

Running Time Analysis and Asymptotic Notation

COMP4500/7500

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What is an algorithm?

- An *algorithm* is a well-defined computation procedure that takes some values as *input* and produces some value, or set of values, as *output* [CLRS CH1].
- Usually defined to solve a specific *computational problem*.
- We would like such algorithms to be *correct* (w.r.t. their problem) and *efficient*.

Sorting Problem

input A sequence of numbers $\langle a_1, a_2, \dots, a_n \rangle$

output A permutation $\langle a'_1, a'_2, \dots, a'_n \rangle$ of the input sequence such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$

Sorting Algorithm: Insertion Sort

INSERTION-SORT(A)

```
1  for  $j = 2$  to  $A.length$ 
2       $key = A[j]$ 
3      // Insert  $A[j]$  into the sorted sequence  $A[1..j - 1]$ 
4       $i = j - 1$ 
5      while  $i > 0$  and  $A[i] > key$ 
6           $A[i + 1] = A[i]$ 
7           $i = i - 1$ 
8       $A[i + 1] = key$ 
```

Try it on $A = [5, 2, 4, 6, 1, 3]$.

Sorting Algorithm: Insertion Sort

INSERTION-SORT(A)

```
1  for  $j = 2$  to  $A.length$ 
2      // Invariant:  $A[1..j-1]$  contains original elements
3      // from  $A[1..j-1]$ , but in sorted order
4       $key = A[j]$ 
5      // Insert  $A[j]$  into the sorted sequence  $A[1..j-1]$ 
6       $i = j - 1$ 
7      while  $i > 0$  and  $A[i] > key$ 
8           $A[i+1] = A[i]$ 
9           $i = i - 1$ 
10      $A[i+1] = key$ 
```

Loop invariants can be used to prove algorithms are correct.

Execution Time

What does it depend on?

- *input size*, e.g. sorting 10 elements versus 1000 elements
- *input value*, e.g. sorting an already sorted list versus a reverse sorted list

Generally we want an upper bound on execution time.

Execution time: Worst, Average and Best case

Definition (Worst case)

$T(n)$ = Maximum execution time over all inputs of size n

Definition (Average case)

$T(n)$ = Average execution time over all inputs of size n ,
weighted by the probability of the input

Definition (Best case)

$T(n)$ = Minimum execution time over all inputs of size n

Running Time Analysis

The *running time* of an algorithm on a given input can be measured in terms of the number of primitive *steps* executed.

Sorting Algorithm: Insertion Sort

Let n be $A.length$.

Let's measure time in terms of the number of array comparisons (in red):

INSERTION-SORT(A)

```

1  for  $j = 2$  to  $A.length$ 
2       $key = A[j]$ 
3      // Insert  $A[j]$  into the sorted sequence  $A[1..j - 1]$ 
4       $i = j - 1$ 
5      while  $i > 0$  and  $A[i] > key$ 
6           $A[i + 1] = A[i]$ 
7           $i = i - 1$ 
8       $A[i + 1] = key$ 

```

Worst case: $T(n) = \sum_{j=2}^n (j-1) = n(n-1)/2$

Best case: $T(n) = \sum_{j=2}^n (1) = n - 1$

Running Time Analysis: Recursion

- More complicated than conditionals and loops.
- Running time can often be described by a **recurrence**
- Overall running time on a problem of size n is described in terms of running time(s) on smaller inputs and functions of n . (see CLRS Ch2 Ex: Merge Sort)

Asymptotic Analysis: the general idea

- Groups functions together based on their *rate of growth*.
 - Merge sort $\Theta(n \lg n)$
 - Insertion sort $\Theta(n^2)$
- For large inputs, difference in *order* outweigh constant factors:
 - E.g. Merge sort is ultimately better for large enough n no matter what the constant factors.
- Ignores implementation dependent constants:
 - machine speed
 - compiler

Growth of functions

Largest instance that can be solved in given time

$T(n)$	1 second	1 day	1 year
n	1,000,000	86,400,000,000	31,536,000,000,000
$n \log n$	62,746	2,755,147,514	798,160,978,500
n^2	1,000	293,938	5,615,692
n^3	100	4,421	31,593
2^n	19	36	44

Asymptotic Analysis: limitations?

- Constant factors are relevant for
 - small input sizes, and
 - algorithms of same order

Asymptotic notation

For functions f and g

$f \in O(g)$ f is asymptotically bounded above by g to within a constant factor

- $n \in O(n^2)$
- $64,000n \in O(n)$

$f \in \Omega(g)$ f is asymptotically bounded below by g to within a constant factor

- $g \in O(f)$
- $n^2 \in \Omega(n)$

$f \in \Theta(g)$ f is asymptotically bounded above and below by g to within a constant factor

- $f \in O(g) \wedge f \in \Omega(g)$
- $42n \in \Theta(n)$
- $n \notin \Theta(n^2)$

Upper Bounds

Definition (Big-O)

$$O(g) = \{f \mid \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq f(n) \leq c \cdot g(n)\}$$

$$f \in O(g) \iff \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq f(n) \leq c \cdot g(n)$$

Upper Bounds

Definition (Big-O)

$$O(g) = \{f \mid \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq f(n) \leq c \cdot g(n)\}$$

Prove that: $2n^3 \in O(n^3)$

Need constants $c, n_0 > 0$ such that $(\forall n \geq n_0 \bullet 0 \leq 2n^3 \leq cn^3)$.

Choosing $c = 2$ and $n_0 = 1$ will suffice since:

$$\begin{aligned} & \forall n \geq 1 \bullet 0 \leq 2n^3 \leq 2n^3 \\ \equiv & \text{ true} \end{aligned}$$

Quick question: upper Bounds

Definition (Big-O)

$$O(g) = \{f | \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq f(n) \leq c \cdot g(n)\}$$

Prove that: $2n^2 \in O(n^3 - n^2)$

Lower Bounds

Definition (Ω)

$$\Omega(g) = \{f \mid \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq c \cdot g(n) \leq f(n)\}$$

$$f \in \Omega(g) \iff \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq c \cdot g(n) \leq f(n)$$

Lower Bounds

Definition (Ω)

$$\Omega(g) = \{f \mid \exists c, n_0 > 0 \bullet \forall n \geq n_0 \bullet 0 \leq c \cdot g(n) \leq f(n)\}$$

Prove that: $2n^3 \in \Omega(n^3)$

Need constants $c, n_0 > 0$ such that $(\forall n \geq n_0 \bullet 0 \leq cn^3 \leq 2n^3)$.

Choosing $c = 2$ and $n_0 = 1$ will suffice since:

$$\begin{aligned} & \forall n \geq 1 \bullet 0 \leq 2n^3 \leq 2n^3 \\ \equiv & \text{ true} \end{aligned}$$

Tight Bounds

Definition (Θ)

$$\Theta(g) = \{f \mid \exists c_1, c_2, n_0 > 0 \bullet \\ \forall n \geq n_0 \bullet 0 \leq c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)\}$$

$$f \in \Theta(g) \iff \exists c_1, c_2, n_0 > 0 \bullet \\ \forall n \geq n_0 \bullet 0 \leq c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)$$

Tight Bounds

Definition (Θ)

$$\Theta(g) = \{f \mid \exists c_1, c_2, n_0 > 0 \bullet \\ \forall n \geq n_0 \bullet 0 \leq c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)\}$$

Prove that: $2n^3 \in \Theta(n^3)$

Need constants $c_1, c_2, n_0 > 0$ such that
($\forall n \geq n_0 \bullet 0 \leq c_1 n^3 \leq 2n^3 \leq c_2 n^3$).

Choosing $c_1 = c_2 = 2$ and $n_0 = 1$ will suffice since:

$$\begin{aligned} & \forall n \geq 1 \bullet 0 \leq 2n^3 \leq 2n^3 \leq 2n^3 \\ \equiv & \text{ true} \end{aligned}$$

Tight Bounds: Prove: $\frac{n^2}{2} - 2n \in \Theta(n^2)$

Need constants $c_1, c_2, n_0 > 0$ such that

$$(\forall n \geq n_0 \bullet 0 \leq c_1 n^2 \leq \frac{n^2}{2} - 2n \leq c_2 n^2) .$$

$$\begin{aligned} & 0 \leq c_1 n^2 \\ \equiv & \text{true} && \text{if } n \geq 0 \end{aligned}$$

$$\begin{aligned} & c_1 n^2 \leq \frac{n^2}{2} - 2n \\ \equiv & 2 \leq n\left(\frac{1}{2} - c_1\right) && \text{if } n > 0 \\ \equiv & 8 \leq n && \text{if } c_1 = \frac{1}{4} \end{aligned}$$

$$\begin{aligned} & \frac{n^2}{2} - 2n \leq c_2 n^2 \\ \equiv & \text{true} && \text{if } n \geq 0 \text{ and } c_2 \geq \frac{1}{2} \end{aligned}$$

Choosing $c_1 = \frac{1}{4}$, $c_2 = \frac{1}{2}$ and $n_0 = 8$ will therefore suffice.

Properties of asymptotic notation

Theorem

$$f \in O(g) \implies g + f \in \Theta(g)$$

For example, $n \in O(n^2) \implies n^2 + n \in \Theta(n^2)$

Theorem

For $k > 0$,

$$k.n^a \in \Theta(n^a)$$

Theorem

For $k > 0$ and $0 \leq a \leq b$

$$k.n^a \in O(n^b)$$

Properties of asymptotic notation

Theorem

For any functions f and g

$$f \in O(g) \iff g \in \Omega(f)$$

Theorem

For any functions f and g

$$f \in \Theta(g) \iff f \in O(g) \wedge f \in \Omega(g)$$

Comparing Functions

Definition (Asymptotically non-negative)

A function f is *asymptotically non-negative* if

$$\exists n_0 \bullet (\forall n \geq n_0 \bullet f(n) \geq 0)$$

Theorem

If f and g are asymptotically non-negative functions, and

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} &= c \geq 0 && \text{then } f \in O(g) \\ &= c > 0 && \text{then } f \in \Theta(g) \\ &= \infty && \text{then } g \in O(f) \end{aligned}$$

where c is a real-valued constant.

Cannot compare all functions

For example the functions

$$n \text{ and } n^{1+\sin n}$$

are not comparable.

Polynomials

$$p(n) = \sum_{k=0}^d a_k n^k = a_0 n^0 + a_1 n^1 + a_2 n^2 + \cdots + a_d n^d$$

Theorem

If $a_d > 0$,

$$p(n) \in \Theta(n^d)$$

$$\begin{aligned} & \lim_{n \rightarrow \infty} \frac{p(n)}{n^d} \\ &= \lim_{n \rightarrow \infty} \sum_{k=0}^d \frac{a_k n^k}{n^d} \\ &= \lim_{n \rightarrow \infty} \frac{a_d n^d}{n^d} + \sum_{k=0}^{d-1} \frac{a_k n^k}{n^d} \\ &= \lim_{n \rightarrow \infty} a_d + \sum_{k=0}^{d-1} \frac{a_k}{n^{d-k}} \\ &= a_d \end{aligned}$$

Polynomials

Theorem

For $a > 1$ and $d \geq 0$,

$$n^d \in O(a^n)$$

$$\begin{aligned}
 & \lim_{n \rightarrow \infty} \frac{n^d}{a^n} \\
 = & \text{by L'Hôpital's rule} \\
 & \lim_{n \rightarrow \infty} \frac{dn^{d-1}}{a^n \ln a} \\
 = & \text{by L'Hôpital's rule} \\
 & \lim_{n \rightarrow \infty} \frac{d(d-1)n^{d-2}}{a^n (\ln a)^2} \\
 = & d \text{ times} \\
 & \lim_{n \rightarrow \infty} \frac{d(d-1)(d-2)\dots 1 n^0}{a^n (\ln a)^d} \\
 = & \lim_{n \rightarrow \infty} \frac{d!}{a^n (\ln a)^d} \\
 = & \text{as } d! \text{ and } (\ln a)^d \text{ are constants and } a^n \text{ tends to } \infty \\
 & 0
 \end{aligned}$$