    λ = np.linalg.eigvals(X)
```

Now, let's look at the output of the htop system monitor on our machine while this code is running:



We can see that 4 of the 8 CPUs are running at full speed.

This is because NumPy's `eigvals` routine neatly splits up the tasks and distributes them to different threads.

16.3.2 A Multithreaded Ufunc

Over the last few years, NumPy has managed to push this kind of multithreading out to more and more operations.

For example, let's return to a maximization problem *discussed previously*:

```
def f(x, y):
    return np.cos(x**2 + y**2) / (1 + x**2 + y**2)

grid = np.linspace(-3, 3, 5000)
x, y = np.meshgrid(grid, grid)
```

```
%timeit np.max(f(x, y))
```

```
472 ms ± 1.86 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

If you have a system monitor such as htop (Linux/Mac) or perfmon (Windows), then try running this and then observing the load on your CPUs.

(You will probably need to bump up the grid size to see large effects.)

At least on our machine, the output shows that the operation is successfully distributed across multiple threads.

This is one of the reasons why the vectorized code above is fast.

16.3.3 A Comparison with Numba

To get some basis for comparison for the last example, let's try the same thing with Numba.

In fact there is an easy way to do this, since Numba can also be used to create custom *ufuncs* with the @vectorize decorator.

```
from numba import vectorize

@vectorize
def f_vec(x, y):
    return np.cos(x**2 + y**2) / (1 + x**2 + y**2)

np.max(f_vec(x, y))  # Run once to compile
```

```
0.9999992797121728
```

```
%timeit np.max(f_vec(x, y))
```

```
334 ms ± 1.15 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
```

At least on our machine, the difference in the speed between the Numba version and the vectorized NumPy version shown above is not large.

But there's quite a bit going on here so let's try to break down what is happening.

Both Numba and NumPy use efficient machine code that's specialized to these floating point operations.

However, the code NumPy uses is, in some ways, less efficient.

The reason is that, in NumPy, the operation `np.cos(x**2 + y**2) / (1 + x**2 + y**2)` generates several intermediate arrays.

For example, a new array is created when `x**2` is calculated.

The same is true when `y**2` is calculated, and then `x**2 + y**2` and so on.

Numba avoids creating all these intermediate arrays by compiling one function that is specialized to the entire operation.

But if this is true, then why isn't the Numba code faster?

The reason is that NumPy makes up for its disadvantages with implicit multithreading, as we've just discussed.

16.3.4 Multithreading a Numba Ufunc

Can we get both of these advantages at once?

In other words, can we pair

- the efficiency of Numba's highly specialized JIT compiled function and
- the speed gains from parallelization obtained by NumPy's implicit multithreading?

It turns out that we can, by adding some type information plus `target='parallel'`.

```
@vectorize('float64(float64, float64)', target='parallel')
def f_vec(x, y):
    return np.cos(x**2 + y**2) / (1 + x**2 + y**2)

np.max(f_vec(x, y))  # Run once to compile
```

```
0.9999992797121728
```

```
%timeit np.max(f_vec(x, y))
```

```
130 ms ± 707 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
```

Now our code runs significantly faster than the NumPy version.

16.4 Multithreaded Loops in Numba

We just saw one approach to parallelization in Numba, using the `parallel` flag in `@vectorize`.

This is neat but, it turns out, not well suited to many problems we consider.

Fortunately, Numba provides another approach to multithreading that will work for us almost everywhere parallelization is possible.

To illustrate, let's look first at a simple, single-threaded (i.e., non-parallelized) piece of code.

The code simulates updating the wealth w_t of a household via the rule

$$w_{t+1} = R_{t+1} s w_t + y_{t+1}$$

Here

- R is the gross rate of return on assets
- s is the savings rate of the household and
- y is labor income.

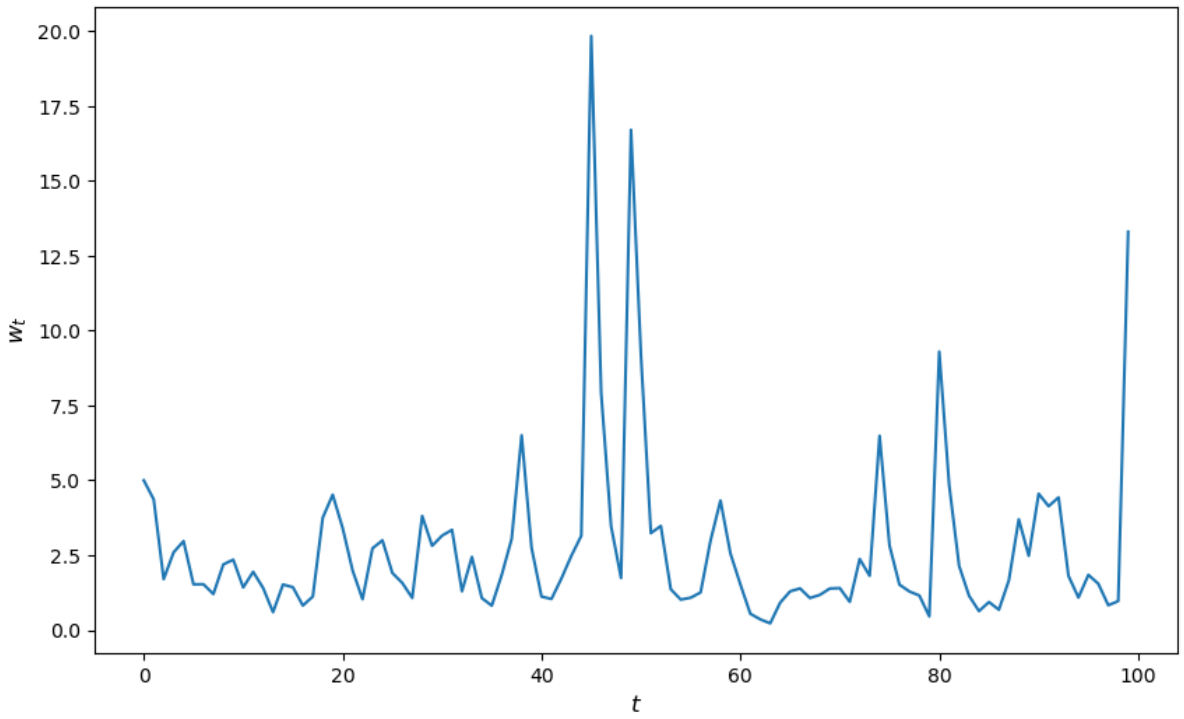
We model both R and y as independent draws from a lognormal distribution.

Here's the code:

```
from numpy.random import randn
from numba import njit

@njit
def h(w, r=0.1, s=0.3, v1=0.1, v2=1.0):
    """
    Updates household wealth.
    """

    # Draw shocks
    R = np.exp(v1 * randn()) * (1 + r)
    y = np.exp(v2 * randn())

    # Update wealth
    w = R * s * w + y
    return w
```

Let's have a look at how wealth evolves under this rule.

```
fig, ax = plt.subplots()

T = 100
w = np.empty(T)
w[0] = 5
for t in range(T-1):
    w[t+1] = h(w[t])

ax.plot(w)
ax.set_xlabel('$t$', fontsize=12)
ax.set_ylabel('$w_{t}$', fontsize=12)
plt.show()
```



Now let's suppose that we have a large population of households and we want to know what median wealth will be.

This is not easy to solve with pencil and paper, so we will use simulation instead.

In particular, we will simulate a large number of households and then calculate median wealth for this group.

Suppose we are interested in the long-run average of this median over time.

It turns out that, for the specification that we've chosen above, we can calculate this by taking a one-period snapshot of what has happened to median wealth of the group at the end of a long simulation.

Moreover, provided the simulation period is long enough, initial conditions don't matter.

- This is due to something called ergodicity, which we will discuss later on.

So, in summary, we are going to simulate 50,000 households by

1. arbitrarily setting initial wealth to 1 and
2. simulating forward in time for 1,000 periods.

Then we'll calculate median wealth at the end period.

Here's the code:

```
@njit
def compute_long_run_median(w0=1, T=1000, num_reps=50_000):

    obs = np.empty(num_reps)
    for i in range(num_reps):
        w = w0
        for t in range(T):
            w = h(w)
        obs[i] = w

    return np.median(obs)
```

Let's see how fast this runs:

```
%%time
compute_long_run_median()
```

```
CPU times: user 5.71 s, sys: 80.4 ms, total: 5.79 s
Wall time: 5.78 s
```

```
1.8336628488163855
```

To speed this up, we're going to parallelize it via multithreading.

To do so, we add the `parallel=True` flag and change `range` to `prange`:

```
from numba import prange

@njit(parallel=True)
def compute_long_run_median_parallel(w0=1, T=1000, num_reps=50_000):

    obs = np.empty(num_reps)
    for i in prange(num_reps):
        w = w0
        for t in range(T):
            w = h(w)
        obs[i] = w

    return np.median(obs)
```

Let's look at the timing:

```
%%time
compute_long_run_median_parallel()
```

```
CPU times: user 6.68 s, sys: 0 ns, total: 6.68 s
Wall time: 1.94 s
```

```
1.8497894505998835
```

The speed-up is significant.

16.4.1 A Warning

Parallelization works well in the outer loop of the last example because the individual tasks inside the loop are independent of each other.

If this independence fails then parallelization is often problematic.

For example, each step inside the inner loop depends on the last step, so independence fails, and this is why we use ordinary `range` instead of `prange`.

When you see us using `prange` in later lectures, it is because the independence of tasks holds true.

When you see us using ordinary `range` in a jitted function, it is either because the speed gain from parallelization is small or because independence fails.

16.5 Exercises

Exercise 16.5.1

In *an earlier exercise*, we used Numba to accelerate an effort to compute the constant π by Monte Carlo.

Now try adding parallelization and see if you get further speed gains.

You should not expect huge gains here because, while there are many independent tasks (draw point and test if in circle), each one has low execution time.

Generally speaking, parallelization is less effective when the individual tasks to be parallelized are very small relative to total execution time.

This is due to overheads associated with spreading all of these small tasks across multiple CPUs.

Nevertheless, with suitable hardware, it is possible to get nontrivial speed gains in this exercise.

For the size of the Monte Carlo simulation, use something substantial, such as `n = 100_000_000`.

Solution to Exercise 16.5.1

Here is one solution:

```
from random import uniform

@njit(parallel=True)
def calculate_pi(n=1_000_000):
    count = 0
    for i in prange(n):
        u, v = uniform(0, 1), uniform(0, 1)
        d = np.sqrt((u - 0.5)**2 + (v - 0.5)**2)
        if d < 0.5:
            count += 1

    area_estimate = count / n
    return area_estimate * 4  # dividing by radius**2
```

Now let's see how fast it runs:

```
%time calculate_pi()
```

```
CPU times: user 367 ms, sys: 28.1 ms, total: 395 ms
Wall time: 382 ms
```

```
3.141416
```

```
%time calculate_pi()
```

```
CPU times: user 17.6 ms, sys: 0 ns, total: 17.6 ms
Wall time: 4.87 ms
```

```
3.140936
```

By switching parallelization on and off (selecting `True` or `False` in the `@njit` annotation), we can test the speed gain that multithreading provides on top of JIT compilation.

On our workstation, we find that parallelization increases execution speed by a factor of 2 or 3.

(If you are executing locally, you will get different numbers, depending mainly on the number of CPUs on your machine.)

Exercise 16.5.2

In *our lecture on SciPy*, we discussed pricing a call option in a setting where the underlying stock price had a simple and well-known distribution.

Here we discuss a more realistic setting.

We recall that the price of the option obeys

$$P = \beta^n \mathbb{E} \max\{S_n - K, 0\}$$

where

1. β is a discount factor,
2. n is the expiry date,
3. K is the strike price and
4. $\{S_t\}$ is the price of the underlying asset at each time t.

Suppose that `n, β, K = 20, 0.99, 100`.

Assume that the stock price obeys

$$\ln \frac{S_{t+1}}{S_t} = \mu + \sigma_t \xi_{t+1}$$

where

$$\sigma_t = \exp(h_t), \quad h_{t+1} = \rho h_t + \nu \eta_{t+1}$$

Here $\{\xi_t\}$ and $\{\eta_t\}$ are IID and standard normal.

(This is a **stochastic volatility** model, where the volatility σ_t varies over time.)

Use the defaults `μ, ρ, ν, S0, h0 = 0.0001, 0.1, 0.001, 10, 0`.

(Here `S0` is S_0 and `h0` is h_0.)

By generating M paths $s_0, \ldots, s_n$, compute the Monte Carlo estimate

$$\hat{P}_M := \beta^n \mathbb{E} \max\{S_n - K, 0\} \approx \frac{1}{M} \sum_{m=1}^{M} \max\{S_n^m - K, 0\}$$

of the price, applying Numba and parallelization.

Solution to Exercise 16.5.2

With $s_t := \ln S_t$, the price dynamics become

$$s_{t+1} = s_t + \mu + \exp(h_t)\xi_{t+1}$$

Using this fact, the solution can be written as follows.

```
from numpy.random import randn
M = 10_000_000

n, β, K = 20, 0.99, 100
μ, ρ, ν, S0, h0 = 0.0001, 0.1, 0.001, 10, 0

@njit(parallel=True)
def compute_call_price_parallel(β=β,
                                μ=μ,
                                S0=S0,
                                h0=h0,
                                K=K,
                                n=n,
                                ρ=ρ,
                                ν=ν,
                                M=M):
    current_sum = 0.0
    # For each sample path
    for m in prange(M):
        s = np.log(S0)
        h = h0
        # Simulate forward in time
        for t in range(n):
            s = s + μ + np.exp(h) * randn()
            h = ρ * h + ν * randn()
        # And add the value max{S_n - K, 0} to current_sum
        current_sum += np.maximum(np.exp(s) - K, 0)

    return β**n * current_sum / M
```

Try swapping between `parallel=True` and `parallel=False` and noting the run time.

If you are on a machine with many CPUs, the difference should be significant.

CHAPTER

SEVENTEEN

JAX

New website

We have replaced this lecture with a new lecture series on quantitative economics using JAX:

See Quantitative Economics with JAX

Part IV

Advanced Python Programming

CHAPTER

EIGHTEEN

WRITING GOOD CODE

Contents

> "Any fool can write code that a computer can understand. Good programmers write code that humans can understand." – Martin Fowler

18.1 Overview

When computer programs are small, poorly written code is not overly costly.

But more data, more sophisticated models, and more computer power are enabling us to take on more challenging problems that involve writing longer programs.

For such programs, investment in good coding practices will pay high returns.

The main payoffs are higher productivity and faster code.

In this lecture, we review some elements of good coding practice.

We also touch on modern developments in scientific computing — such as just in time compilation — and how they affect good program design.

18.2 An Example of Poor Code

Let's have a look at some poorly written code.

The job of the code is to generate and plot time series of the simplified Solow model

$$k_{t+1} = sk_t^\alpha + (1-\delta)k_t, \quad t = 0, 1, 2, \ldots \tag{18.1}$$

Here

- k_t is capital at time t and
- s, α, δ are parameters (savings, a productivity parameter and depreciation)

For each parameterization, the code

1. sets $k_0 = 1$
2. iterates using (18.1) to produce a sequence $k_0, k_1, k_2 \ldots, k_T$
3. plots the sequence

The plots will be grouped into three subfigures.

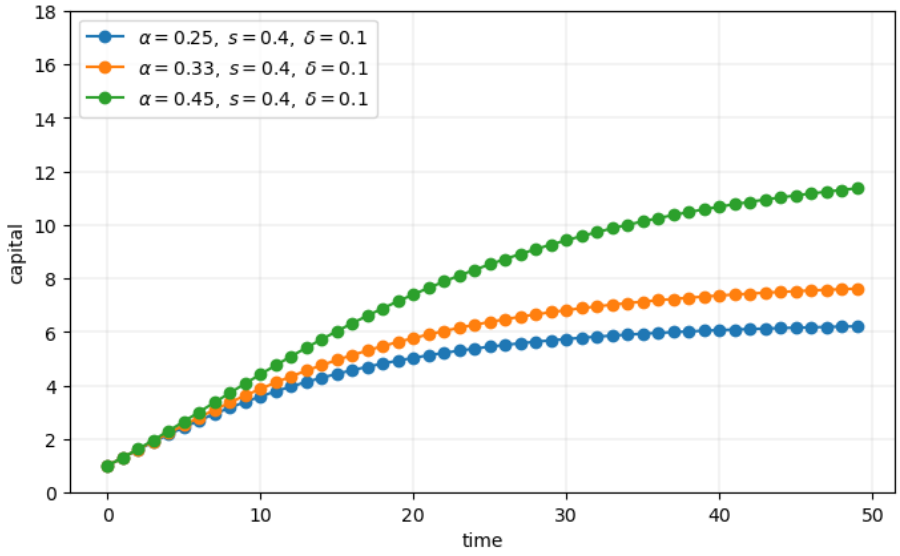
In each subfigure, two parameters are held fixed while another varies

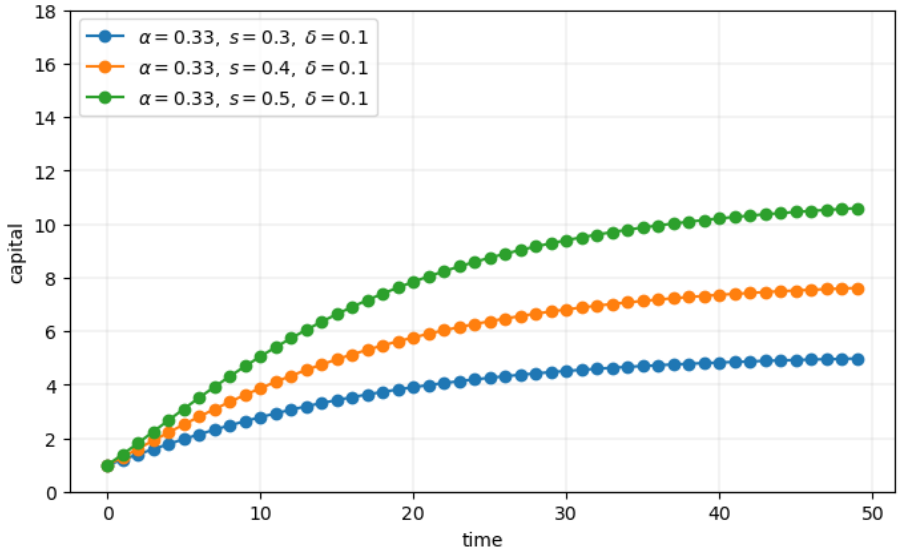
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)

# Allocate memory for time series
k = np.empty(50)

fig, axes = plt.subplots(3, 1, figsize=(8, 16))

# Trajectories with different α
δ = 0.1
s = 0.4
α = (0.25, 0.33, 0.45)

for j in range(3):
    k[0] = 1
    for t in range(49):
        k[t+1] = s * k[t]**α[j] + (1 - δ) * k[t]
    axes[0].plot(k, 'o-', label=rf"$\alpha = {α[j]},\; s = {s},\; \delta={δ}$")

axes[0].grid(lw=0.2)
axes[0].set_ylim(0, 18)
axes[0].set_xlabel('time')
axes[0].set_ylabel('capital')
axes[0].legend(loc='upper left', frameon=True)

# Trajectories with different s
δ = 0.1
α = 0.33
s = (0.3, 0.4, 0.5)

for j in range(3):
    k[0] = 1
```

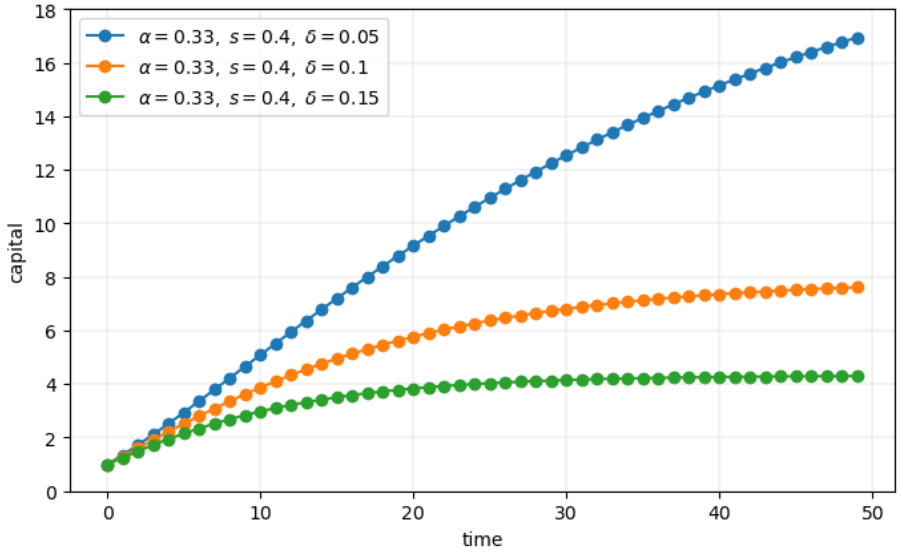
(continues on next page)

(continued from previous page)

```
    for t in range(49):
        k[t+1] = s[j] * k[t]**α + (1 - δ) * k[t]
    axes[1].plot(k, 'o-', label=rf"$\alpha = {α},\; s = {s[j]},\; \delta={δ}$")

axes[1].grid(lw=0.2)
axes[1].set_xlabel('time')
axes[1].set_ylabel('capital')
axes[1].set_ylim(0, 18)
axes[1].legend(loc='upper left', frameon=True)

# Trajectories with different δ
δ = (0.05, 0.1, 0.15)
α = 0.33
s = 0.4

for j in range(3):
    k[0] = 1
    for t in range(49):
        k[t+1] = s * k[t]**α + (1 - δ[j]) * k[t]
    axes[2].plot(k, 'o-', label=rf"$\alpha = {α},\; s = {s},\; \delta={δ[j]}$")

axes[2].set_ylim(0, 18)
axes[2].set_xlabel('time')
axes[2].set_ylabel('capital')
axes[2].grid(lw=0.2)
axes[2].legend(loc='upper left', frameon=True)

plt.show()
```


$\alpha = 0.25,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.45,\ s = 0.4,\ \delta = 0.1$
capital
time


$\alpha = 0.33,\ s = 0.3,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.5,\ \delta = 0.1$
capital
time


$\alpha = 0.33,\ s = 0.4,\ \delta = 0.05$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.15$
capital
time

True, the code more or less follows PEP8.

At the same time, it's very poorly structured.

Let's talk about why that's the case, and what we can do about it.

18.3 Good Coding Practice

There are usually many different ways to write a program that accomplishes a given task.

For small programs, like the one above, the way you write code doesn't matter too much.

But if you are ambitious and want to produce useful things, you'll write medium to large programs too.

In those settings, coding style matters **a great deal**.

Fortunately, lots of smart people have thought about the best way to write code.

Here are some basic precepts.

18.3.1 Don't Use Magic Numbers

If you look at the code above, you'll see numbers like `50` and `49` and `3` scattered through the code.

These kinds of numeric literals in the body of your code are sometimes called "magic numbers".

This is not a compliment.

While numeric literals are not all evil, the numbers shown in the program above should certainly be replaced by named constants.

For example, the code above could declare the variable `time_series_length = 50`.

Then in the loops, `49` should be replaced by `time_series_length - 1`.

The advantages are:

- the meaning is much clearer throughout
- to alter the time series length, you only need to change one value

18.3.2 Don't Repeat Yourself

The other mortal sin in the code snippet above is repetition.

Blocks of logic (such as the loop to generate time series) are repeated with only minor changes.

This violates a fundamental tenet of programming: Don't repeat yourself (DRY).

- Also called DIE (duplication is evil).

Yes, we realize that you can just cut and paste and change a few symbols.

But as a programmer, your aim should be to **automate** repetition, **not** do it yourself.

More importantly, repeating the same logic in different places means that eventually one of them will likely be wrong.

If you want to know more, read the excellent summary found on this page.

We'll talk about how to avoid repetition below.

18.3.3 Minimize Global Variables

Sure, global variables (i.e., names assigned to values outside of any function or class) are convenient.

Rookie programmers typically use global variables with abandon — as we once did ourselves.

But global variables are dangerous, especially in medium to large size programs, since

- they can affect what happens in any part of your program
- they can be changed by any function

This makes it much harder to be certain about what some small part of a given piece of code actually commands.

Here's a useful discussion on the topic.

While the odd global in small scripts is no big deal, we recommend that you teach yourself to avoid them.

(We'll discuss how just below).

JIT Compilation

For scientific computing, there is another good reason to avoid global variables.

As *we've seen in previous lectures*, JIT compilation can generate excellent performance for scripting languages like Python.

But the task of the compiler used for JIT compilation becomes harder when global variables are present.

Put differently, the type inference required for JIT compilation is safer and more effective when variables are sandboxed inside a function.

18.3.4 Use Functions or Classes

Fortunately, we can easily avoid the evils of global variables and WET code.

- WET stands for "we enjoy typing" and is the opposite of DRY.

We can do this by making frequent use of functions or classes.

In fact, functions and classes are designed specifically to help us avoid shaming ourselves by repeating code or excessive use of global variables.

Which One, Functions or Classes?

Both can be useful, and in fact they work well with each other.

We'll learn more about these topics over time.

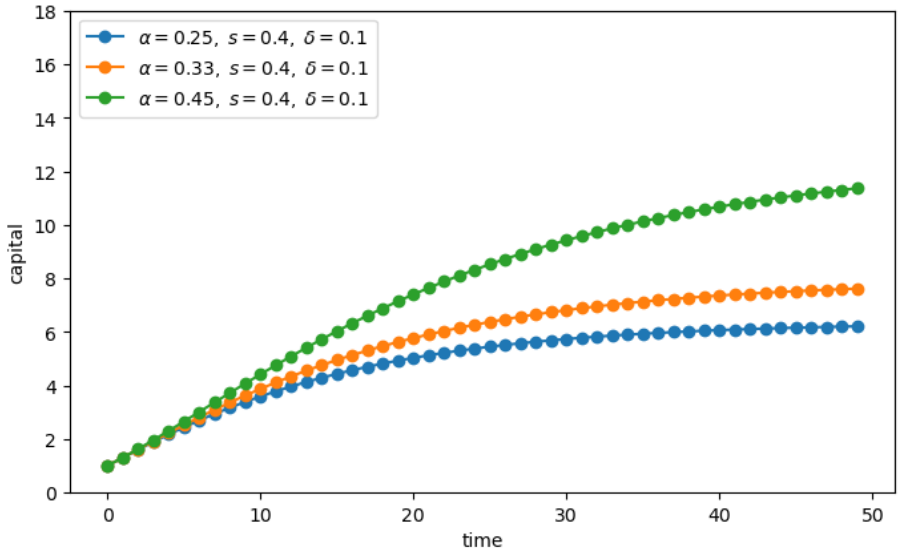
(Personal preference is part of the story too)

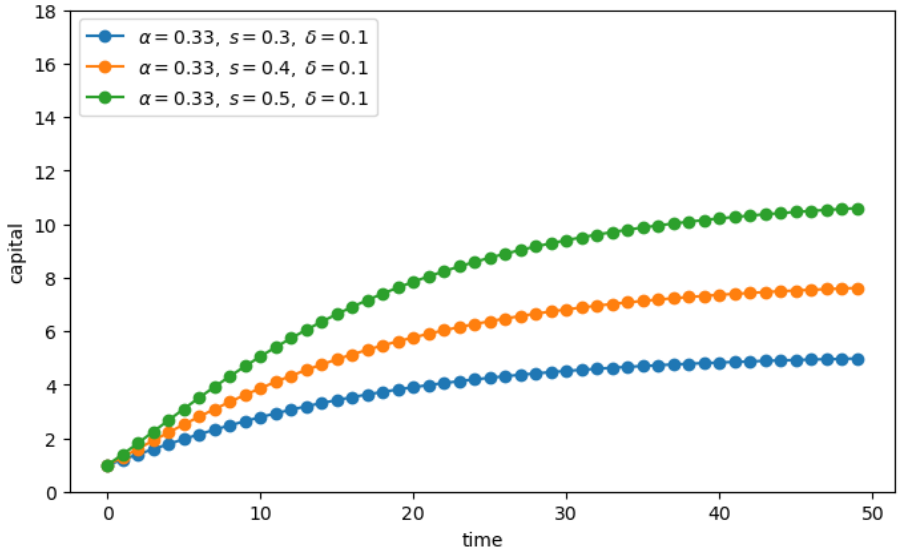
What's really important is that you use one or the other or both.

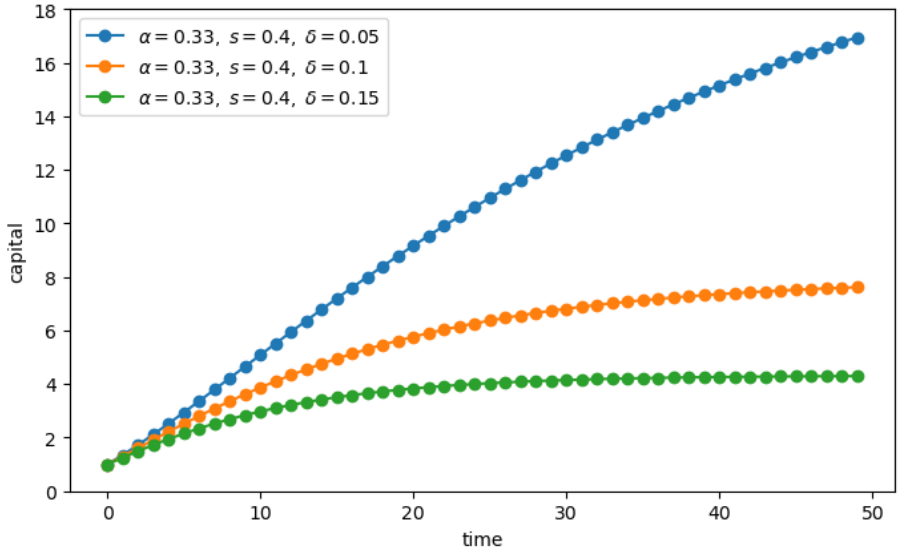
18.4 Revisiting the Example

Here's some code that reproduces the plot above with better coding style.

```
from itertools import product

def plot_path(ax, αs, s_vals, δs, time_series_length=50):
    """
    Add a time series plot to the axes ax for all given parameters.
    """
    k = np.empty(time_series_length)

    for (α, s, δ) in product(αs, s_vals, δs):
        k[0] = 1
        for t in range(time_series_length-1):
            k[t+1] = s * k[t]**α + (1 - δ) * k[t]
        ax.plot(k, 'o-', label=rf"$\alpha = {α},\; s = {s},\; \delta = {δ}$")

    ax.set_xlabel('time')
    ax.set_ylabel('capital')
    ax.set_ylim(0, 18)
    ax.legend(loc='upper left', frameon=True)

fig, axes = plt.subplots(3, 1, figsize=(8, 16))

# Parameters (αs, s_vals, δs)
set_one = ([0.25, 0.33, 0.45], [0.4], [0.1])
set_two = ([0.33], [0.3, 0.4, 0.5], [0.1])
set_three = ([0.33], [0.4], [0.05, 0.1, 0.15])

for (ax, params) in zip(axes, (set_one, set_two, set_three)):
    αs, s_vals, δs = params
    plot_path(ax, αs, s_vals, δs)

plt.show()
```


$\alpha = 0.25,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.45,\ s = 0.4,\ \delta = 0.1$
capital
time


$\alpha = 0.33,\ s = 0.3,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.5,\ \delta = 0.1$
capital
time


$\alpha = 0.33,\ s = 0.4,\ \delta = 0.05$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.1$
$\alpha = 0.33,\ s = 0.4,\ \delta = 0.15$
capital
time

If you inspect this code, you will see that

- it uses a function to avoid repetition.
- Global variables are quarantined by collecting them together at the end, not the start of the program.
- Magic numbers are avoided.
- The loop at the end where the actual work is done is short and relatively simple.

18.5 Exercises

Exercise 18.5.1

Here is some code that needs improving.

It involves a basic supply and demand problem.

Supply is given by

$$q_s(p) = \exp(\alpha p) - \beta.$$

The demand curve is

$$q_d(p) = \gamma p^{-\delta}.$$

The values α, β, γ and δ are **parameters**

The equilibrium p^* is the price such that $q_d(p) = q_s(p)$.

We can solve for this equilibrium using a root finding algorithm. Specifically, we will find the p such that $h(p) = 0$, where

$$h(p) := q_d(p) - q_s(p)$$

This yields the equilibrium price p^*. From this we get the equilibrium quantity by $q^* = q_s(p^*)$

The parameter values will be

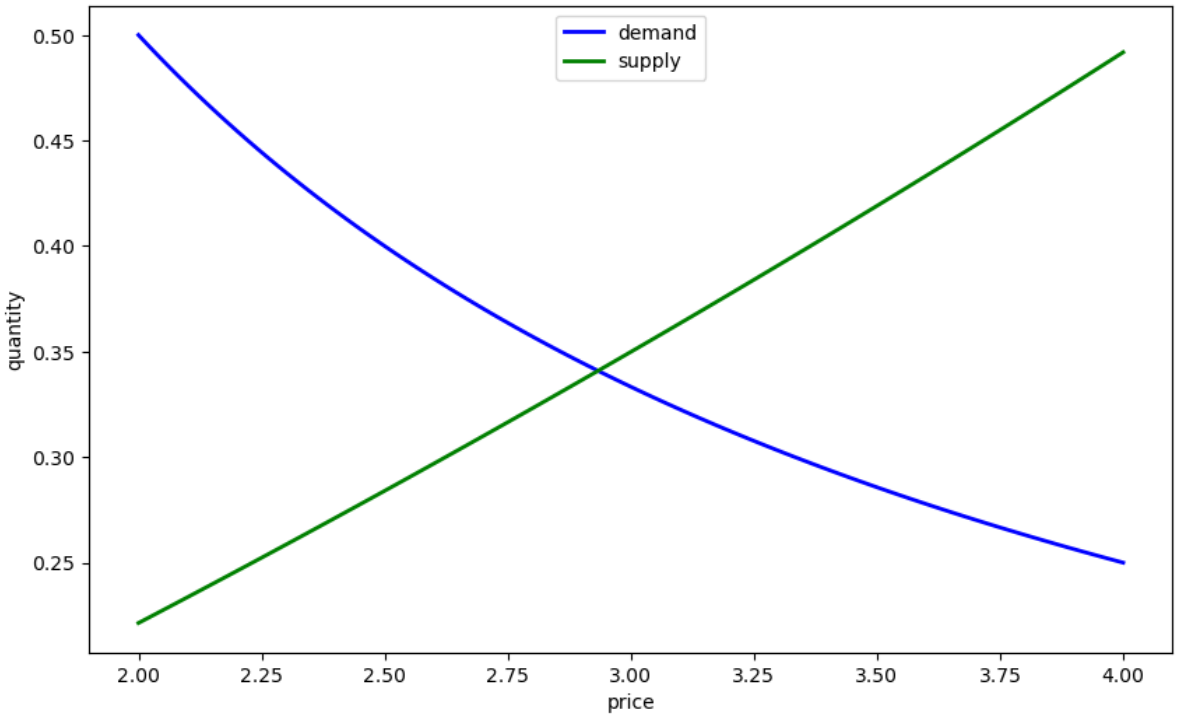
- $\alpha = 0.1$
- $\beta = 1$
- $\gamma = 1$
- $\delta = 1$

```
from scipy.optimize import brentq

# Compute equilibrium
def h(p):
    return p**(-1) - (np.exp(0.1 * p) - 1)  # demand - supply

p_star = brentq(h, 2, 4)
q_star = np.exp(0.1 * p_star) - 1

print(f'Equilibrium price is {p_star: .2f}')
print(f'Equilibrium quantity is {q_star: .2f}')
```

```
Equilibrium price is  2.93
Equilibrium quantity is  0.34
```

Let's also plot our results.

```
# Now plot
grid = np.linspace(2, 4, 100)
fig, ax = plt.subplots()

qs = np.exp(0.1 * grid) - 1
qd = grid**(-1)


ax.plot(grid, qd, 'b-', lw=2, label='demand')
ax.plot(grid, qs, 'g-', lw=2, label='supply')

ax.set_xlabel('price')
ax.set_ylabel('quantity')
ax.legend(loc='upper center')

plt.show()
```



We also want to consider supply and demand shifts.

For example, let's see what happens when demand shifts up, with γ increasing to 1.25:

```
# Compute equilibrium
def h(p):
    return 1.25 * p**(-1) - (np.exp(0.1 * p) - 1)

p_star = brentq(h, 2, 4)
```

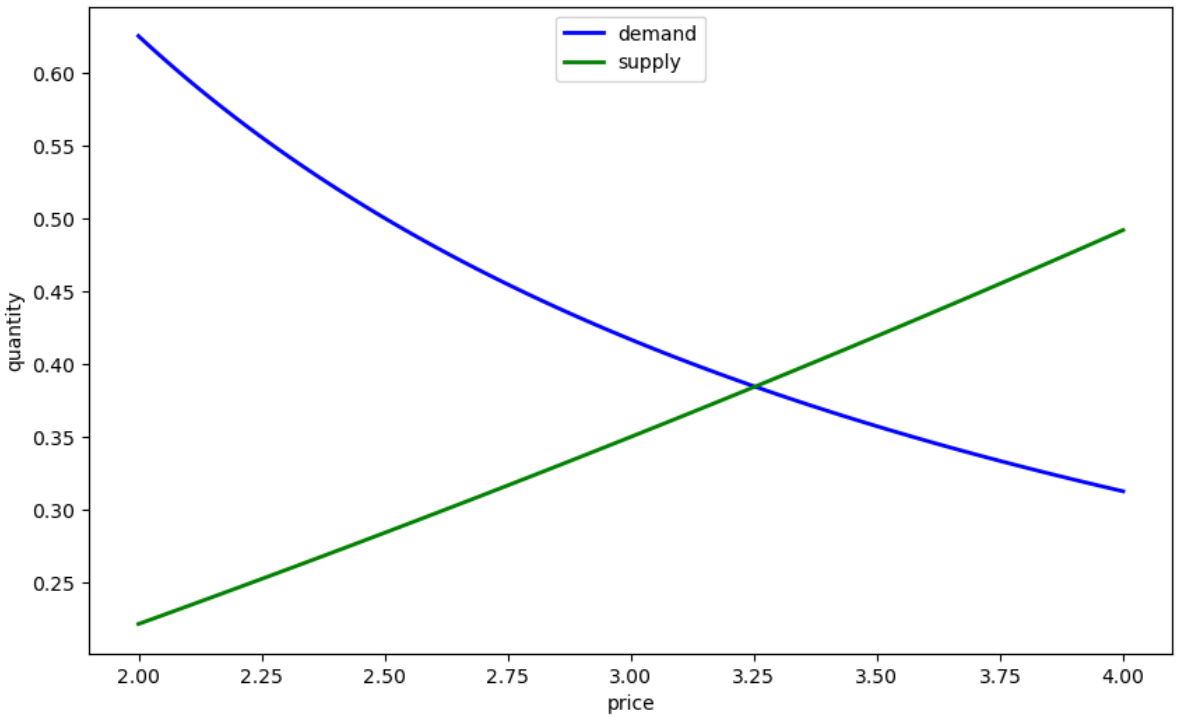
(continues on next page)

(continued from previous page)

```
q_star = np.exp(0.1 * p_star) - 1

print(f'Equilibrium price is {p_star: .2f}')
print(f'Equilibrium quantity is {q_star: .2f}')
```

```
Equilibrium price is  3.25
Equilibrium quantity is  0.38
```

```
# Now plot
p_grid = np.linspace(2, 4, 100)
fig, ax = plt.subplots()

qs = np.exp(0.1 * p_grid) - 1
qd = 1.25 * p_grid**(-1)


ax.plot(grid, qd, 'b-', lw=2, label='demand')
ax.plot(grid, qs, 'g-', lw=2, label='supply')

ax.set_xlabel('price')
ax.set_ylabel('quantity')
ax.legend(loc='upper center')

plt.show()
```



Now we might consider supply shifts, but you already get the idea that there's a lot of repeated code here.

Refactor and improve clarity in the code above using the principles discussed in this lecture.

Solution to Exercise 18.5.1

Here's one solution, that uses a class:

```
class Equilibrium:

    def __init__(self, α=0.1, β=1, γ=1, δ=1):
        self.α, self.β, self.γ, self.δ = α, β, γ, δ

    def qs(self, p):
        return np.exp(self.α * p) - self.β

    def qd(self, p):
        return self.γ * p**(-self.δ)

    def compute_equilibrium(self):
        def h(p):
            return self.qd(p) - self.qs(p)
        p_star = brentq(h, 2, 4)
        q_star = np.exp(self.α * p_star) - self.β

        print(f'Equilibrium price is {p_star: .2f}')
        print(f'Equilibrium quantity is {q_star: .2f}')

    def plot_equilibrium(self):
        # Now plot
        grid = np.linspace(2, 4, 100)
        fig, ax = plt.subplots()

        ax.plot(grid, self.qd(grid), 'b-', lw=2, label='demand')
        ax.plot(grid, self.qs(grid), 'g-', lw=2, label='supply')

        ax.set_xlabel('price')
        ax.set_ylabel('quantity')
        ax.legend(loc='upper center')

        plt.show()
```

Let's create an instance at the default parameter values.

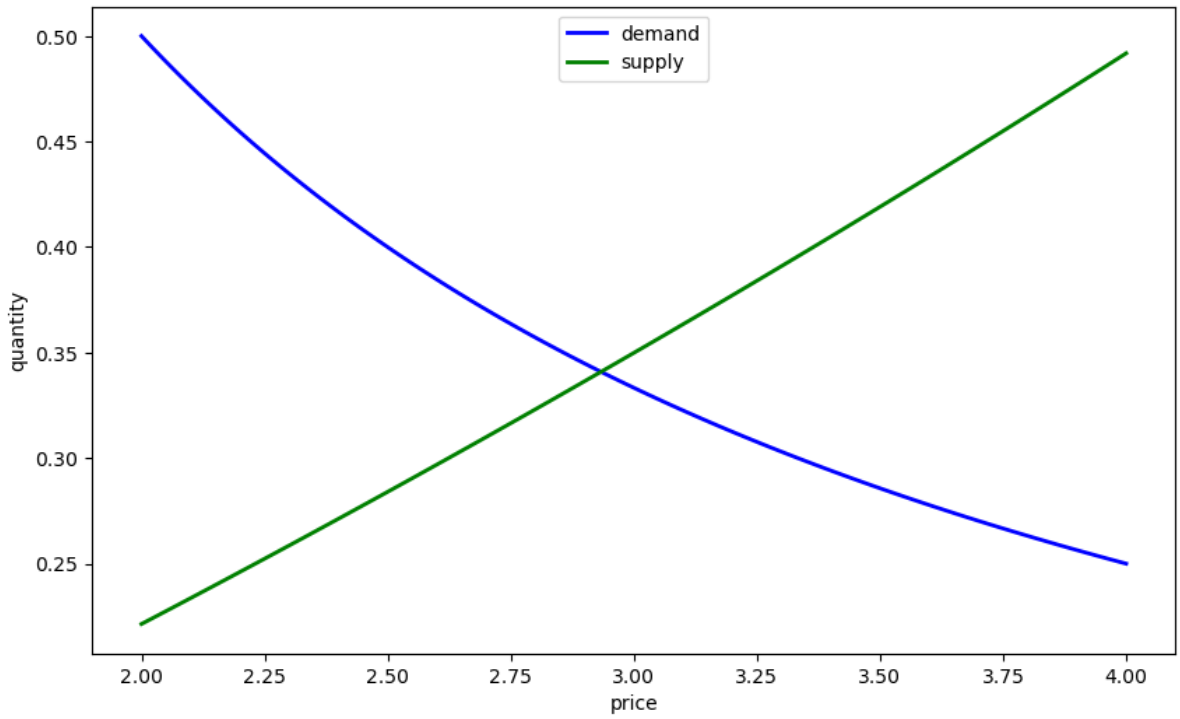
```
eq = Equilibrium()
```

Now we'll compute the equilibrium and plot it.

```
eq.compute_equilibrium()
```

```
Equilibrium price is  2.93
Equilibrium quantity is  0.34
```

```
eq.plot_equilibrium()
```



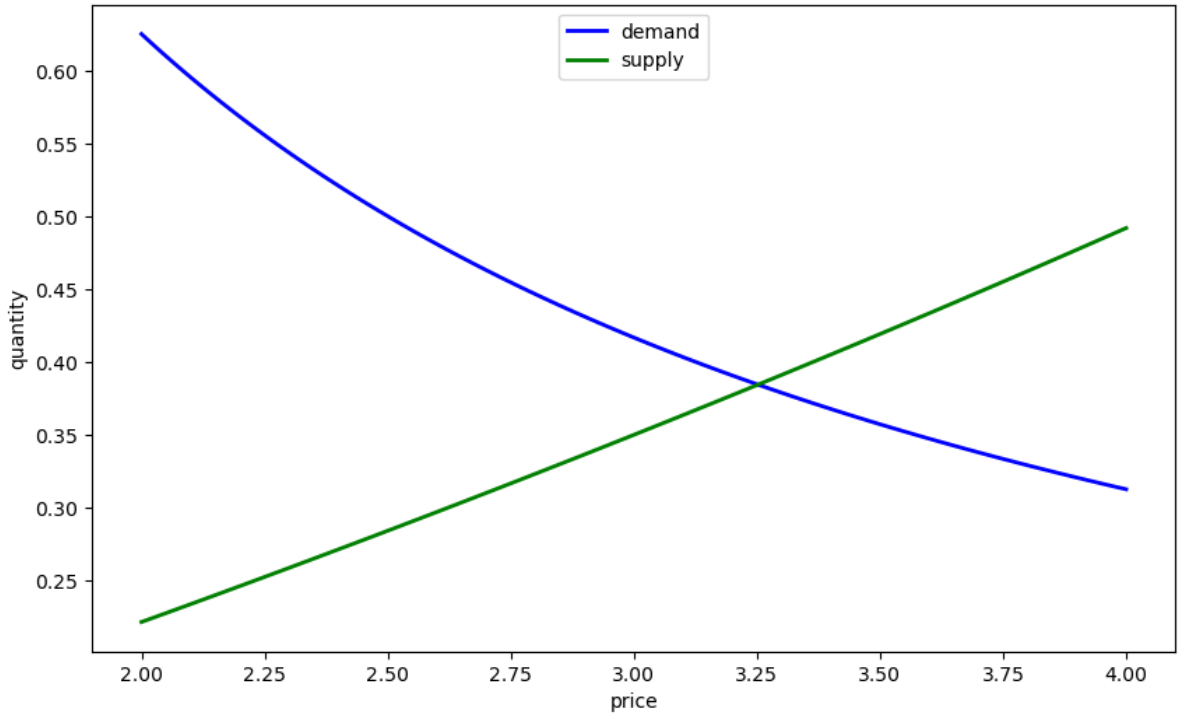
One of the nice things about our refactored code is that, when we change parameters, we don't need to repeat ourselves:

```
eq.y = 1.25
```

```
eq.compute_equilibrium()
```

```
Equilibrium price is  3.25
Equilibrium quantity is  0.38
```

```
eq.plot_equilibrium()
```


demand
supply
quantity
price
0.60
0.55
0.50
0.45
0.40
0.35
0.30
0.25
2.00
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00

CHAPTER

NINETEEN

MORE LANGUAGE FEATURES

Contents

19.1 Overview

With this last lecture, our advice is to **skip it on first pass**, unless you have a burning desire to read it.

It's here

1. as a reference, so we can link back to it when required, and
2. for those who have worked through a number of applications, and now want to learn more about the Python language

A variety of topics are treated in the lecture, including iterators, decorators and descriptors, and generators.

19.2 Iterables and Iterators

We've *already said something* about iterating in Python.

Now let's look more closely at how it all works, focusing in Python's implementation of the `for` loop.

19.2.1 Iterators

Iterators are a uniform interface to stepping through elements in a collection.

Here we'll talk about using iterators—later we'll learn how to build our own.

Formally, an *iterator* is an object with a `__next__` method.

For example, file objects are iterators .

To see this, let's have another look at the *US cities data*, which is written to the present working directory in the following cell

```
%%file us_cities.txt
new york: 8244910
los angeles: 3819702
chicago: 2707120
houston: 2145146
philadelphia: 1536471
phoenix: 1469471
san antonio: 1359758
san diego: 1326179
dallas: 1223229
```

```
Writing us_cities.txt
```

```
f = open('us_cities.txt')
f.__next__()
```

```
'new york: 8244910\n'
```

```
f.__next__()
```

```
'los angeles: 3819702\n'
```

We see that file objects do indeed have a `__next__` method, and that calling this method returns the next line in the file.

The next method can also be accessed via the builtin function `next()`, which directly calls this method

```
next(f)
```

```
'chicago: 2707120\n'
```

The objects returned by `enumerate()` are also iterators

```
e = enumerate(['foo', 'bar'])
next(e)
```

```
(0, 'foo')
```

```
next(e)
```

```
(1, 'bar')
```

as are the reader objects from the `csv` module .

Let's create a small csv file that contains data from the NIKKEI index

```
%%file test_table.csv
Date,Open,High,Low,Close,Volume,Adj Close
2009-05-21,9280.35,9286.35,9189.92,9264.15,133200,9264.15
2009-05-20,9372.72,9399.40,9311.61,9344.64,143200,9344.64
2009-05-19,9172.56,9326.75,9166.97,9290.29,167000,9290.29
2009-05-18,9167.05,9167.82,8997.74,9038.69,147800,9038.69
2009-05-15,9150.21,9272.08,9140.90,9265.02,172000,9265.02
2009-05-14,9212.30,9223.77,9052.41,9093.73,169400,9093.73
2009-05-13,9305.79,9379.47,9278.89,9340.49,176000,9340.49
2009-05-12,9358.25,9389.61,9298.61,9298.61,188400,9298.61
2009-05-11,9460.72,9503.91,9342.75,9451.98,230800,9451.98
2009-05-08,9351.40,9464.43,9349.57,9432.83,220200,9432.83
```

```
Writing test_table.csv
```

```
from csv import reader

f = open('test_table.csv', 'r')
nikkei_data = reader(f)
next(nikkei_data)
```

```
['Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'Adj Close']
```

```
next(nikkei_data)
```

```
['2009-05-21', '9280.35', '9286.35', '9189.92', '9264.15', '133200', '9264.15']
```

19.2.2 Iterators in For Loops

All iterators can be placed to the right of the `in` keyword in `for` loop statements.

In fact this is how the `for` loop works: If we write

```
for x in iterator:
    <code block>
```

then the interpreter

- calls `iterator.__next__()` and binds `x` to the result
- executes the code block
- repeats until a `StopIteration` error occurs

So now you know how this magical looking syntax works

```
f = open('somefile.txt', 'r')
for line in f:
    # do something
```

The interpreter just keeps

1. calling `f.__next__()` and binding `line` to the result
2. executing the body of the loop

This continues until a `StopIteration` error occurs.

19.2.3 Iterables

You already know that we can put a Python list to the right of `in` in a `for` loop

```
for i in ['spam', 'eggs']:
    print(i)
```

```
spam
eggs
```

So does that mean that a list is an iterator?

The answer is no

```
x = ['foo', 'bar']
type(x)
```

```
list
```

```
next(x)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[12], line 1
----> 1 next(x)

TypeError: 'list' object is not an iterator
```

So why can we iterate over a list in a `for` loop?

The reason is that a list is *iterable* (as opposed to an iterator).

Formally, an object is iterable if it can be converted to an iterator using the built-in function `iter()`.

Lists are one such object

```
x = ['foo', 'bar']
type(x)
```

```
list
```

```
y = iter(x)
type(y)
```

```
list_iterator
```

```
next(y)
```

```
'foo'
```

```
next(y)
```

```
'bar'
```

```
next(y)
```

```
---------------------------------------------------------------------------
StopIteration                             Traceback (most recent call last)
Cell In[17], line 1
----> 1 next(y)

StopIteration:
```

Many other objects are iterable, such as dictionaries and tuples.

Of course, not all objects are iterable

```
iter(42)
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[18], line 1
----> 1 iter(42)

TypeError: 'int' object is not iterable
```

To conclude our discussion of `for` loops

- `for` loops work on either iterators or iterables.
- In the second case, the iterable is converted into an iterator before the loop starts.

19.2.4 Iterators and built-ins

Some built-in functions that act on sequences also work with iterables

- `max()`, `min()`, `sum()`, `all()`, `any()`

For example

```
x = [10, -10]
max(x)
```

```
10
```

```
y = iter(x)
type(y)
```

```
list_iterator
```

```
max(y)
```

```
10
```

One thing to remember about iterators is that they are depleted by use

```
x = [10, -10]
y = iter(x)
max(y)
```

```
10
```

```
max(y)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Cell In[23], line 1
----> 1 max(y)

ValueError: max() arg is an empty sequence
```

19.3 * and ** Operators

`*` and `**` are convenient and widely used tools to unpack lists and tuples and to allow users to define functions that take arbitrarily many arguments as input.

In this section, we will explore how to use them and distinguish their use cases.

19.3.1 Unpacking Arguments

When we operate on a list of parameters, we often need to extract the content of the list as individual arguments instead of a collection when passing them into functions.

Luckily, the `*` operator can help us to unpack lists and tuples into positional arguments in function calls.

To make things concrete, consider the following examples:

Without `*`, the `print` function prints a list

```
l1 = ['a', 'b', 'c']

print(l1)
```

```
['a', 'b', 'c']
```

While the `print` function prints individual elements since `*` unpacks the list into individual arguments

```
print(*l1)
```

```
a b c
```

Unpacking the list using `*` into positional arguments is equivalent to defining them individually when calling the function

```
print('a', 'b', 'c')
```

```
a b c
```

However, `*` operator is more convenient if we want to reuse them again

```
l1.append('d')

print(*l1)
```

```
a b c d
```

Similarly, `**` is used to unpack arguments.

The difference is that `**` unpacks *dictionaries* into *keyword arguments*.

`**` is often used when there are many keyword arguments we want to reuse.

For example, assuming we want to draw multiple graphs using the same graphical settings, it may involve repetitively setting many graphical parameters, usually defined using keyword arguments.

In this case, we can use a dictionary to store these parameters and use `**` to unpack dictionaries into keyword arguments when they are needed.

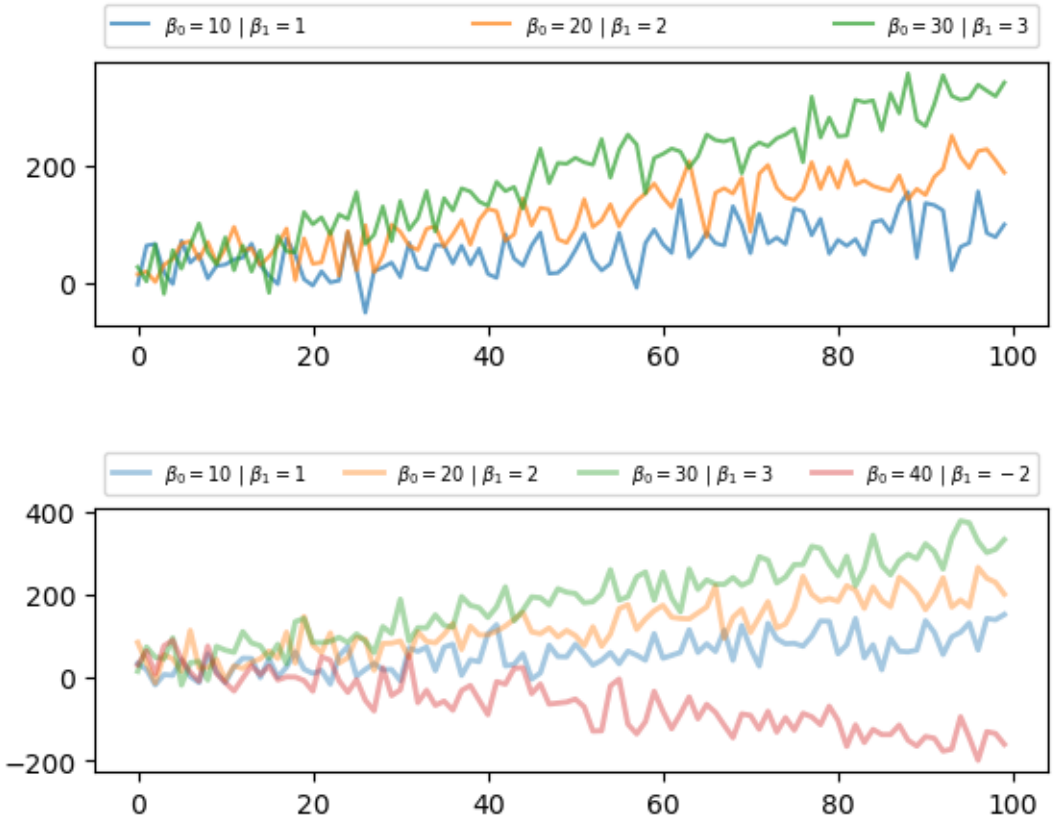
Let's walk through a simple example together and distinguish the use of `*` and `**`

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

# Set up the frame and subplots
```

(continues on next page)

(continued from previous page)

```
fig, ax = plt.subplots(2, 1)
plt.subplots_adjust(hspace=0.7)

# Create a function that generates synthetic data
def generate_data(β_0, β_1, σ=30, n=100):
    x_values = np.arange(0, n, 1)
    y_values = β_0 + β_1 * x_values + np.random.normal(size=n, scale=σ)
    return x_values, y_values

# Store the keyword arguments for lines and legends in a dictionary
line_kargs = {'lw': 1.5, 'alpha': 0.7}
legend_kargs = {'bbox_to_anchor': (0., 1.02, 1., .102),
                'loc': 3,
                'ncol': 4,
                'mode': 'expand',
                'prop': {'size': 7}}

β_0s = [10, 20, 30]
β_1s = [1, 2, 3]

# Use a for loop to plot lines
def generate_plots(β_0s, β_1s, idx, line_kargs, legend_kargs):
    label_list = []
    for βs in zip(β_0s, β_1s):

        # Use * to unpack tuple βs and the tuple output from the generate_data␣
↪function
        # Use ** to unpack the dictionary of keyword arguments for lines
        ax[idx].plot(*generate_data(*βs), **line_kargs)

        label_list.append(f'$β_0 = {βs[0]}$ | $β_1 = {βs[1]}$')

    # Use ** to unpack the dictionary of keyword arguments for legends
    ax[idx].legend(label_list, **legend_kargs)

generate_plots(β_0s, β_1s, 0, line_kargs, legend_kargs)

# We can easily reuse and update our parameters
β_1s.append(-2)
β_0s.append(40)
line_kargs['lw'] = 2
line_kargs['alpha'] = 0.4

generate_plots(β_0s, β_1s, 1, line_kargs, legend_kargs)
plt.show()
```



In this example, `*` unpacked the zipped parameters `βs` and the output of `generate_data` function stored in tuples, while `**` unpacked graphical parameters stored in `legend_kargs` and `line_kargs`.

To summarize, when `*list/*tuple` and `**dictionary` are passed into *function calls*, they are unpacked into individual arguments instead of a collection.

The difference is that `*` will unpack lists and tuples into *positional arguments*, while `**` will unpack dictionaries into *keyword arguments*.

19.3.2 Arbitrary Arguments

When we *define* functions, it is sometimes desirable to allow users to put as many arguments as they want into a function.

You might have noticed that the `ax.plot()` function could handle arbitrarily many arguments.

If we look at the documentation of the function, we can see the function is defined as

```
Axes.plot(*args, scalex=True, scaley=True, data=None, **kwargs)
```

We found `*` and `**` operators again in the context of the *function definition*.

In fact, `*args` and `**kargs` are ubiquitous in the scientific libraries in Python to reduce redundancy and allow flexible inputs.

`*args` enables the function to handle *positional arguments* with a variable size

```
l1 = ['a', 'b', 'c']
l2 = ['b', 'c', 'd']
```

(continues on next page)

(continued from previous page)

```
def arb(*ls):
    print(ls)

arb(l1, l2)
```

```
(['a', 'b', 'c'], ['b', 'c', 'd'])
```

The inputs are passed into the function and stored in a tuple.

Let's try more inputs

```
l3 = ['z', 'x', 'b']
arb(l1, l2, l3)
```

```
(['a', 'b', 'c'], ['b', 'c', 'd'], ['z', 'x', 'b'])
```

Similarly, Python allows us to use `**kargs` to pass arbitrarily many *keyword arguments* into functions

```
def arb(**ls):
    print(ls)

# Note that these are keyword arguments
arb(l1=l1, l2=l2)
```

```
{'l1': ['a', 'b', 'c'], 'l2': ['b', 'c', 'd']}
```

We can see Python uses a dictionary to store these keyword arguments.

Let's try more inputs

```
arb(l1=l1, l2=l2, l3=l3)
```

```
{'l1': ['a', 'b', 'c'], 'l2': ['b', 'c', 'd'], 'l3': ['z', 'x', 'b']}
```

Overall, `*args` and `**kargs` are used when *defining a function*; they enable the function to take input with an arbitrary size.

The difference is that functions with `*args` will be able to take *positional arguments* with an arbitrary size, while `**kargs` will allow functions to take arbitrarily many *keyword arguments*.

19.4 Decorators and Descriptors

Let's look at some special syntax elements that are routinely used by Python developers.

You might not need the following concepts immediately, but you will see them in other people's code.

Hence you need to understand them at some stage of your Python education.

19.4.1 Decorators

Decorators are a bit of syntactic sugar that, while easily avoided, have turned out to be popular.

It's very easy to say what decorators do.

On the other hand it takes a bit of effort to explain *why* you might use them.

An Example

Suppose we are working on a program that looks something like this

```
import numpy as np

def f(x):
    return np.log(np.log(x))

def g(x):
    return np.sqrt(42 * x)

# Program continues with various calculations using f and g
```

Now suppose there's a problem: occasionally negative numbers get fed to `f` and `g` in the calculations that follow.

If you try it, you'll see that when these functions are called with negative numbers they return a NumPy object called `nan` .

This stands for "not a number" (and indicates that you are trying to evaluate a mathematical function at a point where it is not defined).

Perhaps this isn't what we want, because it causes other problems that are hard to pick up later on.

Suppose that instead we want the program to terminate whenever this happens, with a sensible error message.

This change is easy enough to implement

```
import numpy as np

def f(x):
    assert x >= 0, "Argument must be nonnegative"
    return np.log(np.log(x))

def g(x):
    assert x >= 0, "Argument must be nonnegative"
    return np.sqrt(42 * x)

# Program continues with various calculations using f and g
```

Notice however that there is some repetition here, in the form of two identical lines of code.

Repetition makes our code longer and harder to maintain, and hence is something we try hard to avoid.

Here it's not a big deal, but imagine now that instead of just `f` and `g`, we have 20 such functions that we need to modify in exactly the same way.

This means we need to repeat the test logic (i.e., the `assert` line testing nonnegativity) 20 times.

The situation is still worse if the test logic is longer and more complicated.

In this kind of scenario the following approach would be neater

```
import numpy as np

def check_nonneg(func):
    def safe_function(x):
        assert x >= 0, "Argument must be nonnegative"
        return func(x)
    return safe_function

def f(x):
    return np.log(np.log(x))

def g(x):
    return np.sqrt(42 * x)

f = check_nonneg(f)
g = check_nonneg(g)
# Program continues with various calculations using f and g
```

This looks complicated so let's work through it slowly.

To unravel the logic, consider what happens when we say `f = check_nonneg(f)`.

This calls the function `check_nonneg` with parameter `func` set equal to `f`.

Now `check_nonneg` creates a new function called `safe_function` that verifies `x` as nonnegative and then calls `func` on it (which is the same as `f`).

Finally, the global name `f` is then set equal to `safe_function`.

Now the behavior of `f` is as we desire, and the same is true of `g`.

At the same time, the test logic is written only once.

Enter Decorators

The last version of our code is still not ideal.

For example, if someone is reading our code and wants to know how `f` works, they will be looking for the function definition, which is

```
def f(x):
    return np.log(np.log(x))
```

They may well miss the line `f = check_nonneg(f)`.

For this and other reasons, decorators were introduced to Python.

With decorators, we can replace the lines

```
def f(x):
    return np.log(np.log(x))

def g(x):
    return np.sqrt(42 * x)

f = check_nonneg(f)
g = check_nonneg(g)
```

with

```
@check_nonneg
def f(x):
    return np.log(np.log(x))

@check_nonneg
def g(x):
    return np.sqrt(42 * x)
```

These two pieces of code do exactly the same thing.

If they do the same thing, do we really need decorator syntax?

Well, notice that the decorators sit right on top of the function definitions.

Hence anyone looking at the definition of the function will see them and be aware that the function is modified.

In the opinion of many people, this makes the decorator syntax a significant improvement to the language.

19.4.2 Descriptors

Descriptors solve a common problem regarding management of variables.

To understand the issue, consider a `Car` class, that simulates a car.

Suppose that this class defines the variables `miles` and `kms`, which give the distance traveled in miles and kilometers respectively.

A highly simplified version of the class might look as follows

```
class Car:

    def __init__(self, miles=1000):
        self.miles = miles
        self.kms = miles * 1.61

    # Some other functionality, details omitted
```

One potential problem we might have here is that a user alters one of these variables but not the other

```
car = Car()
car.miles
```

```
1000
```

```
car.kms
```

```
1610.0
```

```
car.miles = 6000
car.kms
```

```
1610.0
```

In the last two lines we see that `miles` and `kms` are out of sync.

What we really want is some mechanism whereby each time a user sets one of these variables, *the other is automatically updated*.

A Solution

In Python, this issue is solved using *descriptors*.

A descriptor is just a Python object that implements certain methods.

These methods are triggered when the object is accessed through dotted attribute notation.

The best way to understand this is to see it in action.

Consider this alternative version of the `Car` class

```
class Car:

    def __init__(self, miles=1000):
        self._miles = miles
        self._kms = miles * 1.61

    def set_miles(self, value):
        self._miles = value
        self._kms = value * 1.61

    def set_kms(self, value):
        self._kms = value
        self._miles = value / 1.61

    def get_miles(self):
        return self._miles

    def get_kms(self):
        return self._kms

    miles = property(get_miles, set_miles)
    kms = property(get_kms, set_kms)
```

First let's check that we get the desired behavior

```
car = Car()
car.miles
```

```
1000
```

```
car.miles = 6000
car.kms
```

```
9660.0
```

Yep, that's what we want — `car.kms` is automatically updated.

How it Works

The names `_miles` and `_kms` are arbitrary names we are using to store the values of the variables.

The objects `miles` and `kms` are *properties*, a common kind of descriptor.

The methods `get_miles`, `set_miles`, `get_kms` and `set_kms` define what happens when you get (i.e. access) or set (bind) these variables

- So-called "getter" and "setter" methods.

The builtin Python function `property` takes getter and setter methods and creates a property.

For example, after `car` is created as an instance of `Car`, the object `car.miles` is a property.

Being a property, when we set its value via `car.miles = 6000` its setter method is triggered — in this case `set_miles`.

Decorators and Properties

These days its very common to see the `property` function used via a decorator.

Here's another version of our `Car` class that works as before but now uses decorators to set up the properties

```
class Car:

    def __init__(self, miles=1000):
        self._miles = miles
        self._kms = miles * 1.61

    @property
    def miles(self):
        return self._miles

    @property
    def kms(self):
        return self._kms

    @miles.setter
    def miles(self, value):
        self._miles = value
        self._kms = value * 1.61

    @kms.setter
    def kms(self, value):
        self._kms = value
        self._miles = value / 1.61
```

We won't go through all the details here.

For further information you can refer to the descriptor documentation.

19.5 Generators

A generator is a kind of iterator (i.e., it works with a `next` function).

We will study two ways to build generators: generator expressions and generator functions.

19.5.1 Generator Expressions

The easiest way to build generators is using *generator expressions*.

Just like a list comprehension, but with round brackets.

Here is the list comprehension:

```
singular = ('dog', 'cat', 'bird')
type(singular)
```

```
tuple
```

```
plural = [string + 's' for string in singular]
plural
```

```
['dogs', 'cats', 'birds']
```

```
type(plural)
```

```
list
```

And here is the generator expression

```
singular = ('dog', 'cat', 'bird')
plural = (string + 's' for string in singular)
type(plural)
```

```
generator
```

```
next(plural)
```

```
'dogs'
```

```
next(plural)
```

```
'cats'
```

```
next(plural)
```

```
'birds'
```

Since `sum()` can be called on iterators, we can do this

```
sum((x * x for x in range(10)))
```

```
285
```

The function `sum()` calls `next()` to get the items, adds successive terms.

In fact, we can omit the outer brackets in this case

```
sum(x * x for x in range(10))
```

```
285
```

19.5.2 Generator Functions

The most flexible way to create generator objects is to use generator functions.

Let's look at some examples.

Example 1

Here's a very simple example of a generator function

```
def f():
    yield 'start'
    yield 'middle'
    yield 'end'
```

It looks like a function, but uses a keyword `yield` that we haven't met before.

Let's see how it works after running this code

```
type(f)
```

```
function
```

```
gen = f()
gen
```

```
<generator object f at 0x7fbfd1dd9850>
```

```
next(gen)
```

```
'start'
```

```
next(gen)
```

```
'middle'
```

```
next(gen)
```

```
'end'
```

```
next(gen)
```

```
---------------------------------------------------------------------------
StopIteration                             Traceback (most recent call last)
Cell In[62], line 1
----> 1 next(gen)

StopIteration:
```

The generator function `f()` is used to create generator objects (in this case `gen`).

Generators are iterators, because they support a `next` method.

The first call to `next(gen)`

- Executes code in the body of `f()` until it meets a `yield` statement.
- Returns that value to the caller of `next(gen)`.

The second call to `next(gen)` starts executing *from the next line*

```
def f():
    yield 'start'
    yield 'middle'  # This line!
    yield 'end'
```

and continues until the next `yield` statement.

At that point it returns the value following `yield` to the caller of `next(gen)`, and so on.

When the code block ends, the generator throws a `StopIteration` error.

Example 2

Our next example receives an argument `x` from the caller

```
def g(x):
    while x < 100:
        yield x
        x = x * x
```

Let's see how it works

```
g
```

```
<function __main__.g(x)>
```

```
gen = g(2)
type(gen)
```

```
generator
```

```
next(gen)
```

```
2
```

```
next(gen)
```

```
4
```

```
next(gen)
```

```
16
```

```
next(gen)
```

```
---------------------------------------------------------------------------
StopIteration                             Traceback (most recent call last)
Cell In[70], line 1
----> 1 next(gen)

StopIteration:
```

The call `gen = g(2)` binds `gen` to a generator.

Inside the generator, the name `x` is bound to `2`.

When we call `next(gen)`

- The body of `g()` executes until the line `yield x`, and the value of `x` is returned.

Note that value of `x` is retained inside the generator.

When we call `next(gen)` again, execution continues *from where it left off*

```
def g(x):
    while x < 100:
        yield x
        x = x * x  # execution continues from here
```

When `x < 100` fails, the generator throws a `StopIteration` error.

Incidentally, the loop inside the generator can be infinite

```
def g(x):
    while 1:
        yield x
        x = x * x
```

19.5.3 Advantages of Iterators

What's the advantage of using an iterator here?

Suppose we want to sample a binomial(n,0.5).

One way to do it is as follows

```
import random
n = 10000000
draws = [random.uniform(0, 1) < 0.5 for i in range(n)]
sum(draws)
```

```
4997254
```

But we are creating two huge lists here, `range(n)` and `draws`.

This uses lots of memory and is very slow.

If we make `n` even bigger then this happens

```
n = 100000000
draws = [random.uniform(0, 1) < 0.5 for i in range(n)]
```

We can avoid these problems using iterators.

Here is the generator function

```
def f(n):
    i = 1
    while i <= n:
        yield random.uniform(0, 1) < 0.5
        i += 1
```

Now let's do the sum

```
n = 10000000
draws = f(n)
draws
```

```
<generator object f at 0x7fbfd2095b60>
```

```
sum(draws)
```

```
4998844
```

In summary, iterables

- avoid the need to create big lists/tuples, and
- provide a uniform interface to iteration that can be used transparently in `for` loops

19.6 Exercises

Exercise 19.6.1

Complete the following code, and test it using this csv file, which we assume that you've put in your current working directory

```
def column_iterator(target_file, column_number):
    """A generator function for CSV files.
    When called with a file name target_file (string) and column number
    column_number (integer), the generator function returns a generator
    that steps through the elements of column column_number in file
    target_file.
    """
    # put your code here

dates = column_iterator('test_table.csv', 1)

for date in dates:
    print(date)
```

Solution to Exercise 19.6.1

One solution is as follows

```
def column_iterator(target_file, column_number):
    """A generator function for CSV files.
    When called with a file name target_file (string) and column number
    column_number (integer), the generator function returns a generator
    which steps through the elements of column column_number in file
    target_file.
    """
    f = open(target_file, 'r')
    for line in f:
        yield line.split(',')[column_number - 1]
    f.close()

dates = column_iterator('test_table.csv', 1)

i = 1
for date in dates:
    print(date)
    if i == 10:
        break
    i += 1
```

```
Date
2009-05-21
```

(continues on next page)

(continued from previous page)

```
2009-05-20
2009-05-19
2009-05-18
2009-05-15
2009-05-14
2009-05-13
2009-05-12
2009-05-11
```

CHAPTER

TWENTY

DEBUGGING AND HANDLING ERRORS

Contents

> "Debugging is twice as hard as writing the code in the first place. Therefore, if you write the code as cleverly as possible, you are, by definition, not smart enough to debug it." – Brian Kernighan

20.1 Overview

Are you one of those programmers who fills their code with `print` statements when trying to debug their programs?

Hey, we all used to do that.

(OK, sometimes we still do that…)

But once you start writing larger programs you'll need a better system.

You may also want to handle potential errors in your code as they occur.

In this lecture, we will discuss how to debug our programs and improve error handling.

20.2 Debugging

Debugging tools for Python vary across platforms, IDEs and editors.

For example, a visual debugger is available in JupyterLab.

Here we'll focus on Jupyter Notebook and leave you to explore other settings.

We'll need the following imports

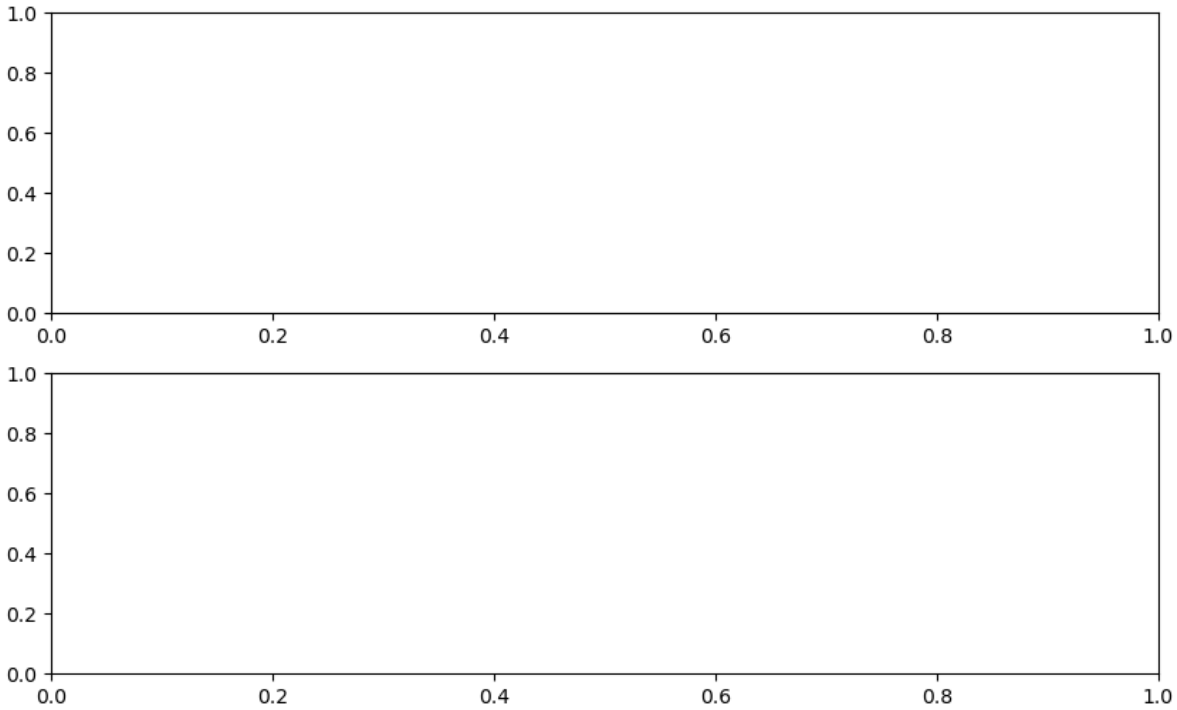
```
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (10,6)
```

20.2.1 The debug Magic

Let's consider a simple (and rather contrived) example

```
def plot_log():
    fig, ax = plt.subplots(2, 1)
    x = np.linspace(1, 2, 10)
    ax.plot(x, np.log(x))
    plt.show()

plot_log()  # Call the function, generate plot
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[2], line 7
      4     ax.plot(x, np.log(x))
      5     plt.show()
----> 7 plot_log()

Cell In[2], line 4, in plot_log()
      2 fig, ax = plt.subplots(2, 1)
      3 x = np.linspace(1, 2, 10)
----> 4 ax.plot(x, np.log(x))
      5 plt.show()

AttributeError: 'numpy.ndarray' object has no attribute 'plot'
```



This code is intended to plot the `log` function over the interval $[1, 2]$.

But there's an error here: `plt.subplots(2, 1)` should be just `plt.subplots()`.

(The call `plt.subplots(2, 1)` returns a NumPy array containing two axes objects, suitable for having two subplots on the same figure)

The traceback shows that the error occurs at the method call `ax.plot(x, np.log(x))`.

The error occurs because we have mistakenly made `ax` a NumPy array, and a NumPy array has no `plot` method.

But let's pretend that we don't understand this for the moment.

We might suspect there's something wrong with `ax` but when we try to investigate this object, we get the following exception:

```
ax
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[3], line 1
----> 1 ax

NameError: name 'ax' is not defined
```

The problem is that `ax` was defined inside `plot_log()`, and the name is lost once that function terminates.

Let's try doing it a different way.

We run the first cell block again, generating the same error

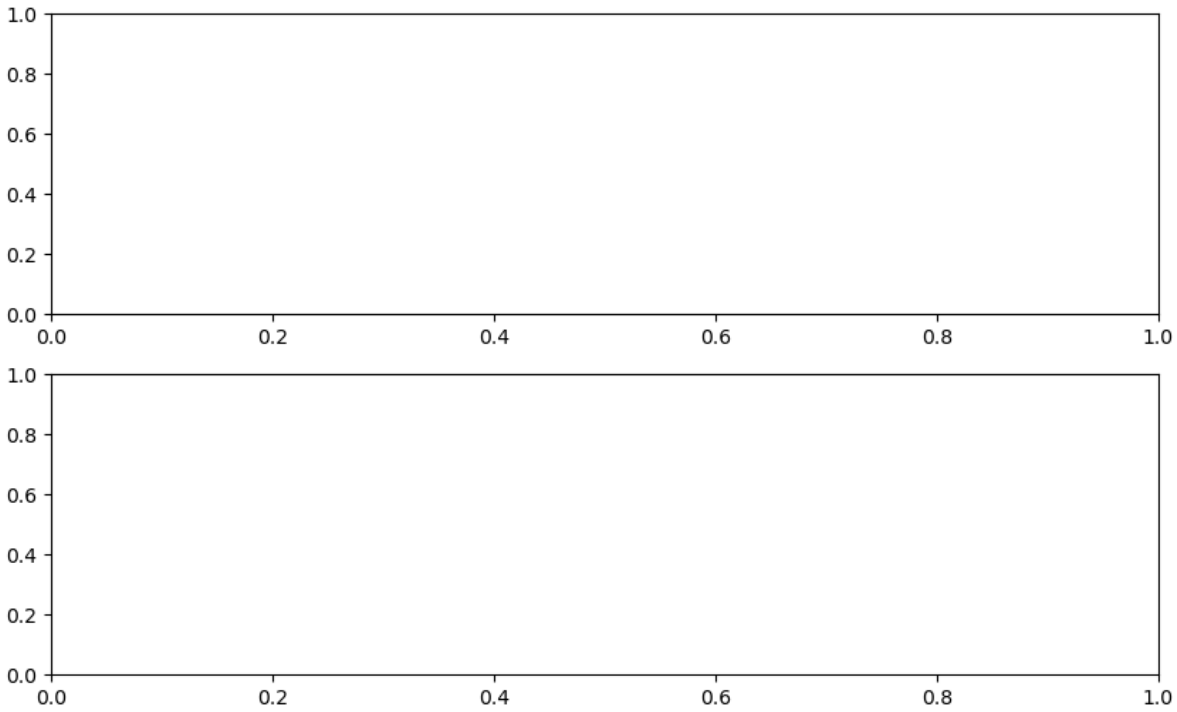
```
def plot_log():
    fig, ax = plt.subplots(2, 1)
```

(continues on next page)

(continued from previous page)

```
    x = np.linspace(1, 2, 10)
    ax.plot(x, np.log(x))
    plt.show()

plot_log()  # Call the function, generate plot
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
Cell In[4], line 7
      4     ax.plot(x, np.log(x))
      5     plt.show()
----> 7 plot_log()

Cell In[4], line 4, in plot_log()
      2 fig, ax = plt.subplots(2, 1)
      3 x = np.linspace(1, 2, 10)
----> 4 ax.plot(x, np.log(x))
      5 plt.show()

AttributeError: 'numpy.ndarray' object has no attribute 'plot'
```



But this time we type in the following cell block

```
%debug
```

You should be dropped into a new prompt that looks something like this

```
ipdb>
```

(You might see pdb> instead)

Now we can investigate the value of our variables at this point in the program, step forward through the code, etc.

For example, here we simply type the name `ax` to see what's happening with this object:

```
ipdb> ax
array([<matplotlib.axes.AxesSubplot object at 0x290f5d0>,
       <matplotlib.axes.AxesSubplot object at 0x2930810>], dtype=object)
```

It's now very clear that `ax` is an array, which clarifies the source of the problem.

To find out what else you can do from inside `ipdb` (or `pdb`), use the online help

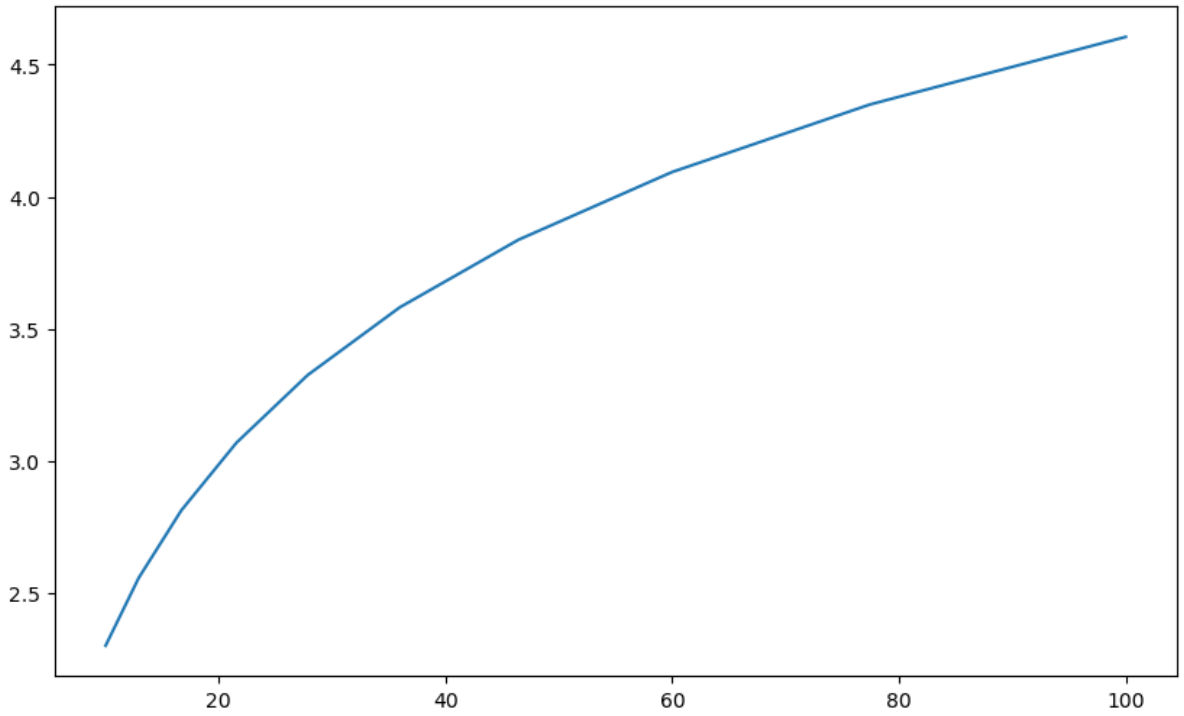
```
ipdb> h

Documented commands (type help <topic>):
========================================
EOF    bt         cont      enable  jump  pdef   r        tbreak   w
a      c          continue  exit    l     pdoc   restart  u        whatis
alias  cl         d         h       list  pinfo  return   unalias  where
args   clear      debug     help    n     pp     run      unt
b      commands   disable   ignore  next  q      s        until
break  condition  down      j       p     quit   step     up

Miscellaneous help topics:
==========================
exec  pdb

Undocumented commands:
======================
retval  rv

ipdb> h c
c(ont(inue))
Continue execution, only stop when a breakpoint is encountered.
```

20.2.2 Setting a Break Point

The preceding approach is handy but sometimes insufficient.

Consider the following modified version of our function above

```
def plot_log():
    fig, ax = plt.subplots()
    x = np.logspace(1, 2, 10)
    ax.plot(x, np.log(x))
    plt.show()

plot_log()
```



Here the original problem is fixed, but we've accidentally written `np.logspace(1, 2, 10)` instead of `np.linspace(1, 2, 10)`.

Now there won't be any exception, but the plot won't look right.

To investigate, it would be helpful if we could inspect variables like `x` during execution of the function.

To this end, we add a "break point" by inserting `breakpoint()` inside the function code block

```
def plot_log():
    breakpoint()
    fig, ax = plt.subplots()
    x = np.logspace(1, 2, 10)
    ax.plot(x, np.log(x))
    plt.show()

plot_log()
```

Now let's run the script, and investigate via the debugger

```
> <ipython-input-6-a188074383b7>(6)plot_log()
-> fig, ax = plt.subplots()
(Pdb) n
> <ipython-input-6-a188074383b7>(7)plot_log()
-> x = np.logspace(1, 2, 10)
(Pdb) n
> <ipython-input-6-a188074383b7>(8)plot_log()
-> ax.plot(x, np.log(x))
(Pdb) x
array([ 10.        ,  12.91549665,  16.68100537,  21.5443469 ,
        27.82559402,  35.93813664,  46.41588834,  59.94842503,
        77.42636827, 100.        ])
```

We used `n` twice to step forward through the code (one line at a time).

Then we printed the value of `x` to see what was happening with that variable.

To exit from the debugger, use `q`.

20.2.3 Other Useful Magics

In this lecture, we used the `%debug` IPython magic.

There are many other useful magics:

- `%precision 4` sets printed precision for floats to 4 decimal places
- `%whos` gives a list of variables and their values
- `%quickref` gives a list of magics

The full list of magics is here.

20.3 Handling Errors

Sometimes it's possible to anticipate bugs and errors as we're writing code.

For example, the unbiased sample variance of sample $y_1, \ldots, y_n$ is defined as

$$s^2 := \frac{1}{n-1} \sum_{i=1}^{n} (y_i - \bar{y})^2 \qquad \bar{y} = \text{ sample mean}$$

This can be calculated in NumPy using `np.var`.

But if you were writing a function to handle such a calculation, you might anticipate a divide-by-zero error when the sample size is one.

One possible action is to do nothing — the program will just crash, and spit out an error message.

But sometimes it's worth writing your code in a way that anticipates and deals with runtime errors that you think might arise.

Why?

- Because the debugging information provided by the interpreter is often less useful than what can be provided by a well written error message.
- Because errors that cause execution to stop interrupt workflows.
- Because it reduces confidence in your code on the part of your users (if you are writing for others).

In this section, we'll discuss different types of errors in Python and techniques to handle potential errors in our programs.

20.3.1 Errors in Python

We have seen `AttributeError` and `NameError` in *our previous examples*.

In Python, there are two types of errors – syntax errors and exceptions.

Here's an example of a common error type

```
def f:
```

```
  Cell In[6], line 1
    def f:
         ^
SyntaxError: expected '('
```

Since illegal syntax cannot be executed, a syntax error terminates execution of the program.

Here's a different kind of error, unrelated to syntax

```
1 / 0
```

```
---------------------------------------------------------------------------
ZeroDivisionError                         Traceback (most recent call last)
Cell In[7], line 1
----> 1 1 / 0

ZeroDivisionError: division by zero
```

Here's another

```
x1 = y1
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[8], line 1
----> 1 x1 = y1

NameError: name 'y1' is not defined
```

And another

```
'foo' + 6
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
Cell In[9], line 1
----> 1 'foo' + 6

TypeError: can only concatenate str (not "int") to str
```

And another

```
X = []
x = X[0]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[10], line 2
      1 X = []
----> 2 x = X[0]

IndexError: list index out of range
```

On each occasion, the interpreter informs us of the error type

- `NameError`, `TypeError`, `IndexError`, `ZeroDivisionError`, etc.

In Python, these errors are called *exceptions*.

20.3.2 Assertions

Sometimes errors can be avoided by checking whether your program runs as expected.

A relatively easy way to handle checks is with the `assert` keyword.

For example, pretend for a moment that the `np.var` function doesn't exist and we need to write our own

```
def var(y):
    n = len(y)
    assert n > 1, 'Sample size must be greater than one.'
    return np.sum((y - y.mean())**2) / float(n-1)
```

If we run this with an array of length one, the program will terminate and print our error message

```
var([1])
```

```
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
Cell In[12], line 1
----> 1 var([1])

Cell In[11], line 3, in var(y)
      1 def var(y):
      2     n = len(y)
----> 3     assert n > 1, 'Sample size must be greater than one.'
      4     return np.sum((y - y.mean())**2) / float(n-1)

AssertionError: Sample size must be greater than one.
```

The advantage is that we can

- fail early, as soon as we know there will be a problem
- supply specific information on why a program is failing

20.3.3 Handling Errors During Runtime

The approach used above is a bit limited, because it always leads to termination.

Sometimes we can handle errors more gracefully, by treating special cases.

Let's look at how this is done.

Catching Exceptions

We can catch and deal with exceptions using `try – except` blocks.

Here's a simple example

```
def f(x):
    try:
        return 1.0 / x
    except ZeroDivisionError:
        print('Error: division by zero.  Returned None')
    return None
```

When we call `f` we get the following output

```
f(2)
```

```
0.5
```

```
f(0)
```

```
Error: division by zero.  Returned None
```

```
f(0.0)
```

```
Error: division by zero.  Returned None
```

The error is caught and execution of the program is not terminated.

Note that other error types are not caught.

If we are worried the user might pass in a string, we can catch that error too

```
def f(x):
    try:
        return 1.0 / x
    except ZeroDivisionError:
        print('Error: Division by zero.  Returned None')
    except TypeError:
        print(f'Error: x cannot be of type {type(x)}.  Returned None')
    return None
```

Here's what happens

```
f(2)
```

```
0.5
```

```
f(0)
```

```
Error: Division by zero.  Returned None
```

```
f('foo')
```

```
Error: x cannot be of type <class 'str'>.  Returned None
```

If we feel lazy we can catch these errors together

```
def f(x):
    try:
        return 1.0 / x
    except:
        print(f'Error.  An issue has occurred with x = {x} of type: {type(x)}')
    return None
```

Here's what happens

```
f(2)
```

```
0.5
```

```
f(0)
```

```
Error.  An issue has occurred with x = 0 of type: <class 'int'>
```

```
f('foo')
```

```
Error.  An issue has occurred with x = foo of type: <class 'str'>
```

In general it's better to be specific.

20.4 Exercises

Exercise 20.4.1

Suppose we have a text file `numbers.txt` containing the following lines

```
prices
3
8

7
21
```

Using `try` – `except`, write a program to read in the contents of the file and sum the numbers, ignoring lines without numbers.

You can use the `open()` function we learnt *before* to open `numbers.txt`.

Solution to Exercise 20.4.1

Let's save the data first

```
%%file numbers.txt
prices
3
8

7
21
```

```
Writing numbers.txt
```

```
f = open('numbers.txt')

total = 0.0
for line in f:
    try:
        total += float(line)
    except ValueError:
        pass

f.close()

print(total)
```

```
39.0
```

Part V

Other

CHAPTER

TWENTYONE

TROUBLESHOOTING

Contents

This page is for readers experiencing errors when running the code from the lectures.

21.1 Fixing Your Local Environment

The basic assumption of the lectures is that code in a lecture should execute whenever

1. it is executed in a Jupyter notebook and
2. the notebook is running on a machine with the latest version of Anaconda Python.

You have installed Anaconda, haven't you, following the instructions in *this lecture*?

Assuming that you have, the most common source of problems for our readers is that their Anaconda distribution is not up to date.

Here's a useful article on how to update Anaconda.

Another option is to simply remove Anaconda and reinstall.

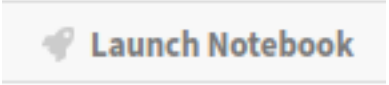
You also need to keep the external code libraries, such as QuantEcon.py up to date.

For this task you can either

- use conda upgrade quantecon on the command line, or
- execute !conda upgrade quantecon within a Jupyter notebook.

If your local environment is still not working you can do two things.

First, you can use a remote machine instead, by clicking on the Launch Notebook icon available for each lecture



Second, you can report an issue, so we can try to fix your local set up.

We like getting feedback on the lectures so please don't hesitate to get in touch.

21.2 Reporting an Issue

One way to give feedback is to raise an issue through our issue tracker.

Please be as specific as possible. Tell us where the problem is and as much detail about your local set up as you can provide.

Another feedback option is to use our discourse forum.

Finally, you can provide direct feedback to contact@quantecon.org

CHAPTER

TWENTYTWO

EXECUTION STATISTICS

This table contains the latest execution statistics.

Document	Modified	Method	Run Time (s)	Status
about_py	2023-12-20 22:51	cache	2.91	✅
debugging	2023-12-20 22:51	cache	2.25	✅
functions	2023-12-20 22:51	cache	1.89	✅
getting_started	2023-12-20 22:51	cache	1.56	✅
intro	2023-12-20 22:51	cache	0.93	✅
jax_intro	2023-12-20 22:51	cache	0.84	✅
matplotlib	2023-12-20 22:51	cache	4.72	✅
need_for_speed	2023-12-20 22:51	cache	10.09	✅
numba	2023-12-20 22:52	cache	12.9	✅
numpy	2023-12-20 22:52	cache	7.7	✅
oop_intro	2023-12-20 22:52	cache	1.7	✅
pandas	2023-12-20 22:53	cache	41.49	✅
parallelization	2023-12-20 22:53	cache	41.0	✅
python_advanced_features	2023-12-20 22:54	cache	17.68	✅
python_by_example	2023-12-20 22:54	cache	6.79	✅
python_essentials	2023-12-20 22:54	cache	1.74	✅
python_oop	2023-12-20 22:54	cache	2.41	✅
scipy	2023-12-20 22:54	cache	10.87	✅
status	2023-12-20 22:51	cache	0.93	✅
sympy	2023-12-20 22:54	cache	6.19	✅
troubleshooting	2023-12-20 22:51	cache	0.93	✅
workspace	2023-12-20 22:51	cache	0.93	✅
writing_good_code	2023-12-20 22:54	cache	2.73	✅

These lectures are built on `linux` instances through `github actions`.

INDEX

Q

R

S

V

Y