

# CMPSCI 311 Section 2: Introduction to Algorithms

## Lecture 2: Asymptotic Notation and Efficiency

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## Algorithm design

- ▶ Formulate the problem precisely
- ▶ Design an algorithm to solve the problem
- ▶ Prove the algorithm is correct
- ▶ **Analyze the algorithm's running time**

## Big-O: Motivation

What is the running time of this algorithm? How many "primitive steps" are executed for an input of size  $n$ ?

```
sum = 0
for i= 1 to n do
  for j= 1 to n do
    sum += A[i]*A[j]
  end for
end for
```

The running time is

$$T(n) = 2n^2 + n + 1 .$$

For large values of  $n$ ,  $T(n)$  is less than some multiple of  $n^2$ . We say  $T(n)$  is  $O(n^2)$  and we typically don't care about other terms.

## Big-O: Formal Definition

**Definition:** The function  $T(n)$  is  $O(f(n))$  if there exist constants  $c \geq 0$  and  $n_0 \geq 0$  such that

$$T(n) \leq cf(n) \text{ for all } n \geq n_0$$

We say that  $f$  is an **asymptotic upper bound** for  $T$ .

**Examples:**

- ▶ If  $T(n) = n^2 + 1000000n$  then  $T(n)$  is  $O(n^2)$
- ▶ If  $T(n) = n^3 + n \log n$  then  $T(n)$  is  $O(n^3)$
- ▶ If  $T(n) = 2^{\sqrt{\log n}}$  then  $T(n)$  is  $O(n)$
- ▶ If  $T(n) = n^3$  then  $T(n)$  is  $O(n^4)$  but it's also  $O(n^3)$ ,  $O(n^5)$  etc.

## Big-O: What it Is and Isn't

- ▶ **Is:** a way to categorize growth rate of (non-negative) functions relative to other functions.
- ▶ **Is not:** "the running time of my function"

**Correct usage:**

- ▶ The running time of my algorithm in input of size  $n$  is  $T(n)$ .  
**Statement about algorithm only.**
- ▶  $T(n)$  is  $O(n^3)$ . **Statement about the function  $T(n)$  only.**
- ▶ The running time of my algorithm is  $O(n^3)$ .  
**About algorithm and  $T(n)$ .**

**Incorrect usage:**

- ▶  $O(n^3)$  is *the* running time of my algorithm

## Properties of Big-O Notation

**Claim (Transitivity):** If  $f$  is  $O(g)$  and  $g$  is  $O(h)$ , then  $f$  is  $O(h)$ .

**Proof:** we know from the definition that

- ▶  $f(n) \leq cg(n)$  for all  $n \geq n_0$
- ▶  $g(n) \leq c'h(n)$  for all  $n \geq n'_0$

Therefore

$$\begin{aligned} f(n) &\leq cg(n) && \text{if } n \geq n_0 \\ &\leq c(c'h(n)) && \text{if } n \geq n_0 \text{ and } n \geq n'_0 \\ &= \underbrace{cc'}_{c''} h(n) && \text{if } n \geq \underbrace{\max\{n_0, n'_0\}}_{n''_0} \end{aligned}$$

Know how to do proofs using Big-O definition.

## Properties of Big-O Notation

### Claims (Additivity):

- ▶ If  $f$  is  $O(h)$  and  $g$  is  $O(h)$ , then  $f + g$  is  $O(h)$ .
- ▶ If  $f_1, f_2, \dots, f_k$  are each  $O(h)$ , then  $f_1 + f_2 + \dots + f_k$  is  $O(h)$ .
- ▶ If  $f$  is  $O(g)$ , then  $f + g$  is  $O(g)$ .

We'll go through a couple of examples...

## Consequences of Additivity

- ▶ OK to drop lower order terms. E.g., if

$$f(n) = 4.1n^3 + 23n + n \log n$$

then  $f(n)$  is  $O(n^3)$

- ▶ Polynomials: Only highest degree term matters. E.g., if

$$f(n) = a_0 + a_1n + a_2n^2 + \dots + a_dn^d, \quad a_d > 0$$

then  $f(n)$  is  $O(n^d)$

## Other Useful Facts: Log vs. Poly vs. Exp

**Fact:**  $\log_b(n)$  is  $O(n^d)$  for all  $b$  and  $d$

All polynomials grow faster than logarithm of any base

**Fact:**  $n^d$  is  $O(r^n)$  when  $r > 1$

Exponential functions grow faster than polynomials

## Logarithm review

**Definition:**  $\log_b(a)$  is the unique number  $c$  such that  $b^c = a$

Informally: the number of times you can divide  $a$  into  $b$  parts until each part has size one

### Properties:

- ▶ Log of product  $\rightarrow$  sum of logs

- ▶  $\log(xy) = \log x + \log y$
- ▶  $\log(x^k) = k \log x$

- ▶  $\log_b(\cdot)$  is inverse of  $b^{(\cdot)}$

- ▶  $\log_b(b^n) = n$
- ▶  $b^{\log_b(n)} = n$

When using big-O, it's OK not to specify base. Assume  $\log_2$  if not specified.

## Big-O sorting

Which grows faster?

$$n(\log n)^3 \text{ vs. } n^{4/3}$$

$$(\log n)^3 \text{ vs. } n^{1/3}$$

$$\log n \text{ vs. } n^{1/9}$$

- ▶ We know  $\log n$  is  $O(n^d)$  for all  $d$ 
  - ▶  $\Rightarrow \log n$  is  $O(n^{1/9})$
  - ▶  $\Rightarrow n(\log n)^3$  is  $O(n^{4/3})$

Apply transformations (monotone, invertible) to both functions. Try taking log.

## Big- $\Omega$ Motivation

Algorithm **foo**  
**for**  $i = 1$  to  $n$  **do**  
  **for**  $j = 1$  to  $n$  **do**  
    **for**  $k = 1$  to  $n$  **do**  
      do something...  
    **end for**  
  **end for**  
**end for**

Fact: run time is  $O(n^3)$

Conclusion: **foo** and **bar** have the same asymptotic running time.  
What is wrong?

Algorithm **bar**  
**for**  $i = 1$  to  $n$  **do**  
  **for**  $j = 1$  to  $n$  **do**  
    **for**  $k = 1$  to  $n$  **do**  
      do something else..  
    **end for**  
  **end for**  
**end for**

Fact: run time is  $O(n^3)$

## More Big-Ω Motivation

Algorithm **sum-product**

```
sum = 0
for i= 1 to n do
  for j= i to n do
    sum += A[i]*A[j]
  end for
end for
```

What is the running time of **sum-product**?

Easy to see it is  $O(n^2)$ . Could it be better?  $O(n)$ ?

## Big-Ω

Informally:  $T$  grows at least as fast as  $f$

**Definition:** The function  $T(n)$  is  $\Omega(f(n))$  if there exist constants  $c \geq 0$  and  $n_0 \geq 0$  such that

$$T(n) \geq cf(n) \text{ for all } n \geq n_0$$

$f$  is an **asymptotic lower bound** for  $T$

## Big-Ω

Exercise: let  $T(n)$  be the running time of **sum-product**. Show that  $T(n)$  is  $\Omega(n^2)$

Algorithm **sum-product**

```
sum = 0
for i= 1 to n do
  for j= i to n do
    sum += A[i]*A[j]
  end for
end for
```

Do on board: easy way and hard way

## Exercise review

Hard way

- ▶ Count exactly how many times the loop executes

$$1 + 2 + \dots + n = \frac{n(n+1)}{2} = \Omega(n^2)$$

Easy way

- ▶ Ignore all loop executions where  $i > n/2$  or  $j < n/2$
- ▶ The inner statement executes at least  $(n/2)^2 = \Omega(n^2)$  times

## Big-Θ

**Definition:** the function  $T(n)$  is  $\Theta(f(n))$  if it is both  $O(f(n))$  and  $\Omega(f(n))$ .

$f$  is an **asymptotically tight bound** of  $T$

## Big-Θ example

How do we correctly compare the running time of these algorithms?

Algorithm **foo**

```
for i= 1 to n do
  for j= 1 to n do
    do something...
  end for
end for
```

Algorithm **bar**

```
for i= 1 to n do
  for j= 1 to n do
    for k= 1 to n do
      do something else..
    end for
  end for
end for
```

Answer: **foo** is  $\Theta(n^2)$  and **bar** is  $\Theta(n^3)$ . They do not have the same asymptotic running time.

## Additivity Revisited

Suppose  $f$  and  $g$  are two (non-negative) functions and  $f$  is  $O(g)$

Old version: Then  $f + g$  is  $O(g)$

New version: Then  $f + g$  is  $\Theta(g)$

Example:

$$\underbrace{n^2}_g + \underbrace{42n + n \log n}_f \text{ is } \Theta(n^2)$$

## Next Time

- ▶ When is an algorithm efficient?
- ▶ Graphs