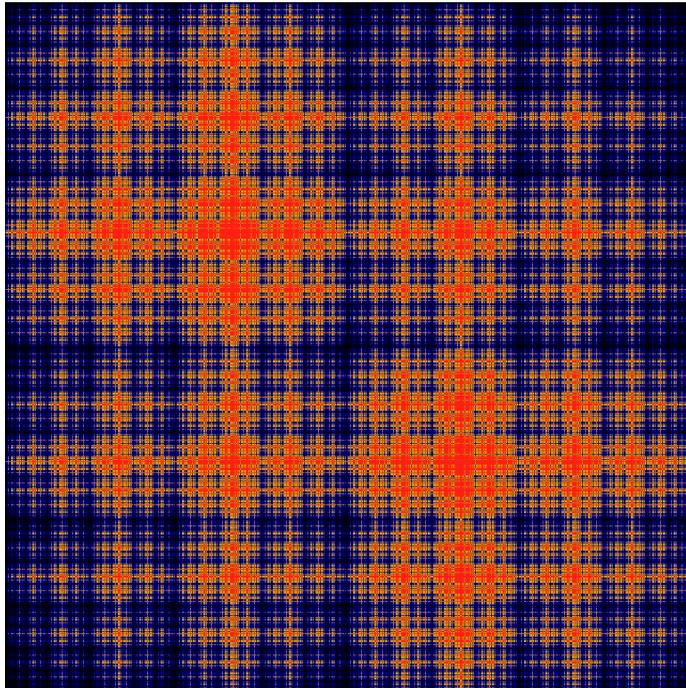


Applied Mathematics and Computing

Volume I



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Preface

This lab manual is designed to accompany the textbook *Foundations of Applied Mathematics* by Dr. J. Humpherys.

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https://github.com/ayr0/numerical_computing

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Introduction to Python

This IPython notebook provides an introduction into some of the basics of python and the coding idioms of Python. We will start by reviewing the different types of data that can be stored in Python and proceed to other topics from there. While you work through this notebook it would be wise to either be playing with the code in the notebook itself or in a ipython console that you open on your own. I will provide some comments intended for the reader that are denoted by a # in Python. Remember that while you are learning Python and even once you master Python that Google will be your best friend. If you ever have a question about how to do something then you will almost certainly be able to find an answer online. Following the information in this notebook, there will be several problems that you will be asked to turn in.

Types of Data in Python

This section will introduce you to several different types of data that you will frequently use in Python. We will touch on strings, integers, floats, and lists (Note: There are complex numbers as well, but they are very similar to floats and I also suggest learning a little about sets and dictionaries). Each of these will have different uses and you will need them to complete future labs. As a note prior to beginning. In python, `x = _`, denotes `x` as whatever fills in the blank space after the equal sign. This is known as being an identifier. You can use whatever variable/word you want with the exception of beginning your identifier with a number and for several words that python has claimed for itself (and, del, from, not, while, as, elif, global, or, with, assert, else, if, pass, break, except, import, print, class, exec, in, raise, continue, finally, is, return, def, for, lambda, try). Below we define `num` as an identifier for the object 1. Notice when we tell python to print the identifier `num` that it returns 1. Another important to note is that python begins indexing at element 0. If you want the first element from a list or string then it will be denoted as the 0th element.

```
In [23]: num = 1
         print(num)  # This will return what num is tied to (1)
```

1

```
In [24]: testlist = [0, 1, 2, 3, 4]
         print(testlist[0])  # Notice this gives us the first element of testlist.
```

0

Strings

Strings are a list of characters(includes numbers and symbols) in a certain order. These are declared in python by using quotation marks (' , " , or """"). Notice below that when we ask python to print what type 'hello' is that it returns type str. This is letting us know that 'hello' is a string.

```
In [3]: print(type('hello'))
        'hello'
```

```
<type 'str'>
```

```
Out[3]: 'hello'
```

There are several operations that can be done to strings. Typically strings are useful for printing updates or information from the code, but they can be used for other things as well (such as creating urls to direct python to). For example, when printing, you can print multiple lines within one print statement by using `\n`. You can also concatenate(add). Look at the difference between the examples below.

```
In [27]: str1 = 'welcome'
        str2 = 'to'
        str3 = 'bootcamp'
        print(str1 + str2 + str3) # Here we just print the strings concatenated t
```

```
welcometobootcamp
```

```
In [29]: print(str1 + ' \n'+str2 + ' \n'+str3) # Here we concatenate&printthe string
```

```
welcome
to
bootcamp
```

We can also slice(pull specific elements from) strings. Look at the examples below (The %s is a place holder for what comes after %):

```
In [36]: practicestr = 'abcdefghi'
        print('first element of practicestr is "%s"' % practicestr[0])
```

```
first element of practicestr is "a"
```

We can also access a range of elements from strings in the following way.

```
In [39]: pracstr = 'abcdefghi'
        print(pracstr[0:]) # The : means everything afterwards. This will print
        print(pracstr[5:]) # This will print from element 5 on
```

```
abcdefghi
fg
```

Now see what the command `[:-1]` does after the string.

```
In [41]: pracstr = 'abcdefghi'
        # Write your practice command here
```

There are other things that you can do with strings, but this should suffice for now. A couple of the other cool things are included below (The actual command is after the %). If you want more instruction on any of these, ask questions.

```
In [73]: string = 'thisisasentencestring'
capitallets = 'ABCDEFGH'
print('number of a\'s in string = %s') %string.count('a')
print('string in all upper case is %s') %string.upper()
print('capitallets in all lower case is %s') %capitallets.lower()
print('replace D in capitallets with another A is %s') %capitallets.replace('D', 'A')
print('a is in the %s element of string') %string.find('a')
```

```
number of a's in string = 1
string in all upper case is THISISASENTENCESTRING
capitallets in all lower case is abcdefgh
replace D in capitallets with another A is ABCAIEFGH
```

Integers and Floats

Integers are exactly what they sound like. Integers are all positive and negative integers; for you math folk it is \mathbb{Z} . Floats are all of the real numbers, \mathbb{R} . It is important to note the difference in programming between integers and floats because their operations will do different things. To declare a number as a float, you either need to tell the computer it is a float via command or add a decimal place. See below:

```
In [46]: type(1) # Just a normal integer will be recorded as an integer
```

```
Out[46]: int
```

```
In [45]: type(1.0) # Just adding a decimal place is the easiest way to declare a float
```

```
Out[45]: float
```

```
In [47]: type(float(1)) # but you can tell python that something is a float.
```

```
Out[47]: float
```

```
In [63]: print(int(5.5))
```

```
5
```

```
In [64]: print(float(5))
```

```
5.0
```

I told you that they were going to be a little different so let me show you the difference. We obviously know that $2/4$ should be equal to $.5$, but lets see what happens when we try it with integers.

```
In [48]: 2/4
```

```
Out[48]: 0
```

Integer division gave us 0 for $2/4$. This is the wrong answer. The explanation is actually pretty simple. The division algorithm says:

Let a, b be integers with $b > 0$ then there exist unique integers q and r such that

$$a = bq + r \text{ and } 0 \leq r < b$$

Note that r is actually the remainder. Integer division simply returns the q from this equation.

Now if we do this division in floats, we will get the answer that we are looking for.

```
In [49]: 2.0/4.0
```

```
Out[49]: 0.5
```

Integer operations certainly have their place, but typically you will want to be using float division. If at least one of the numbers is a float then the output will be returned as a float. There is also a small cheat you can put at the beginning of your file that will declare all of your division as float division for your whole script. That cheat is to write `from __future__ import division` at the beginning of your script. That will make all division float division.

```
In [54]: from __future__ import division
         4/3
```

```
Out[54]: 1.3333333333333333
```

The rest of the operations should work pretty similarly between the two, but it is always better to be safe and work with floats if you want to be in the real numbers. Another operation that tends to be very useful is modulus. You do modulus with `%`. The modulus will return the r from the division algorithm. This will be useful in many instances. For example, if you need to know whether a number is even or odd then you can check the number modulus 2.

```
In [57]: 4%2 # gives us 0 so 2 must divide evenly into 4
```

```
Out[57]: 0
```

```
In [58]: 5%2 # gives us 1 so 2 doesn't divide evenly into 5
```

```
Out[58]: 1
```

```
In [59]: 1436213623%2 # gives us 1 so 2 doesn't divide evenly into that number
```

```
Out[59]: 1
```

In many programming languages the exponent is denoted as $^$, but this is not true in python. If you want to take something to a power then you need to use `**`. See below:

```
In [60]: 3**2
```

```
Out[60]: 9
```

```
In [61]: 11**4
```

```
Out[61]: 14641
```

Lists

Lists are extremely useful for keeping track of information. A list can contain floats, integers, strings or any combination of them. A list is declared by using the square brackets, `[]`. You can append/remove new items to/from a list.

```
In [90]: practicelist = [1, 2, 3, 4]
        practicelist
```

```
Out[90]: [1, 2, 3, 4]
```

```
In [91]: practicelist.append(5)  # append 5 to our list
        practicelist
```

```
Out[91]: [1, 2, 3, 4, 5]
```

```
In [92]: practicelist.remove(1)  # remove 1 from our list
        practicelist
```

```
Out[92]: [2, 3, 4, 5]
```

You can also replace elements within a list.

```
In [95]: anotherlist = ['a', 2, 3, 4]
        print('this is the first element of another list', anotherlist[0])

        ('this is the first element of another list', 'a')
```

```
In [97]: anotherlist[0] = 1
        print('now this is the first element of another list', anotherlist[0])

        ('now this is the first element of another list', 1)
```

Taking slices of lists works the same way as taking slices of strings.

```
In [99]: list1 = [1, 2, 3, 4, 5, 6, 7]
list1[2:5] # take elements 2 through 5
```

```
Out[99]: [3, 4, 5]
```

We can also concatenate lists just like we did with strings.

```
In [93]: list1 = [1, 2]
list2 = ['a', 'b']
list1 + list2
```

```
Out[93]: [1, 2, 'a', 'b']
```

In addition to being able to do these things that you were able to do in a string, lists allow you to find the max and min (among other things) within the list.

```
In [108]: list1 = [1, 2, 36, 256, 2562, 56]
print('The max is %s' %max(list1))
print('The min is %s' %min(list1))
```

```
The max is 2562
The min is 1
```

One of the built in commands to build lists is with the range command. Below we will build a list of numbers from 0 to 9 using range in several different ways.

```
In [100]: range(10) # if you just input an integer it will build up until that number
```

```
Out[100]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

```
In [101]: range(0,10,1) # you can tell it to start at 0 and go to 10 taking 1 unit
```

```
Out[101]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

```
In [102]: range(1,10) # we can go from 1 to 9 as well by specifying to start at 1
```

```
Out[102]: [1, 2, 3, 4, 5, 6, 7, 8, 9]
```

Conditionals, Loops, and Booleans

Conditional statements, loops, and booleans permit a programmer increased flexibility. These permit you to give your computer specific commands that save you a lot of coding. For example, if you want to remove all of the even numbers from a list then you can say something like below:

Also some symbols that will be useful: < less than

greater than <= less than or equal = greater than or equal != not equal == equal to

```
In [113]: list1 = range(25)
          print(list1)

[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,
20, 21, 22, 23, 24]
```

```
In [112]: list2 = [list1[n] for n in list1 if n%2!=0] # This removes all even numbers
          print(list2)

[1, 3, 5, 7, 9, 11, 13, 15, 17, 19, 21, 23]
```

Booleans are just values tied to certain expressions that evaluate to either true or false. If and while statements are evaluated based on these values. For example, below we said $5 < 3$ and the computer says False because that isn't true

```
In [117]: 5 < 3
```

```
Out[117]: False
```

The conditional statements that you should be most familiar with are "if/elif/else" and "while". They are used exactly how you would imagine that they are used. You want to tell the computer if something is true then do this, else do this other thing. You could also tell your computer while this condition is true then continue doing what I told you to do. Below are two examples (Note where the indentations (done by inserting 4 spaces) are):

```
In [118]: x = 3
          if x < 3:
              print('x is less than 3')
          elif x < 4:
              print('x is less than 4')
          else:
              print('x is not less than 4')

x is less than 4
```

```
In [115]: x = 1
          while x < 7:
              print('x is still less than 7')
              x = x + 1 # Increase x by 1

x is still less than 7
x is still less than 7
```

```
x is still less than 7
```

For conditional statements, if you are asking whether something is equal you need to use two equals. This is because python thinks one equals means that you are setting something equal to that, but you are asking whether it is or isn't. See example:

```
In [124]: x = 6
         if x == 6:
             print('told ya so :)')

told ya so :)
```

Looping is a very similar to a while loop, but you give it a specific number of times it should do something. For example if we had a list and we wanted to square every element, we could use a for loop.

```
In [121]: list1 = [1, 2, 3, 4, 5, 6]

         for i in range(len(list1)): # len(list1) tells us how many elements we need
             list1[i] = list1[i]**2 # The ith element of list1 = (ith element of list1)**2

         print('list1 squared is %s' %list1)

list1 squared is [1, 4, 9, 16, 25, 36]
```

Developing a Function and Exploring Modules

Python Modules

One of the biggest benefits of python is the fact that it is open source. This means that there are almost constantly individuals contributing to python to build modules. Modules are just files that contain python code that you are able to use. Some of the modules that you will use very frequently are: math, numpy, pandas, byumcl, and other modules you might write for yourself. Although you will use these most, if you ever think that something would be nice to be able to do then most likely someone has written a module that does that task. Once again, google will be your best friend in finding these.

You need to import modules into your session to be able to use them. You need to do all of your imports at the very beginning when you are writing a script. These imports are done like this:

```
In [106]: import numpy as np # the 'as np' part creates a nickname for functions from numpy
         import math
         import os
         from filename import * # will import functions that you have written in a file
```

```
"""
Here you would write the rest of your script
"""

x = math.pi
```

You have to refer to the module you just imported in order to call an object from that module. For example: We wrote `math.pi` in the code above. This tells python to look in the `math` module and call the function `pi`. When we write things like the "import `numpy` as `np`", we are giving `numpy` a nickname and we can write `np.numpy_function` instead of writing `numpy.numpy_function`. It is also helpful to try `help(module)` to see if you can find documentation. You can also use `module.object(??)` to open the documentation for a specific object in a module.

Defining Functions

Although python provides you with many built in functions, sometimes you need to write functions that perform very specific actions. Luckily, python allows you to write your own functions. This is actually very simple. All you need to do is follow is give your function a name, ask for inputs, write the function, and return something. Indentation is important here as well. See example:

```
In [125]: def square(x): # We give the function the name square and say we pass in x
          '''
          Really pretty documentation that you should write all the time

          Parameters
          -----
          ....

          Outputs
          -----
          ...
          '''

          output = x * x # define some variable that we will be the output of c
          return output # return the variable output
```

```
In [126]: square(45)
```

```
Out[126]: 2025
```

Writing Scripts and the Zen of Python

Writing a Script

Writing a script is pretty simple, so I will try and go over it pretty quick. A script should start with all of your imports and then you write your code. It should be neat and you should leave one clean line at the end of your script or the code monster will come and eat you. Example of a script:

```
In [128]: import math
import os
from __future__ import division

x = 2.0

y = x * math.pi

finalstuff = square(y)
```

After you have written a script then you need to enter your ipython console. From there, direct your computer to the directory where the script is stored and type "run script.py" That's it for running scripts.

Zen of Python (PEP 20)

The Zen of Python is a set of basic rules that one should follow when writing python code. They are important to follow as they will make your code readable and will bring good code karma to you and your family. Anytime that you forget these rules, type "import this" into your console.

Beautiful is better than ugly.

Explicit is better than implicit.

Simple is better than complex.

Complex is better than complicated.

Flat is better than nested.

Sparse is better than dense.

Readability counts.

Special cases aren't special enough to break the rules.

Although practicality beats purity.

Errors should never pass silently.

Unless explicitly silenced.

In the face of ambiguity, refuse the temptation to guess.

There should be one-- and preferably only one --obvious way to do it.

Although that way may not be obvious at first unless you're Dutch.

Now is better than never.

Although never is often better than *right* now.

If the implementation is hard to explain, it's a bad idea.

If the implementation is easy to explain, it may be a good idea.

Namespaces are one honking great idea -- let's do more of those!

```
In [129]: import this
```

```
The Zen of Python, by Tim Peters
```

```
Beautiful is better than ugly.  
Explicit is better than implicit.  
Simple is better than complex.  
Complex is better than complicated.  
Flat is better than nested.  
Sparse is better than dense.  
Readability counts.  
Special cases aren't special enough to break the rules.  
Although practicality beats purity.  
Errors should never pass silently.  
Unless explicitly silenced.  
In the face of ambiguity, refuse the temptation to guess.  
There should be one-- and preferably only one --obvious way to do it.  
Although that way may not be obvious at first unless you're Dutch.  
Now is better than never.  
Although never is often better than *right* now.  
If the implementation is hard to explain, it's a bad idea.  
If the implementation is easy to explain, it may be a good idea.  
Namespaces are one honking great idea -- let's do more of those!
```

Style Guide for Python (PEP 8)

PEP 8 is too long to put into this document, but I would highly suggest reading through it. The suggestions in PEP 8 are very helpful in making your code readable and in line with the Zen of Python. I will include a few of the tips that I find important.

Indentation: Use 4 spaces per indentation level. Python's implicit line joining inside parentheses, brackets and braces, or using a hanging indent. When using a hanging indent the following considerations should be applied; there should be no arguments on the first line and further indentation should be used to clearly distinguish itself as a continuation line.

Maximum Line Length: Limit all lines to a maximum of 79 characters.

Blank Lines: Separate top-level function and class definitions with two blank lines. Method definitions inside a class are separated by a single blank line. Extra blank lines may be used (sparingly) to separate groups of related functions. Blank lines may be omitted between a bunch of related one-liners (e.g. a set

of dummy implementations).

Whitespace in Expressions: Avoid extraneous whitespace in the following situations: Immediately inside parentheses, brackets or braces; Immediately before a comma, semicolon, or colon, Immediately before the open parenthesis that starts the argument list of a function call, Immediately before the open parenthesis that starts an indexing or slicing, More than one space around an assignment (or other) operator to align it with another. If operators with different priorities are used, consider adding whitespace around the operators with the lowest priority(ies). Use your own judgement; however, never use more than one space, and always have the same amount of whitespace on both sides of a binary operator. For example:

Yes

```
In [130]: x = 0
          x += 1
          x = x + 1
          x = x**2 + 2
          test = x*x + 2*x
          y = (x+2) * (x-3)
```

No

```
In [ ]: x=x+1
        x +=1
        x = 2 * x + 1
        y = (x + 2) * (x - 3)
```

Comments: Comments that contradict the code are worse than no comments. Always update comments! Comments should be complete sentences.

We are hoping to edit your code and give you tips on how to make it stay consistent with PEP 8 and PEP 20. We recommend using the `sublime_linter` in Sublimetext 2 to stay in line with PEP 8.

Problems:

All scripts submitted should obviously be in line with PEP 8 and PEP 20 for this assignment because that is one of the topics covered. Include comments.

Problem 1: Write a script that generates the following:

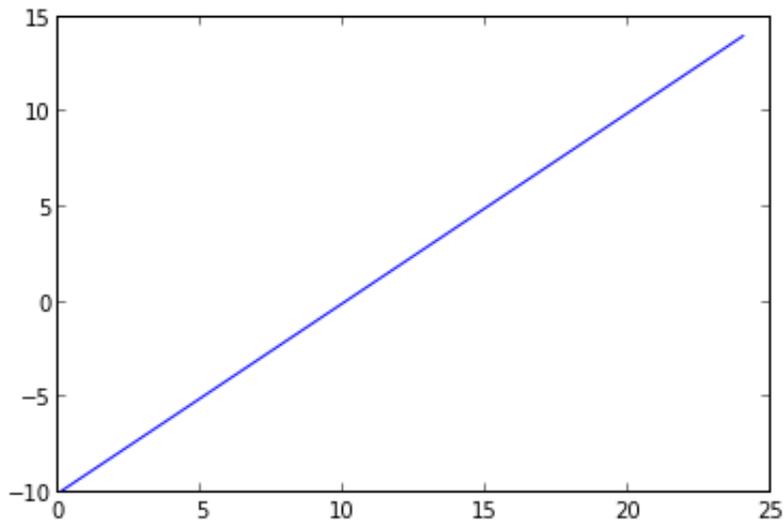
- i) A list with all of the elements from 0 to 100
- ii) A list with all of the even elements from 0 to 100
- iii) A list that contains all of the even numbers starting at 100 and going to 0

Problem 2: Write a script that creates a piecewise function $f(x) = y$ that satisfies the following:

- i) When $x < 0$ then $y = 0$
- ii) When $0 < x \leq 5$ then $y = x^2$
- iii) When $x > 5$ then $y = 25$
- iv) Now copy the following code to create a plot

```
In [132]: import matplotlib.pyplot as plt
# Define function in here
test = range(-10, 15, 1)
plt.plot(f(test)) # Note this isn't your actual function being plotted be
```

Out[132]: [



Problem 3: If we list all the natural numbers below 10 that are multiples of 3 or 5, we get 3, 5, 6 and 9. The sum of these multiples is 23.

Write a script that prints the sum of all the multiples of 3 or 5 below 1000.

In []:

Lab 3

Essentials: NumPy

Why Arrays?

Problem 1 Let's begin with a simple demonstration of why arrays are important for numerical computation. Why use arrays when Python already has decently efficient list object? In this demonstration, we will try squaring a matrix. The matrix will be represented as a two dimensional list (i.e. a list of lists).

Write a function that will accept two matrices (two dimensional list), A and B , and return AB following the rules of matrix multiplication.

```
k = 10
a = [range(i, i+k) for i in range(0, k**2, k)]
```

Time how long your function takes to square matrices for increasing values of k .

Now import NumPy and create a NumPy array, b as shown below. We demonstrate how to square NumPy arrays as matrices below. $b*b$ does not square the array, but rather multiplies b with itself element-wise. To get matrix multiplication for NumPy arrays, you must use `np.dot`

```
import numpy as np
b = np.array([range(i, i+k) for i in range(0, k**2, k)])
np.dot(b, b)
```

Time how long NumPy takes to square arrays for increasing sizes of k .

What do you notice about the time needed to square a two dimensional list vs. a two dimensional NumPy array?

NumPy

NumPy is a fundamental package for scientific computing with Python. It provides an efficient n -dimensional array object for fast computations. This lab will focus on

how to use these powerful objects. NumPy is commonly imported as shown below.

```
: import numpy as np
```

Before beginning this lab, it will be useful to understand certain concepts and terms used to describe NumPy arrays.

N-Dimensions

One, two, and three dimensional arrays are easy to visualize. But how do we visualize a four, ten, or fifteen dimensional array? NumPy arrays are best thought of as arrays within arrays. A one dimensional array consists of only elements. A two dimensional array is really just an array containing arrays which contain elements. Extending this metaphor, a three dimensional array is an array of arrays of arrays. Can you guess what a five dimensional array is? Let's define a three dimensional array.

```
: arr = np.random.randint(50, size=(5, 4, 3))
```

Arrays have several attributes. We use *shape* and *size* to describe the how big an array is. *Shape* tells how many dimensions an array has and how big each dimension is. *Size* gives the total number of elements in the array.

```
: arr.shape
(5, 4, 3)
: arr.size
60
```

If we want to know how much memory an array takes to store, we can use `arr.nbytes`. The number of bytes is dependent on the data type (*dtype*) of the array. The data types that NumPy uses are different from Python data types. An integer in NumPy is not the same as an integer Python. Remembering this is vital. NumPy uses machine data types to speed up calculations. However, these datatypes are susceptible to a problem called *overflow*. A 64 bit integer has enough bits to represent integers between $-9,223,372,036,854,775,808$ and $9,223,372,036,854,775,807$. If we have an array with $-9,223,372,036,854,775,808$ and we decide to subtract 1, the integer wraps around and becomes $9,223,372,036,854,775,807$!

```
: arr.dtype
dtype('int64')
: arr.nbytes
480
```

Each element of the array has a unique address that describes its location. Indexing always starts at 0. Also, like Python lists, negative indices are valid and count from the tail of the array. We will discuss indexing in detail later in this lab.

```
: arr[0, 0, 0] # returns the first element of arr
: arr[-1, -1, -1] # returns the last element of arr
```

Creating Arrays

NumPy has several methods for creating and initializing arrays. When creating an array, we can optionally specify the data type that is stored in the array. NumPy arrays only store elements of the same data type, however, that data type can be any arbitrary object. The array order dictates how the array is laid out in memory. There is C order and Fortran order. C ordered arrays are also known as row-major arrays. This means that the fastest changing index correspond to the rows of the array. Fortran ordered arrays are column-major. Let's look at a few of the ways we can create arrays in NumPy.

- `np.array`: Makes an array from a Python list or tuple.
- `np.empty`: Allocates an array of a specific size without initializing the elements.
- `np.ones`: Allocates an array and initializes each element to 1.
- `np.zeros`: Allocates an array and initializes each element to 0.
- `np.identity`: Allocates a 2D array array with the main diagonal initialized to 1 and zeros everywhere else.

Indexing Arrays

Array Views and Copies

Before we begin accessing arrays, it is important to understand that NumPy has two ways of returning an array. Slice operations always return a *view* and fancy indexing always returns a *copy*. Understand that even though they may look the same, views and copies completely different.

Views are special arrays that reference other arrays. Changing elements in a view changes the array it references. Below we demonstrate the behavior of a view. Notice that `c` looks like a copy of `b`, but it is, in fact, not at all.

```

: b = np.arange(25).reshape(5,5); b
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24]])
: c = b[:]; c #looks like c is a copy of b
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24]])
: id(c) == id(b) #We have unique objects
False
: c[2] = 500; c
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [500, 500, 500, 500, 500],
       [15, 16, 17, 18, 19],

```

```

        [ 20,  21,  22,  23,  24]])
: b #changing c also changed b!
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [500, 500, 500, 500, 500],
       [ 15, 16, 17, 18, 19],
       [ 20, 21, 22, 23, 24]])

```

The reason that changing the array `c` also changed the array `b` is because `c` and `b` share the same memory, even though they are different Python objects. Views reduce the overhead of making copies of arrays and are useful when we want to change certain parts of the array.

A copy of an array is a separate array that is allocated separately.

```

: b = np.arange(25).reshape(5, 5); b
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24]])
: c = b.copy()
: id(c) == id(b) #we still have separate objects
False
: c[2] = 500
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [500, 500, 500, 500, 500],
       [ 15, 16, 17, 18, 19],
       [ 20, 21, 22, 23, 24]])
: b
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24]])

```

Changing the data in a copy of an array, doesn't change the data in the original array. The two arrays address different locations in memory.

Slices

Each element of an array has a unique address that we can use to retrieve that element. Indexing NumPy arrays is syntactically the same as indexing Python lists. We will demonstrate on a random 2D array. Remember that slicing arrays always return views of the array. In this case, the indexing object is a Python tuple.

```

: arr = np.arange(25).reshape(5,5); arr
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14],
       [15, 16, 17, 18, 19],
       [20, 21, 22, 23, 24]])
: arr[0, 0] #access the first element
0
: arr[-1, -1] #access the last element

```

```
24
: arr[0] #access the first row
array([0, 1, 2, 3, 4])
```

We can access ranges of elements using Python lists. NumPy, though, has a much faster, more concise way to select ranges using the `arr[start:stop:step]` notation.

```
: arr[::2] #get every other row. equivalent to arr[range(0, len(arr),
2)]
array([[ 0,  1,  2,  3,  4],
       [10, 11, 12, 13, 14],
       [20, 21, 22, 23, 24]])
: arr[:, ::2] #get every other row and every other column
array([[ 0,  2,  4],
       [10, 12, 14],
       [20, 22, 24]])
: arr[3:, 3:] #extract lower right 2x2 subarray
array([[18, 19],
       [23, 24]])
: arr[:, 1] #extract second column
array([ 1,  6, 11, 16, 21])
```

Fancy Indexing

When the indexing object is an object other than a tuple, NumPy behaves slightly different. One difference is that fancy indexes always return a copy of an array instead of a view. There are two types of fancy indexes: boolean and integer. Boolean indexing returns an array of `True` or `False` values depending on some evaluating condition.

```
: bmask = (arr > 15) & (arr < 23)
array([[False, False, False, False, False],
       [False, False, False, False, False],
       [False, False, False, False, False],
       [False, True, True, True, True],
       [ True, True, True, False, False]], dtype=bool)
: arr[bmask]
array([16, 17, 18, 19, 20, 21, 22])
: arr[(arr > 15) & (arr < 23)] #this is the shortened form
array([16, 17, 18, 19, 20, 21, 22])
: arr[~bmask] #invert the mask
```

```
: arr[(0, 2, 4), (0, 2, 4)] #grab every other element of diagonal
array([ 0, 12, 24])
: arr[range(0, 5, 2), range(0, 5, 2)] #same as above, but with ranges
array([ 0, 12, 24])
: arr[:, [0, -1]] #grab first and last column
array([[ 0,  4],
       [ 5,  9],
       [10, 14],
       [15, 19],
       [20, 24]])
```

Array Broadcasting

Array broadcasting allows NumPy to effectively work with arrays with sizes that don't match exactly. There are four basic rules to determine the behavior of broadcasted arrays

1. All input arrays of lesser dimension than the input array with largest dimension have 1's prepended to their shapes.
2. The size in each dimension of the output shape is the maximum of all the input sizes in that dimension.
3. An input can be used in the calculation if its size in a particular dimension either matches the output size in that dimension, or has a value exactly 1.
4. If an input has a dimension size of 1 in its shape, the first data entry in that dimension will be used for all calculations along that dimension.

To broadcast arrays, at least one of the following must be true.

1. All input arrays have exactly the same shape.
2. All input arrays are of the same dimension and the length of corresponding dimensions match or is 1.
3. All input arrays of fewer dimension can have 1 prepended to their shapes to satisfy the second criteria.

Problem 2 Explore array broadcasting. Create example for each of the three cases where arrays are broadcasted.

Saving Arrays

Sometimes it is desirable to save an array to a file to be used for later. NumPy provides several easy to use methods for saving and loading array data to files.

<code>np.save(file, arr)</code>	Save an array to a binary file
<code>np.savez(file, *arrs)</code>	Save multiple arrays to a binary file
<code>np.savetxt(file, arr)</code>	Save an array to a text file

<code>np.load(file)</code>	Load and return an array from a binary file
<code>np.loadtxt(file)</code>	Load and return an array from text file

Let's practice saving an array to a file and loading it again. Note that when saving an array, NumPy automatically appends the extension `.npy` if it does not already exist.

```
a = np.arange(30)
np.save('test_arr', a)
new_a = np.load('test_arr.npy')
np.savez('test_multi', a=a, new_a=new_a)
arrs = np.load('test_multi.npz')
```

The variable `arrs` points to a dictionary object with the keys `a` and `new_a` which reference the arrays that have been saved.

Lab 4

Algorithms: Python Essentials (Arrays)

Lesson Objective: *This lesson explains basic matrix operations in Python.*

Matrices form the core data structure of NumPy and SciPy. Thus, we will explore the ways one can manipulate matrices in Python.

Before we begin, we make a few important comments about how Python works with matrices. First, matrices can be represented in NumPy in two ways. NumPy has a matrix data type and an array data type. Matrix objects are a special case of the array object. The main differences are that the matrix object allows for a clearer, more MATLAB style syntax. In these labs, we will use arrays because most functions in NumPy accept arrays as input. We can easily convert arrays to matrices using the `.asmatrix()` method. As such, all future references to matrices in the context of NumPy will be mentioned as arrays (a matrix being a 2D array). When using arrays it is important to be sure that the dimensions are compatible.

We also note that arrays are by default accessed row by row. This is called row-major. This is the opposite of MATLAB, which is column-major. However, NumPy arrays can be converted to column-major arrays.

Finally, with all code examples in these labs we assume that you have already imported the SciPy library (type `import scipy as sp` when you first open ipython).

To begin, we will work with vectors. We will demonstrate a variety of methods to create vectors. You should follow these demonstrations on your own computer and experiment as you go. Vectors are at least one dimensional arrays. There are several ways to create vectors in Python. Try the following in IPython:

```
: a = sp.array([1,2,3,4]); a  
array([1, 2, 3, 4])
```

Notice the square brackets and the commas. The square brackets denote a list in Python with values separated by commas. This is a row vector. The `; a` is responsible for printing the current value of `a`. How do we make a column vector? We simply pass the `array()` method a list of lists containing a single value each.

```
: b = sp.array([[3],[4],[6],[1]]); b
array([[3],
       [4],
       [6],
       [1]])
```

We can also use the `hstack()` and `vstack()` methods (meaning horizontal stack and vertical stack).

```
: a1 = sp.hstack([5,6,7,8])
: b1 = sp.vstack([9,0,1,2])
```

We combine vectors together by placing two or more of equal dimension inside square brackets. The technical term for this is concatenation. Remember that the dimensions of each array must match. Try the following.

```
: c = sp.concatenate((b,b1), axis=1); c
```

There are several methods to automate vector creation. For example, we can build a vector of consecutive values using the `arange()` method.

```
: sp.arange(5)
```

Notice how the values start at zero and increment up to, but *not* including 5. This is standard Python behaviour. The `arange()` method also allows us to specify step size. This syntax also allows us to specify step size:

```
: sp.arange(1,3,step=0.5)
```

We can similarly use negative step sizes (note that the starting must be greater than the endpoint).

```
: sp.arange(3,1,step=-.5)
```

A related function is called `linspace()`. It allows us to specify two endpoints and the number of equidistant values we want between the two. Unlike `arange()`, `linspace()` will always include both endpoints.

```
: sp.linspace(1,2,5)
```

The `plot()` function uses two vectors to create a graph, the first vector representing x -values and the second representing the corresponding y -values. To use `plot()`, we need to import the Matplotlib library. As an example we plot a line of slope two using the following commands (See figure 1.1):

```
: import matplotlib.pyplot as plt
: x = sp.linspace(-2,2,20)
: plt.plot(x,2*x)
: plt.show()
```

By typing `plt.plot?` into the command line we can find the exact syntax and options for the `plot()` function. For example we can type `plot(x,2*x,'r*')` to plot red star data points instead of a line.

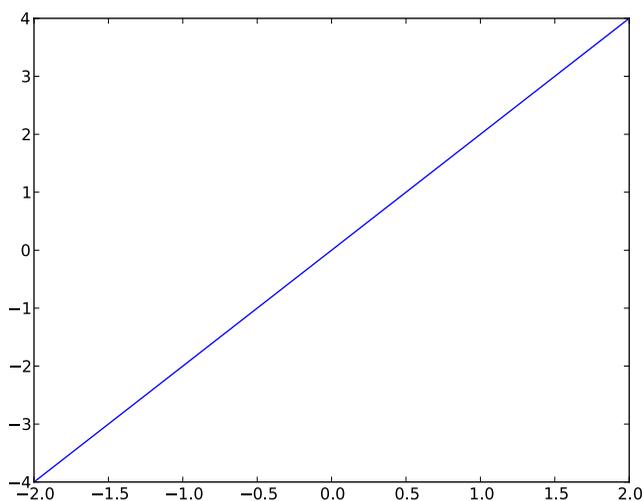


Figure 4.1: A simple graph

Problem 1 Plot a line with slope three with black diamond data points. Plot for the domain $x \in [-5, 5]$.

Creating is done by concatenating vectors in the correct manner. For example:

```
: sp.array([[1, 2, 3],[4, 5, 6],[7, 8, 9]])
```

Problem 2 Create a matrix showing the times table from 1 to 6. Do not enter each number manually. Instead, create a variable $x = \text{sp.arange}(1,7)$ and let the rows of the matrix be multiples of x .

Another technique for creating matrices is using outer products. An outer product is the method of multiplying two vectors to get a matrix. For example, if we want to make a matrix that is two repeated rows of the vector 1:5 we can do the following:

```
: sp.vstack([1,1])*sp.arange(1,6)
```

Here we are multiplying a 2×1 vector and a 1×5 vector, which yields a 2×5 matrix. The two rows are identical since the entries of the first vector are all ones.

Problem 3 Create the same matrix from problem 2, using outer products this time. This implementation, although perhaps more difficult to conceptualize, makes for much more concise code.

You can also combine matrices in the same way as vectors, as long as the dimensions match correctly, i.e. the same number of rows or the same number of columns. Try the following:

```
: D = sp.hstack((b, c))
: E = sp.concatenate([D.T, sp.vander(sp.arange(1,5))])
```

Here we used the `vander()` method, which accepts a vector of length n and creates an $n \times n$ matrix. The columns of this matrix are powers of the input vector (evaluated point-wise). More information about the `vander()` method by typing `sp.vander?`.

To briefly review, vectors are built using the square brackets, with semi-colons to build columns and spaces to build rows. Matrices are built in exactly the same way, using vectors or matrices instead of individual numbers.

Often while writing code it is necessary to know information about the properties of an array. The matrix properties can be accessed as follows.

```
: E.ndim           #dimension of E
: E.nbytes         #size of E in memory (bytes)
: E.size           #total area of E (the product of the dimensions)
: E.shape          #size of E in each dimension
```

For this next problem we will need to read an array from a file. SciPy provides a method for loading data from text files. We are going to load `bucky.csv` as an array.

```
: bucky = sp.loadtxt("bucky.csv", delimiter=",")
```

This array represents the connections between vertices of a truncated isocahedron. This soccer ball like shape is found in certain types of carbon molecules known as fullerenes (specifically C_{60} , shown in `shaped`)

Problem 4 The bucky matrix represents the connections between the vertices of a truncated isocahedron. This structure matches both the structure of a standard soccer ball, and also of certain types of carbon molecules known as fullerenes (specifically C_{60} , shown in `??`). It is also related to the structure of the geodesic dome. Find the size of this matrix.

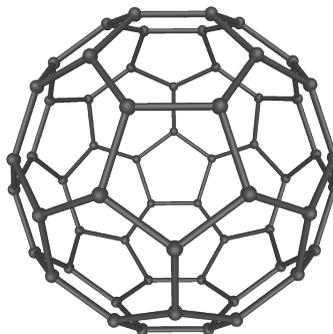


Figure 4.2: The structure of the C_{60} molecule.

To access information in an array, you put the index you wish to access inside square brackets after the variable name. This works for both variable assignment and retrieval. Remember that indices start at zero in SciPy.

```
: rand_mat = sp.random.randint(10, size=(3,5))
: rand_mat[0,0]
: rand_mat[2,2] = 37
```

The colon operator is used to retrieve an entire row or column from an array. For example, enter the following to get the third column of an array:

```
: rand_mat[:,2]
```

We similarly retrieve the first row:

```
: rand_mat[0,:]
```

Note that each retrieved row or column is returned as a single dimensional array (meaning that row or column loses its meaning). If we want to retain the retrieved row as a column or row we can write instead `rand_mat[:,[2]]`.

It is also possible to retrieve multiple columns or rows at once. For example, we retrieve the second and fourth columns of an array by entering:

```
: rand_mat[:,[1,3]]
```

We list the entries of an array as a single dimensional array using the `flatten()` method.

```
: rand_mat.flatten() #flattens along the rows (C like arrays)
: rand_mat.flatten('F') #flattens along the columns (Fortran like
  arrays)
```

The following line tells Python to retrieve the entries in the second row, from the second column to the end:

```
: rand_mat[1,1:]
```

Deleting a row or column can be done by using the `delete()` method. The last argument is the axis along which to delete. If the deletion axis is not specified, then the array will be flattened before being returned. Here we remove the column at index 1.

```
: sp.delete(rand_mat, 1, 1)
```

Problem 5 Try to assign a vector of incorrect size to a piece of a matrix. What happens? Also, try to concatenate two matrices that don't have matching dimensions. What error message do you get? It is important to learn how to read error messages for troubleshooting purposes.

Numerical operations are by default done element-wise on arrays. A common mistake is to use `*` for matrix multiplication. This simply multiplies each element by a constant. To perform matrix multiplication, SciPy provides the `dot()` method. To take the transpose of an array, use the `.T` property. Observe the behavior of the array operations.

```
: b = sp.vstack([8,0,2])
: c = sp.vstack([4,2,1])
: b+c
array([[12],
       [ 2],
       [ 3]])
: b-c
array([[ 4],
       [-2],
       [ 1]])
: A = sp.array([0,4,5,4,0,2,9,4,6]).reshape((3,3))
: A*b #b is a column vector, so each row is multiplied by a constant
array([[ 0, 32, 40],
       [ 0,  0,  0],
       [18,  8, 12]])
: A*b.T #b.T is a row vector, so each column multiplied by a constant
array([[ 0,  0, 10],
       [32,  0,  4],
       [72,  0, 12]])
: sp.dot(A,b)
array([[10],
       [36],
       [84]])
: sp.power(A,2) #this is A^2
array([[ 0, 16, 25],
       [16,  0,  4],
       [81, 16, 36]])
: A/2 #notice that type is perserved. This is integer division
array([[0, 2, 2],
       [2, 0, 1],
       [4, 2, 3]])
: A/2. #divide by a float yields an array of floats.
```

```
array([[ 0. ,  2. ,  2.5],
       [ 2. ,  0. ,  1. ],
       [ 4.5,  2. ,  3. ]])
```

The majority of elementary functions, such as `sin`, `cos`, `exp`, etc. act element-wise on arrays as well. In fact, for any operation in SciPy, expect it to act element-wise unless otherwise noted. For example:

```
: sp.sin(sp.arange(4)*sp.pi/4)
array([ 0.          ,  0.70710678,  1.          ,  0.70710678])
```

Also, as a matter of reference, raising a value to a power is done using `**`. This is a convention from older programming languages that has carried over.

There are a variety of functions that let us summarize information about a given array. For example, the `sum()` function returns the sum along a given axis of an array. When an axis is not specified, all elements in the array are summed together.

```
: B = sp.arange(9).reshape((3,3))
: sp.sum(B) #all entries are summed together
36
: sp.sum(B, axis=0) #sum each column
array([ 9, 12, 15])
: sp.sum(B, axis=1) #sum each row
array([ 3, 12, 21])
```

Some other functions that summarize information about the entries of an array are contained in the Table 1.1. Note that each of these functions reduces the size of the matrix (which makes sense, since they are summarizing functions). These functions work across columns by default, although most of them allow you to specify an axis to work across.

These functions can be incredibly useful. For example, suppose that we want to estimate the derivative of $\sin(x^2)$. A simple approximation for a derivative is

$$f'(x) \approx \frac{f(x+h) - f(x)}{h}$$

Presumably this approximation is good when h is small. We use the `diff()` function to perform this approximation using the following code:

```
: h = .001
: x = sp.arange(0, sp.pi, h)
: approx = sp.diff(sp.sin(x**2))/h
```

We have just approximated the derivative of $\sin x^2$ at several thousand points between 0 and π . The approximated derivatives are stored in the array `approx`. Now let's compute the actual derivative at each point using the formula:

$$f'(x) = 2x\cos(x^2)$$

```
: actual = 2*sp.cos(x**2)*x;
```

Function	Description	Usage
<code>max</code>	Returns maximum entries	<code>A.max(axis)</code>
<code>min</code>	Returns minimum entries	<code>A.min(axis)</code>
<code>mean</code>	Returns the mean	<code>A.mean(axis)</code>
<code>scipy.median</code>	Returns the median	<code>sp.median(A, axis)</code>
<code>std</code>	Returns the standard deviation	<code>A.std(axis)</code>
<code>scipy.diff</code>	Returns the differences between entries	<code>sp.diff(A, axis)</code>
<code>prod</code>	Returns the product of entries	<code>A.prod(axis)</code>
<code>any</code>	Returns 1 if there are non-zero entries, zero otherwise	<code>A.any(axis)</code>
<code>all</code>	Returns 1 if all entries are non-zero, zero otherwise	<code>A.all(axis)</code>
<code>nonzero</code>	Returns indices of non-zero entries	<code>A.nonzero(axis)</code>
<code>scipy.linalg.norm</code>	Returns the norm	<code>norm(A, order)</code>

Table 4.1: Various summarizing functions

Plot the approximated derivative and the actual derivative on two different plots. They should look almost identical.

```

: from matplotlib import pyplot as plt
: plt.figure(1) #create an empty figure
: plt.subplot(211) #create an empty subplot in figure
: plt.plot(x, approx)
: plt.subplot(212) #create another subplot in same figure
: plt.plot(x, actual)
: plt.show()

```

Problem 6 Now use the `max()` command to find the maximum difference between the estimated derivative and the actual derivative (the dimensions will not match exactly (why?); fix this by removing the last entry from one of the vectors). Try plotting the approximation, actual derivatives, and the error on the same graph. What does it look like?

Problem 7 The command `sp.rand()` returns an array of a specified shape with values “randomly” selected from a uniform distribution between zero and one. Create

a vector with ten thousand entries using this command. The theoretical values for the mean(μ) and standard deviation(σ) of a uniformly distributed random variable between a and b are

$$\mu = \frac{a + b}{2}$$

$$\sigma = \frac{b - a}{\sqrt{12}}$$

These values are calculated using moment-generating functions. Use the `mean()` and `std()` methods on the vector you created earlier. How do these compare to the theoretical values?

The canonical problem in linear algebra is solving the equation $Ax = b$ for x , where A is an $n \times n$ matrix and b is a $1 \times n$ vector. One method for solving this equation is by calculating the matrix inverse of A (A^{-1}) and multiplying $A^{-1}b$. To find the inverse of an array, use the `linalg.inv()` method. For example, we create a random system $Ax = b$ and solve it using the `inv()` method (you may check the calculations by hand):

```
: A = sp.array([1,5,2,3,5,1,4,7,2]).reshape((3,3))
: b = sp.vstack([1, 3, 11./3])
: from scipy import linalg as la
: sol = sp.dot(la.inv(A),b); sol
array([[ 0.66666667],
       [ 0.33333333],
       [-0.66666667]])
```

Recall that a norm is a measurement on the size of a vector. For example, the Euclidean norm measures the straight line distance from the origin to the “end” of a vector.

$$\|x\| = \sqrt{x_1^2 + \dots + x_n^2}$$

If the norm of the difference of two vectors is close to zero, then they are good approximations of each other. The `linalg.norm()` function calculates the euclidean norm of an input vector, and thus we use it to verify that our approximation of the derivative is close to the actual derivative:

```
: la.norm(b-sp.dot(A,sol))
5.5288660751834285e-15
```

However, computing the inverse of a large matrix is difficult. Not only that, but not all matrices have inverses. There is a much more efficient and general way to solve $Ax = b$ in SciPy. This method is similar to the backslash method found in MATLAB. It is the `linalg.solve()` method. Compare the results obtained with the `linalg.solve()` method to those of the `linalg.inv()` method.

```

: sol2 = la.solve(A,b); sol2
array([[ 0.66666667],
       [ 0.33333333],
       [-0.66666667]])
: la.norm(sol2-sol)
4.5775667985222375e-16

```

We mentioned that `linalg.solve()` is more efficient than using the function `inv`, meaning it returns a result faster. Create the following script to compare the efficiency of each method:

```

import scipy as sp
from scipy import linalg as la
from timer import timer

def invMethod(A, b):
    return sp.dot(la.inv(A),b)

def solveMethod(A, b):
    return la.solve(A,b)

n = 300
A = sp.rand(n,n)
b = sp.rand(n,1)

with timer(repeats=3, loops=10) as t:
    t.time(invMethod,A,b)
    t.time(solveMethod,A,b)
    t.printTimes()

```

Now run the script. You should notice a significant difference in execution time (you may need to scale n appropriately). Are you surprised that `invMethod()` is significantly slower than `solveMethod`? Specifically, SciPy uses the LU factorization and backwards substitution to solve the linear system without any matrix inversions.

The `linalg.solve()` method can also be used to solve several systems at once. For example:

```

: c = sp.rand(n, 1)
: la.solve(A, sp.c_[b,c]) #sp.c_[] concatenates column vectors

```

You might now be asking why we would want to do this. We can answer this by investigating the time it takes to solve two systems. Open a new script file and write the following:

```

import scipy as sp
from timer import timer
n = 3000
A = sp.rand(n,n)
b = sp.rand(n,1)
c = sp.rand(n,1)

def multSys(A, *col_vecs):
    return la.solve(A, sp.hstack(col_vecs))

```

```
def singSys(A, *col_vecs):
    return [la.solve(A, x) for x in col_vecs]

with timer(repeats=3, loops=100) as t:
    t.time(multSys,A,b,c)
    t.time(singSys,A,b,c)
    t.printTimes()
```

This script creates a random 3000×3000 matrix, and two random 3000×1 vectors (you can experiment with different sizes of matrices and vectors). It then solves the two systems of equations twice, once using two backslash commands and the other using only one. Remember that the semi-colons suppress the output in the script.

Now execute this script. You should notice that the first method takes about twice as long as the second method. This is because `linalg.solve()` uses the LU decomposition, and in the second method it only has to execute this factorization once. This highlights the importance of understanding the algorithms that python uses: we can solve problems much faster if we understand what python is doing.

A number of other important operators that you will need are found in Table 1.2.

Method	Description	Usage
<code>linalg.inv()</code>	Matrix inverse	<code>la.inv(A)</code>
<code>rank()</code>	Rank	<code>sp.rank(A)</code>
<code>linalg.norm()</code>	Norm (default: 2-norm)	<code>la.norm(A, ord)</code>
<code>linalg.expm()</code>	Matrix exponential	<code>la.expm(A)</code>
<code>linalg.det()</code>	Determinant	<code>la.det(A)</code>
<code>linalg.eig()</code>	Eigenvalue decomposition	<code>la.eig(A)</code>
<code>linalg.svd()</code>	Singular value decomposition	<code>la.svd(A)</code>
<code>linalg.lu()</code>	LU decomposition	<code>la.lu(A)</code>
<code>linalg.qr()</code>	QR factorization	<code>la.qr(A)</code>
<code>linalg.cholesky()</code>	Cholesky factorization	<code>la.cholesky(A)</code>

Table 4.2: Useful matrix operations

Problem 8 The `linalg.lstsq()` method can be also used to solve overdetermined systems. This is sometimes also known as the least squares method. The formula is $(A^T A)^{-1} A^T * b$. Create a script to verify numerically that the `linalg.lstsq()` method and the least squares formula yield the same result. Hint: Use the `linalg.norm()` function to verify equality, as we did with `linalg.inv()` and `linalg.solve()`.

Lab 5

Algorithms: Matrix Operations and Algorithmic Complexity

Lesson Objective: *This section explains how to create specific types of large matrices. It also introduces the concept of temporal complexity. Finally, it explores SciPy's special methods for working with sparse matrices.*

Temporal Complexity

One of the most important questions in scientific computing is: How long will this operation take? The concept of temporal complexity attempts to answer this question by determining how much time a function needs to operate on a given size of input. For example suppose calculating the inverse of a matrix of size n requires the following number of calculations.

$$f(n) = \frac{3n^3}{2} + 75n^2 + 250n + 30$$

What is the most important part of this expression? When our input gets very large the only relevant term in this equation is n^3 . For this reason we say that $f(n) \in O(n^3)$, or more commonly that $f(n)$ is $O(n^3)$ (spoken “Big O of n cubed” or “Order of n cubed”). This notation is borrowed from analysis. This notation captures the salient behavior of our temporal complexity, or more precisely the growth rate we can expect of the execution time of our algorithm. We will discuss this concept later, but this is a simple introduction to the notion of complexity and Big O. Spatial complexity is the amount of memory an algorithm uses, and is defined similarly.

Advanced Matrix Tools

We now introduce a few different ways to build matrices. Two important methods available for building matrices are `zeros()` and `ones()`. These commands allow us to

build matrices populated entirely with zeros or ones, respectively. For example, to build a 3-vector filled with zeros we enter the following command:

```
: import scipy as sp
: sp.zeros((3,1))
array([[ 0.],
       [ 0.],
       [ 0.]])
```

To find additional options for these methods, you can use the help system.

One important use of the `zeros()` method is to allow us to pre-allocate memory. Pre-allocation is simply the practice of reserving a chunk of memory for later use. We can always add more space to a matrix using the methods we learned in lab 1, but this requires many extra internal operations because of way arrays are stored in memory. Thus, it is generally faster to allocate a matrix with its final size and modify its values rather than building an array as you go.

Table 1.3 gives a few commands that allow us to build types of useful matrices.

Function	Description	Usage
<code>eye()</code>	Identity matrix	<code>sp.eye(m, n)</code>
<code>zeros()</code>	Zero matrix	<code>sp.zeros((m, n))</code>
<code>ones()</code>	One matrix	<code>sp.ones((m, n))</code>
<code>diag()</code>	Building (or retrieving) along a diagonal	
<code>linalg.toeplitz()</code>	Matrix with constant diagonals	<code>la.toeplitz()</code>
<code>linalg.triu()</code>	Upper triangular	
<code>linalg.tril()</code>	Lower triangular	
<code>rand</code>	Pseudo-random matrix, uniformly distributed	
<code>randn</code>	Pseudo-random matrix, normally distributed	
<code>random.randint()</code>	Pseudo-random matrix, uniformly distributed integers	<code>sp.random.randint()</code>
<code>tile()</code>	Copy across a given dimension	<code>sp.tile(A, reps)</code>

Table 5.1: Special matrix creation commands

For example, suppose that we want to create a matrix with -2 on the diagonal, and ones on the super and sub diagonal. We can do this by using the following command:

```
: from scipy import linalg as la
: la.toeplitz([-2,1,0])
array([[ -2,  1,  0],
       [  1, -2,  1],
```

```
[ 0, 1, -2]])
```

This matrix is useful because it numerically approximates the second derivative of a function. We investigate some properties of this matrix in Problem 6 of this lab, and explain more about this matrix later.

Problem 1 Use the `diagflat()` method to create the following matrices. All of these matrices should be easily scaleable (ie only minor modification would be required to change the size).

$$\begin{pmatrix} 1 & 2 & 3 & 4 & 5 \\ 0 & 1 & 2 & 3 & 4 \\ 0 & 0 & 1 & 2 & 3 \\ 0 & 0 & 0 & 1 & 2 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad \begin{pmatrix} 1 & 1/2 & 1/3 & 1/4 & 1/5 \\ 1/2 & 1 & 1/2 & 1/3 & 1/4 \\ 1/3 & 1/2 & 1 & 1/2 & 1/3 \\ 1/4 & 1/3 & 1/2 & 1 & 1/2 \\ 1/5 & 1/4 & 1/3 & 1/2 & 1 \end{pmatrix}$$

Problem 2 Create the matrices from Problem 1 using the methods `linalg.toeplitz()` or `linalg.triu()`. Which method is easier? Now use whichever command is easiest to create the matrix:

$$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 4 & 0 \\ 0 & 0 & 0 & 0 & 5 \end{pmatrix}$$

Sparse Matrices

In this section we discuss how sparse matrices are used and constructed. A sparse matrix is a matrix that has few non-zero entries (where few is generally relative to the number of entries in the matrix). SciPy has several different ways of storing sparse matrices. Each way has its pros and cons (the reader is encouraged to read the help for way).

Type the following into IPython.

```
: from scipy import sparse as spar
: A = sp.diagflat([2,3,4])
: B = spar.csc_matrix(A)
: C = B.todense()
```

Notice that the matrix A has only three non-zero entries, and so we can consider it sparse. In memory, an array stores a bit of data (be it an integer, float,

Function	Description
<code>sparse.bsr()</code>	Compressed Block Sparse Row
<code>sparse.coo()</code>	Coordinate
<code>sparse.csc()</code>	Compressed Sparse Column
<code>sparse.csr()</code>	Compress Sparse Row
<code>sparse.dia()</code>	Sparse Diagonal
<code>sparse.dok()</code>	Dictionary of Keys
<code>sparse.lil()</code>	Linked List

Table 5.2: Sparse matrix representations in SciPy

or complex number) each entry, meaning that a 3×3 matrix requires a total 9 blocks of memory. However, if we leverage the sparsity of A we realize that we only need to store 3 numbers. The `sparse` methods do exactly this: they store only the non-zero entries and their locations in the matrix. No longer are we working with array. SciPy has many methods for performing operations on sparse arrays. To convert back to a dense matrix, we use the `.todense()` property of the sparse matrix. We can also convert between the different types sparse arrays.

We remark that if you want to make a sparse diagonal matrix, the best way to do it isn't to use `diagflat()` followed by `sparse`, it's actually better to use the `sparse.spdiags()` method:

```
: spar.spdiags([2,3,4],0,3,3)
```

This is because oftentimes when we are using sparse matrices we are dealing with matrices that are too large to be handled efficiently by python when represented in full form.

Banded Matrices

A banded matrix is one whose only non-zero entries are diagonal strips. For example, the matrix

$$A = \begin{pmatrix} 1 & 2 & 0 & 0 \\ 3 & 4 & 5 & 0 \\ 0 & 6 & 7 & 8 \\ 0 & 0 & 9 & 10 \end{pmatrix}$$

is banded because there are three nonzero diagonals. This particular type of banded matrix is called a tri-diagonal matrix.

You can easily create banded matrices using the `diagflat()` method. For example, the matrix A above can be created by entering

```
: sp.diagflat([3,6,9],-1) + sp.diagflat([1,4,7,10],0) + sp.diagflat([2,5,8],1)
```

Often a better way to create a tri-diagonal is to use the `spar.spdiags()` method. This is because many diagonal matrices are sparse. For example, we create the same matrix in Python (while designating that it is sparse) using the command:

```
: Z = sp.array([[3, 1, 0],[6, 4, 2],[9, 7, 5],[0,10,8]]) .T
: spar.spdiags(Z,[-1,0,1],4,4)
```

For more information, check the documentation by typing `spar.spdiags?`. For example we create a tri-diagonal array with uniformly distributed random entries. This example also demonstrates the efficiency of using sparse arrays.

```
: B = sp.rand(3,10000)
: A = spar.spdiags(B,range(-1,2),10000,10000)
: denseA = A.todense() #only do this step if you have _lots_ of
   memory!
: A.data.nbytes
240000 #about 0.24MB of memory
: denseA.nbytes
800000000 #about 762.9MB of memory!
```

We can't use the `full` command in this case because the computer will almost certainly run out of memory (the matrix is $10,000 \times 10,000$). However, we can still visualize this matrix using the `plt.spy()` command from matplotlib, which essentially shows the location of non-zero entries in a matrix. The output of `plt.spy(A)` in this case is shown in Figure 1.2:

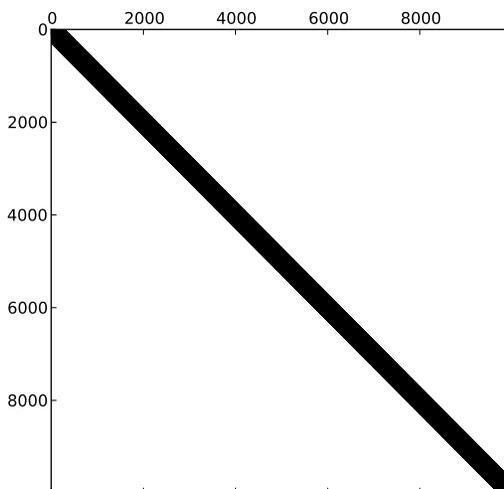


Figure 5.1: The output of the `spy` command.

Using Sparse Matrices

Consider the linear system $Ax = b$, where A is a $100,000 \times 100,000$ tri-diagonal matrix. To store a full matrix of that size in your computer, it would normally require 10 billion double-precision floating-point numbers. Since it takes 8 bytes to store a double, it would take roughly 80GB to store the full matrix. For most desktop computers, that fact alone makes the system numerically prohibitive to solve. The temporal complexity of the problem is even more problematic. Methods for directly solving an arbitrary linear system are usually $O(n^3)$. As a result, even if the computer could store an 80GB matrix in RAM, it would still take several weeks to solve the system. However, since we don't have computers with that much available RAM, most of the matrix would have to be stored on the hard drive, so the computation would probably take between 6 months to a year.

The point is that even the next generation of computers will struggle with solving arbitrary linear systems of this size in a reasonable period of time. However, if we take advantage of the sparse structure of the tri-diagonal matrix, we can solve the linear system, even with a modest modern computer. This is because all of those zeros don't need to be stored and we don't need to do as many operations to row reduce the tri-diagonal system.

Let's first compute the spatial complexity of the above system when considered as a sparse matrix. There are three diagonals that have roughly 100,000 non-zero entries. That's 300,000 double-precision floating point numbers, which is about 2.4 MB (Less storage than your favorite song). As a result, it will easily fit into the computer's RAM. Furthermore, the temporal complexity for solving a tri-diagonal matrix is $O(n)$. Let's see how long it takes to solve the system for random data:

```

: from scipy.sparse import linalg as sparsa
: from timer import timer
: D = sp.rand(3, 100000)
: b = sp.rand(1, 100000)
: A = sparsa.spdiags(D, [-1, 0, 1], 100000, 100000)
: def solSys():
....: return sparsa.spsolve(A, b)
: with timer() as t:
....: t.time(solSys)
....: t.printTimes()

```

Problem 3 Write a function that returns a full $n \times n$ tri-diagonal array with 2's along the diagonal and -1's along the two sub-diagonals above and below the diagonal. Hint: Use the `la.toeplitz()` method. Note that this is the second derivative matrix that we discussed at the beginning of this lab.

Problem 4 Write another function that builds the same array as above, but as a

sparse array. You must build this as a sparse matrix from the beginning. Hint: Use the `spar.spdiags()` method.

Problem 5 Solve the linear system $Ax = b$ where A is the $n \times n$ tri-diagonal array from the above two problems and b is randomly generated. How high can you go for each method? Make a table for several different values of n and the time it took to solve for each run. What conclusions can you draw?

Problem 6 Using the sparse array above and the method `la.eigs()`, calculate the smallest eigenvalue λ of the array as the array's size goes to infinity. What value does λn^2 approach? Hint: It's the square of an important number. This is related to operator theory: the second derivative operator has this eigenvalue in certain cases.

Other Sparse Commands

One important method of sparse array objects is the `nonzero()` method, which is related to the number of nonzero entries in an array. This number is important because it is an indicator of the amount of time and space that is required to operate on the sparse array. You should be aware that there is some overhead to using and storing the sparse array data structure. Sparsely represented arrays are very beneficial when the number of nonzero entries is relatively small compared to the total number of entries. When the array has many nonzero entries, a sparse representation becomes disadvantageous. To see this, create and execute a script with the following code:

```
: A = sp.rand(600,600); B = spar.csc_matrix(A)
: def square(A): return sp.power(A, 2)
: with timer() as t:
....: t.time(square, A)
....: t.time(square, B)
```

Run the script and note the two different runtimes. Notice that it takes much longer to square the sparse array. This is because the sparse array data structure is optimized for arrays that are actually sparse. The array A is entirely nonzero. Thus, you incur the overhead of the sparse array representation without any benefits since there are no entries you are not required to store or compute. To summarize, only use a sparse array when your array is in fact sparse. Using sparse arrays for mostly nonzero arrays will negatively impact performance and memory requirements.

Just as with dense arrays, we can pre-allocate sparse arrays. Sometimes it is necessary to create sparse matrices that do not have a nice banded pattern. We initialize a sparse array just like any other array. The most efficient sparse array for pre-allocation is LIL. Once you are done constructing your sparse array and wish to perform calculations, you should convert to a more efficient sparse array (CSR or CSC).

```
: Z = spar.lil_matrix((400,300))
<400x300 sparse matrix of type '<type 'numpy.float64''>'
  with 0 stored elements in LInked List format>
: Z[1,34] = 23
: Z[23,32] = 56
: Z[2,:] = 13.2
```

This code snippet creates a 400×300 LIL sparse array. We can then work with the sparse array as though it were a dense array. When the array is initialized all of the entries are assumed to be zero.

Lab 6

Applications: Markov Chains I

Lesson Objective: *This section teaches about two simple applications of Linear Algebra. First it teaches about Markov Chains, which in this context represent discrete random transitions. Second it teaches about Graph Theory, which can be used to represent many physical problems.*

Markov Chains

A Markov Chain describe a particular type of random variable. This type of random variable is characterized by the fact that all relevant information is related to its current state. We can easily model this type of random variable using matrices. We will start with a canonical example of a frog jumping from one lily pad to another.

Fredo the Frog hops around between the three lily pads A , B , and C . If he's on lily pad A and jumps, there is a 25% chance that he will land back on lily pad A , a 25% chance that he will land on lily pad B , and a 50% chance that he will land on lily pad C . In Figure '2.1, we have a transition diagram that reflects the various probabilities from which Fredo will go from one lily pad to another.

We can convert our transition diagram into a transition matrix, where the (i, j) -entry of the matrix corresponds to the probability that Fredo jumps from the j^{th} lily pad to the i^{th} lily pad (where of course A is the first lily pad, B is the second, and so on). In Fredo's case, the transition matrix is

$$A = \begin{pmatrix} 1/4 & 1/2 & 1/2 \\ 1/4 & 1/6 & 1/2 \\ 1/2 & 1/3 & 0 \end{pmatrix}$$

Note that all of the columns add up to one. This is important.

If Fredo is on lily pad A , where will he be after two jumps? By multiplying the matrix A by itself, we have (approximately)

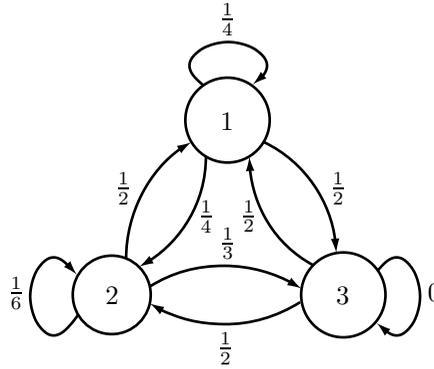


Figure 6.1: Transition diagram for Fredo the Frog

$$A^2 = \begin{pmatrix} 0.4375 & 0.3750 & 0.3750 \\ 0.3542 & 0.3194 & 0.2083 \\ 0.2083 & 0.3056 & 0.4167 \end{pmatrix}$$

From this, we infer that there is a 43.75% chance he will still be on lily pad A after two jumps. Note that he might have jumped from A to A to A , denoted $A \rightarrow A \rightarrow A$, or he could have jumped to one of the other lily pads and then back again, that is, either $A \rightarrow B \rightarrow A$ or $A \rightarrow C \rightarrow A$. In addition, there is a 35.42% chance he will be on lily pad B and a 20.83% chance that he will be on lily pad C . Using Python, we can type in our transition matrix and see where Fredo will be after 5, 10, 20 or 100 jumps.

```
#Remember, the 1.'s in the numerator force floating point division
: A = sp.array([[1./4,1./2,1./2],[1./4,1./6,1./2],[1./2,1./3,0]])
: np.linalg.matrix_power(A,5)
: np.linalg.matrix_power(A,10)
: np.linalg.matrix_power(A,20)
: np.linalg.matrix_power(A,100)
```

Note that in the limit that the number of jumps goes to infinity, we get

$$A^\infty = \begin{pmatrix} 0.4 & 0.4 & 0.4 \\ 0.3 & 0.3 & 0.3 \\ 0.3 & 0.3 & 0.3 \end{pmatrix}$$

This means that after several jumps, the probability that we will find Fredo on a given lily pad will have nothing to do with where he started initially.

Markov Chains

We can generalize this notion beyond that of frogs and lily pads. Let the state of our system be represented by a probability vector

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

where each entry represents the probability of being in that state. Note that each entry is nonnegative and the sum of all the entries adds up to one. For example, in the case of Fredo, if we know initially that he is on lily pad A , then we have the state vector

$$\mathbf{x}_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$

because we know for certainty (100%) that Fredo is in the first state. After one jump, we have

$$\mathbf{x}_1 = A\mathbf{x}_0 = \begin{bmatrix} 0.25 \\ 0.25 \\ 0.50 \end{bmatrix}$$

After two jumps, we have

$$\mathbf{x}_2 = A\mathbf{x}_1 = A^2\mathbf{x}_0 = \begin{bmatrix} 0.4375 \\ 0.3542 \\ 0.2083 \end{bmatrix}$$

After a large number of jumps ($n \gg 1$), we have

$$\mathbf{x}_n = A\mathbf{x}_{n-1} = \cdots = A^n\mathbf{x}_0 \approx \begin{bmatrix} 0.4 \\ 0.3 \\ 0.3 \end{bmatrix}$$

Since all of the columns are the same for A^∞ , then for any initial probability vector \mathbf{x}_0 , we get the same limiting output, or in other words, all initial vectors converge to the same point, call it \mathbf{x}_∞ . Moreover, we have that

$$\mathbf{x}_\infty = A\mathbf{x}_\infty$$

This is called a stable fixed point. How can we check that a stable fixed point exists? Hint: Think eigenvalues and eigenvectors.

Example

Consider the Markov chain given by

$$A = \begin{pmatrix} 0.5 & 0.3 & 0.4 \\ 0.2 & 0.2 & 0.3 \\ 0.3 & 0.5 & 0.3 \end{pmatrix}.$$

We show that it has a stable fixed point by checking that it has a single eigenvalue $\lambda = 1$. We do this via Python:

```
: A = sp.array([[.5, .3, .4], [.2, .2, .3], [.3, .5, .3]])
: v = la.eig(A)[1]
```

Note that the entries in the $\lambda = 1$ eigenvector do not generally add up to one. Indeed, any multiple of an eigenvector is an eigenvector. So we need to multiply it by the appropriate constant so that all of the entries add up to one.

```
: x = v[:,0]
: x = x/sp.sum(x); x
array([ 0.41836735,  0.23469388,  0.34693878])
```

We can check this answer by taking A to a high exponent, say A^{100} .

Problem 1 Suppose a basketball player's success at shooting free throws can be described with the following Markov chain

$$A = \begin{pmatrix} .75 & .50 \\ .25 & .50 \end{pmatrix}$$

where the first state corresponds to success and the second state to failure.

1. If the player makes his first free throw, what is the probability that he also makes his third one?
2. What is the player's average free throw percentage?

Problem 2 Consider the Markov process given by the transition diagram in Figure 2 below:

1. Find the transition matrix.
2. If the Markov process is in state A , initially, find the probability that it is in state B after 2 periods.
3. Find the stable fixed point if it exists.

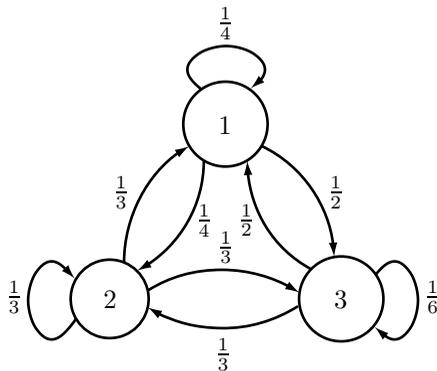
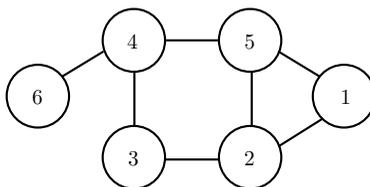


Figure 6.2: Transition diagram

Graph Theory



Graph theory is an important branch of mathematics and computer science. It describes how objects are connected to one another. In a rigorous sense, a graph is composed of two sets: a set of nodes and a set of edges that connect these nodes.

A graph is directed if connections are uni-directional, and undirected if they are bi-directional. The above graphic shows an undirected graph. We can write a matrix that describes this type of graph. We let each row of our matrix represent our starting point and each column represent our destination. We put a 1 if there is a path and a 0 if there is not. For the above graph we generate the following matrix:

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

This matrix is called an adjacency matrix. Note that this matrix is symmetric, since the graph is undirected.

What happens if we square an adjacency matrix? It turns out that raising an adjacency matrix to the n power yields the number of paths of length n between two vertices. For example by squaring the above matrix Python gives:

```
: np.linalg.matrix_power(A,2)
array([[2, 1, 1, 1, 1, 0],
       [1, 3, 0, 2, 1, 0],
       [1, 0, 2, 0, 2, 1],
       [1, 2, 0, 3, 0, 0],
       [1, 1, 2, 0, 3, 1],
       [0, 0, 1, 0, 1, 1]])
```

Now try to find the number of connections of length 6 from node 3 to itself. This is simple to do in Python:

```
: np.linalg.matrix_power(A,6)
array([[45, 54, 38, 45, 54, 16],
       [54, 86, 29, 77, 51, 11],
       [38, 29, 55, 15, 70, 27],
       [45, 77, 15, 75, 31, 4],
       [54, 51, 70, 31, 93, 34],
       [16, 11, 27, 4, 34, 14]])
```

It turns out that there are 55 unique paths of length 6 from node 3 to itself. Imagine trying to count all of those paths by hand! It would be very easy to count incorrectly. However, this method makes it very simple to count paths without any mistakes.

Problem 3 Let the following matrix represent a directed graph

$$A = \begin{pmatrix} 0 & 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

The greatest number of paths of length five are from which node to each node? From which node to which node is their no path of length seven?

The astute reader may ask now why this matters. It turns out that the study of graphs and connectivity have many important applications. For example, connections between web pages can be described as graphs. So can flights between airports or friends on social networking sites. The same ideas are applied frequently in computer chip design and in the preservation of endangered species. We will explore one surprising application to chemistry.

Remember the `bucky` array we explored in chapter one? The graph that this matrix represents is a graph for a geodesic dome, which has structure almost identical to certain types of carbon atoms. Understanding the graphs of certain types of molecules allows scientists to better understand the structure of the molecule, making identification and manipulation easier.

We will manipulate the matrix the `bucky` to simulate the types of analysis a scientist could do on a complex carbon atom. For our purposes, each column and row of the `bucky` matrix represents an atom in our molecule, and connections are chemical bonds from one atom to another.

Problem 4 Find the number of connections between atoms in our molecule (the command `sp.count_nonzero` may be useful). Then find the number of atoms that are connected by paths of length two. Three? At what path length are all of the atoms connected? A nifty way to visualize this is the `plt.spy` command. Read the documentation for `plt.spy` and then use `plt.spy` to visualize how the graph is connected at path length one, two, four and ten. Remember, to load ‘`bucky.csv`’ into an array use the command `bucky = sp.loadtxt ("bucky.csv", delimiter = ",")`.

Lab 7

Algorithms: RREF / Elementary Matrices

Lesson Objective: *In this section we will use elementary matrices to find the RREF and to find the LU decomposition.*

In Linear algebra there are 3 elementary row operations: switching two rows, multiplying a row by a constant, and adding a multiple of one row to another row. We carry out each of these operations with a corresponding elementary matrix. These matrices are easy to construct. Suppose A is an $m \times n$ matrix and you want to perform one of the three elementary operations on A . You can do this by constructing the $m \times m$ identity matrix, I , performing the elementary row operation on I to obtain E and then multiplying EA . For example, consider the matrix

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \end{pmatrix}$$

If we want to swap the first two rows, we can left multiply the matrix A by:

$$E = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix},$$

then

$$EA = \begin{pmatrix} a_{21} & a_{22} & a_{23} & a_{24} \\ a_{11} & a_{12} & a_{13} & a_{14} \\ a_{31} & a_{32} & a_{33} & a_{34} \end{pmatrix}.$$

E in this case is called a type I matrix.

Now let's examine the next row operation. If we want to multiply, say, the second row of A by the constant b , we can left multiply the matrix A by the following

matrix:

$$\tilde{E} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & 1 \end{pmatrix}.$$

Then

$$\tilde{E}A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ ba_{21} & ba_{22} & ba_{23} & ba_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \end{pmatrix}.$$

\tilde{E} is called a type II matrix.

Now let's examine the last row operation. If we want to multiply, say, the first row of A by a constant c and add it to the second row, we can left multiply the matrix A by the following matrix:

$$\hat{E} = \begin{pmatrix} 1 & 0 & 0 \\ c & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}.$$

Then

$$\hat{E}A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ ca_{11} + a_{21} & ca_{12} + a_{22} & ca_{13} + a_{23} & ca_{14} + a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \end{pmatrix}.$$

\hat{E} is called a type III matrix.

Below, the elementary matrices corresponding to each row operation is implemented in Python.

```

1 from scipy import eye
2
3 def rowswap(n, j, k):
4     """Swaps two rows
5
6     INPUTS: n -> matrix size
7             j, k -> the two rows to swap"""
8     out = eye(n)
9     out[j,j]=0
10    out[k,k]=0
11    out[j,k]=1
12    out[k,j]=1
13    return out
14
15 def cmult(n, j, const):
16     """Multiplies a row by a constant
17
18     INPUTS: n -> array size
19             j -> row
20             const -> constant"""
21    out = eye(n)
22    out[j,j]=const
23    return out
24
25 def cmultadd(n, j, k, const):
26     """Multiplies a row (k) by a constant and adds the result to
27        another row (j)"""

```

```

28 out = eye(n)
    out[j,k] = const
    return out

```

row_ops.py

Programming Row Reduction

A fundamental problem in linear algebra is using matrix representations to solve systems of linear equations. In this section, we do this by using elementary matrices to reduce a matrix into “row echelon form” (REF), as opposed to “reduced row echelon form” (RREF). We remark that to solve a linear system, it is actually faster computationally to use REF and then finish with back-substitution, than it is to use RREF. Consider the following matrix:

$$\begin{pmatrix} 4 & 5 & 6 & 3 \\ 2 & 4 & 6 & 4 \\ 7 & 8 & 0 & 5 \end{pmatrix}$$

By iteratively left multiplying by elementary matrices, we can reduce as follows:

Remember that our functions returns the elementary array corresponding to the desired row operation. Also note that setting the type of our initial array is crucial.

```

: import scipy as sp
: import row_ops as op
: A = sp.array([[4, 5, 6, 3],[2, 4, 6, 4],[7, 8, 0, 5]], dtype='
float32')
array([[ 4.,  5.,  6.,  3.],
       [ 2.,  4.,  6.,  4.],
       [ 7.,  8.,  0.,  5.]], dtype=float32)
: A1 = sp.dot(op.cmultadd(3,1,0,-A[1,0]/A[0,0]), A); A1
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 0. ,  1.5,  3. ,  2.5],
       [ 7. ,  8. ,  0. ,  5. ]])
: A2 = sp.dot(op.cmultadd(3,2,0,-A1[2,0]/A1[0,0]), A1); A2
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 0. ,  1.5,  3. ,  2.5 ],
       [ 0. , -0.75, -10.5 , -0.25]])
: A3 = sp.dot(op.cmultadd(3,2,1,-A2[2,1]/A2[1,1]), A2); A3
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 0. ,  1.5,  3. ,  2.5],
       [ 0. ,  0. , -9. ,  1. ]])

```

To complete REF we would need to divide each row by its leading coefficient. We can do that using Type II matrices. We leave it to you to carry this out.

Problem 1 Write a Python function, which takes as input an $n \times (n+1)$ matrix (in other words and *augmented* matrix) and performs the above naive row reduction to REF using elementary matrices. (You do not need to worry about underdetermined matrices or getting zeros on the main diagonal)

LU Decomposition

Again, consider the matrix A . By iteratively left multiplying by Type 3 elementary matrices, we reduce as follows:

```

: E1 = op.cmultadd(3,1,0,-A[1,0]/A[0,0]); E1
array([[ 1. ,  0. ,  0. ],
       [-0.5,  1. ,  0. ],
       [ 0. ,  0. ,  1. ]])
: B1 = sp.dot(E1, A)
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 0. ,  1.5,  3. ,  2.5],
       [ 7. ,  8. ,  0. ,  5. ]])
: E2 = op.cmultadd(3,2,0,-B1[2,0]/B1[0,0])
: B2 = sp.dot(E2, B1)
: E3 = op.cmultadd(3,2,1,-B2[2,1]/B2[1,1])
: U = sp.dot(E3, B2); U
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 0. ,  1.5,  3. ,  2.5],
       [ 0. ,  0. , -9. ,  1. ]])

```

Note that we have reduced the above matrix into upper-triangular form, denoted as U . Hence, we have

$$U = E_3 E_2 E_1 A.$$

Since the elementary matrices are invertible, we also have

$$(E_3 E_2 E_1)^{-1} U = A.$$

This can be re-written as

$$E_1^{-1} E_2^{-1} E_3^{-1} U = A.$$

Then we define L to be

$$L = E_1^{-1} E_2^{-1} E_3^{-1},$$

which yields $LU = A$.

```

: from scipy import linalg as la
: I = lambda x: la.inv(x)
: L = sp.dot(sp.dot(I(E1), I(E2)), I(E3)); L
array([[ 1. ,  0. ,  0. ],
       [ 0.5,  1. ,  0. ],
       [ 1.75, -0.5,  1. ]])
: sp.dot(L, U)
array([[ 4. ,  5. ,  6. ,  3. ],
       [ 2. ,  4. ,  6. ,  4. ],
       [ 7. ,  8. ,  0. ,  5. ]])

```

What makes LU decomposition so easy is that the inverses of elementary matrices are elementary matrices. For example, the inverse of a Type 3 elementary matrix is the same matrix with the opposite sign in the (j, k) entry. In the above problem, we have: Note that the minus signs are gone. Doing it this way, we don't have to actually invert anything to compute L . This makes the computation much faster.

Why Should I Care?

The LU Decomposition isn't very useful when doing matrix computation by hand. It is, however, very important in scientific computation for the following reasons:

- If you want to solve the matrix equation $Ax = b$, for several different b 's, you can replace A with L and U , giving $LUx = b$. Then solve the equations $Ly = b$ and $Ux = y$, using forward and backward substitution, respectively. This is actually faster than solving them with row reduction.
- The LU decomposition allows quick computation of both inverses and determinants.
- For very large matrices the LU decomposition is crucial. Indeed one can perform the LU decomposition on a given matrix A without needing additional space, that is, the program actually over-writes A with L and U . Note that since the diagonal of L are all ones, they don't need to be stored, and so the upper diagonal (including the diagonal) is U and the lower diagonal (not including the diagonal) is L .

Problem 2 Write a Python function which takes as input a random $n \times n$ matrix, performs the LU decomposition and returns L and U . To verify that it works, multiply L and U together and compare to A . Note: you should not use the `inv` function when you do this. You should only use the elementary matrices that we just created. Additionally, have your function count the number of operations needed to perform the LU decomposition.

Problem 3 Write a Python function which uses the solution to Problem 2 to find the determinant of A .