PV248 Python

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Programming vs Languages

- python is **unobtrusive** (by design)
- if you can program, you can program in python
- there are idiosyncracies (of course)
- but you will mostly get by

Programming vs Jobs

- we all want to write beautiful programs
 - but you didn't sleep for 2 nights
 - and this thing is going into production tomorrow
- sometimes you get a chance to clean up later
 and sometimes you don't

Engineering Flowchart



Python makes for decent duct tape and WD 40.

In This Course

- you will not learn to write beautiful programs
- we will try to do things with minimum effort
 perfect is the enemy of good
- ugly comes in shades
 - you should always write passable code
 - there is a **balance** to strike

... ugly, cont'd

- there are two main schools of writing software do the right thing
 - worse is better
- https://www.jwz.org/doc/worse-is-better.html

The Right Thing

- simplicity: interface first, implementation second
- correctness: required
- consistency: required
- completeness: more important than simplicity

Worse is Better

- simplicity: implementation first
- correctness: simplicity goes first
- consistency: less important than both
- completeness: least important

Design Schools

- there are **pros** and **cons** to both
- right thing is often expensive
- worse is better often wins
- which one do you think python belongs to?

Disclaimer

- I am not a python programmer
- please don't ask sneaky language-lawyer questions

Goals

- learn to use python in practical situations
- have a look at existing packages and what they can do
- code up some cool stuff, have fun

Organisation

- the lecture and the seminars are every other week
- that's 7 lectures + 7 seminars
- there will be 6 homework assignments
- seminar attendance is semi-compulsory

Homework Grading

- grading will be fully automatic
 - performed every Thursday at midnight
 - starting 7 days after the assignment is given
- assignments are binary: pass/fail
- passing tests early gets you bonus points

Obtaining Points

- you can get up to
 - 12 points for assignments
 - 6 points for passing tests early
 - 2 points for seminar attendance
 - 3 points for peer reviews
 - 1 point for activity in the seminar
- you need 16 points to pass

Semester Plan

- 1. Object and Memory Model
- 2. Text, JSON, SQL and Persistence
- 3. Advanced Language Constructs
- 4. Numeric & Symbolic Math, Statistics
- 5. Communication, HTTP, asyncio
- 6. Testing, Debugging, Profiling & Pitfalls
- 7. Quantum Computation

Part 1: Object and Memory Model

Objects

- the basic 'unit' of OOP
- they bundle data and behaviour
- provide encapsulation
- make code re-use easier
- also known as 'instances'

Classes

- templates for objects (class Foo: pass)
- each (python) object belongs to a class
- classes themselves are also objects
- calling a class creates an instance
 - my_foo = Foo()

Poking at Classes

- {}.__class__
- {}.__class__.__class__
- (0).__class__
- [].__class__
- compare type(0), etc.
- n = numbers.Number(); n.__class__

Types vs Objects

- class system is a type system
- 'duck typing': quacks, walks like a duck
- since python 3, types are classes
- everything is dynamic in python
 - you can create new classes at runtime
 - you can pass classes as function parameters

Encapsulation

- objects hide implementation details
- classic types structure data
 - objects also structure behaviour
- facilitates weak coupling

Weak Coupling

- coupling is a degree of interdependence
- more coupling makes things harder to change
 it also makes reasoning harder
- good programs are weakly coupled
- cf. modularity, composability

Polymorphism

- objects are (at least in python) polymorphic
- different implementation, same interface
- only the interface matters for composition
- facilitates genericity and code re-use
- cf. 'duck typing'

Generic Programming

- code re-use often saves time
 - not just coding but also debugging
 - re-usable code often couples weakly
- but not everything that can be re-used should be
 - code can be too generic
 - and too hard to read

Attributes

- data members of objects
- each instance gets its own copy
- like variables scoped to object lifetime
- they get names and values

Methods

- functions (procedures) tied to objects
- they can access the object (self)
- implement the behaviour of the object
- their signatures (usually) provide the interface
- methods are also objects

Class and Instance Methods

- methods are usually tied to instances
- recall that classes are also objects
- class methods work on the class (cls)
- static methods are just namespaced functions
- decorators (classmethod, (staticmethod

Inheritance



- class Ellipse(Shape): ...
- usually encodes an is-a relationship

Multiple Inheritance

- more than one base class is possible
- many languages restrict this
- python allows general M-I
 class Bat(Mammal, Winged): pass
- 'true' M-I is somewhat rare
 - typical use cases: mixins and interfaces

Mixins

- used to pull in implementation
 - not part of the is-a relationship
 - by convention, not enforced by the language
- common bits of functionality
 - e.g. implement __gt__, __eq__ &c. using __lt__
 - you only need to implement $__lt_$ in your class

Interfaces

- realized as 'abstract' classes in python
 - just throw a NotImplemented exception
 - document the intent in a docstring
- participates in is-a relationships
- partially displaced by duck typing
 - more important in other languages (think Java)

Composition

- attributes of objects can be other objects
 (also, everything is an object in python)
- encodes a has-a relationship
 - a circle has a center and a radius
 - a circle is a shape

Constructors

- this is the __init__ method
- initializes the attributes of the instance
- can call superclass constructors explicitly
 - not called automatically (unlike C++, Java)
 - MySuperClass.__init__(self)
 - super().__init__ (if unambiguous)

Class and Object Dictionaries

- most objects are basically dictionaries
- try e.g. foo.__dict__ (for a suitable foo)
- saying foo.x means foo.__dict__["x"]
 - if that fails, type(foo).__dict__["x"] follows
 - then superclasses of type(foo), according to MRO

Writing Classes

```
class Person:
    def __init__( self, name ):
        self.name = name
    def greet( self ):
        print( "hello " + self.name )
```

p = Person("you")
p.greet()

Modules in Python

- modules are just normal .py files
- import executes a file by name
 - it will look into system-defined locations
 - the search path includes the current directory
 - they typically only define classes & functions
- import sys → lets you use sys.argv
- from sys import $argv \rightarrow you can write just argv$

Functions

- top-level functions/procedures are possible
- they are usually 'scoped' via the module system
- functions are also objects
 - try print.__class__ (or type(print))
- some functions are built in (print, len, ...)
Memory

- most program data is stored in 'memory'
 - an array of byte-addressable data storage
 - address space managed by the OS
 - 32 or 64 bit numbers as addresses
- typically backed by RAM

Language vs Computer

- programs use high-level concepts
 - objects, procedures, closures
 - values can be passed around
- the computer has a single array of bytes
 and, well, a bunch of registers

Memory Management

- deciding where to store data
- high-level objects are stored in flat memory
 - they have a given (usually fixed) size
 - can contain references to other objects
 - have limited lifespan

Memory Management Terminology

- object: an entity with an address and size
 not the same as language-level object
- lifetime: when is the object valid
 - live: references exist to the object
 - dead: the object unreachable garbage

Memory Management by Type

- manual: malloc and free in C
- static automatic
 - e.g. stack variables in C and C++
- dynamic automatic
 - pioneered by LISP, widely used

Automatic Memory Management

- static vs dynamic
 - when do we make decisions about lifetimecompile time vs run time
- safe vs unsafe
 - can the program read unused memory?

Object Lifetime

- the time between malloc and free
- another view: when is the object needed
 - often impossible to tell
 - can be safely over-approximated
 - at the expense of memory leaks

Static Automatic

- usually binds lifetime to lexical scope
- no passing references up the call stack
 may or may not be enforced
- no lexical closures
- examples: C, C++

Dynamic Automatic

- over-approximate lifetime dynamically
- usually easiest for the programmer
 until you need to debug a space leak
- reference counting, mark & sweep collectors
- examples: Java, almost every dynamic language

Reference Counting

- attach a counter to each object
- whenever a reference is made, increase
- whenever a reference is lost, decrease
- the object is dead when the counter hits 0
- fails to reclaim reference cycles

Mark and Sweep

- start from a root set (in-scope variables)
- follow references, mark every object encountered
- sweep: throw away all unmarked memory
- usually stops the program while running
- garbage is retained until the GC runs

Memory Management in CPython

- primarily based on reference counting
- optional mark & sweep collector
 - enabled by default
 - configure via import gc
 - reclaims cycles

Refcounting Advantages

- simple to implement in a 'managed' language
- reclaims objects quickly
- no need to pause the program
- easily made concurrent

Refcounting Problems

- significant memory overhead
- problems with cache locality
- bad performance for data shared between threads
- fails to reclaim cyclic structures

Data Structures

- an abstract description of data
- leaves out low-level details
- makes writing programs easier
- makes reading programs easier, too

Building Data Structures

- there are two kinds of types in python
 - built-in, implemented in C
 - user-defined (includes libraries)
- both kinds are based on objects
 - but built-ins only look that way

Mutability

- some objects can be modified
 - we say they are mutable
 - otherwise, they are immutable
- immutability is an abstraction
 - physical memory is always mutable
- in python, immutability is not 'recursive'

Built-in: int

- arbitrary precision integer
 - no overflows and other nasty behaviour
- it is an object, i.e. held by reference
 - uniform with any other kind of object
 - immutable
- both of the above make it slow
 - machine integers only in C-based modules

Additional Numeric Objects

- bool: True or False
 - how much is True + True?
 - is 0 true? is empty string?
- numbers.Real: floating point numbers
- numbers.Complex: a pair of above

Built-in: bytes

- a sequence of bytes (raw data)
- exists for efficiency reasons
 in the abstract is just a tuple
- models data as stored in files
 - or incoming through a socket
 - or as stored in raw memory

Properties of bytes

- can be indexed and iterated
 - both create objects of type int
 - try this sequence: id(x[1]), id(x[2])
- mutable version: bytearray
 - the equivalent of C char arrays

Built-in: <mark>str</mark>

- immutable unicode strings
 - **not** the same as bytes
 - bytes must be decoded to obtain str
 - (and str encoded to obtain bytes)
- represented as utf-8 sequences in CPython
 - implemented in PyCompactUnicodeObject

Built-in: tuple

- an immutable sequence type
 - the number of elements is fixed
 - so is the type of each element
- but elements themselves may be mutable
 - x = [] then y = (x, 0)
 - x.append(1) \rightarrow y == ([1], 0)
- implemented as a C array of object references

Built-in: list

- a mutable version of tuple
 - items can be assigned x[3] = 5
 - items can be append-ed
- implemented as a dynamic array
 - many operations are amortised O(1)
 - insert is O(n)

Built-in: dict

- implemented as a hash table
- some of the most performance-critical code
 - dictionaries appear everywhere in python
 - heavily hand-tuned C code
- both keys and values are objects

Hashes and Mutability

- dictionary keys must be hashable
 this implies recursive immutability
 - what would be paper if a low is mutated
- what would happen if a key is mutated?
 - most likely, the hash would change
 - all hash tables with the key become invalid
 - this would be very expensive to fix

Built-in: set

- implements the math concept of a set
- also a hash table, but with keys only
 a separate C implementation
- mutable items can be added
 - but they must be hashable
 - hence cannot be changed

Built-in: frozenset

- an immutable version of set
- always hashable (since all items must be)
 - can appear in set or another frozenset
 - can be used as a key in dict
- the C implementation is shared with set

Efficient Objects: __slots__

- fixes the attribute names allowed in an object
- saves memory: consider 1-attribute object
 - with <u>__dict__</u>: 56 + 112 bytes
 - with __slots__: 48 bytes
- makes code faster: no need to hash anything
 - more compact in memory \rightarrow better cache efficiency

Part 2: Text, JSON, SQL and Persistence

Transient Data

- lives in program memory
- data structures, objects
- interpreter state
- often implicit manipulation
- more on this next week

Persistent Data

- (structured) text or binary files
- relational (SQL) databases
- object and 'flat' databases (NoSQL)
- manipulated explicitly

Persistent Storage

- 'local' file system
 - stored on HDD, SSD, ...
 - stored somwhere in a local network
- 'remote', using an application-level protocol
 - local or remote databases
 - cloud storage &c.

Reading Files

- opening files: open('file.txt', 'r')
- files can be iterated

```
f = open( 'file.txt', 'r' )
for line in f:
    print( line )
```

Resource Acquisition

- plain open is prone to resource leaks
 - what happens during an exception?
 - holding a file open is not free
- pythonic solution: with blocks
 - defined in PEP 343
 - binds resources to scopes

Detour²: PEP

- PEP stands for Python Enhancement Proposal
- akin to RFC documents managed by IETF
- initially formalise future changes to python
 - later serve as documentation for the same
- <https://www.python.org/dev/peps/>
Using with with open('/etc/passwd', 'r') as f: for line in f: do_stuff(line)

• still safe if do_stuff raises an exception

Finalizers

- there is a <u>__del__</u> method
- but it is not guaranteed to run
 - it may run arbitrarily late
 - or never
- not very good for resource management

Context Managers

- with has an associated protocol
- you can use with on any context manager
- which is an object with __enter__ and __exit__
- you can create your own

Representing Text

- ASCII: one byte = one character
 - total of 127 different characters
 - not very universal
- 8-bit encodings: 255 characters
- multi-byte encodings for non-Latin scripts

Unicode

- one character encoding to rule them all
- supports all extant scripts and writing systems
 and a whole bunch of dead scripts, too
- collation, segmentation, comparison, ...
- approx. 137000 code points

Code Point

- basic unit of encoding characters
- letters, punctuation, symbols
- combining diacritical marks
- not the same thing as a character
- code points range from 1 to 10FFFF

Unicode Encodings

- deals with representing code points
- UCS = Universal Coded Character Set
 - fixed-length encoding
 - two variants: UCS-2 (16 bit) and UCS-4 (32 bit)
- UTF = Unicode Transformation Format
 - variable-length encoding
 - variants: UTF-8, UTF-16 and UTF-32

Grapheme

- technically 'extended grapheme cluster'
- a logical character, as expected by users
 encoded using 1 or more code points
- multiple encodings of the same grapheme
 - e.g. composed vs decomposed
 - U+0041 U+0300 vs U+0C00: À vs À

Segmentation

- breaking text into smaller units
 - graphemes, words and sentences
- algorithms defined by the unicode spec
 - Unicode Standard Annex #29
 - graphemes and words are quite reliable
 - sentences not so much (too much ambiguity)

Normal Form

- Unicode defines 4 canonical (normal) forms
 NFC, NFD, NFKC, NFKD
 - NFC = Normal Form Composed
 - NFD = Normal Form Decomposed
- K variants = looser, lossy conversion
- all normalization is idempotent
- NFC does not give you 1 code point per grapheme

str vs bytes

- iterating bytes gives individual bytes
 indexing is fast fixed-size elements
- iterating str gives code points
 - slightly slower, because it uses UTF-8
 - does not iterate over graphemes
- going back and forth: str.encode, bytes.decode

Python vs Unicode

- no native support for unicode segmentation
 - hence no grapheme iteration or word splitting
- convert everything into NFC and hope for the best
 unicodedata.normalize()
 - will sometimes break (we'll discuss regexes in a bit)
 - most people don't bother
 - correctness is overrated \rightarrow worse is better

Regular Expressions

- compiling: r = re.compile(r"key: (.*)")
- matching: m = r.match("key: some value")
- extracting captures: print(m.group(1))
 - prints some value
- substitutions: s2 = re.sub(r"\s*\$", '', s1)
 - strips all trailing whitespace in s1

Detour: Raw String Literals

- the r in r"...." stands for raw (not regex)
- normally, \setminus is magical in strings
 - but \setminus is also magical in regexes
 - nobody wants to write \\s &c.
 - not to mention $\$ to match a literal $\$
- not super useful outside of regexes

Detour²: Other Literal Types

- byte strings: b"abc" → bytes
- formatted string literals: f"x {y}"

x = 12print(f''x = {x}'')

• triple-quote literals: """xy"""

Regular Expressions vs Unicode

```
import re
s = "\u0041\u0300" # À
t = "\u00c0" # À
print( s, t )
print( re.match( "...", s ), re.match( "...", t ) )
print( re.match( "\w+$", s ), re.match( "\w+$", t ) )
print( re.match( "Å", s ), re.match( "Å", t ) )
```

Regexes and Normal Forms

- some of the problems can be fixed by NFC
 - some go away completely (literal unicode matching)
 - some become rarer (the ".." and "\w" problems)
- most text in the wild is already in NFC
 - but not all of it
 - case in point: filenames on macOS (NFD)

Decomposing Strings

- recall that str is immutable
- splitting: str.split(':')

• None = split on any whitespace

- split on first delimiter: partition
- better whitespace stripping: s2 = s1.strip()
 also lstrip() and rstrip()

Searching and Matching

- startswith and endswith
 - often convenient shortcuts
- find = index
 - generic substring search

Building Strings

- format literals and str.format
- str.replace substring search and replace
- str.join turn lists of strings into a string

JSON

- structured, text-based data format
- atoms: integers, strings, booleans
- objects (dictionaries), arrays (lists)
- widely used around the web &c.
- simple (compared to XML or YAML)

```
JSON: Example
     "composer": ["Bach, Johann Sebastian"],
```

JSON: Writing

- printing JSON seems straightforward enough
- but: double quotes in strings
- strings must be properly \-escaped during output
- also pesky commas
- keeping track of indentation for human readability
- better use an existing library: `import json`

JSON in Python

- json.dumps = short for dump to string
- python dict/list/str/... data comes in
- a string with valid JSON comes out

Workflow

- just convert everything to dict and list
- run json.dumps or json.dump(data, file)

Python Example
d = {}
d["composer"] = ["Bach, Johann Sebastian"]
d["key"] = "g"
d["voices"] = { 1: "oboe", 2: "bassoon" }
json.dump(d, sys.stdout, indent=4)

Beware: keys are always strings in JSON

Parsing JSON

- import json
- json.load is the counterpart to json.dump from abovede-serialise data from an open file
 - builds lists, dictionaries, etc.
- json.loads corresponds to json.dumps

XML

- meant as a lightweight and consistent redesign of SGML
 turned into a very complex format
- heaps of invalid XML floating around
 - parsing real-world XML is a nightmare
 - even valid XML is pretty challenging

```
XML: Example
```

```
<Order OrderDate="1999-10-20">
  <Address Type="Shipping">
    <Name>Ellen Adams</Name>
    <Street>123 Maple Street</Street>
 </Address>
  <Item PartNumber="872-AA">
    <ProductName>Lawnmower</ProductName>
    <Ouantity>1</Ouantity>
 </Item>
</Order>
```

```
XML: Another Example
```

```
<BLOKY_OBSAH>
```

<STUDENT>

<OBSAH>25 bodů</OBSAH>

<UC0>72873</UC0>

<ZMENENO>20160111104208</ZMENENO>

<ZMENIL>395879</ZMENIL>

</STUDENT>

</BLOKY_OBSAH>

XML Features

- offers extensible, rich structure
 - tags, attributes, entities
 - suited for structured hierarchical data
- schemas: use XML to describe XML
 - allows general-purpose validators
 - self-documenting to a degree

XML vs JSON

- both work best with trees
- JSON has basically no features
 - basic data structures and that's it
- JSON data is ad-hoc and usually undocumented
 - but: this often happens with XML anyway

XML Parsers

- DOM = Document Object Model
- **SAX** = Simple API for XML
- expat = fast SAX-like parser (but not SAX)
- ElementTree = DOM-like but more pythonic

XML: DOM

- read the entire XML document into memory
- exposes the AST (Abstract Syntax Tree)
- allows things like XPath and CSS selectors
- the API is somewhat clumsy in python

XML: SAX

- event-driven XML parsing
- much more efficient than DOM
 - but often harder to use
- only useful in python for huge XML files
 - otherwise just use ElementTree

XML: ElementTree

for child in root:
 print child.tag, child.attrib

Order { OrderDate: "1999-10-20" }

- supports tree walking, XPath
- supports serialization too

NoSQL / Non-relational Databases

- umbrella term for a number of approaches
 - flat key/value and column stores
 - document and graph stores
- no or minimal schemas
- non-standard query languages
Key-Value Stores

- usually very fast and very simple
- completely unstructured values
- keys are often database-global
 - workaround: prefixes for namespacing
 - or: multiple databases

NoSQL & Python

- redis (redis-py) module (Redis is Key-Value)
- memcached (another Key-Value store)
- PyMongo for talking to MongoDB (document-oriented)
- CouchDB (another document-oriented store)
- neo4j or cayley (module pyley) for graph structures

SQL and RDBMS

- SQL = Structured Query Language
- RDBMS = Relational DataBase Management System
- SQL is to NoSQL what XML is to JSON
- heavily used and extremely reliable

SQL: Example

join group on group.id = enrollment.group;

SQL: Relational Data

- JSON and XML are hierarchical
 or built from functions if you like
- SQL is relational
 - relations = generalized functions
 - can capture more structure
 - much harder to efficiently process

SQL: Data Definition

- mandatory, unlike XML or JSON
- gives the data a rather rigid structure
- tables (relations) and columns (attributes)
- static data types for columns
- additional consistency constraints

SQL: Constraints

- help ensure consistency of the data
- foreign keys: referential integrity
 - ensures there are no dangling references
 - but: does not prevent accidental misuse
- unique constraints
- check constraints: arbitrary consistency checks

SQL: Query Planning

- an RDBMS makes heavy use of indexing
 - using **B** trees, hashes and similar techniques
 - indices are used automatically
- all the heavy lifting is done by the backend
 - highly-optimized, low-level code
 - efficient handling of large data

SQL: Reliability and Flexibility

- most RDBMS give ACID guarantees
 - transparently solves a lot of problems
 - basically impossible with normal files
- support for schema alterations
 - alter table and similar
 - nearly impossible in ad-hoc systems

SQLite

- lightweight in-process SQL engine
- the entire database is in a single file
- convenient python module, sqlite3
- stepping stone for a "real" database

Other Databases

- you can talk to most SQL DBs using python
- postgresql (psycopg2, ...)
- mysql / mariadb (mysql-python, mysql-connector, ...)
- big & expensive: Oracle (cx_oracle), DB2 (pyDB2)
- most of those are much more reliable than SQLite

SQL Injection

sql = "SELECT * FROM t WHERE name = '" + n + '"'

- the above code is bad, never do it
- consider the following
 - n = "x'; drop table students --"
 - n = "x'; insert into passwd (user, pass) ..."

Avoiding SQL Injection

- use proper SQL-building APIs
 - this takes care of escaping internally
- templates like insert ... values (?, ?)
 - the ? get safely substituted by the module
 - e.g. the execute method of a cursor

PEP 249

- informational PEP, for library writers
- describes how database modules should behave
 - ideally, all SQL modules have the same interface
 - makes it easy to swap a database backend
- but: SQL itself is not 100% portable

SQL Pitfalls

- sqlite does not enforce all constraints
 you need to pragma foreign_keys = on
- no portable syntax for autoincrement keys
- not all (column) types are supported everywhere
- no portable way to get the key of last insert

More Resources & Stuff to Look Up

- SQL:https://www.w3schools.com/sql/
- https://docs.python.org/3/library/sqlite3.html
- Object-Relational Mapping
- SQLAlchemy: constructing portable SQL

Part 3: Advanced Constructs

Callable Objects

- user-defined functions (module-level def)
- user-defined methods (instance and class)
- built-in functions and methods
- class objects
- objects with a __call__ method

User-defined Functions

- come about from a module-level def
- metadata: __doc__, __name__, __module__
- scope: __globals__, __closure__
- arguments: __defaults__, __kwdefaults__
- type annotations: __annotations__
- the code itself: __code__

Positional and Keyword Arguments

- user-defined functions have positional arguments
- and keyword arguments
 - print("hello", file=sys.stderr)
 - arguments are passed by name
 - which style is used is up to the caller
- variadic functions: def foo(*args, **kwargs)
 - args is a tuple of unmatched positional args
 - kwargs is a dict of unmatched keyword args

Lambdas

- def functions must have a name
- lambdas provide anonymous functions
- the body must be an expression
- syntax: lambda x: print("hello", x)
- standard user-defined functions otherwise

Instance Methods

- comes about as object.method
 print(x.foo) → <bound method Foo.foo of ...>
- combines the class, instance and function itself
- __func__ is a user-defined function object
- let bar = x.foo, then
 - x.foo() → bar.__func__(bar.__self__)

Iterators

- objects with __next__ (since 3.x)
 - iteration ends on raise StopIteration
- iterable objects provide ___iter___
 - sometimes, this is just return self
 - any iterable can appear in for x in iterable

```
class FooIter:
   def __init__(self):
        self.x = 10
   def __iter__(self): return self
   def __next__(self):
        if self.x:
            self.x -= 1
        else:
            raise StopIteration
        return self.x
```

Generators (PEP 255)

- written as a normal function or method
- they use yield to generate a sequence
- represented as special callable objects
 exist at the C level in CPython

```
def foo(*lst):
    for i in lst: yield i + 1
list(foo(1, 2)) # prints [2, 3]
```

yield from

- calling a generator produces a generator object
- how do we call one generator from another?
- same as for x in foo(): yield x

```
def bar(*lst):
    yield from foo(*lst)
    yield from foo(*lst)
list(bar(1, 2)) # prints [2, 3, 2, 3]
```

Native Coroutines (PEP 492)

- created using async def (since Python 3.5)
- generalisation of generators
 - yield from is replaced with await
 - an __await__ magic method is required
- a coroutine can be suspended and resumed

Coroutine Scheduling

- coroutines need a scheduler
- one is available from asyncio.get_event_loop()
- along with many coroutine building blocks
- coroutines can actually run in parallel
 - via asyncio.create_task (since 3.7)
 - via asyncio.gather

Async Generators (PEP 525)

- async def + yield
- semantics like simple generators
- but also allows await
- iterated with async for
 - async for runs sequentially

Decorators

- written as @decor before a function definition
- decor is a regular function (def decor(f))
 - f is bound to the decorated function
 - the decorated function becomes the result of decor
- classes can be decorated too
- you can 'create' decorators at runtime
 - (mkdecor("moo") (mkdecor returns the decorator)
 - you can stack decorators

```
def decor(f):
    return lambda: print("bar")
def mkdecor(s):
    return lambda g: lambda: print(s)
```

```
@decor
def foo(f): print("foo")
@mkdecor("moo")
def moo(f): print("foo")
```

foo() prints "bar", moo() prints "moo"

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List Comprehension

- a concise way to build lists
- combines a filter and a map

[2 * x for x in range(10)]
[x for x in range(10) if x % 2 == 1]
[2 * x for x in range(10) if x % 2 == 1]
[(x, y) for x in range(3) for y in range(2)]

Operators

- operators are (mostly) syntactic sugar
- x < y rewrites to x.__lt__(y)
- is and is not are special
 - are the operands the same object?
 - also the ternary (conditional) operator

Non-Operator Builtins

- $len(x) \rightarrow x...len_()$ (length)
- $abs(x) \rightarrow x._abs__()$ (magnitude)
- $str(x) \rightarrow x._str_()$ (printing)
- repr(x) \rightarrow x.__repr__() (printing for eval)
- bool(x) and if x: x.__bool__()

Arithmetic

- a standard selection of operators
- / is floating point, // is integral
- += and similar are somewhat magical
 - $x += y \rightarrow x = x$.__iadd___(y) if defined
 - otherwise x = x.__add__(y)

x = 7 # an int is immutable x = 3 # works, x = 10, id(x) char

lst = [7, 3] lst[0] += 3 # works too, id(lst) stays same

tup = (7, 3) # a tuple is immutable tup += (1, 1) # still works (id changes) tup[0] += 3 # fails
Relational Operators

- operands can be of different types
- equality: !=, ==
 - by default uses object identity
- ordering: <, <=, >, >= (TypeError by default)
- consistency is not enforced

Relational Consistency

- ___eq___ must be an equivalence relation
- x.__ne__(y) must be the same as not x.__eq__(y)
- __lt__ must be an ordering relation
 - compatible with __eq__
 - consistent with each other
- each operator is separate (mixins can help)
 - or perhaps a class decorator

Collection Operators

- in is also a membership operator (outside for)
 implemented as __contains__
- indexing and slicing operators
 - del x[y] \rightarrow x.__delitem__(y)
 - $x[y] \rightarrow x_{\dots}getitem_{\dots}(y)$
 - $x[y] = z \rightarrow x$.__setitem__(y, z)

Conditional Operator

- also known as a ternary operator
- written x if cond else y
 in C: cond ? x : y
- forms an expression, unlike if
 - can e.g. appear in a lambda
 - or in function arguments, &c.

Concurrency & Parallelism

- threading thread-based parallelism
- multiprocessing
- concurrent future-based programming
- subprocess
- sched, a general-purpose event scheduler
- queue, for sending objects between threads

Threading

- low-level thread support, module threading
- Thread objects represent actual threads
 - threads provide start() and join()
 - the run() method executes in a new thread
- mutexes, semaphores &c.

The Global Interpreter Lock

- memory management in CPython is not thread-safe
 - Python code runs under a global lock
 - pure Python code cannot use multiple cores
- C code usually runs without the lock
 - this includes numpy crunching

Multiprocessing

- like threading but uses processes
- works around the GIL
 - each worker process has its own interpreter
- queued/sent objects must be pickled
 - see also: the pickle module
 - this causes substantial overhead
 - functions, classes &c. are pickled by name

Futures

- like coroutine await but for subroutines
- a Future can be waited for using f.result()
- scheduled via concurrent.futures.Executor
 - Executor.map is like asyncio.gather
 - Executor.submit is like asyncio.create_task
- implemented using process or thread pools

Exceptions

- an exception interrupts normal control flow
- it's called an exception because it is exceptionalnever mind StopIteration
- causes methods to be interrupted
 - until a matching except block is found
 - also known as stack unwinding

Life Without Exceptions int fd = socket(...); if (fd < 0)if (bind(fd, ...) < 0) if (listen(fd, 5) < 0)

```
With Exceptions
  try:
     sock = socket.socket( ... )
     sock.bind( ... )
     sock.listen( ... )
  except ...:
```

Exceptions vs Resources

- x = open("file.txt")
 # stuff
 raise SomeError
- who calls x.close()
- this would be a resource leak

Using finally try: x = open("file.txt") # stuff finally: x.close()

• works, but tedious and error-prone

- with takes care of the finally and close
- with x as y sets y = x.__enter__()
 - and calls x.__exit__(...) when leaving the block

The **(property** decorator

- attribute syntax is the preferred one in Python
- writing useless setters and getters is boring

```
class Foo:
    @property
    def x(self): return 2 * self.a
    @x.setter
    def x(self, v): self.a = v // 2
```

Execution Stack

- made up of activation frames
- holds local variables
- and return addresses
- in dynamic languages, often lives in the heap

Variable Capture

- variables are captured lexically
- definitions are a dynamic / run-time construct
 - a nested definition is executed
 - creates a closure object
- always by reference in Python
 - but can be by-value in other languages

Using Closures

- closures can be returned, stored and called
 - they can be called multiple times, too
 - they can capture arbitrary variables
- closures naturally retain state
- this is what makes them powerful

Objects from Closures

- so closures are essentially code + state
- wait, isn't that what an object is?
- indeed, you can implement objects using closures

The Role of GC

- memory management becomes a lot more complicated
- forget C-style 'automatic' stack variables
- this is why the stack is actually in the heap
- this can go as far as form reference cycles

Coroutines

- coroutines are a generalisation of subroutines
- they can be suspended and re-entered
- coroutines can be closures at the same time
- the code of a coroutine is like a function
- a suspended coroutine is like an activation frame

Yield

- suspends execution and 'returns' a value
- may also obtain a new value (cf. send)
- when re-entered, continue where we left off

for i in range(5): yield i

Send

- with yield, we have one-way communication
- but in many cases, we would like two-way
- a suspended coroutine is an object in Python
 - with a send method which takes a value
 - send re-enters the coroutine

Yield From and Await

- yield from is mostly a generator concept
- await basically does the same thing
 - call out to another coroutine
 - when it suspends, so does the entire stack

Suspending Native Coroutines

- this is not actually possible
 - not with async-native syntax anyway
- you need a yield
 - for that, you need a generator
 - use the types.coroutine decorator

Event Loop

- not required in theory
- useful also without coroutines
- there is a synergistic effect
 - event loops make coroutines easier
 - coroutines make event loops easier

Part 4: Math and Statistics

Numbers in Python

- recall that numbers are objects
- a tuple of real numbers has 300% overhead
 - compared to a C array of float values
 - and 350% for integers
- this causes extremely poor cache use
- integers are arbitrary-precision

Math in Python

- numeric data usually means arrays
 - this is inefficient in python
- we need a module written in C
 - but we don't want to do that ourselves
- enter the SciPy project
 - pre-made numeric and scientific packages

The SciPy Family

- numpy: data types, linear algebra
- scipy: more computational machinery
- pandas: data analysis and statistics
- matplotlib: plotting and graphing
- sympy: symbolic mathematics

Aside: External Libraries

- until now, we only used bundled packages
- for math, we will need external libraries
- you can use pip to install those
 - use pip install --user <package>

Aside: The Python Package Index

- colloquially known as PyPI (or cheese shop)
 do not confuse with PyPy (Python in almost-Python)
- both source packages and binaries
 - the latter known as wheels (PEP 427, 491)
 - previously python eggs
- <https://pypi.python.org>

Aside: Installing numpy

- the easiest way may be with pip
 - this would be pip3 on aisa
- linux distributions usually also have packages
- another option is getting the Anaconda bundle
- detailed instructions on https://scipy.org

Arrays in numpy

- compact, C-implemented data types
- flexible multi-dimensional arrays
- easy and efficient re-shaping
 - typically without copying the data

Entering Data

- most data is stored in numpy.array
- can be constructed from a list a list of lists for 2D arrays
- or directly loaded from / stored to a file
 - binary: numpy.load, numpy.save
 - text: numpy.loadtxt, numpy.savetxt
LAPACK and BLAS

- BLAS is a low-level vector/matrix package
- LAPACK is built on top of BLASprovides higher-level operations
 - tuned for modern CPUs with multiple caches
- both are written in Fortran
 - ATLAS and C-LAPACK are C implementations

Element-wise Functions

- the basic math function arsenal
- powers, roots, exponentials, logarithms
- trigonometric (sin, cos, tan, ...)
- hyperbolic (sinh, cosh, tanh, ...)
- cyclometric (arcsin, arccos, arctan, ...)

Matrix Operations in numpy

- import numpy.linalg
- multiplication, inversion, rank
- eigenvalues and eigenvectors
- linear equation solver
- pseudo-inverses, linear least squares

Additional Linear Algebra in scipy

- import scipy.linalg
- LU, QR, polar, etc. decomposition
- matrix exponentials and logarithms
- matrix equation solvers
- special operations for banded matrices

Where is my Gaussian Elimination?

- used in lots of school linear algebra
- but not the most efficient algorithm
- a few problems with numerical stability
- not directly available in numpy

Numeric Stability

• floats are imprecise / approximate

 $1 / (0.1 \times 2 - 0.01) \# 5.8 \cdot 10^{17}$

• multiplication is not associative

$$a = (0.1 * 0.1) * 10$$

$$b = 0.1 * (0.1 * 10)$$

$$1 / (a - b) \# 7.21 \cdot 10^{16}$$

iteration amplifies the errors

LU Decomposition

- decompose matrix A into simpler factors
- PA = LU where
 - *P* is a permutation matrix
 - *L* is a lower triangular matrix
 - *U* is an upper triangular matrix
- fast and numerically stable

Uses for LU

- equations, determinant, inversion, ...
- as an example
 - $\det(A) = \det(P^{-1}) \cdot \det(L) \cdot \det(U)$
 - where $det(U) = \sum_{i} U_{ii}$ and
 - $det(L) = \sum_{i} U_{ii}$

Numeric Math

- float arithmetic is messy but incredibly fast
- measured data is approximate anyway
- stable algorithms exist for many things
 - and are available from libraries
- we often don't care about exactness
 - think computer graphics, signal analysis, ...

Symbolic Math

- numeric math sucks for 'textbook' math
- there are problems where exactness matters pure math and theoretical physics
- incredibly slow computation
 - but much cleaner interpretation

Linear Algebra in sympy

- uses exact math
 - e.g. arbitrary precision rationals
 - and roots thereof
 - and many other computable numbers
- wide repertoire of functions
 - including LU, QR, etc. decompositions

Exact Rationals in sympy

from sympy import *
a = QQ(1) / 10 # QQ = rationals
Matrix([[sqrt(a**3), 0, 0],
 [0, sqrt(a**3), 0],
 [0, 0, 1]]).det()
result: 1/1000

```
numpy for Comparison
```

```
import numpy as np
import numpy.linalg as la
a = 0.1
la.det( [ [ np.sqrt( a**3 ), 0, 0 ],
        [ 0, np.sqrt( a**3 ), 0 ],
        [ 0, 0, 1 ] ] )
# result: 0.00100000000000002
```

General Solutions in Symbolic Math

```
from sympy import *
x = symbols( 'x' )
Matrix( [ [ x, 0, 0 ],
            [ 0, 1, 0 ],
            [ 0, 0, x ] ] ).det()
# result: x ** 2
```

Symbolic Differentation

x = symbols('x')
diff(x**2 + 2*x + log(x/2))
result: 2*x + 2 + 1/x
diff(x**2 * exp(x))
result: x**2 * exp(x) + 2 * x * exp(x)

Algebraic Equations solve(x**2 - 7) solve($x \star 2 - exp(x)$) solve($x \star \star 4 - x$)

Ordinary Diffrential Equations

- f = Function('f')
 dsolve(f(x).diff(x)) # f'(x) = 0
 # result: Eq(f(x), C1)
 dsolve(f(x).diff(x) f(x)) # f'(x) = f(x)
 # result: Eq(f(x), C1 * exp(x))
- dsolve(f(x).diff(x) + f(x)) # f'(x) = -f(x)
 # result: Eq(f(x), C1 * exp(-x))

Symbolic Integration integrate(x**2) integrate(log(x)) integrate(cos(x) ** 2) Numeric Sparse Matrices

- sparse = most elements are 0
- available in scipy.sparse
- special data types (not numpy arrays)
 - do not use numpy functions on those
- less general, but more compact and faster

Fourier Transform

- continuous: $\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x) \exp(-2\pi i x \xi) dx$
- series:

•
$$f(x) = \sum_{n=-\infty}^{\infty} c_n \exp\left(\frac{i2\pi nx}{P}\right)$$

• real series:

•
$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} \left(a_n \sin\left(\frac{2\pi nx}{p}\right) + b_n \cos\left(\frac{2\pi nx}{p}\right) \right)$$

• $c_n = \frac{1}{2}(a_n - ib_n)$

Discrete Fourier Transform

- available in numpy.fft
- goes between time and frequency domains
- a few different variants are covered
 - real-valued input (for signals, rfft)
 - inverse transform (ifft, irfft)
 - multiple dimensions (fft2, fftn)

Polynomial Series

- the numpy.polynomial package
- Chebyshev, Hermite, Laguerre and Legendre
 - arithmetic, calculus and special-purpose operations
 - numeric integration using Guassian quadrature
 - fitting (polynomial regression)

Statistics in numpy

- a basic statistical toolkit
 - averages, medians
 - variance, standard deviation
 - histograms
- random sampling and distributions

Linear Regression

- very fast model-fitting method
 - both in computational and human terms
 - quick and dirty first approximation
- widely used in data interpretation
 - biology and sociology statistics
 - finance and economics, especially prediction

Polynomial Regression

- higher-order variant of linear regression
- can capture acceleration or deceleration
- harder to use and interpret
 - also harder to compute
- usually requires a model of the data

Interpolation

- find a line or curve that approximates data
- it must pass through the data points
 this is a major difference to regression
- more dangerous than regression
 - runs a serious risk of overfitting

Linear and Polynomial Regression, Interpolation

- regressions using the least squares method
 - linear: numpy.linalg.lstsq
 - polynomial: numpy.polyfit
- interpolation: scipy.interpolate
 - e.g. piecewise cubic splines
 - Lagrange interpolating polynomials

Pandas: Data Analysis

- the Python equivalent of R
 - works with tabular data (CSV, SQL, Excel)
 - time series (also variable frequency)
 - primarily works with floating-point values
- partially implemented in C and Cython

Pandas Series and DataFrame

- Series is a single sequence of numbers
- DataFrame represents tabular data
 - powerful indexing operators
 - index by column \rightarrow series
 - index by condition \rightarrow filtering

Pandas Example

Part 5: Communication, HTTP & asyncio

PV248 Python

Running Programs (the old way)

- os.system is about the simplest
 - also somewhat dangerous shell injection
 - you only get the exit code
- os.popen allows you to read output of a program
 - alternatively, you can send input to the program
 - you can't do both (would likely deadlock anyway)
 - runs the command through a shell, same as os.system

Low-level Process API

- POSIX-inherited interfaces (on POSIX systems)
- os.exec: replace the current process
- os.fork: split the current process in two
- os.forkpty: same but with a PTY

Detour: bytes vs str

- strings (class str) represent text
 - that is, a sequence of unicode points
- files and network connections handle data
 represented in Python as bytes
- the bytes constructor can convert from str
 e.g. b = bytes("hello", "utf8")

Running Programs (the new way)

- you can use the subprocess module
- subprocess can handle bidirectional IO
 - it also takes care of avoiding IO deadlocks
 - set input to feed data to the subprocess
- internally, run uses a Popen object
 if run can't do it, Popen probably can

Getting subprocess Output

- available via run since Python 3.7
- the run function returns a CompletedProcess
- it has attributes stdout and stderr
- both are bytes (byte sequences) by default
- or str if text or encoding were set
- available if you enabled capture_output
Running Filters with Popen

- if you are stuck with 3.6, use Popen directly
- set stdin in the constructor to PIPE
- use the communicate method to send the input
- this gives you the outputs (as bytes)

Subprocesses with asyncio

- import asyncio.subprocess
- create_subprocess_exec, like subprocess.run
 - but it returns a Process instance
 - Process has a communicate async method
- can run things in background (via tasks)
 - also multiple processes at once

Protocol-based asyncio subprocesses

- let loop be an implementation of the asyncio event loop
- there's subprocess_exec and subprocess_shellsets up pipes by default
- integrates into the asyncio transport layer (see later)
- allows you to obtain the data piece-wise
- https://docs.python.org/3/library/asyncio-protocol.html

Sockets

- the socket API comes from early BSD Unix
- socket represents a (possible) network connection
- sockets are more complicated than normal files
 - establishing connections is hard
 - messages get lost much more often than file data

Socket Types

- sockets can be internet or unix domain
 - internet sockets connect to other computers
 - Unix sockets live in the filesystem
- sockets can be stream or datagram
 - stream sockets are like files (TCP)
 - you can write a continuous stream of data
 - datagram sockets can send individual messages (UDP)

Sockets in Python

- the socket module is available on all major OSes
- it has a nice object-oriented API
 - failures are propagated as exceptions
 - buffer management is automatic
- useful if you need to do low-level networking
 - hard to use in non-blocking mode

Sockets and asyncio

- asyncio provides sock_* to work with socket objects
- this makes work with non-blocking sockets a lot easier
- but your program needs to be written in async style
- only use sockets when there is no other choice
 - asyncio protocols are both faster and easier to use

Hyper-Text Transfer Protocol

- originally a simple text-based, stateless protocol
- however
 - SSL/TLS, cryptography (https)
 - pipelining (somewhat stateful)
 - cookies (somewhat stateful in a different way)
- typically between client and a front-end server
- but also as a back-end protocol (web server to app server)

Request Anatomy

- request type (see below)
- header (text-based, like e-mail)
- content

Request Types

- GET asks the server to send a resource
- HEAD like GET but only send back headers
- POST send data to the server

Python and HTTP

- both client and server functionality
 - import http.client
 - import http.server
- TLS/SSL wrappers are also available
 - import ssl
- synchronous by default

Serving Requests

- derive from BaseHTTPRequestHandler
- implement a do_GET method
- this gets called whenever the client does a GET
- also available: do_HEAD, do_POST, etc.
- pass the class (not an instance) to HTTPServer

Serving Requests (cont'd)

- HTTPServer creates a new instance of your Handler
- the BaseHTTPRequestHandler machinery runs
- it calls your do_GET etc. method
- request data is available in instance variables
 self.path, self.headers

Talking to the Client

- HTTP responses start with a response code
 self.send_response(200, 'OK')
- the headers follow (set at least Content-Type)
 self.send_header('Connection', 'close')
- headers and the content need to be separatedself.end_headers()
- finally, send the content by writing to self.wfile

Sending Content

- self.wfile is an open file
- it has a write() method which you can use
- sockets only accept byte sequences, not str
- use the bytes(string, encoding) constructormatch the encoding to your Content-Type

HTTP and asyncio

- the base asyncio currently doesn't directly support HTTP
- but: you can get aiohttp from PyPI
- contains a very nice web server
 - from aiohttp import web
 - minimum boilerplate, fully asyncio-ready

SSL and TLS

- you want to use the ssl module for handling HTTPS
 - this is especially true server-side
 - aiohttp and http.server are compatible
- you need to deal with certificates (loading, checking)
- this is a rather important but complex topic

Certificate Basics

- certificate is a cryptographically signed statement
 - it ties a server to a certain public key
 - the client ensures the server knows the private key
- the server loads the certificate and its private key
- the client must validate the certificate
 - this is typically a lot harder to get right

SSL in Python

- start with import ssl
- almost everything happens in the SSLContext class
- get an instance from ssl.create_default_context()
 - you can use wrap_socket to run an SSL handshake
 - you can pass the context to aiohttp
- if httpd is a http.server.HTTPServer:

httpd.socket = ssl.wrap_socket(httpd.socket, ...)

HTTP Clients

- there's a very basic http.client
- for a more complete library, use urllib.request
- aiohttp has client functionality
- all of the above can be used with ssl
- another 3rd party module: Python Requests

IO at the OS Level

- often defaults to blocking
 - read returns when data is available
 - this is usually OK for files
- but what about network code?
 - could work for a client

Threads and IO

- there may be work to do while waiting
 - waiting for IO can be wasteful
- only the calling (OS) thread is blocked
 - another thread may do the work
 - but multiple green threads may be blocked

Non-Blocking IO

- the program calls read
 - read returns immediately
 - even if there was no data
- but how do we know when to read?
 - we could poll
 - for example call read every 30ms

Polling

- trade-off between latency and throughput
 - sometimes, polling is okay
 - but is often too inefficient
- alternative: IO dispatch
 - useful when multiple IOs are pending
 - wait only if all are blocked

select

- takes a list of file descriptors
- block until one of them is ready
 next read will return data immediately
- can optionally specify a timeout
- only useful for OS-level resources

Alternatives to select

- select is a rather old interface
- there is a number of more modern variants
- poll and epoll system calls
 - despite the name, they do not poll
 - epoll is more scalable
- kqueue and kevent on BSD systems

Synchronous vs Asynchronous

- the select family is synchronous
 - you call the function
 - it may wait some time
 - you proceed when it returns
- OS threads are fully asynchronous

The Thorny Issue of Disks

- a file is always 'ready' for reading
- this may still take time to complete
- there is no good solution on UNIX
- POSIX AIO exists but is sparsely supported
- OS threads are an option

IO on Windows

- select is possible (but slow)
- Windows provides real asynchronous IO
 quite different from UNIX
 - the IO operation is directly issued
 - but the function returns immediately
- comes with a notification queue

The asyncio Event Loop

- uses the select family of syscalls
- why is it called async IO?
 - select is synchronous in principle
 - this is an implementation detail
 - the IOs are asynchronous to each other

How Does It Work

- you must use asyncio functions for IO
- an async read does not issue an OS read
- it yields back into the event loop
- the fd is put on the select list
- the coroutine is resumed when the fd is ready

Timers

- asyncio allows you to set timers
- the event loop keeps a list of those
- and uses that to set the select timeout
 - just uses the nearest timer expiry
- when a timer expires, its owner is resumed

Blocking IO vs asyncio

- all user code runs on the main thread
- you must not call any blocking IO functions
- doing so will stall the entire application
 - in a server, clients will time out
 - even if not, latency will suffer

DNS

- POSIX: getaddrinfo and getnameinfo
 also the older API gethostbyname
- those are all blocking functions
 - and they can take a while
 - but name resolution is essential
- asyncio internally uses OS threads for DNS

Signals

- signals on UNIX are very asynchronous
- interact with OS threads in a messy way
- asyncio hides all this using C code

Native Coroutines (Reminder)

• delared using async def

async def foo():
 await asyncio.sleep(1)

- calling foo() returns a suspended coroutine
- which you can await
 - or turn it into an asyncio.Task
Tasks

- asyncio.Task is a nice wrapper around coroutines
 create with asyncio.create_task()
- can be stopped prematurely using cancel()
- has an API for asking things:
 - done() tells you if the coroutine has finished
 - result() gives you the result

Tasks and Exceptions

- what if a coroutine raises an exception?
- calling result will re-raise it
 - i.e. it continues propagating from result()
- you can also ask directly using exception()
 returns None if the coroutine ended normally

Asynchronous Context Managers

- normally, we use with for resource acquisition
 this internally uses the context manager protocol
- but sometimes you need to wait for a resource
 __enter__() is a subroutine and would block
 - this won't work in async-enabled code
- we need __enter__() to be itself a coroutine

async with

- just like wait but uses __aenter__(), __aexit__()
 those are async def
- the async with behaves like an await
 - it will suspend if the context manager does
 - the coroutine which owns the resource can continue
- mainly used for locks and semaphores

Part 6: Testing, Pitfalls

Mixing Languages

- for many people, Python is not a first language
- some things look similar in Python and Java (C++, ...)
 sometimes they do the same thing
 - sometimes they do something very different
 - sometimes the difference is subtle

Python vs Java: Decorators

- Java has a thing called annotations
- looks very much like a Python decorator
- in Python, decorators can drastically change meaning
- in Java, they are just passive metadata
 - other code can use them for meta-programming though

```
Class Body Variables

class Foo:

some_attr = 42
```

- in Java/C++, this is how you create instance variables
- in Python, this creates class attributes
 - i.e. what C++/Java would call static attributes

Very Late Errors if a == 2: priiiint("a is not 2")

- no error when loading this into python
- it even works as long as a != 2
- most languages would tell you much earlier

Very Late Errors (cont'd)
try:
 foo()
except TyyyypeError:
 print("my mistake")

- does not even complain when running the code
- you only notice when foo() raises an exception

Late Imports

if a == 2: import foo foo.say_hello()

- unless a == 2, mymod is not loaded
- any syntax errors don't show up until a == 2
 - it may even fail to exist

Block Scope

for i in range(10): pass print(i) # not a NameError

- in Python, local variables are function-scoped
- in other languages, i is confined to the loop

```
Assignment Pitfalls
    x = [ 1, 2 ]
    y = x
    x.append( 3 )
    print( y ) # prints [ 1, 2, 3 ]
```

- in Python, everything is a reference
- assignment does not make copies

Equality of Iterables

- $[0, 1] == [0, 1] \rightarrow$ True (obviously)
- range(2) == range(2) \rightarrow True
- list(range(2)) == $[0, 1] \rightarrow$ True
- $[0, 1] == range(2) \rightarrow False$

Equality of bool

- if 0: print("yes") \rightarrow nothing
- if 1: print("yes") \rightarrow yes
- False == $0 \rightarrow \text{True}$
- True == $1 \rightarrow$ True
- 0 is False \rightarrow False
- 1 is True \rightarrow False

Equality of bool (cont'd)

- if 2: print("yes") \rightarrow yes
- True == $2 \rightarrow False$
- False == $2 \rightarrow False$
- if '': print("yes") \rightarrow nothing
- if 'x': print("yes") \rightarrow yes
- '' == False \rightarrow False
- 'x' == True \rightarrow False

Mutable Default Arguments

def foo(x = []): x.append(7) return x foo() # [7] foo() # [7, 7]... wait, what? Late Lexical Capture

f = [lambda x : i * x for i in range(5)]f 4 (3) # 12 f[0](3) # 12 ... ?! g = [lambda x, i = i: i * x for i in range(5)] g 4 (3) # 12 g[0](3) # 0 ... fml $h = \left[(lambda x : i * x) (3) \text{ for } i \text{ in range} (5) \right]$ h # [0, 3, 6, 12] ... i kid you not

Dictionary Iteration Order

- in python <= 3.6
 - small dictionaries iterate in insertion order
 - big dictonaries iterate in 'random' order
- in python 3.7
 - all dictonaries in insertion, but not documented
- in python >= 3.8
 - guaranteed to iterate in insertion order

x = [[1] * 2] * 3
print(x) # [[1, 1], [1, 1], [1, 1]]
x[0][0] = 2
print(x) # [[2, 1], [2, 1], [2, 1]]

Forgotten Await

```
import asyncio
async def foo():
    print( "hello" )
async def main():
    foo()
asyncio.run( main() )
```

• gives warning coroutine 'foo' was never awaited

Python vs Java: Closures

- captured variables are final in Java
- but they are mutable in Python
 - and of course captured by reference
- they are whatever you tell them to be in C++

Explicit super()

- Java and C++ automatically call parent constructors
- Python does not
- you have to call them yourself

Setters and Getters

```
obj.attr
obj.attr = 4
```

- in C++ or Java, this is an assignment
- in Python, it can run arbitrary code
 - this often makes getters/setters redundant

Why Testing

- reading programs is hard
- reasoning about programs is even harder
- testing is comparatively easy
- difference between an example and a proof

What is Testing

- based on trial runs
- the program is executed with some inputs
- the outputs or outcomes are checked
- almost always incomplete

Testing Levels

- unit testing
 - individual classes
 - individual functions
- functional
 - system
 - integration

Testing Automation

- manual testing
 - still widely used
 - requires human
- semi-automated
 - requires human assistance
- fully automated
 - can run unattended

Testing Insight

- what does the test or tester know?
- black box: nothing known about internals
- gray box: limited knowledge
- white box: 'complete' knowledge

Why Unit Testing?

- allows testing small pieces of code
- the unit is likely to be used in other code
 - make sure your code works before you use it
 - the less code, the easier it is to debug
- especially easier to hit all the corner cases

Unit Tests with unittest

- from unittest import TestCase
- derive your test class from TestCase
- put test code into methods named test_*
- run with python -m unittest program.py
 - add -v for more verbose output

```
from unittest import TestCase
class TestArith(TestCase):
    def test_add(self):
        self.assertEqual(1, 4 - 3)
    def test_leq(self):
        self.assertTrue(3 <= 2 * 3)</pre>
```

Unit Tests with pytest

- a more pythonic alternative to unittest
 unittest is derived from JUnit
- easier to use and less boilerplate
- you can use native python assert
- easier to run, too
 - just run pytest in your source repository

Test Auto-Discovery in pytest

- pytest finds your testcases for you no need to register anything
- put your tests in test_.py or _test.py
- name your testcases (functions) test_*

Fixtures in pytest

- sometimes you need the same thing in many testcases
- in unittest, you have the test class
- pytest passes fixtures as parameters
 - fixtures are created by a decorator
 - they are matched based on their names

import pytest import smtplib pytest.fixture def smtp_connection(): return smtplib.SMTP("smtp.gmail.com", 587) def test_ehlo(smtp_connection): response, msg = smtp_connection.ehlo() assert response == 250
Property Testing

- writing test inputs is tedious
- sometimes, we can generate them instead
- useful for general properties like
 - idempotency (e.g. serialize + deserialize)
 - invariants (output is sorted, ...)
 - code does not cause exceptions

Using hypothesis

- property-based testing for Python
- has strategies to generate basic data types
 int, str, dict, list, set, ...
- compose built-in generators to get custom types
- integrated with pytest

import hypothesis import hypothesis.strategies as s hypothesis.given(s.lists(s.integers())) def test_sorted(x): assert sorted(x) == x # should fail hypothesis.given(x=s.integers(), y=s.integers()) def test_cancel(x, y): assert (x + y) - y == x # looks okay

PV248 Python

Going Quick and Dirty

- goal: minimize time spent on testing
- manual testing usually losesbut it has almost 0 initial investment
- if you can write a test in 5 minutes, do it
- useful for testing small scripts

Shell 101

- shell scripts are very easy to write
- they are ideal for testing IO behaviour
- easily check for exit status: set -e
- see what is going on: set -x
- use diff -u to check expected vs actual output

Shell Test Example

set -ex
python script.py < test1.in | tee out
diff -u test1.out out
python script.py < test2.in | tee out
diff -u test2.out out</pre>

Continuous Integration

- automated tests need to be executed
- with many tests, this gets tedious to do by hand
- CI builds and tests your project regularly
 - every time you push some commits
 - every night (e.g. more extensive tests)

CI: Travis

- runs in the cloud (CI as a service)
- trivially integrates with pytest
- virtualenv out of the box for python projects
- integrated with github
- configure in .travis.yml in your repo

CI: GitLab

- GitLab has its own CI solution (similar to travis)
- also available at FI
- runs tests when you push to your gitlab
- drop a .gitlab-ci.yml in your repository
- automatic deployment into heroku &c.

CI: Buildbot

- written in python/twisted
 - basically a **framework** to build a custom CI tool
- self-hosted and somewhat complicated to set up
 - more suited for complex projects
 - much more flexible than most CI tools
- distributed design

CI: Jenkins

- another self-hosted solution, this time in Java
 widely used and well supported
- native support for python projects (including pytest)
 - provides a dashboard with test result graphs &c.
 - supports publishing sphinx-generated documentation

Print-based Debugging

- no need to be ashamed, everybody does it
- less painful in interpreted languages
- you can also use decorators for tracing
- never forget to clean your program up again

The Python Debugger

- run as python -m pdb program.py
- there's a built-in help command
- next steps through the program
- break to set a breakpoint
- cont to run until end or a breakpoint

What is Profiling

- measurement of resource consumption
- essential info for optimising programs
- answers questions about bottlenecks
 - where is my program spending most time?
 - less often: how is memory used in the program

Why Profiling

- 'blind' optimisation is often misdirected
 it is like fixing bugs without triggering them
 program performance is hard to reason about
- tells you exactly which point is too slow
 - allows for best speedup with least work

Profiling in Python

- provided as a library, cProfile
 - alternative: profile is slower, but more flexible
- run as python -m cProfile program.py
- outputs a list of lines/functions and their cost
- use cProfile.run() to profile a single expression

python -m cProfile -s time fib.py

ncalls tottime percall file:line(function) 13638/2 0.032 0.016 fib.py:1(fib_rec) 2 0.000 0.000 {builtins.print} 2 0.000 0.000 fib.py:5(fib_mem)