## Warm-Up

- Claim: Every natural number ≥ 2 has at least one prime factor.
  - Prime positive integer greater than 1 that cannot be formed by multiplying two smaller natural numbers
  - Factor a number that divides another number evenly
- Proof by Induction:

## Warm-Up

• Strong Induction: In inductive step, to prove H(i), we may assume H(1), H(2), ..., H(i-1)

• **Note:** in "weak" induction, we only assume H(i-1) because it is all we need to prove H(i)

• Problems: counting students, stable matching

• Alg. techniques:

• Analysis:

• Proof techniques: (strong) induction, contradiction

## Warm-Up

- Claim: Every natural number ≥ 2 has at least one prime factor.
- Proof by Induction:

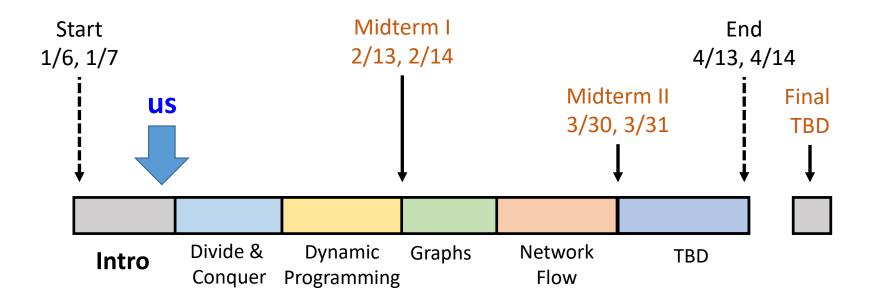
# CS3000: Algorithms & Data Drew van der Poel

#### Lecture 3:

Asymptotic Analysis

Jan 13/14, 2020

#### Outline



Last class: stable matching, proof by contradiction

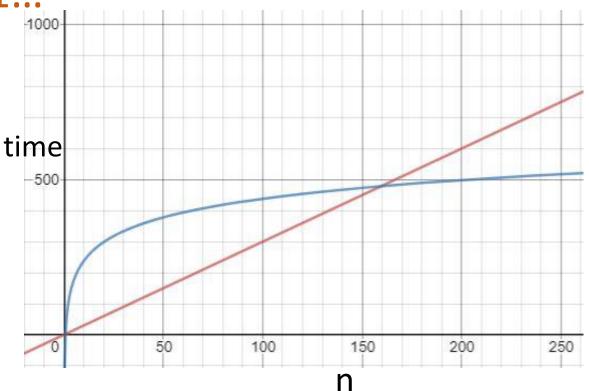
**Next class:** divide and conquer: Mergesort, divide and conquer: multiplying n-digit numbers (Karatsuba)

# **Asymptotic Analysis**

- Tool used to compare algorithms (functions)
- Describes performance based on input size
- Measures speed/size as input grows (gets really big)
  - Focuses on dominant (largest) term of function

#### From Lecture 1...

- Simple counting: 3n time
- Recursive counting:  $60 \log_2 n + 40$  time

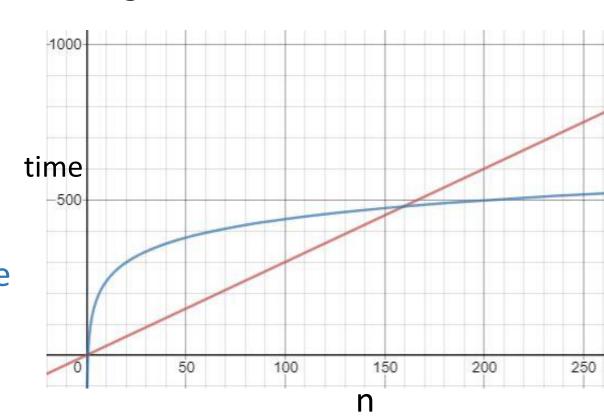


- Compare algorithms by asymptotics!
  - Log-time beats lineartime as  $n \to \infty$

- Predicting the wall-clock time of an algorithm is nigh impossible.
  - What machine will actually run the algorithm?
  - Impossible to exactly time operations

- Mostly we want to compare algorithms, so we can select the right one for the job
- Mostly we don't care about small inputs, we care about how the algorithm will *scale*

- Simple counting: 3n time
- Recursive counting:  $60 \log_2 n + 40$  time



 Asymptotic Analysis: How does the running time grow as the size of the input grows?

- Exact running time (# of operations) vs. order of growth
  - f(n): messy, depends on machine
  - g(n): nice function, summarizes performance

- "Big-Oh" Notation: f(n) = O(g(n)) if there exists  $c \in (0, \infty)$  and  $n_0 \in \mathbb{N}$  such that  $f(n) \leq c \cdot g(n)$  for every  $n \geq n_0$ .
  - Asymptotic version of  $f(n) \leq g(n)$
  - Roughly equivalent to  $\lim_{n\to\infty} \frac{f(n)}{g(n)} < \infty$

• "Big-Oh" Notation: f(n) = O(g(n)) if there exists  $c \in (0, \infty)$  and  $n_0 \in \mathbb{N}$  such that  $f(n) \leq c \cdot g(n)$  for every  $n \geq n_0$ .

• Ex. 
$$3n^{2} + n = O(n^{2})$$
 (= 4,  $n_{0} = 1$ )  
 $3n^{4} + n \le 4 \cdot n^{2}$   $\forall n \ge 1$   
 $3n^{4} + n \le 3n^{4} + n^{4}$ 

#### Ask the Audience

- "Big-Oh" Notation: f(n) = O(g(n)) if there exists  $c \in (0, \infty)$  and  $n_0 \in \mathbb{N}$  such that  $f(n) \leq c \cdot g(n)$  for every  $n \geq n_0$ .
- Which of these statements are true?

• 
$$n^{3} = O(n^{2}) \vdash$$
•  $n \to \infty \frac{h^{3}}{h^{3}} = \infty$ 
•  $10n^{4} = O(n^{5}) \vdash$ 
•  $\log_{2} n = O(\log_{16} n) \vdash$ 
•  $\log_{2} n = O(\log_{16} n) \vdash$ 
•  $\log_{2} n = \log_{2} n$ 

# Asymptotic Analysis Rules



Constant factors can be ignored

• 
$$\forall C > 0$$
  $Cn = O(n)$   $Cn^{3} = O(n^{3})$ 

Lower order terms can be dropped

• E.g. 
$$n^2 + n^{3/2} + n = O(n^2)$$

Smaller exponents are Big-Oh of larger exponents

• 
$$\forall a > b$$
  $n^b = O(n^a)$   $n^3 = O(n^3 \cdot o \circ o \circ f)$ 

• Any logarithm is Big-Oh of any polynomial 
$$\forall a, \varepsilon > 0 \quad \log_2^a \ n = O(n^{\varepsilon}) \quad \log_2^a \ n = O(n^{\varepsilon}) \quad \log_2^a \ n = O(n^{\varepsilon})$$

Any polynomial is Big-Oh of any exponential

• 
$$\forall a > 0, b > 1$$
  $n^a = O(b^n)$   $\eta^{1000} = O(1.000)$ 

#### A Word of Caution

• The notation f(n) = O(g(n)) is weird—do not take it too literally

$$n^{2} = O(n^{3})$$
 Not really "="
 $n^{3} = O(n^{2})$ 
 $n^{3} = O(4^{2})$ 

- "Big-Omega" Notation:  $f(n) = \Omega(g(n))$  if there exists  $c \in (0, \infty)$  and  $n_0 \in \mathbb{N}$  s.t.  $f(n) \geq c \cdot g(n)$  for every  $n \geq n_0$ .
  - Asymptotic version of  $f(n) \ge g(n)$
  - Roughly equivalent to  $\lim_{n\to\infty} \frac{f(n)}{g(n)} > 0$
- "Big-Theta" Notation:  $f(n) = \Theta(g(n))$  if there exists  $c_1 \le c_2 \in (0, \infty)$  and  $n_0 \in \mathbb{N}$  such that  $c_2 \cdot g(n) \ge f(n) \ge c_1 \cdot g(n)$  for every  $n \ge n_0$ .
  - Asymptotic version of f(n) = g(n)
  - Roughly equivalent to  $\lim_{n\to\infty}\frac{f(n)}{g(n)}\in(0,\infty)$
  - Equivalent to:  $f(n) = O(g(n)) AND f(n) = \Omega(g(n))$

#### **Asymptotic Running Times**

- We like to write running time as a Big-Theta
  - More precise than Oh or Omega
  - Note: Sometimes it is considerably easier to just use Oh

## **More Examples**

• 
$$30 \log_2 n + 45 = \Theta(\log n)$$
0:  $C = 75$ ,  $n_0 = \lambda$ 

20  $\log_2 n + 45 \le 75 \log_2 n$   $\forall n \ge \lambda$ 

•  $4n \log_2 2n = \Theta(n \log n)$   $\forall n (\log_2 \lambda + \log_2 n)$ 

•  $9 \log_2 n + \log_2 n + \log_2 n$ 

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•  $9 \log_2 n + \log_2 n + \log_2 n$ 

•  $9 \log_2 n + \log_2 n$ 

•

Strict! 
$$n^2 = o(n^3), n^2 \neq o(n^3)$$

- "Little-Oh" Notation: f(n) = o(g(n)) if for every c > 0 there exists  $n_0 \in \mathbb{N}$  s.t.  $f(n) < c \cdot g(n)$  for every  $n \ge n_0$ .
  - Asymptotic version of f(n) < g(n)
  - Roughly equivalent to  $\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0$
- "Little-Omega" Notation:  $f(n) = \omega(g(n))$  if for every c > 0 there exists  $n_0 \in \mathbb{N}$  such that  $f(n) \ge c \cdot g(n)$  for every  $n \ge n_0$ .
  - Asymptotic version of f(n) > g(n)
  - Roughly equivalent to  $\lim_{n\to\infty} \frac{f(n)}{g(n)} = \infty$

#### Ask the Audience!

- Rank the following functions in increasing order of growth (i.e.  $f_1, f_2, f_3, f_4$  so that  $f_i = O(f_{i+1})$ )
  - $n \log_2 n$
  - $n^2$
  - 100n

• 
$$3\log_2 n = \frac{1093^{109} n}{2^{1093^{3}}} = \frac{1093^{1093^{3}}}{1093^{3}} = \frac{1093^{3}}{1093^{3}} \approx 1.585$$

$$\frac{0}{1.100} = \frac{100}{1.100} = \frac{100}{1.100}$$

## Motivation: How Big of a Difference?

#### # of operations

	n	$n \log_2 n$	$n^2$	$n^3$	1.5 <sup>n</sup>	2 <sup>n</sup>	n!
n = 10	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	4 sec
n = 30	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	18 min	10 <sup>25</sup> years
n = 50	< 1 sec	< 1 sec	< 1 sec	< 1 sec	11 min	36 years	very long
n = 100	< 1 sec	< 1 sec	< 1 sec	1 sec	12,892 years	10 <sup>17</sup> years	very long
n = 1,000	< 1 sec	< 1 sec	1 sec	18 min	very long	very long	very long
n = 10,000	< 1 sec	< 1 sec	2 min	12 days	very long	very long	very long
n = 100,000	< 1 sec	2 sec	3 hours	32 years	very long	very long	very long
n = 1,000,000	1 sec	20 sec	12 days	31,710 years	very long	very long	very long

Instance size

Running time when 1 op. takes ~1 microsecond

#### **Observations:**

- 1. Different polynomials make a BIG difference! (e.g.  $n^2$  vs.  $n^3$  when  $n \ge 1000$
- 2. Things go bad quickly! (look down any polynomial or exponential column)
- 3. Large instances are when there is a difference (log still good!)

Problems: counting students, stable matching

Alg. techniques:

Analysis: asymptotic analysis

• Proof techniques: (strong) induction