CS224N
Python Introduction

Plan for Today

- Intro to Python
- Installing Python
- Python Syntax
- Numpy
- Python Demo

Intro to Python

What is Python?

- General-purpose, high-level scripting language
- Used for a wide variety of purposes including networking and web applications
- Most popular in the scientific community for its ease of use

Pros vs Cons

- Pros:
    - Easy to understand and write, very similar to English
    - Works across systems (Windows, Mac, Linux)
    - Object Oriented
    - Really great standard library
    - Dynamically typed?

- Cons:
    - Python can be slow
    - Not great for mobile development
    - Dynamically typed?

Installing Python

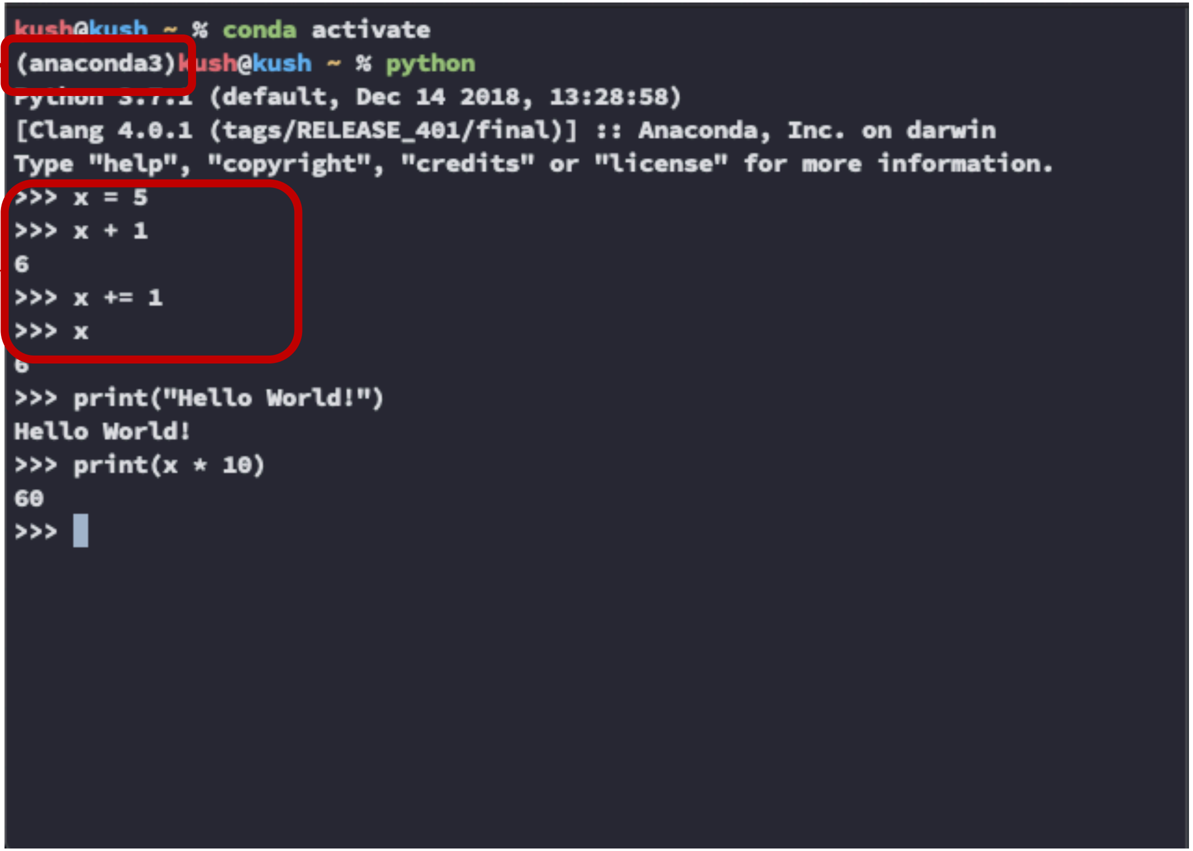
Installing and Running Python

- Download from Anaconda: https://www.anaconda.com/distribution/
  - Includes Python, as well as several packages for scientific computing
- In your terminal, start up the Anaconda installation of Python:
  - `conda activate`
- Because Python is a scripting language, you can try it out right in the terminal; just type: `python`
- Follow instructions on Assign1 to create ‘environments’
  - Help keep your projects separated so there aren’t conflicting installations!

Check Your Installation

Which environment I am using (this is the default)

Python in the terminal! This will be helpful for Numpy when you want to test broadcasting (more on this later)



```
kush@kush ~ % conda activate
(anaconda3) kush@kush ~ % python
Python 3.7.1 (default, Dec 14 2018, 13:28:58)
[Clang 4.0.1 (tags/RELEASE_401/final)] :: Anaconda, Inc. on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>> x = 5
>>> x + 1
6
>>> x += 1
>>> x
6
>>> print("Hello World!")
Hello World!
>>> print(x * 10)
60
>>> 
```

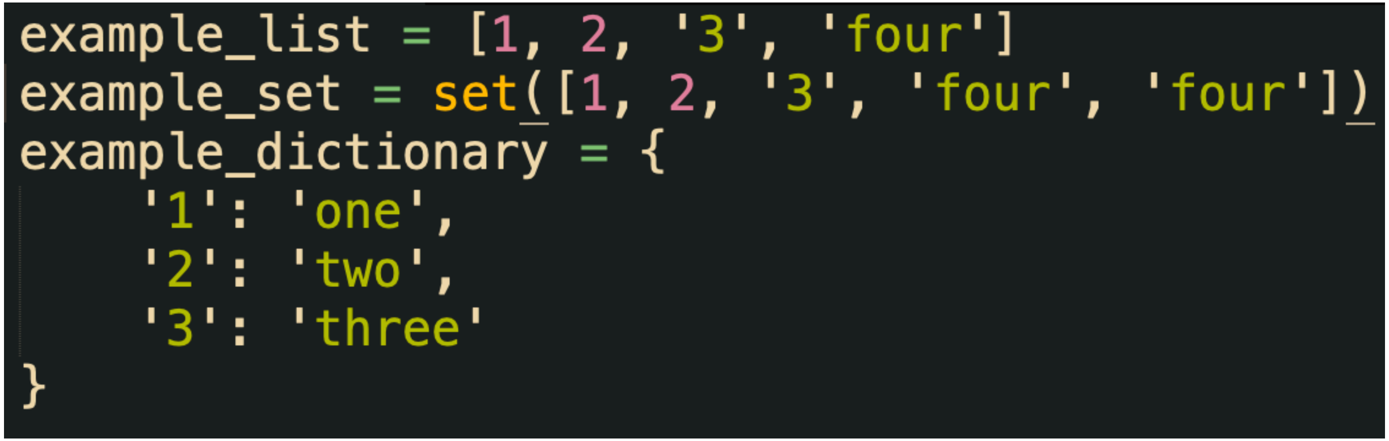
Writing Programs

- For longer tasks, probably want to write in a program that you can run on command
- To write programs, people often use IDEs
  - Pycharm (can get professional version for free since you are a student!)
  - Sublime (after modification with plugins)
  - VSCode (after modification with plugins)
- IDEs include lots of nice bells and whistles like code completion, syntax checking and a debugger
- If you choose to just use a text editor, you can run your program from the terminal by using the command:

```
python <filename>.py
```

Basic Python

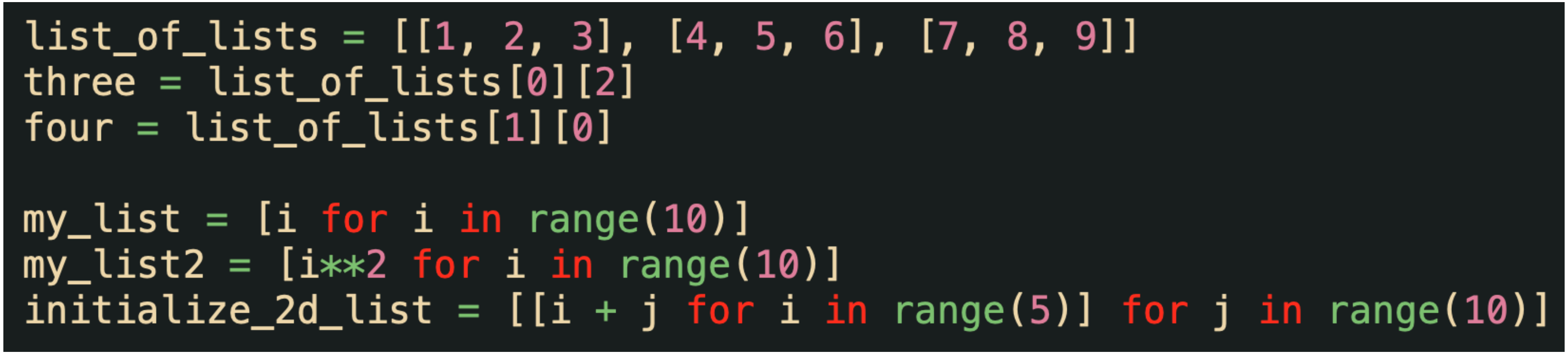
Basic data structures



```python
example_list = [1, 2, '3', 'four']
example_set = set([1, 2, '3', 'four', 'four'])
example_dictionary = {
    '1': 'one',
    '2': 'two',
    '3': 'three'
}
```

- None of these types have a fixed type: can contain anything
- Sets will remove duplicates; only one copy of ‘four’

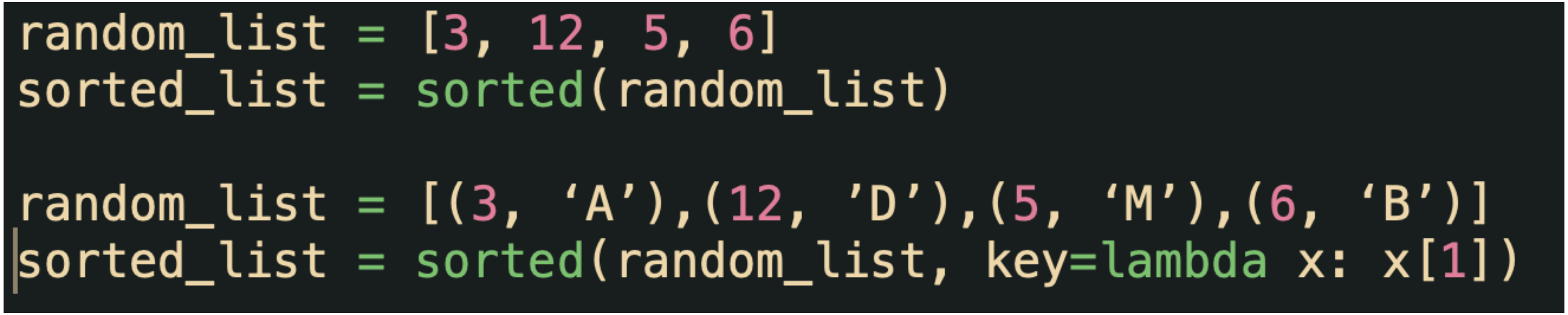
More on Lists



```
list_of_lists = [[1, 2, 3], [4, 5, 6], [7, 8, 9]]
three = list_of_lists[0][2]
four = list_of_lists[1][0]

my_list = [i for i in range(10)]
my_list2 = [i**2 for i in range(10)]
initialize_2d_list = [[i + j for i in range(5)] for j in range(10)]
```

- Can easily create 2D arrays and then index into them
- List comprehensions are a slick way to create lists

Sorting Lists



```
random_list = [3, 12, 5, 6]
sorted_list = sorted(random_list)

random_list = [(3, ‘A’),(12, ’D’),(5, ‘M’),(6, ‘B’)]
sorted_list = sorted(random_list, key=lambda x: x[1])
```

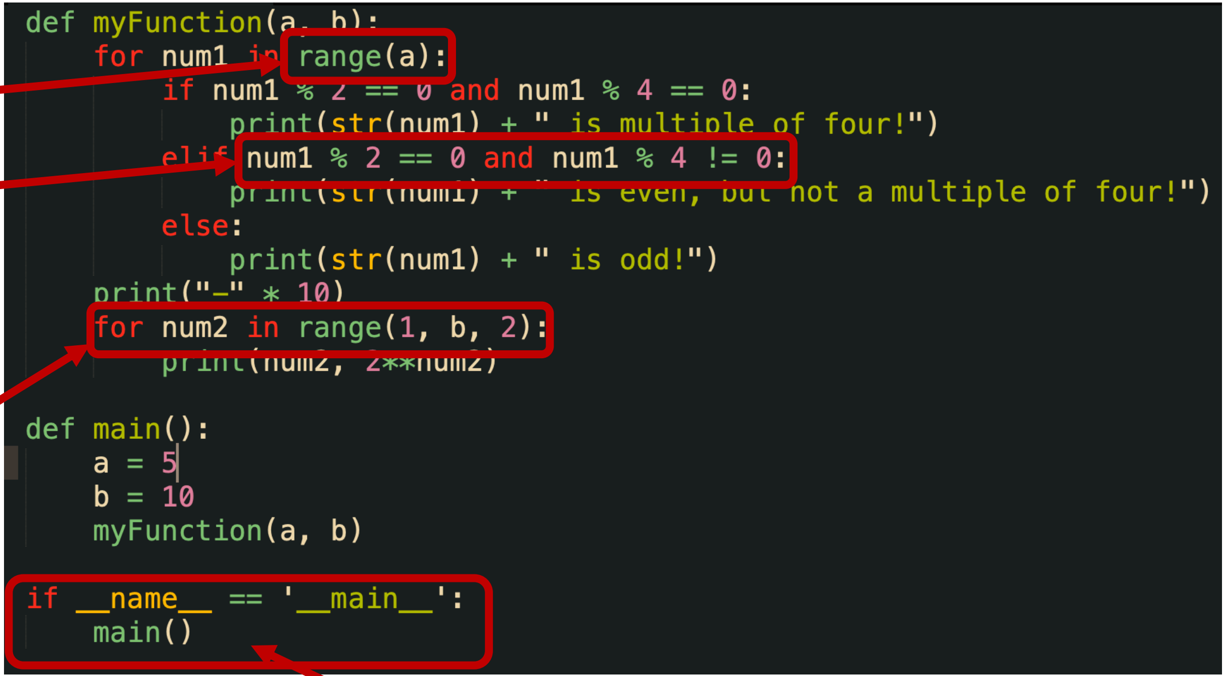
- Sorted function lets you sort a list
- Has additional ‘key’ parameter to which you can pass a function that tells sorted how to compare
- For more details, look up ‘lambda functions’

Functions, Loops and Control Flow

Integers in [0, a)

Boolean statements

Integers from 1 (inclusive) to b (exclusive), counting by 2



```python
def myFunction(a, b):
    for num1 in range(a):
        if num1 % 2 == 0 and num1 % 4 == 0:
            print(str(num1) + " is multiple of four!")
        elif num1 % 2 == 0 and num1 % 4 != 0:
            print(str(num1) + " is even, but not a multiple of four!")
        else:
            print(str(num1) + " is odd!")
    print("-" * 10)
    for num2 in range(1, b, 2):
        print(num2, 2**num2)

def main():
    a = 5
    b = 10
    myFunction(a, b)

if __name__ == '__main__':
    main()
```

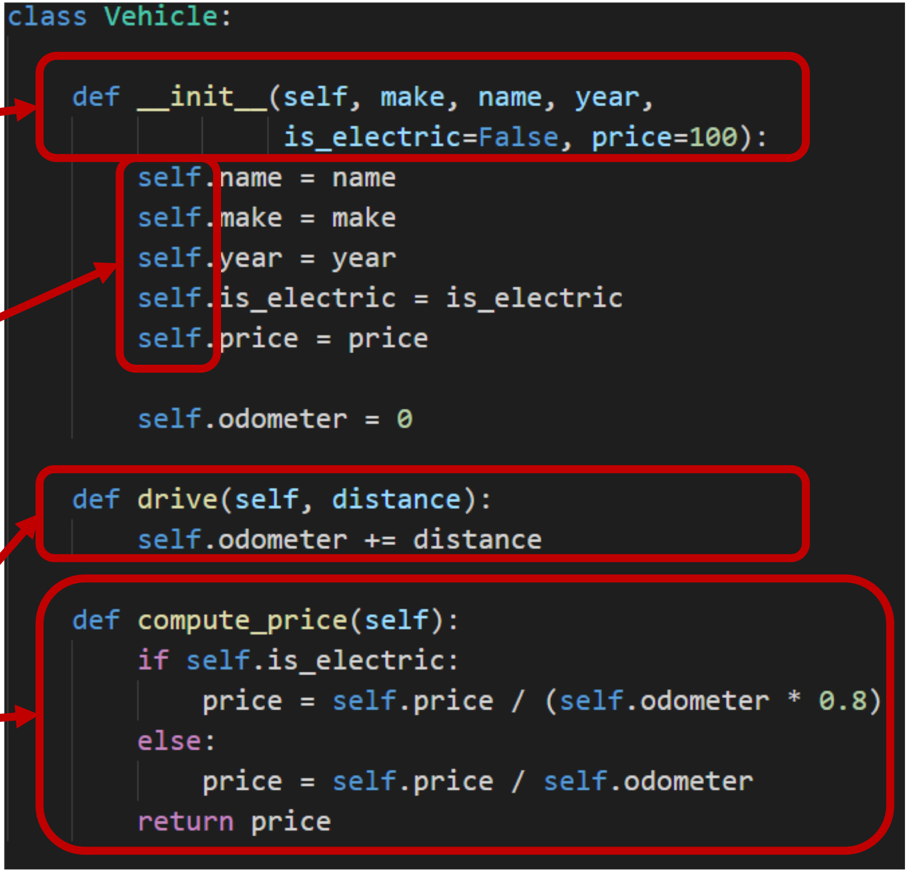
If called from command line

Classes

Initialize the class to get an **instance** using some parameters

Instance variable

Does something with the **instance**



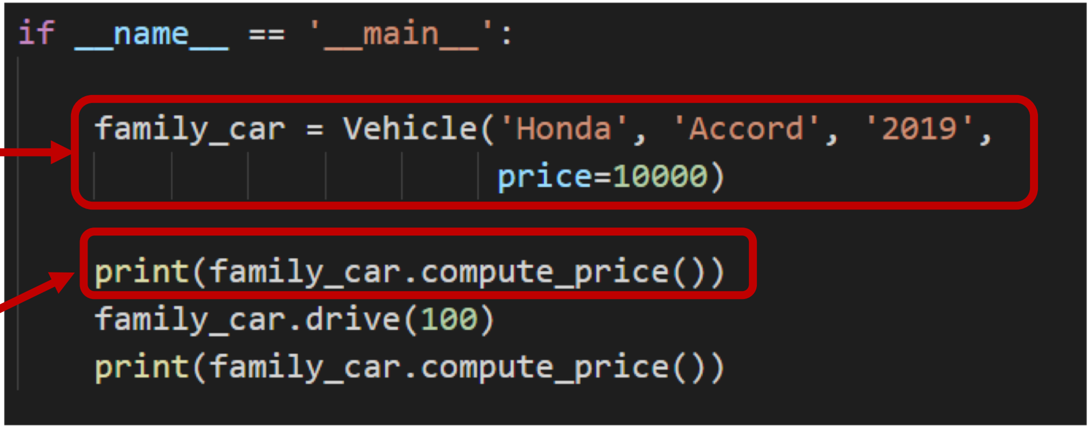
```python
class Vehicle:

    def __init__(self, make, name, year,
                 is_electric=False, price=100):
        self.name = name
        self.make = make
        self.year = year
        self.is_electric = is_electric
        self.price = price

        self.odometer = 0

    def drive(self, distance):
        self.odometer += distance

    def compute_price(self):
        if self.is_electric:
            price = self.price / (self.odometer * 0.8)
        else:
            price = self.price / self.odometer
        return price
```

To use a class

Instantiate a class,

get an **instance**

Call an instance method



```
if __name__ == '__main__':

    family_car = Vehicle('Honda', 'Accord', '2019',
                         price=10000)

    print(family_car.compute_price())
    family_car.drive(100)
    print(family_car.compute_price())
```

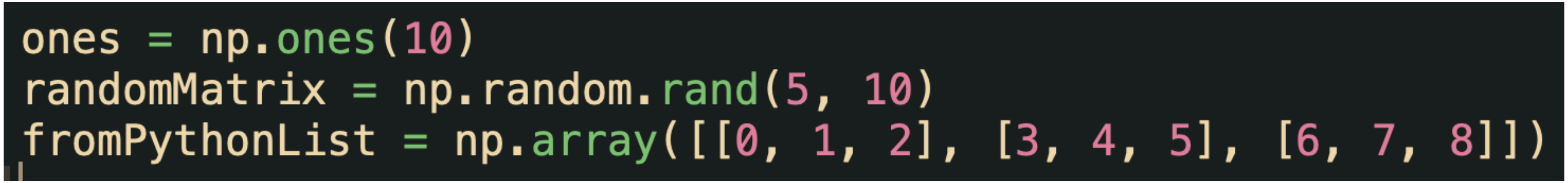
Numpy & Scipy

What is Numpy? What is Scipy?

- Numpy – package for vector and matrix multiplication
- Scipy – package for scientific and technical computing
- The main advantage of numpy and scipy are their speed
- Speed comes from efficient memory representation and low-level machine instructions

Ndarray

- Most important structure in numpy
- Can only contain one type of value
- Extremely fast
- Used to represent vectors, matrices, tensors
- Calling myArray.shape will return a tuple of integers that represent the shape of the ndarray – very important!

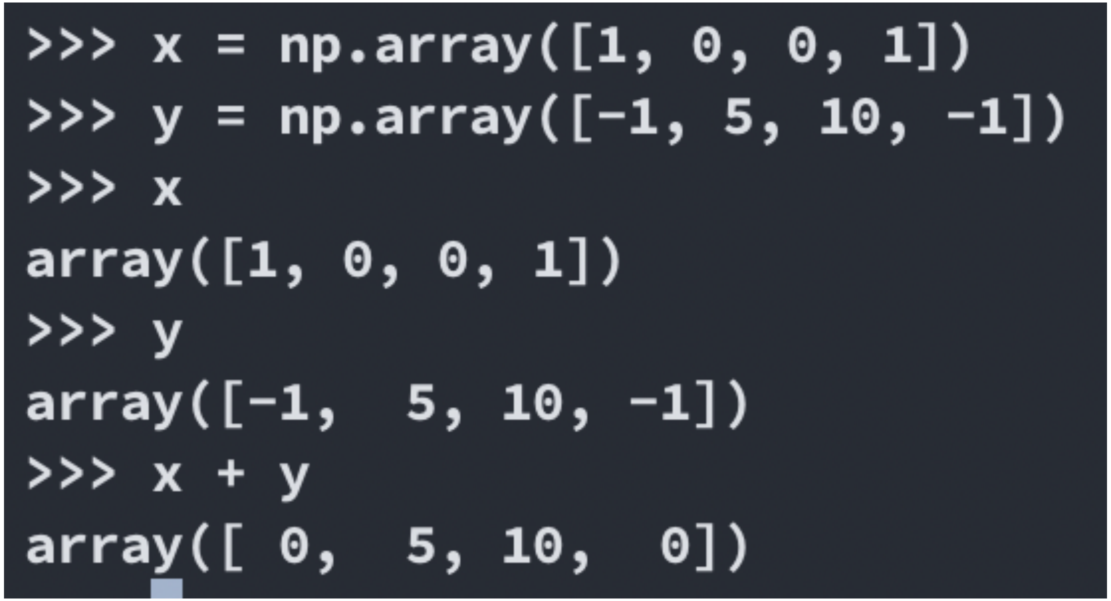


```
ones = np.ones(10)
randomMatrix = np.random.rand(5, 10)
fromPythonList = np.array([[0, 1, 2], [3, 4, 5], [6, 7, 8]])
```

Ndarray – Addition (same shape)

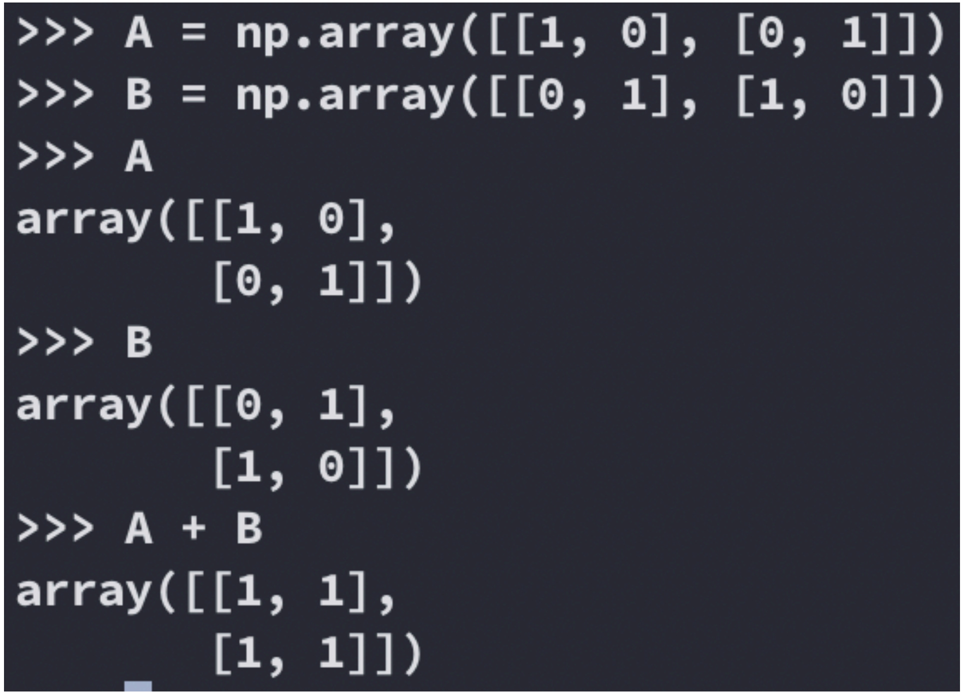
- When two Ndarrays are the same shape, addition acts exactly as you would expect: component wise!
- We will discuss the case when they are not the same shape later

Ndarray – Addition (same shape, example 1)



```
>>> x = np.array([1, 0, 0, 1])
>>> y = np.array([-1, 5, 10, -1])
>>> x
array([1, 0, 0, 1])
>>> y
array([-1,  5, 10, -1])
>>> x + y
array([ 0,  5, 10,  0])
```

Ndarray – Addition (same shape, example 2)

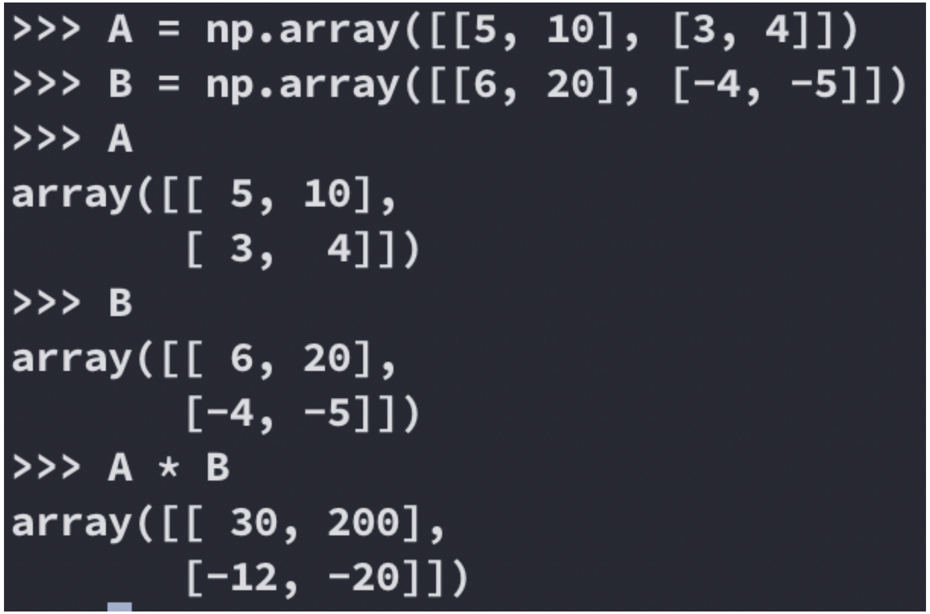


```
>>> A = np.array([[1, 0], [0, 1]])
>>> B = np.array([[0, 1], [1, 0]])
>>> A
array([[1, 0],
       [0, 1]])
>>> B
array([[0, 1],
       [1, 0]])
>>> A + B
array([[1, 1],
       [1, 1]])
```

Ndarray – Component-Wise Multiplication (same shape)

- When two ndarrays are the same dimension and you use the python multiplication operator (*) you get component-wise multiplication, not matrix multiplication!
- When we get to neural networks, we will see that this Hadamard product is very important

Ndarray – Component-Wise Multiplication (same shape, example 1)



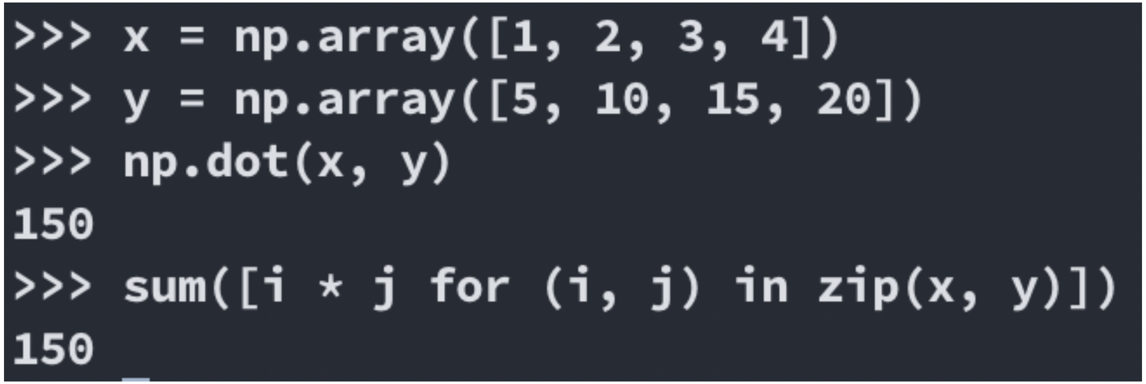
```
>>> A = np.array([[5, 10], [3, 4]])
>>> B = np.array([[6, 20], [-4, -5]])
>>> A
array([[ 5, 10],
       [ 3,  4]])
>>> B
array([[ 6, 20],
       [-4, -5]])
>>> A * B
array([[ 30, 200],
       [-12, -20]])
```

Ndarray – np.dot

- Vector-Vector, Matrix-Vector and Matrix-Matrix products are calculated using np.dot()
- As with most numpy functions, they behave differently depending on the shapes of the input; we will look at the most common uses

Ndarray – np.dot with two vectors

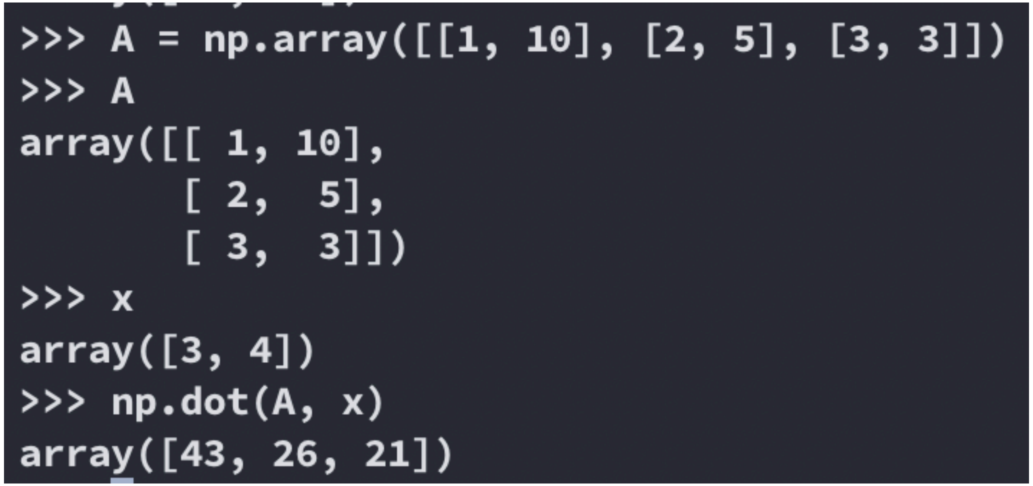
- When the two inputs to np.dot() are both 1d vectors, then the result is the standard dot product



```
>>> x = np.array([1, 2, 3, 4])
>>> y = np.array([5, 10, 15, 20])
>>> np.dot(x, y)
150
>>> sum([i * j for (i, j) in zip(x, y)])
150
```

Ndarray – np.dot with matrix and vector

- In this case, np.dot() acts as matrix-vector multiplication
- Note that dimensions matter!

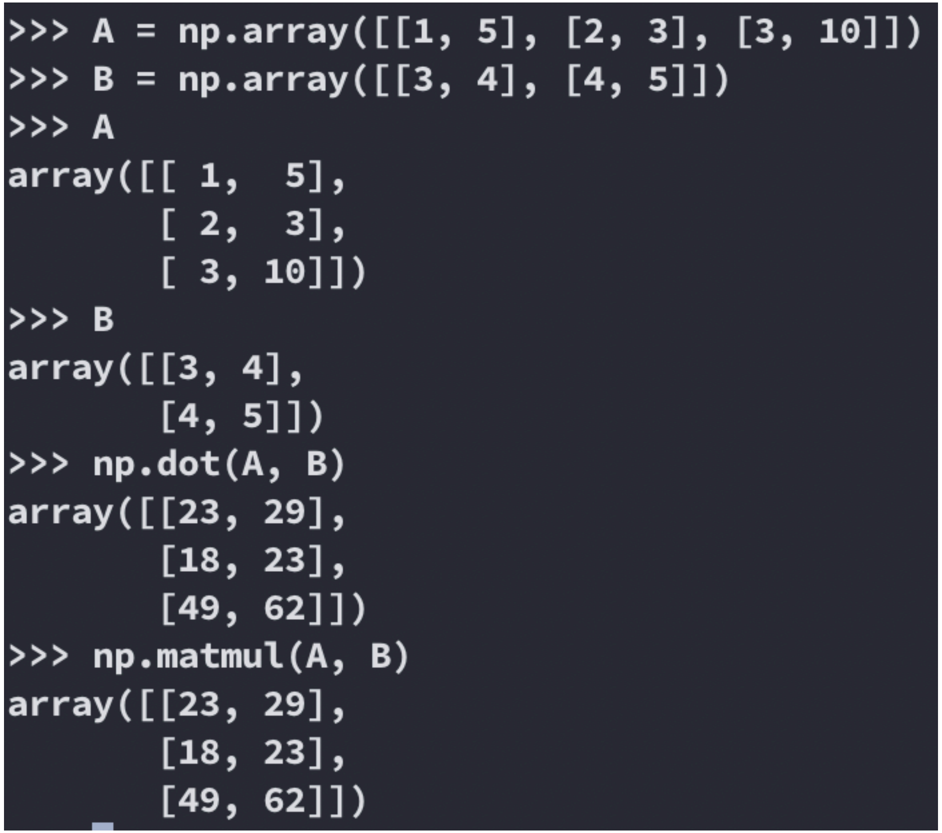


```
>>> A = np.array([[1, 10], [2, 5], [3, 3]])
>>> A
array([[ 1, 10],
       [ 2,  5],
       [ 3,  3]])
>>> x
array([3, 4])
>>> np.dot(A, x)
array([43, 26, 21])
```

Ndarray – np.dot with two matrices

- Here, we have standard matrix multiplication
- However, numpy documentation says that it is preferable to use np.matmul()

Ndarray – np.dot with two matrices (example)



```
>>> A = np.array([[1, 5], [2, 3], [3, 10]])
>>> B = np.array([[3, 4], [4, 5]])
>>> A
array([[ 1,  5],
       [ 2,  3],
       [ 3, 10]])
>>> B
array([[3, 4],
       [4, 5]])
>>> np.dot(A, B)
array([[23, 29],
       [18, 23],
       [49, 62]])
>>> np.matmul(A, B)
array([[23, 29],
       [18, 23],
       [49, 62]])
```

Broadcasting

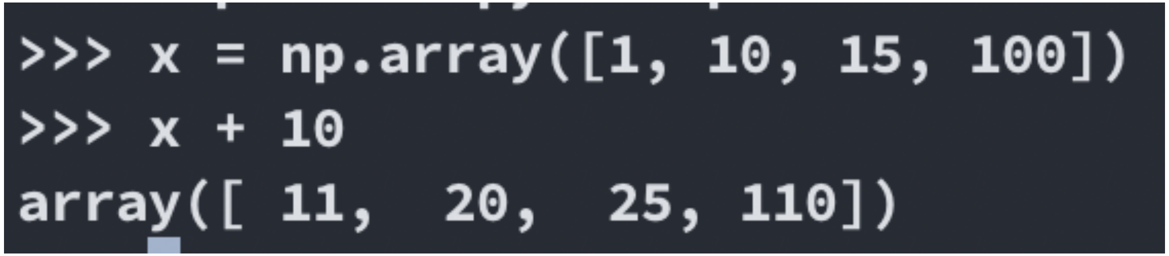
- In math, operations like dot products and matrix addition require the samec dimensions. In numpy, this is not the case
- Up until now, we have used 1d and 2d ndarrays, representing vectors and matrices, and numpy acts as we would expect
- However, the operations we have described work even when the two inputs do not have ‘standard’ shapes, given by a set of very specific rules

General Broadcasting Rules

- Write out the shapes of each ndarray
- Starting from the back, that dimension has compatible values if either:
  - They are the same value, or
  - One of them is a 1
- The size of the resulting array is the maximum along each dimension
- Note: the two ndarrays do not need to have the same number of dimensions

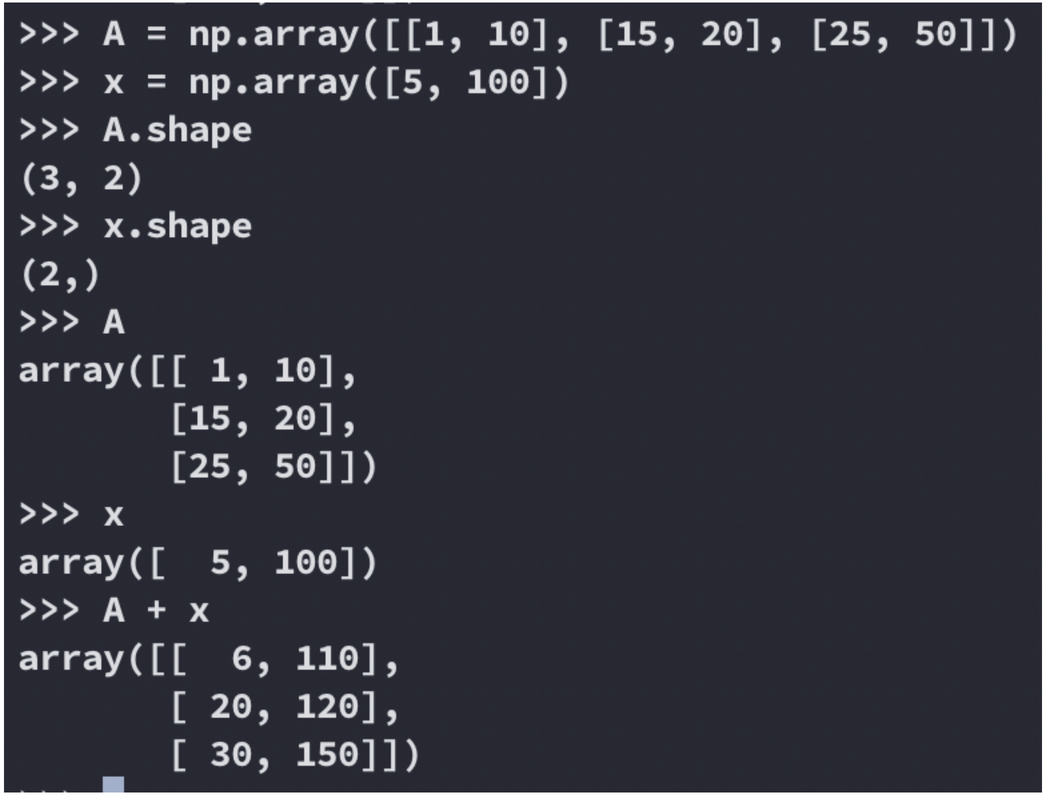
Broadcasting – Example 1 (easiest)

- In this case, we add a scalar to an ndarray
- Numpy automatically adds the scalar to every single element



```
>>> x = np.array([1, 10, 15, 100])
>>> x + 10
array([ 11,  20,  25, 110])
```

Broadcasting – Example 2 (medium)



```
>>> A = np.array([[1, 10], [15, 20], [25, 50]])
>>> x = np.array([5, 100])
>>> A.shape
(3, 2)
>>> x.shape
(2,)
>>> A
array([[ 1, 10],
       [15, 20],
       [25, 50]])
>>> x
array([  5, 100])
>>> A + x
array([[  6, 110],
       [ 20, 120],
       [ 30, 150]])
```

Broadcasting – Example 3 (hardest)

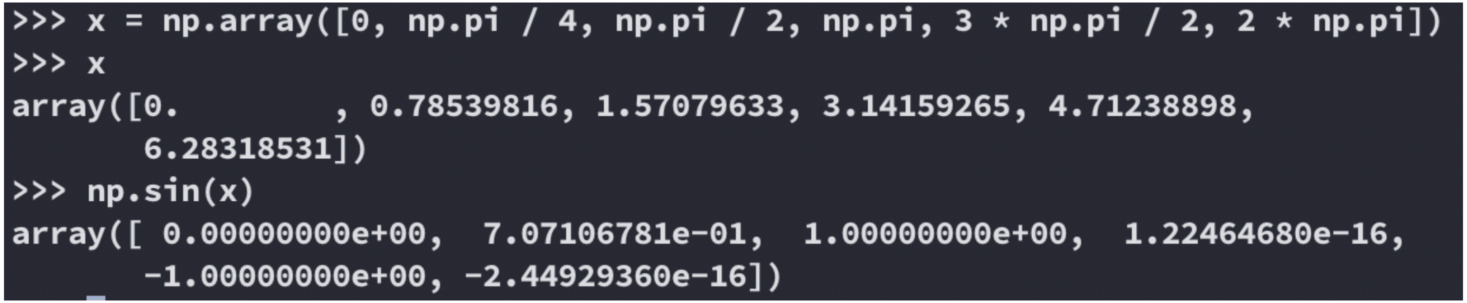
- From the np.matmul() documentation:
  - If either argument is N-D, N > 2, it is treated as a stack of matrices residing in the last two indexes and broadcast accordingly.
- What will be the dimension of the output for a call with the following shapes?
  - (1, 5, 6), (6, 7)
  - (3, 5, 6), (6, 7)
  - (3, 5, 6), (3, 6, 7)
  - (3, 4, 5, 6), (6, 7)
  - (3, 4, 5, 6), (4, 6, 7)
  - (3, 4, 5, 6), (1, 4, 6, 7)

Broadcasting – Example 3 (hardest, one answer)

- Take the fifth example, the shapes are (3, 4, 5, 6) and (4, 6, 7)
- According to the documentation, the last two dimensions represent matrices, so we take those out and broadcast the rest: (3, 4) and (4,)
- Using our broadcasting rules, the result of broadcasting these shapes will be (3, 4)
- Matrix multiplication results in a matrix of shape (5, 7)
- Our output will have shape (3, 4, 5, 7)

Mathematical Functions on Ndarrays

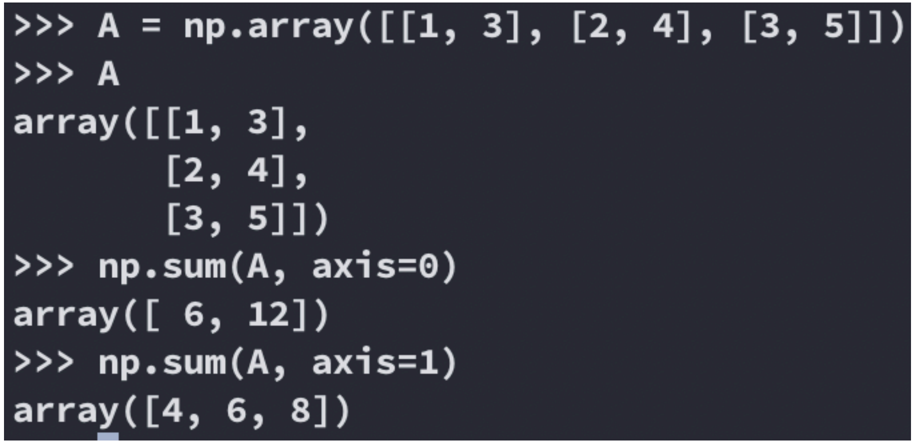
- Numpy has a wide array of mathematical functions that you can apply to arrays



```
>>> x = np.array([0, np.pi / 4, np.pi / 2, np.pi, 3 * np.pi / 2, 2 * np.pi])
>>> x
array([0.        , 0.78539816, 1.57079633, 3.14159265, 4.71238898,
       6.28318531])
>>> np.sin(x)
array([ 0.00000000e+00,  7.07106781e-01,  1.00000000e+00,  1.22464680e-16,
       -1.00000000e+00, -2.44929360e-16])
```

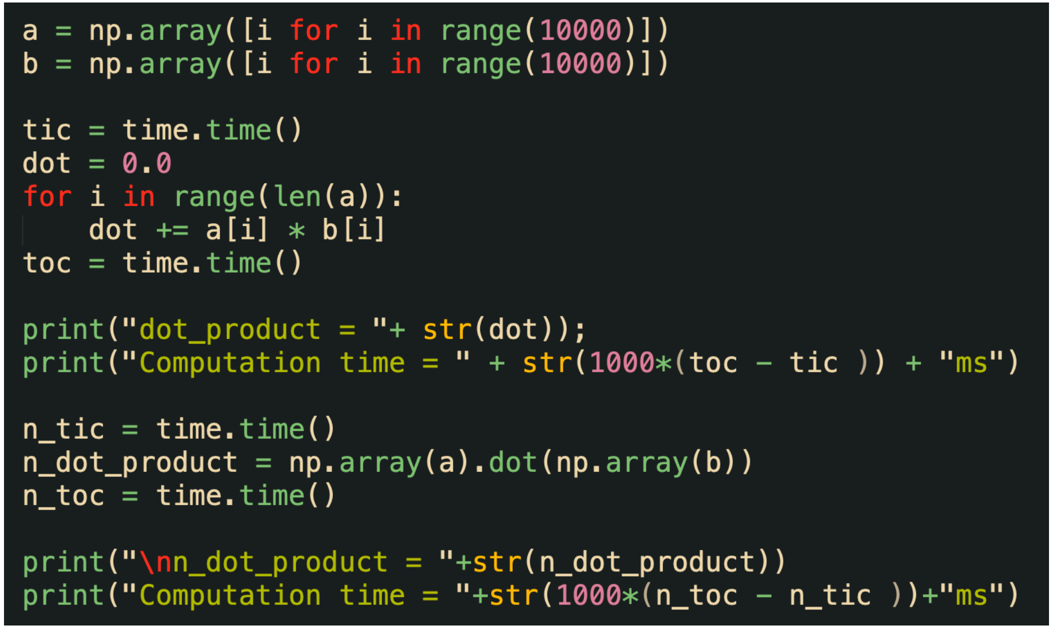
Mathematical Functions on Ndarrays – cont.

- Some functions, like sum and max, can be applied along a given axis
- Applying along that dimension gets rid of that dimension, and replaces it with the function applied across that dimension

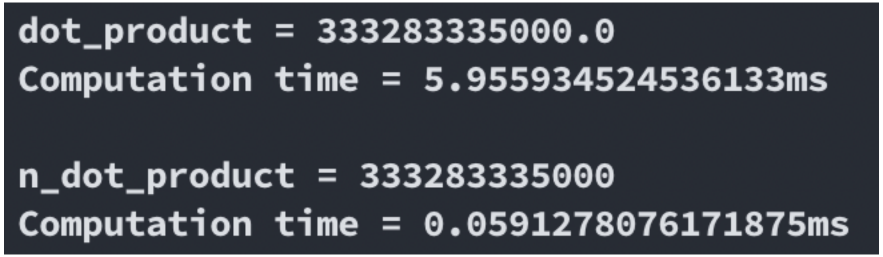


```
>>> A = np.array([[1, 3], [2, 4], [3, 5]])
>>> A
array([[1, 3],
       [2, 4],
       [3, 5]])
>>> np.sum(A, axis=0)
array([ 6, 12])
>>> np.sum(A, axis=1)
array([4, 6, 8])
```

Numpy Speed – Dot Product

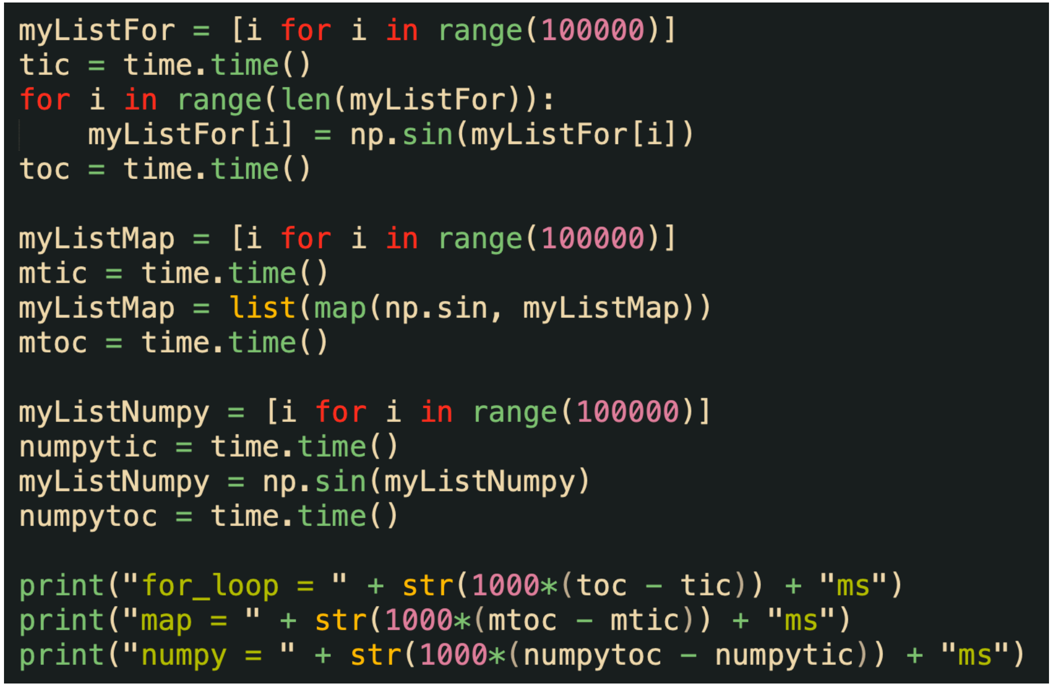


```python
a = np.array([i for i in range(10000)])
b = np.array([i for i in range(10000)])

tic = time.time()
dot = 0.0
for i in range(len(a)):
    dot += a[i] * b[i]
toc = time.time()

print("dot_product = "+ str(dot));
print("Computation time = " + str(1000*(toc - tic )) + "ms")

n_tic = time.time()
n_dot_product = np.array(a).dot(np.array(b))
n_toc = time.time()

print("\nn_dot_product = "+str(n_dot_product))
print("Computation time = "+str(1000*(n_toc - n_tic ))+"ms")
```

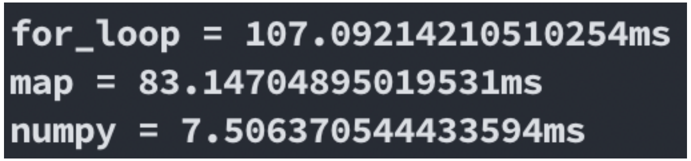


```
dot_product = 333283335000.0
Computation time = 5.955934524536133ms

n_dot_product = 333283335000
Computation time = 0.05912780761718 75ms
```

Numpy Speed – Applying a Function



```
myListFor = [i for i in range(100000)]
tic = time.time()
for i in range(len(myListFor)):
    myListFor[i] = np.sin(myListFor[i])
toc = time.time()

myListMap = [i for i in range(100000)]
mtic = time.time()
myListMap = list(map(np.sin, myListMap))
mtoc = time.time()

myListNumpy = [i for i in range(100000)]
numpytic = time.time()
myListNumpy = np.sin(myListNumpy)
numpytoc = time.time()

print("for_loop = " + str(1000*(toc - tic)) + "ms")
print("map = " + str(1000*(mtoc - mtic)) + "ms")
print("numpy = " + str(1000*(numpytoc - numpytic)) + "ms")
```



```
for_loop = 107.0921421051O254ms
map = 83.14704895019531ms
numpy = 7.506370544433594ms
```

Popular usage, read before use!

Python Command	Description
scipy.linalg.inv	Inverse of matrix (numpy as equivalent)
scipy.linalg.eig	Get eigen value (Read documentation on eigh and numpy equivalent)
scipy.spatial.distance	Compute pairwise distance
np.matmul	Matrix multiply
np.zeros	Create a matrix filled with zeros (Read on np.ones)
np.arange	Start, stop, step size (Read on np.linspace)
np.identity	Create an identity matrix
np.vstack	Vertically stack 2 arrays (Read on np.hstack)

Your friend for debugging

Python Command	Description
array.shape	Get shape of numpy array
array.dtype	Check data type of array (for precision, for weird behavior)
type(stuff)	Get type of a variable
import pdb; pdb.set_trace()	Set a breakpoint (https://docs.python.org/3/library/pdb.html)
print(f’My name is {name}’)	Easy way to construct a message

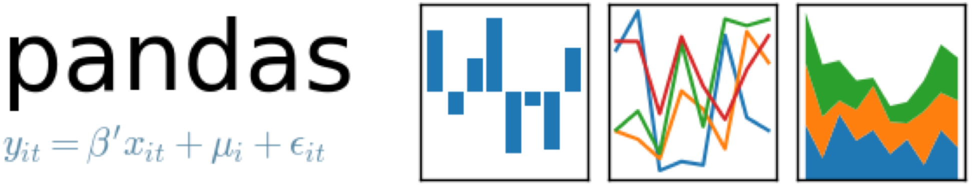
Advice

- If you are unsure how an operation will work on ndarrays of a certain shape, try it out!
- Create random matrices that have the shape you are looking at, do the operation, and check the shape of the output
- Python scripting in the terminal is great for this!

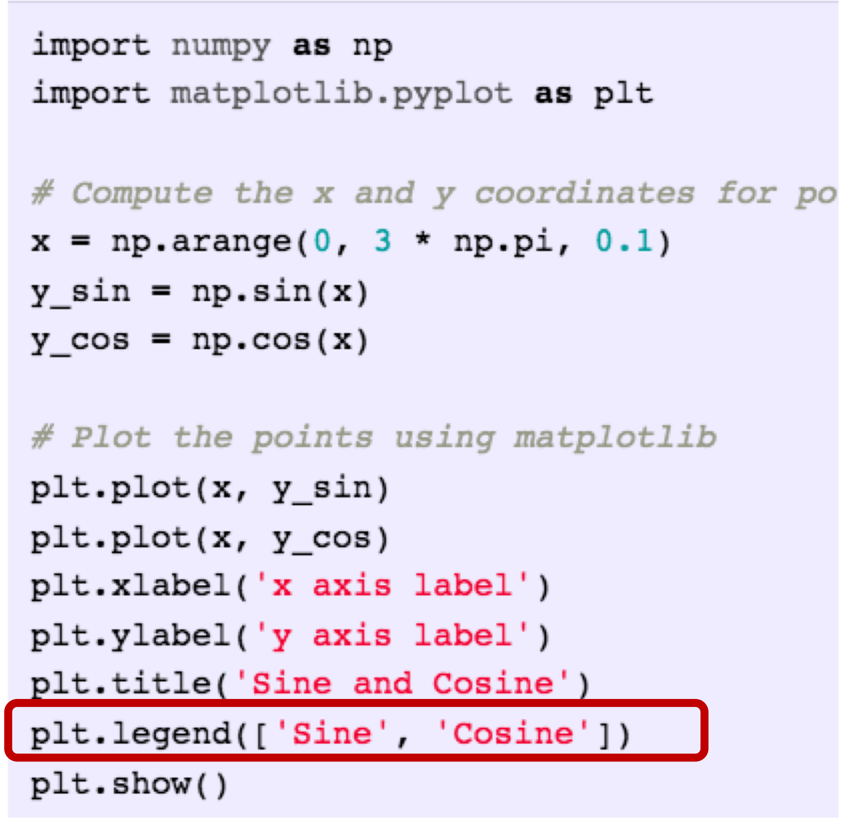
Plotting

More Tools

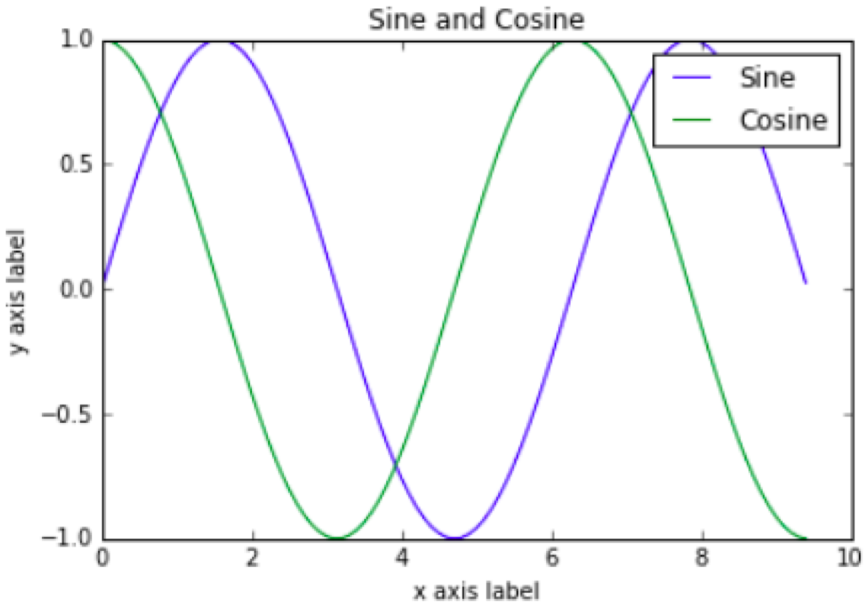
- Scatter plot
- Line plot
- Bar plot (Histogram)
- 3D plot



Plotting Functions



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

# Compute the x and y coordinates for po
x = np.arange(0, 3 * np.pi, 0.1)
y_sin = np.sin(x)
y_cos = np.cos(x)

# Plot the points using matplotlib
plt.plot(x, y_sin)
plt.plot(x, y_cos)
plt.xlabel('x axis label')
plt.ylabel('y axis label')
plt.title('Sine and Cosine')
plt.legend(['Sine', 'Cosine'])
plt.show()
```



Python Live Demo in PyCharm

- Calculate the eigenvector associated with the dominant eigenvalue
- Use the power iteration method:
- $b_{k+1} = \frac{Ab_k}{||Ab_k||}$
- (If not at live session, can download the code from course website)

Links

Python Documentation

Numpy Reference

CS 231N Python Tutorial

Download Pycharm