

Recitation 10 (12/2)

Reminders:

- MQ10 on Monday (12/5)
- PSet 5 due Wednesday (12/7) at 9pm

Lecture Recap: Writing Efficient Programs & Complexity

Writing Efficient Programs

- Until now, we've mostly talked about correctness, but we also need think about efficiency when writing programs.
- When we talk about improving efficiency, we often mean writing a program in a different way so that it is executed faster.

Some ways to evaluate the efficiency of programs

1. With a timer and using the time module

Example:

```
import time # import time module
tstart = time.time() # "start" timer
count = 0
for i in range(1000):
    count += 1
tend = time.time() # "end" timer
dt = tend - tstart
print(dt) # print time to run program
```

2. Counting number of operations

The following steps take constant time:

- a. Mathematical operations
- b. Comparisons
- c. Assignments
- d. Accessing objects in memory

3. Abstraction of order of growth (see next section).

Complexity/Order of Growth

- “Big-O” notation.
- Gives us an idea of how long an algorithm will take to run with respect to the size of its inputs (arguments), regardless of what machine it’s running on.
- Gives the worst case scenario.
- We don’t care about lower-order terms or constants. We are interested in trends as input grows very large, so highest order terms dominate.
 - Adding:
 $O(n^2) + O(n) + O(1) \rightarrow O(n^2 + n + 1) \rightarrow O(n^2)$
 - Multiplicative or additive constants don’t matter
 $O(10*n) \rightarrow O(n)$
 $O(n) * O(n) \rightarrow O(n^2)$
 $O(\log_2(n)) \rightarrow O(\log(n)/\log(2)) \rightarrow O(\log(n))$
 $O(n + 1) \rightarrow O(n)$
- We want the tightest bound possible. Technically, an algorithm that is $O(n)$ is also $O(n^2)$, $O(2^n)$, etc, since O is just \leq , but we want the closest upper bound possible.
- Big Θ bound is a lower and upper bound on the growth of some function – tighter bound:
 $f(x) = \Theta(x^2) \neq \Theta(n^3) \neq \Theta(2^x)$
 $n^2 + 2n + 6 \rightarrow \Theta(n^2)$

Common orders of growth ordered by increasing complexity. Ideally, we want to design algorithms as close to the top of the table as possible.

Complexity	Time	Examples
$O(1)$	Constant	Adding two numbers together, appending to a list – Independent of input size!
$O(\log(n))$	Logarithmic	Binary search
$O(n)$	Linear	list.copy(), or scanning through an entire list to look for a value
$O(n\log(n))$	Log-linear	Merge-sort
$O(n^2)$, $O(n^3)$ etc...	Polynomial	Nested for loops
$O(2^n)$, $O(3^n)$ etc...	exponential	Trying to guess an n-character password

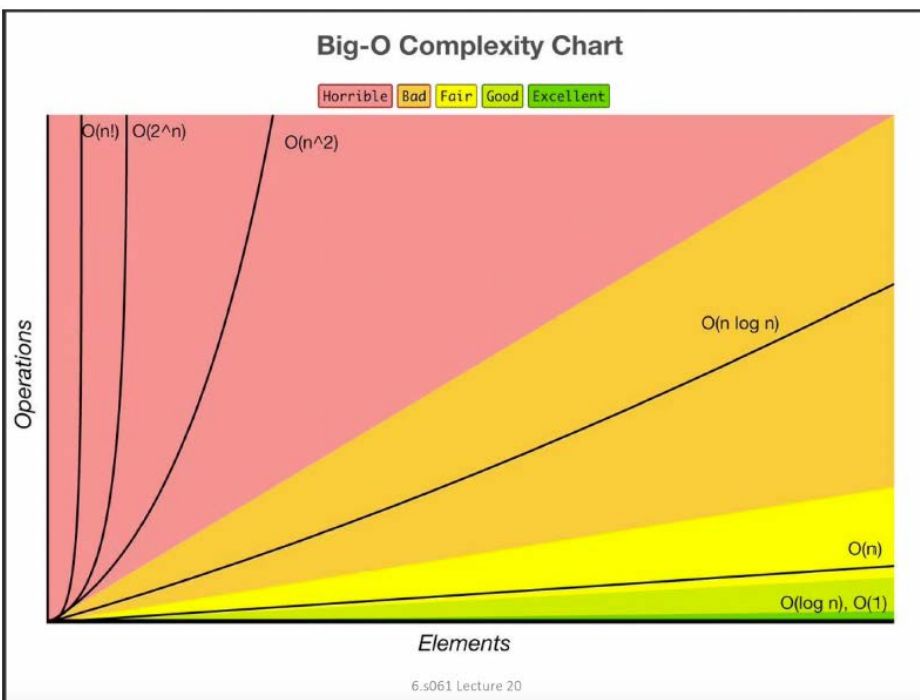
Complexity of Python methods/objects <https://wiki.python.org/moin/TimeComplexity>

- Constant-time operations:
 - Assigning a variable ($x = 1$)
 - Performing basic operations (+, -, /, **, <, >, ==, etc.)
 - Some built-in methods for data structures in Python are also constant-time, but many are not. Although we don't look at the underlying machinery of many built-in methods, the complexity of their implementations affects the complexity analysis of our own methods.
- Dictionaries (will depend on hash function)
 - $O(1)$: lookup, checking if key in dictionary, length, insert, delete
 - $O(n)$: `d.keys()` or `d.values()` - list of length n must be generated
- Lists
 - $O(1)$: append, length
 - $O(n)$: insert, delete (move around elements), copy, check if item in (unsorted) list
 - $O(n \log(n))$: sort

Strategies for Order-of-Growth Analysis

- Loops: # of iterations times cost of each iteration
- Recursive functions
 - How many recursive calls are being made?
 - How much work does each recursive call take?
 - Draw a tree connecting subproblems

Helpful Big-O Complexity Chart



MIT OpenCourseWare
<https://ocw.mit.edu>

6.100L Introduction to CS and Programming Using Python
Fall 2022

For information about citing these materials or our Terms of Use, visit: <https://ocw.mit.edu/terms>