Programming Principles in Python (CSCI 503/490)

Arrays

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CPU-Bound vs. I/O-Bound



Threading

- Threading address the I/O waits by letting separate pieces of a program run at the same time
- Threads run in the same process
- Threads share the same memory (and global variables)
- Operating system schedules threads; it can manage when each thread runs, e.g. round-robin scheduling
- When blocking for I/O, other threads can run













Python Threading Speed

- If I/O bound, threads work great be used by other threads
- Threads do not run simultaneously in standard Python, i.e. they cannot take advantage of multiple cores
- Use threads when code is I/O bound, otherwise no real speed-up plus some overhead for using threads

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• If I/O bound, threads work great because time spent waiting can now be





Python and the GIL

- Solution for reference counting (used for garbage collection)
 Could add locking to every value/data structure, but with multiple locks
- Could add locking to every value/date
 comes possible deadlock
- Python instead has a Global Interpreter Lock (GIL) that must be acquired to execute any Python code
- This effectively makes Python single-threaded (faster execution)
- Python requires threads to give up GIL after certain amount of time
- Python 3 improved allocation of GIL to threads by not allowing a single CPUbound thread to hog it

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Multiprocessing

- most cases
- Big win: can take advantage of multiple cores!

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Multiple processes do not need to share the same memory, interact less Python makes the difference between processes and threads minimal in









Multiprocessing using concurrent.futures

- import concurrent.futures import multiprocessing as mp import time
 - def dummy(num): time.sleep(5) return num ** 2
 - - results = executor.map(dummy, range(10))
- mp.get context('fork') changes from 'spawn' used by default in MacOS, works in notebook

with concurrent.futures.ProcessPoolExecutor(max workers=5, mp context=mp.get context('fork')) as executor:





asyncio

- Single event loop that controls when each task is run
- Tasks can be ready or waiting
- Tasks are **not interrupted** like they are with threading - Task controls when control goes back to the main event loop

 - Either waiting or complete
- Event loop keeps track of whether tasks are ready or waiting - Re-checks to see if new tasks are now ready - Picks the task that has been waiting the longest
- async and await keywords
- Requires support from libraries (e.g. aiohttp)









When to use threading, asyncio, or multiprocessing?

- If your code has a lot of I/O or Network usage:
 - If there is library support, use asyncio
 - Otherwise, multithreading is your best bet (lower overhead)
- If you have a GUI
 - Multithreading so your UI thread doesn't get locked up
- If your code is CPU bound:
 - You should use multiprocessing (if your machine has multiple cores)











Concurrency Comparison

Concurrency Type	Switching Decision	Number o Processor
Pre-emptive multitasking (threading)	The operating system decides when to switch tasks external to Python.	
Cooperative multitasking (asyncio)	The tasks decide when to give up control.	
Multiprocessing (multiprocessing)	The processes all run at the same time on different processors.	Man













<u>Assignment 6</u>

- Object-Oriented Programming & Exceptions
- Classes for an online market
- Use inheritance
- Due today





Assignment 7

- Soon...
- Concurrency, Arrays







What is the difference between an array and a list (or a tuple)?





Arrays

- Usually a fixed size—lists are meant to change size
- Are mutable—tuples are not
- Store only one type of data—lists and tuples can store any combination • Are faster to access and manipulate than lists or tuples
- Can be multidimensional:

 - Can have list of lists or tuple of tuples but no guarantee on shape - Multidimensional arrays are rectangles, cubes, etc.





Why NumPy?

- Fast vectorized array operations for data munging and cleaning, subsetting and filtering, transformation, and any other kinds of computations
- Common array algorithms like sorting, unique, and set operations Efficient descriptive statistics and aggregating/summarizing data
- Data alignment and relational data manipulations for merging and joining together heterogeneous data sets
- Expressing conditional logic as array expressions instead of loops with ifelif-else branches
- Group-wise data manipulations (aggregation, transformation, function) application).





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import numpy as np





Creating arrays

- data1 = [6, 7, 8, 0, 1]arr1 = np.array(data1)
- data2 = [[1.5,2,3,4], [5,6,7,8]]arr2 = np.array(data2)
- data3 = np.array([6, "abc", 3.57]) # !!! check !!!
- Can check the type of an array in dtype property
- Types:
 - arr1.dtype # dtype('int64')
 - arr3.dtype # dtype('<U21'), unicode plus # chars





lypes

- "But I thought Python wasn't stingy about types..."
- numpy aims for speed
- Able to do array arithmetic
- int16, int32, int64, float32, float64, bool, object
- Can specify type explicitly
 - arr1 float = np.array(data1, dtype='float64')
- astype method allows you to convert between different types of arrays:

arr = np.array([1, 2, 3, 4, 5])arr.dtype float arr = arr.astype(np.float64)





numpy data types (dtypes)

Туре	Type code	Descriptio
int8, uint8	i1, u1	Signed an
int16, uint16	i2, u2	Signed an
int32, uint32	i4, u4	Signed an
int64, uint64	i8, u8	Signed an
float16	f2	Half-precis
float32	f4 or f	Standard s
float64	f8 or d	Standard (
		Python +
float128	f16 or g	Extended-
complex64,	c8, c16,	Complex r
complex128,	c32	
complex256		
bool	?	Boolean ty
object	0	Python ob
string_	S	Fixed-leng
		string dty
unicode_	U	Fixed-leng specificati

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- nd unsigned 8-bit (1 byte) integer types
- nd unsigned 16-bit integer types
- nd unsigned 32-bit integer types
- nd unsigned 64-bit integer types
- ision floating point
- single-precision floating point; compatible with C float
- double-precision floating point; compatible with C double and
- loat object
- -precision floating point
- numbers represented by two 32, 64, or 128 floats, respectively
- ype storing True and False values
- bject type; a value can be any Python object
- gth ASCII string type (1 byte per character); for example, to create a pe with length 10, use 'S10'
- gth Unicode type (number of bytes platform specific); same
- ion semantics as string_(e.g., 'U10')

[W. McKinney, Python for Data Analysis]









Array Shape

- Our normal way of checking the size of a collection is... len
- How does this work for arrays?
- arr1 = np.array([1,2,3,6,9]) len(arr1) # 5
- arr2 = np.array([[1.5,2,3,4],[5,6,7,8]])len(arr2) # 2
- All dimension lengths \rightarrow shape: arr2.shape # (2,4)
- Number of dimensions: arr2.ndim # 2
- Can also reshape an array:
 - arr2.reshape(4,2)
 - arr2.reshape(-1,2) # what happens here?







Speed Benefits

- Compare random number generation in pure Python versus numpy
- Python:
 - import random %timeit rolls list = [random.randrange(1,7)
- With NumPy:
 - %timeit rolls array = np.random.randint(1, 7, 60 000)
- Significant speedup (80x+)

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for i in range(0, 60 000)]









Array Programming

- Lists:
 - C = [] for i in range(len(a)): c.append(a[i] + b[i])
- How to improve this?









Array Programming

- Lists:
 - C = | | for i in range(len(a)): c.append(a[i] + b[i])
 - -c = [aa + bb for aa, bb in zip(a,b)]
- NumPy arrays:
 - -c = a + b
- More functional-style than imperative
- Internal iteration instead of external









Operations

- a = np.array([1, 2, 3])b = np.array([6, 4, 3])
- (Array, Array) Operations (**Element-wise**)
 - Addition, Subtraction, Multiplication
 - -a + b # array([7, 6, 6])
- (Scalar, Array) Operations (**Broadcasting**):
 - Addition, Subtraction, Multiplication, Division, Exponentiation
 - a ** 2 # array([1, 4, 9])
 - -b + 3 # array([9, 7, 6])







More on Array Creation

- Zeros: np.zeros(10)
- Ones: np.ones((4,5)) # shape
- Empty: np.empty((2,2))
- _like versions: pass an existing array and matches shape with specified contents
- Range: np.arange(15) # constructs an array, not iterator!







Indexing

- Same as with lists plus shorthand for 2D+
 - $\operatorname{arr1} = \operatorname{np.array}([6, 7, 8, 0, 1])$
 - arr1[1]
 - arr1[-1]
- What about two dimensions?
 - $\operatorname{arr2} = \operatorname{np.array}([[1.5, 2, 3, 4], [5, 6, 7, 8]])$
 - arr[1][1]
 - arr[1,1] # shorthand









2D Indexing



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	axis 1	
0	1	2
, 0	0, 1	0, 2
, 0	1, 1	1, 2
, 0	2, 1	2, 2

[W. McKinney, Python for Data Analysis]









Slicing

- 1D: Similar to lists
 - arr1 = np.array([6, 7, 8, 0, 1])
 - arr1[2:5] # np.array([8, 0, 1]), sort of
- Can **mutate** original array:
 - arr1[2:5] = 3 # supports assignment
 - arr1 # the original array changed
- Slicing returns views (copy the array if original array shouldn't change)
 - arr1[2:5] # a view
 - arr1[2:5].copy() # a new array









Slicing

- 2D+: comma separated indices as shorthand:
 - $\operatorname{arr2} = \operatorname{np.array}([[1.5, 2, 3, 4], [5, 6, 7, 8]])$
 - a[1:3,1:3]
 - a[1:3,:] # works like in single-dimensional lists
- Can combine index and slice in different dimensions
 - a[1,:] # gives a row
 - a[:,1] # gives a column









2D Array Slicing

How to obtain the blue slice from array arr?

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[W. McKinney, Python for Data Analysis]



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