DATA STRUCTURE AND ALGORITHMS

Algorithmic Complexity

Overview

Computational complexity

- How much time will it take a program to run?
- How much memory will it need to run?
- Need to balance minimizing computational complexity with conceptual complexity

Measuring complexity

- Goals in designing programs
 - 1. It returns the correct answer on all legal inputs
 - 2. It performs the computation efficiently
- Typically (1) is most important, but sometimes (2) is also critical
- Even when (1) is most important, it is valuable to understand and optimize (2)

How do we measure complexity?

- Given a function, would like to answer: "How long will this take to run?"
- Problem is that this depends on:
 - 1. Speed of compute.
 - 2. Specifics of Programming Language implementation
 - 3. Value of input
- Avoid (1) and (2) by measuring time in terms of number of basic steps executed
- For point (3), measure time in terms of size of input

Cases for measuring complexity

- Best case: minimum running time over all possible inputs of a given size
 - For linearSearch constant, i.e. independent of size of inputs
- Worst case: maximum running time over all possible inputs of a given size
 - For linearSearch linear in size of list
- Average (or expected) case: average running time over all possible inputs of a given size
- We will focus on worst case a kind of **upper bound** on running time

```
def fact(n):
    answer = 1
    while n > 0:
        answer *= n
        n -= 1
    return answer
```

- Number of steps:
- 1 (for assignment)
- 5*n (1 for test, plus 2 for first assignment, plus 2 for second assignment in while; repeated n times through while)
- 1 (for return)
- 5*n+2steps
- But as n gets large, 2 is irrelevant, so basically 5*n steps

Big-Oh notation!

- Gives us a meaningful way to talk about the running time of an algorithm, independent of programming language, computing platform, etc., without having to count all the operations.
- Focus on how the runtime scales with n (the input size).

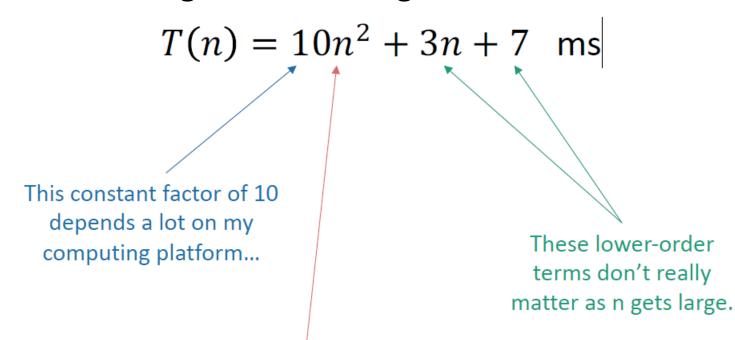
Big-Oh Example

Number of operations	Asymptotic Running Time
$\frac{1}{10}$ $\cdot n^2 + 100$	$O(n^2)$
$0.063 \cdot n^25 n + 12.7$	$O(n^2)$
$100 \cdot n^{1.5} - 10^{10000} \sqrt{n}$	$O(n^{1.5})$
$11 \left(n \log(n) + 1 \right)$	$O(n\log(n))$

We say this algorithm is "asymptotically faster" than the others.

Why is this a good idea?

Suppose the running time of an algorithm is:



We're just left with the n² term! That's what's meaningful.

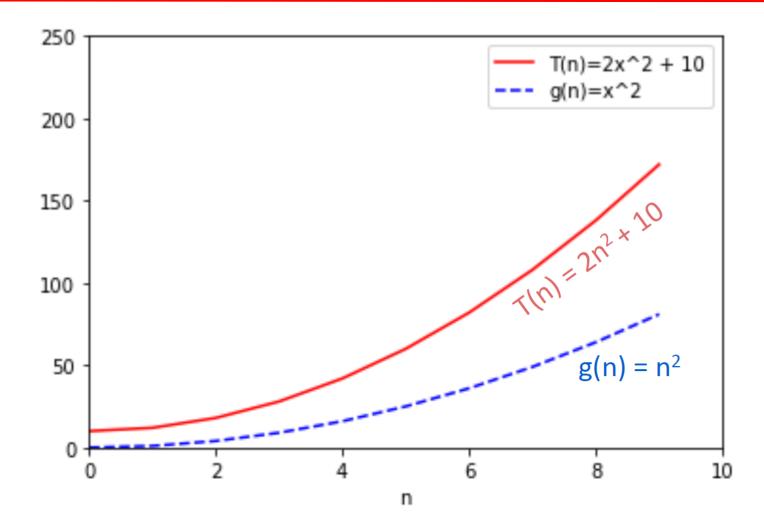
Formal definition of O(...)

- Let T(n), g(n) be functions of positive integers.
 - Think of T(n) as a runtime: positive and increasing in n.
- Formally,

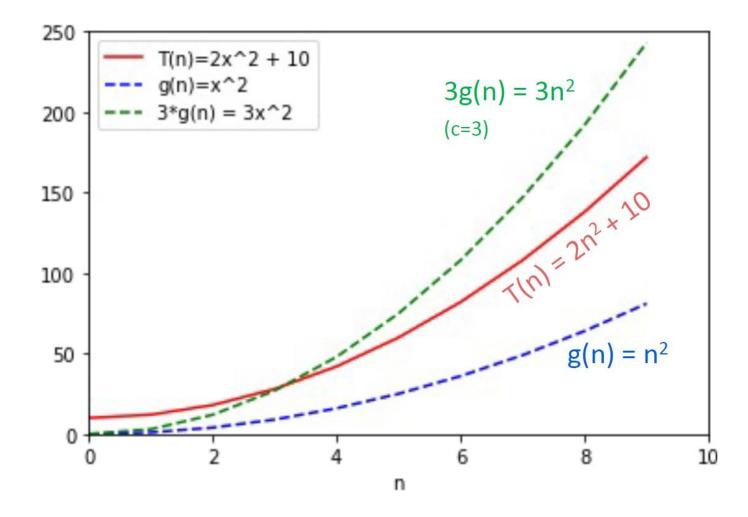
$$T(n) = O\big(g(n)\big)$$
 "For all"
$$\exists c > 0, n_0 \ s. \ t. \ \forall n \geq n_0,$$

$$T(n) \leq c \cdot g(n)$$
 "such that"

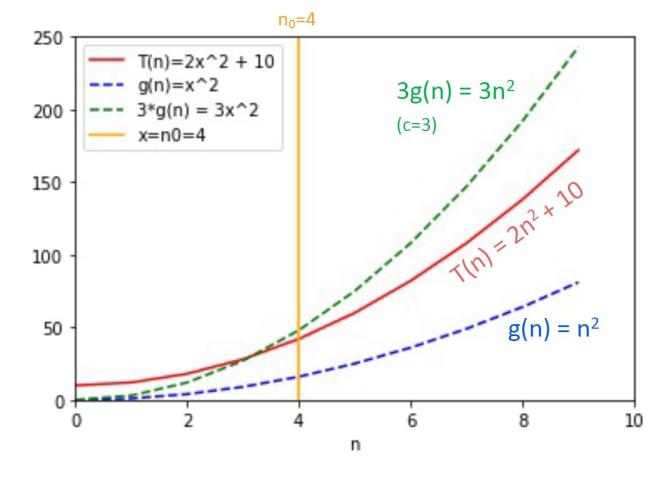
• $2n^2 + 10 = O(n^2)$



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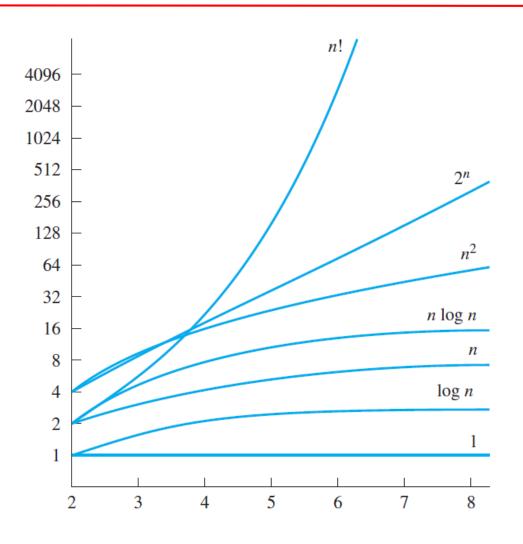


• $2n^2 + 10 = O(n^2)$



Choose c = 3 Choose n_0 = 4 Then: $\forall n \geq 4, 2n^2 + 10 \leq 3n^2$

Growth of functions commonly used in big-O



Exercise

• Determine whether each of these functions is O(x).

a)
$$f(x) = 10$$

b)
$$f(x) = 3x + 7$$

c)
$$f(x) = x^2 + x + 1$$

$$d) \ f(x) = 5\log(x)$$

$\Omega(...)$ means a lower bound

- Let T(n), g(n) be functions of positive integers.
 - Think of T(n) as a runtime: positive and increasing in n.
- Formally,

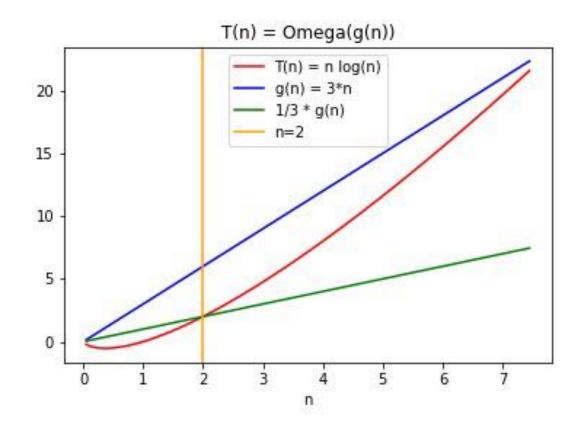
$$T(n) = \Omega(g(n))$$

$$\Leftrightarrow$$

$$\exists c > 0, n_0 \text{ s.t. } \forall n \geq n_0,$$

$$c \cdot g(n) \leq T(n)$$
Switched these!!

• $nlog_2(n) = \Omega(3n)$



- Choose c = 1/3
- Choose $n_0 = 2$
- Then $\forall n \geq 2, \frac{3n}{3} \leq nlog_2(n)$

$\Theta(...)$ means both!

• T(n) is $\Theta(g(n))$ iff both:

$$T(n) = O(g(n))$$

and
 $T(n) = \Omega(g(n))$

Exercise: Show that

• $3x^2 + 8x \log x = \Theta(x^2)$

Exercise

• Arrange the functions logn, n, nlogn, n^m , $m > 1,2^n$,n! in a list so that each function is big-O of the next function.