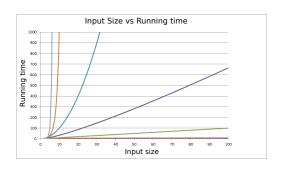
#### CS311H: Discrete Mathematics

Asymptotic Analysis

Instructor: Ișil Dillig

### Complexity Theory Intro

- ► Algorithmic complexity theory: How fast does the running time of an algorithm grow with respect to input size?
- Some algorithms scale better as input size grows



# Complexity Theory

- Complexity theory is concerned with expressing the running time of an algorithm with respect to input size
- Idea 1: Express running time in terms of the number of operations – abstract away choice of hardware and PL
- ▶ Idea 2: Not interested in exact number of operations, just an asymptotic estimate
  - Number of operations proportional to some function f(n) s.t. they become equal as  $n \to \infty$
  - e.g., instead of  $2 \cdot n^3 + \frac{1}{2}n^2 + \frac{11}{9}n + 4log(n)$ , we just say running time is cubic

# **Big-O Notation**

- Useful tool for asymptotic analysis is Big-O notation
- Intuition: If algorithm is O(f(n)), then running time is bounded by a function proportional to f(n) for sufficiently large n
- **Example:** If algorithm is O(1), this means it's constant-time, i.e., running time of algorithm does not depend on input size
- **Example:** If algorithm is O(n), running time of algorithm grows linearly in input size

## Formal Definition of Big-O

A function f(n) is O(g(n)) if there exist positive constants C, k such that:

$$\forall n > k. |f(n)| \le C|g(n)|$$

ightharpoonup i.e., for sufficiently large  $n,\,f(n)$  is bounded from above by a function proportional to g(n)



# An Assumption in this Course

A function f(n) is O(g(n)) if there exist positive constants C, k such that:

$$\forall n > k. |f(n)| \le C|g(n)|$$

- In the context of algorithmic complexity, f(n) represents the number of operations performed
- ▶ Hence, both f(n) and g(n) will always be positive you can assume this for this class, so we'll omit the absolute value

# Example I

Prove that 4n + 2 is O(n)

- $\triangleright$

## Example II

Prove that  $\frac{1}{2}n^2$  is not O(n)

▶ Proof by contradiction – suppose there was some C, k s.t.:

$$\forall n > k. \ \frac{1}{2}n^2 \le Cn$$

- ▶ Implies  $\forall n > k$ .  $n \leq 2C$
- ightharpoonup But this is not true because  $k,\,C$  are constants and we can make n arbitrarily large

# Example III

Prove that  $\log_2(3n^2+1)$  is  $O(\log_2 n)$ 

- $\blacktriangleright$

#### Useful Theorem

Let f(n) be a polynomial of degree d. Then f(n) is  $O(n^d)$ .

- ▶ f(n) must be  $a_d n^d + a_{d-1} n^{d-1} + \ldots + a_0$
- ▶ Observe:  $f(n) = n^d (a_d + \frac{a_{d-1}}{n} + \dots \frac{a_0}{n^d})$
- ► Since n > 1,  $f(n) \le n^d (a_d + a_{d-1} + \ldots + a_0)$
- Now, pick  $C = a_d + a_{d-1} + \ldots + a_0$ , and k = 1
- ▶ Hence,  $\forall n > 1$ .  $f(n) \leq C \cdot n^d$

#### Growth of Combination of Functions

- We are often interested in understanding the combined growth of multiple functions
- ► Consider a procedure P(n) = foo(n); bar(n);
- ▶ If we know foo is O(f(n)) and bar is O(g(n)), what can we say about P?

#### Growth of Sum of Two Functions

```
Suppose f_1(x) is O(g_1(x)) and f_2(x) is O(g_2(x)). Then, (f_1 + f_2)(x) is O(\max(g_1(x), g_2(x)))
```

- •

# Example

- ▶ Find a Big-O estimate for  $f(n) = log(3n^2 + 1) + \frac{11}{6}n^2$
- •

### Another Example

- ► Consider a procedure P(n) = foo(n); bar(n);
- ▶ If complexity of foo is O(n) and that of bar is  $O(n \log n)$ , what can we say about complexity of P?

#### Another Useful Theorem

Suppose  $f_1(x)$  is  $O(g_1(x))$  and  $f_2(x)$  is  $O(g_2(x))$ . Then,  $(f_1 \cdot f_2)(x)$  is  $O((g_1(x) \cdot g_2(x)))$ 

▶ We know  $\exists C_1, C_2, k_1, k_2$  such that:

$$\forall n > k_1. \ f_1(x) \le C_1 \cdot g_1(x)$$
  
$$\forall n > k_2. \ f_2(x) \le C_2 \cdot g_2(x)$$

- Let  $k = \max(k_1, k_2)$  and  $C = C_1 C_2$
- ▶ Hence,  $\forall n > k$ .  $(f_1 \cdot f_2)(x) \leq C \cdot g_1(x) \cdot g_2(x)$
- ▶ Thus,  $(f_1 \cdot f_2)(x)$  is  $O(g_1(x) \cdot g_2(x))$

### Example

- ▶ Find a Big-O estimate for  $f(n) = (\frac{1}{2}n^2 + 5)(\log(3n^2 + 1))$
- •
- •

### Another example

Assuming complexity of g is  $O(\log n)$ , find a Big-O estimate for the following procedure f:

```
f(n) = \{ for(i = 0; i < n; i+=2) \{ g(i, n) \} \}
```

- ▶ Total # of operations = # of times loop executes \* # of operations performed by g
- What is big-O estimate for the loop?
- ▶ Big-O estimate for *f*:

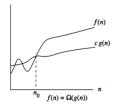
## Big-Omega Notation

- ▶ Big-O notation is useful for giving an upper bound for f(n) for large values of n
- But sometimes we are also interested in a lower bound!
- $\blacktriangleright$  For this purpose, we use the Big-Omega  $\Omega$  notation, which represents asymptotic lower bounds

### Formal Definition of Big-Omega

A function f(n) is  $\Omega(g(n))$  if there exist positive constants C, k such that:

$$\forall n > k. |f(n)| \ge C|g(n)|$$



- i.e., for sufficiently large n, f(n) is bounded from below by a function proportional to g(n)
- ▶ As before, we will assume f(n) and g(n) are positive

### Example

- 1. Prove that  $2n^2 + n$  is  $\Omega(n)$ 
  - ightharpoonup Find a C and k:

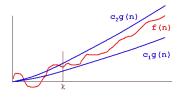
- 2. Prove that 5n + 1 is not  $\Omega(n^2)$ 
  - Suppose there exists constants such that:

$$\forall n > k. \ 5n + 1 \ge C \cdot n^2$$

- ▶ Implies  $\forall n > k$ .  $C \cdot n^2 5n 1 \le 0$
- ▶ But since C>0,  $C\cdot n^2-5n-1$  is an upward-looking looking parabola  $\Rightarrow$  for n large enough,  $C\cdot n^2-5n-1$  is positive

# Big Theta

- So far: Big-O gives asymptotic upper bounds, and Big-Omega gives asymptotic lower bounds
- But sometimes we are interested in a function that serves both as an asymptotic lower and upper bound



This is expressed using Big-Theta notation

## Formal Definition of Big-Theta

- ▶ A function f(x) is said to be  $\Theta(g(x))$  if f(x) is both  $\Omega(g(x))$  and O(g(x))
- Another way of saying this:

$$\exists C_1, C_2, k > 0. \ \forall n > k. \ C_1|g(x)| \le |f(x)| \le C_2|g(x)|$$

# Example I

Prove that  $10n + 4^{\log_2 n}$  is  $\Theta(n^2)$ 

- •

### Example II

Prove that  $\log n! = \Theta(n \log n)$ 

▶ First show  $\log n!$  is  $O(n \log n)$ :

### Example II, cont.

▶ Now show that  $\log n!$  is  $\Omega(n \log n)$ :

#### A Useful Theorem

1. f(x) is O(g(x)) if:

$$\lim_{x \to \infty} \left| \frac{f(x)}{g(x)} \right| < \infty$$

2. f(x) is  $\Omega(g(x))$  if:

$$\lim_{x \to \infty} \left| \frac{f(x)}{g(x)} \right| > 0$$

3. f(x) is  $\Theta(g(x))$  if:

$$0 < \lim_{x \to \infty} \left| \frac{f(x)}{g(x)} \right| < \infty$$

## Example I

- ▶ Show that  $\frac{x^2+1}{x+1}$  is  $\Theta(x)$
- ▶ Use previous theorem:

$$\lim_{x\to\infty}\frac{x^2+1}{x+1}\cdot\frac{1}{x}=1$$

▶ Hence, it's case (3)  $\Rightarrow \Theta(x)$