

# CS 161: Design and Analysis of Algorithms

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# Outline

- Why study algorithms?
- What makes a good algorithm?
- What We'll See
  - Example: Multiplication
- Asymptotics review
- Course information

# Why Study Algorithms?

- Required for CS majors
- Algorithms are everywhere in CS
  - OS (CS 140)
  - Compilers (CS 143)
  - Crypto (CS 155)
  - Etc.
- Algorithms important in other fields
  - Economics (Game Theory)
  - Biology
- Exciting!

# What Makes a Good Algorithm

- Computes desired result
  - Always?
  - With high probability?
  - On real-world inputs?
- Uses resources efficiently
  - Time?
  - Space?
  - Disk I/O?
  - Programmer Effort?

# CS 161 Concepts

- Data Structures
- Graph Algorithms
- Greedy Algorithms
- Divide & Conquer
- Dynamic Programming
- Linear Programming
- NP-Completeness

# Algorithms We'll See

- Integer/Matrix Multiplication
- Fast Fourier Transform (FFT)
- Shortest Paths
- Sequence Alignment
- Minimum Spanning Trees
- Maximum Flows

# Integer Multiplication

- Grade-school algorithm

$$\begin{array}{r} 3764 \\ \times 689 \\ \hline 33876 \end{array}$$

$$\begin{array}{r} 3764 \\ \times 9 \\ \hline 33876 \end{array}$$

$$\begin{array}{r} 3764 \\ \times 8 \\ \hline 30112 \end{array}$$

$$\begin{array}{r} 301120 \\ + 2258400 \\ \hline 2593396 \end{array}$$

$$\begin{array}{r} 3764 \\ \times 6 \\ \hline 22584 \end{array}$$

Can we do better? Yes!

# Matrix Multiplication

$$\begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1} & a_{n,2} & \cdots & a_{n,n} \end{pmatrix} \times \begin{pmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,n} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n,1} & b_{n,2} & \cdots & b_{n,n} \end{pmatrix} = \begin{pmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ c_{n,1} & c_{n,2} & \cdots & c_{n,n} \end{pmatrix}$$

$$c_{i,j} = \sum_{k=1}^n a_{i,k} b_{k,j}$$

- Computing each term uses  $n$  multiplications and  $(n-1)$  additions
- Total:  $\sim 2n^3$  operations

Can we do better? Yes!



# Discrete Fourier Transform (DFT)

- Given a sequence  $a=(a_1, a_2, \dots, a_n)$ , the DFT of  $a$  is defined as  $A=(A_1, A_2, \dots, A_n)$  where

$$A_k = \sum_{i=1}^n a_i \omega_n^{ik}$$

- Important in signal processing, solving differential equations, polynomial multiplication, and integer multiplication!

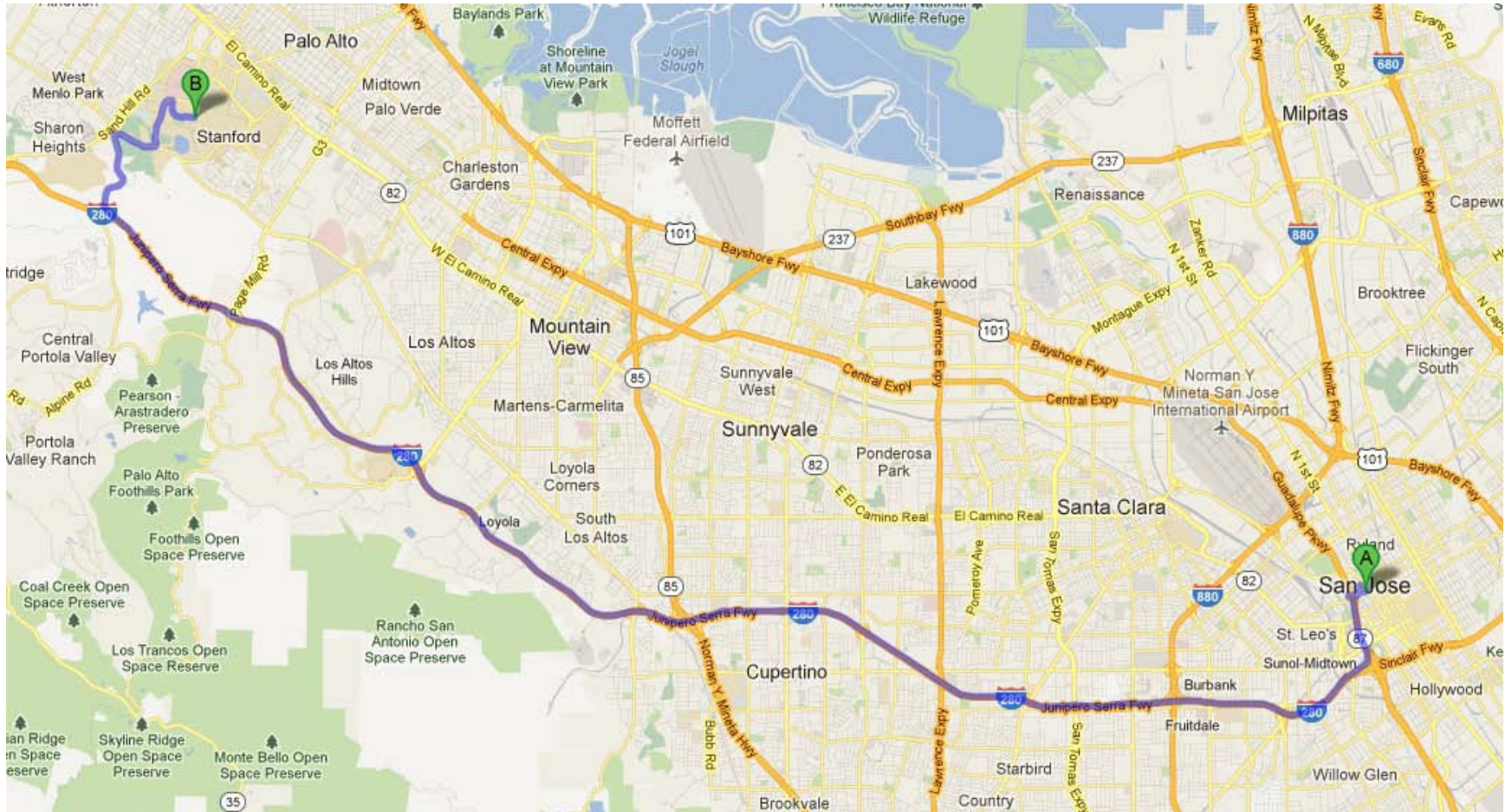
# Discrete Fourier Transform (DFT)

$$A_k = \sum_{i=1}^n a_i \omega_n^{ik}$$

- Appears to require  $\sim n^2$  additions and multiplications.

Can we do better? Yes!

# Shortest Paths



How do we determine the shortest path without exploring all paths?

# Sequence Alignment

- How close is “snowy” to “sunny”?

- Cost: 3 modifications:

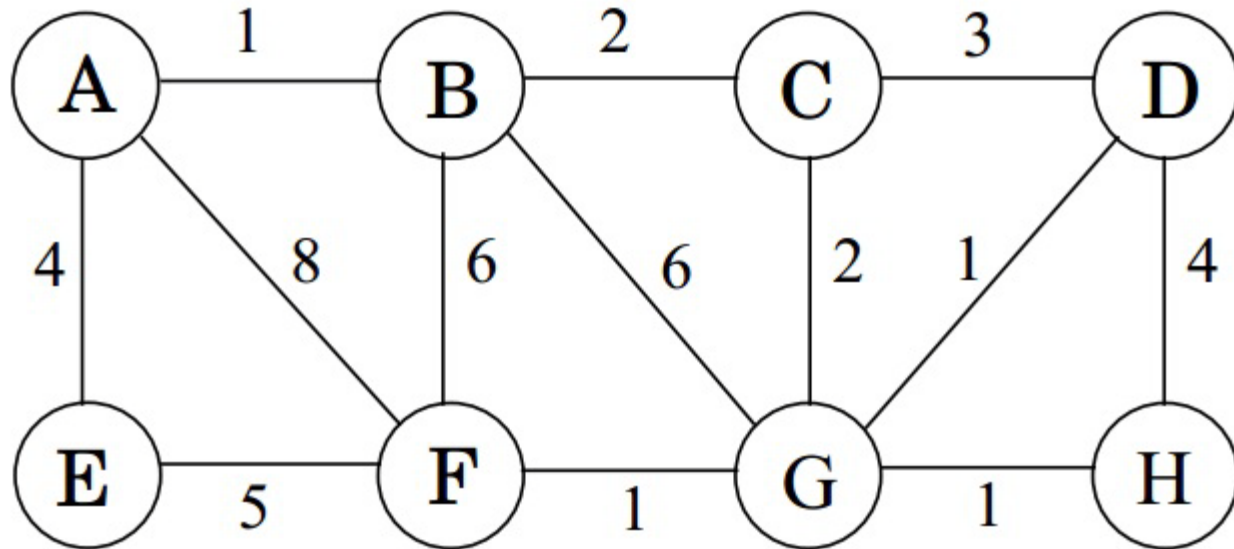
S	-	N	O	W	Y
S	U	N	N	-	Y

- Applications:

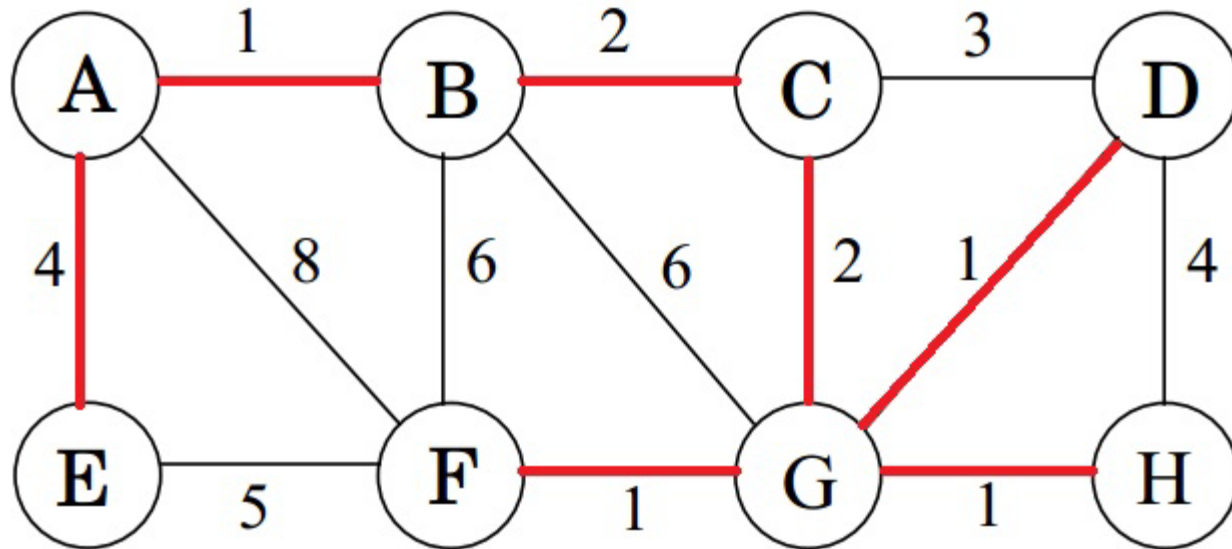
- Spell-checkers: If I have a misspelled word, what did I mean?

- Biology: Identify sections of DNA that are similar

# Minimum Spanning Trees

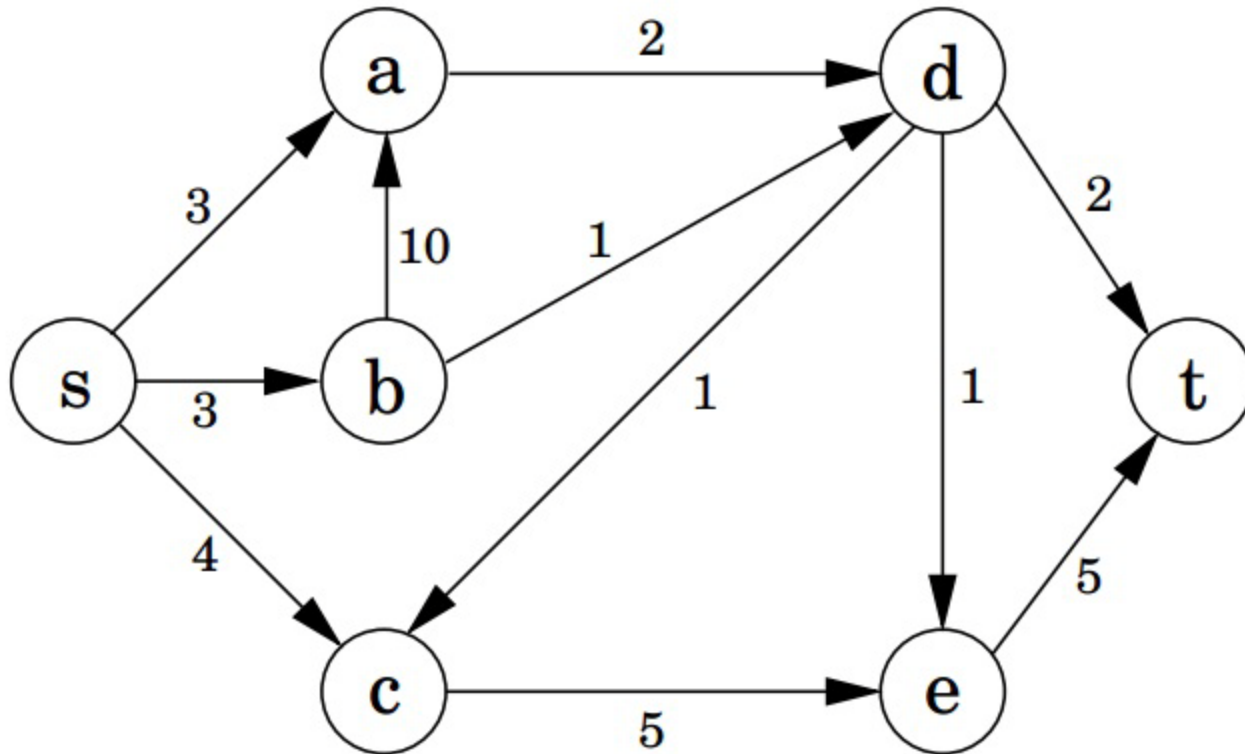


# Minimum Spanning Trees

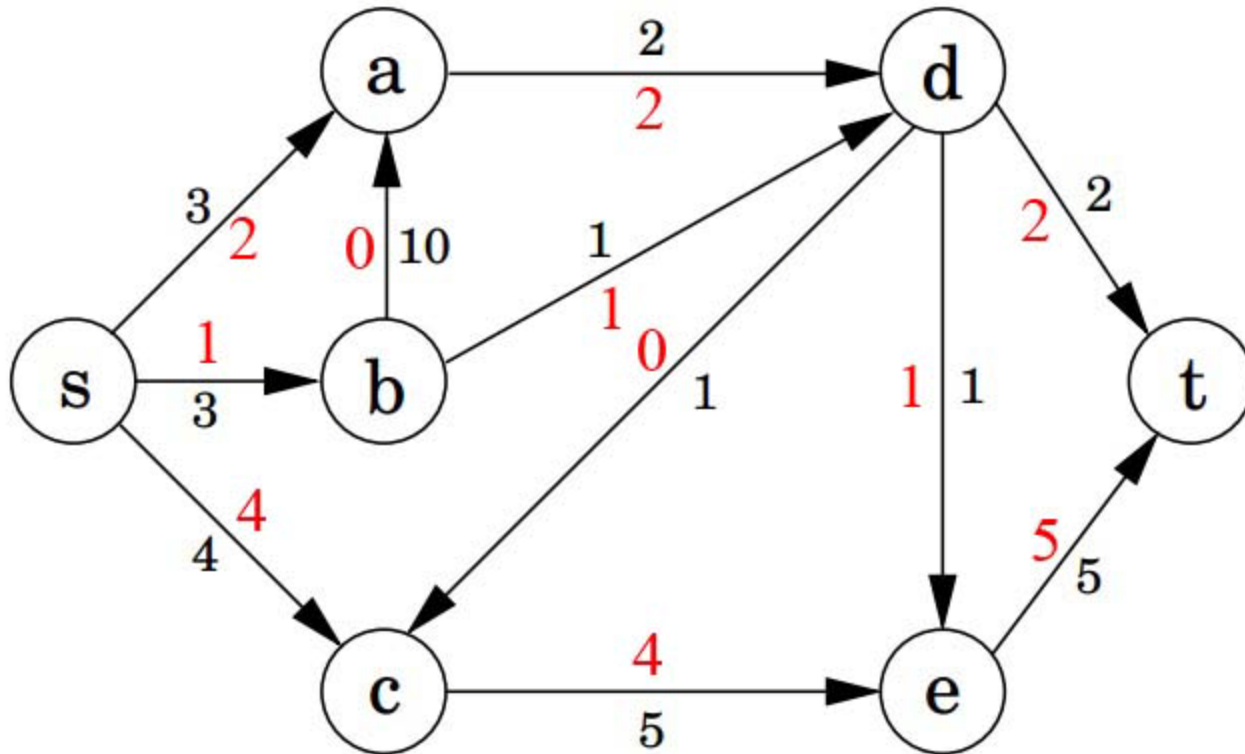


- Applications to network design, approximation algorithms, and more.

# Maximum Flows



# Maximum Flows



- Used in solutions for a host of different problems



# Example: Integer Multiplication

- Algorithm 1: Grade-school algorithm

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# Example: Integer Multiplication

- Algorithm 1: Grade-school algorithm
  - For simplicity, assume running time dominated by single-digit multiplications
  - Number of single-digit multiplications:  $n^2$
  - Can we do better?

# Example: Integer Multiplication

- Algorithm 2: Recursive algorithm
  - Write  $n$ -digit number  $x$  as  $10^{n/2} x_1 + x_2$ 
    - $x_1, x_2$  are  $n/2$ -digit numbers
  - Write  $y$  as  $10^{n/2} y_1 + y_2$
  - $xy = 10^n x_1 y_1 + 10^{n/2}(x_1 y_2 + x_2 y_1) + x_2 y_2$
  - Can multiply  $n$ -digit numbers by performing 4 multiplications of  $n/2$ -digit numbers.

# Example: Integer Multiplication

- Algorithm 2: Recursive algorithm
  - $xy = 10^n x_1y_1 + 10^{n/2}(x_1y_2 + x_2y_1) + x_2y_2$
  - Claim: the number of single-digit multiplications for algorithm 2 is  $n^2$ .
    - True for  $n=1$
    - Assume true for  $n/2$ . Then #(multiplications for  $n$ -bits) =  $4$  #(multiplications for  $n/2$  bits) =  $4 (n/2)^2 = n^2$ .

# Example: Integer Multiplication

- Which algorithm is better?
  - Both require  $n^2$  single-digit multiplications, so running time almost the same

# Example: Integer Multiplication

- Algorithm 3: Another Recursive Algorithm
  - We need the quantities  $x_1y_1$ ,  $(x_1y_2 + x_2y_1)$ , and  $x_2y_2$
  - Can we compute  $x_1y_2 + x_2y_1$  using one multiplication?
  - Gauss:  $x_1y_2 + x_2y_1 = (x_1 + x_2)(y_1 + y_2) - x_1y_1 - x_2y_2$ 
    - Already have  $x_1y_1$  and  $x_2y_2$ !

# Example: Integer Multiplication

- Algorithm 3: Another Recursive Algorithm
  - Compute  $P = x_1y_1$ ,  $Q = x_2y_2$ .
  - Let  $x_3 = x_1 + x_2$ ,  $y_3 = y_1 + y_2$ .
  - Compute  $R = x_3y_3$
  - Let  $S = R - P - Q$ .
  - $xy = 10^n P + 10^{n/2} S + Q$

# Example: Integer Multiplication

- Algorithm 3: Another Recursive Algorithm
  - Replaced 4 multiplications with 3, seems like it should be faster.
  - Not so simple:
    - One of the multiplications is slightly larger.
    - Added some extra overhead (additions and subtractions)
  - Possible to show  $< 4n^{1.6}$  single-digit multiplications



# Example: Integer Multiplication

- Which algorithm is faster?
  - $4n^{1.6} > n^2$  for  $n < 32$ .
  - $4n^{1.6} < n^2$  for  $n > 32$ .
- Algorithm 3 slower for  $n < 32$ , faster for  $n > 32$ .
- How do we compare?

# How to Compare Algorithms

- Say we want to compute a function  $f(n)$ 
  - Algorithm 1 runs in  $100,000n$  seconds
  - Algorithm 2 runs in  $n^2$  seconds
- Which algorithm is better?
  - Algorithm 2 runs faster if  $n < 100,000$
  - Algorithm 1 runs faster if  $n > 100,000$
  - The ratio of run times goes to infinity

# How to Compare Algorithms

- Say we want to compute a function  $g(n)$ 
  - Algorithm 1 runs in  $20n$  seconds
  - Algorithm 2 runs in  $10n+30$  seconds
- Which algorithm is better?
  - Algorithm 2 is faster than Algorithm 1 when  $n > 3$
  - However, it is only twice as fast

# Asymptotics/Big Oh

- We say Algorithm 1 is “at least as fast as” Algorithm 2 if, for large enough inputs, Algorithm 1 is at most a constant factor slower than Algorithm 2.
- For this class, we will compare algorithms using “at least as fast as”.

# Big Oh

$$O(f(n)) =$$

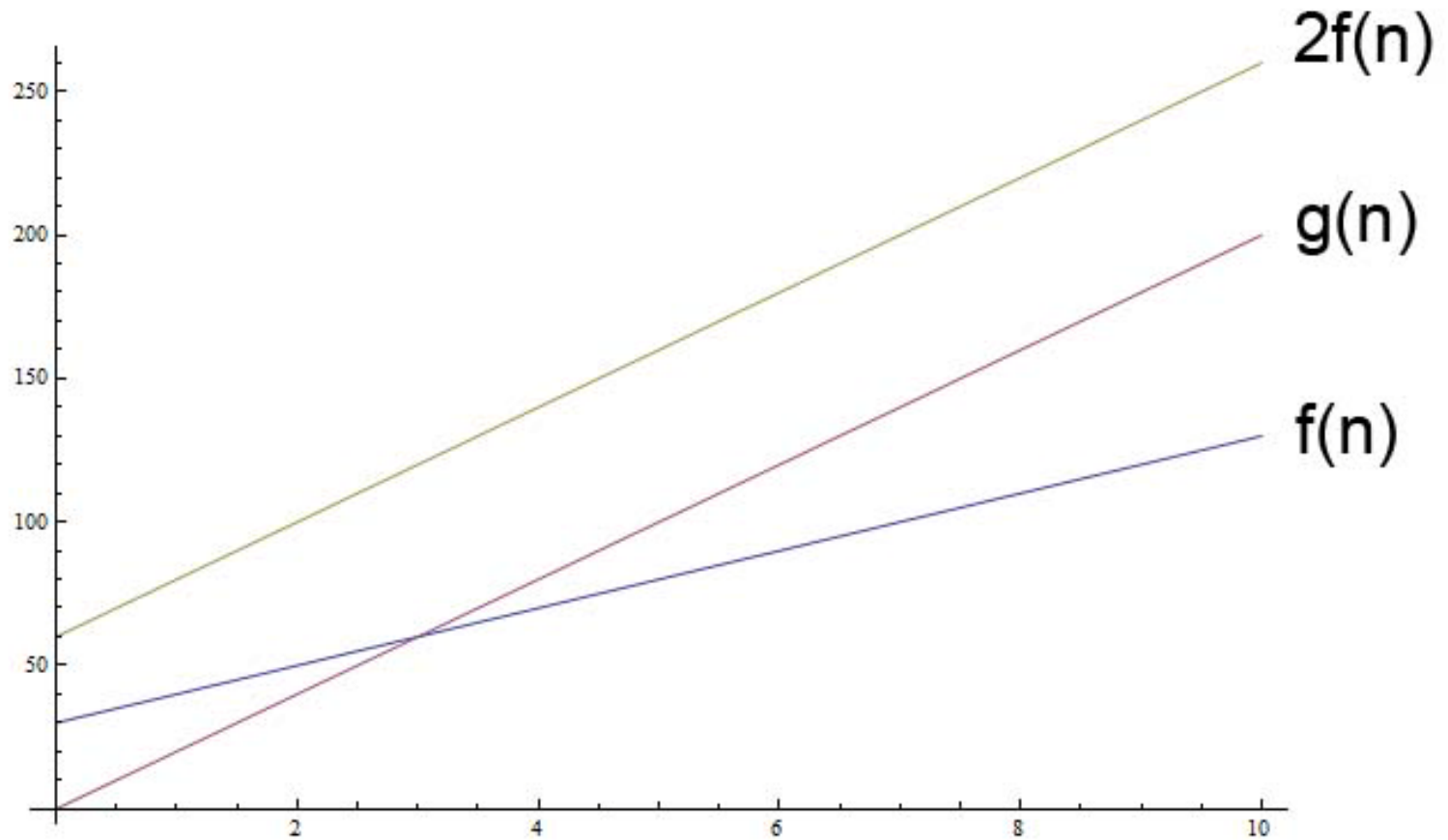
$$\{g(n) : \exists c, n_0 \text{ such that } g(n) \leq c f(n) \forall n \geq n_0\}$$

- So  $g(n) \in O(f(n))$  if
  - There are  $c$  and  $n_0$  such that
  - $g(n) \leq c f(n)$  for all  $n \geq n_0$ .
- Sometimes write  $g(n) = O(f(n))$ .

# Big Oh Example 1

- $f(n) = 10n+30, g(n) = 20n$
- $f(n) \in O(g(n))$ 
  - Proof: Let  $c = 1, n_0 = 3$ .
  - If  $n \geq n_0$ , then  $f(n)=10n+30 \leq 20n = c g(n)$ .
- $g(n) \in O(f(n))$ 
  - Proof: Let  $c = 2, n_0 = 1$ .
  - If  $n \geq n_0$ , then  $g(n)=20n \leq 2 \times (10n+30) = c f(n)$ .

# Big Oh Example 1



# Big Oh Example 2

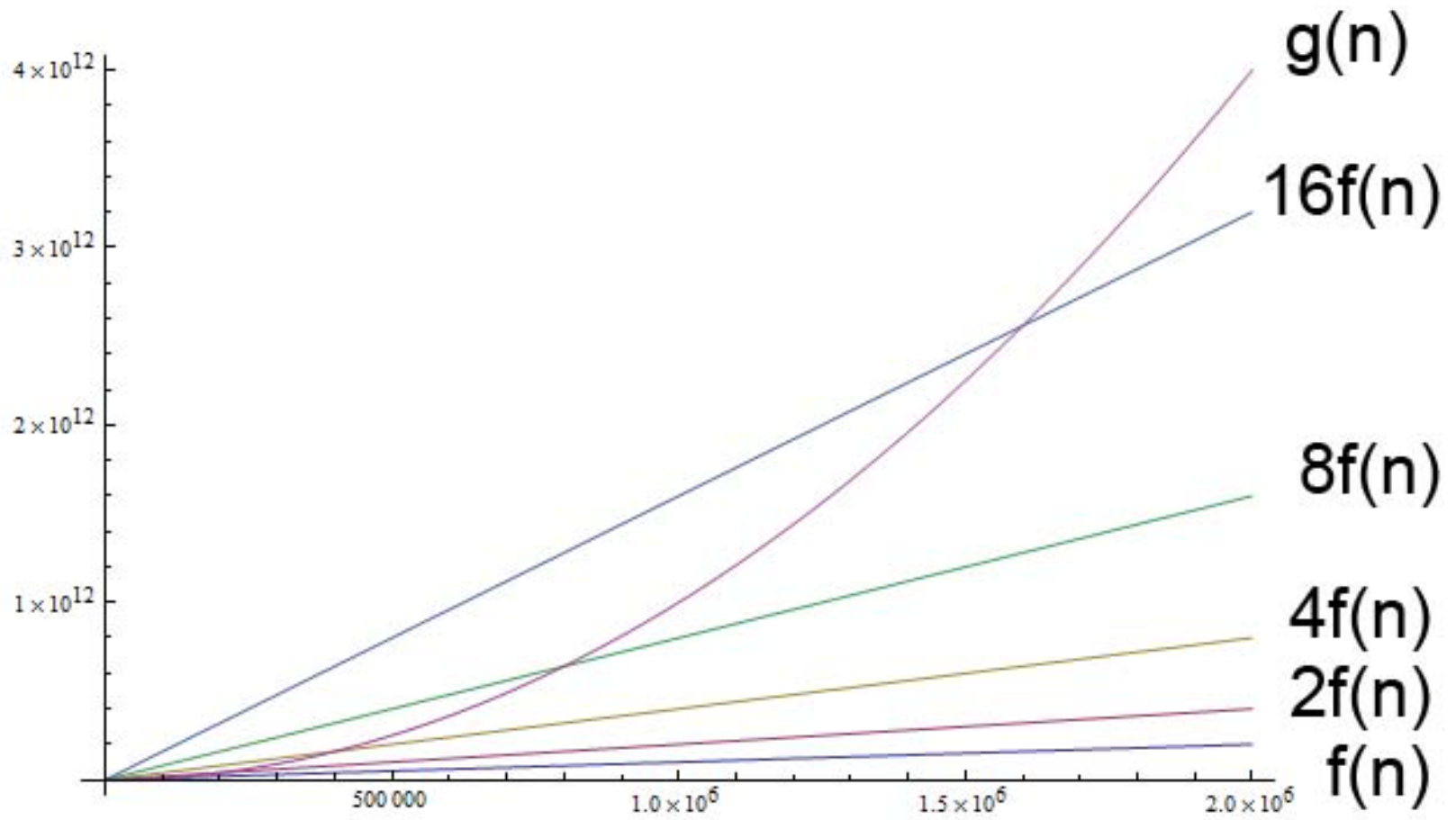
- $f(n) = 100,000n$ ,  $g(n) = n^2$ .
- $f(n) \in O(g(n))$ 
  - Proof: Let  $c = 1$ ,  $n_0 = 100,000$ .
  - If  $n \geq n_0$ , then  $f(n) = 100,000n \leq n^2 = c g(n)$ .
- $g(n) \in O(f(n))$ ?



# Big Oh Example 2

- $f(n) = 100,000n$ ,  $g(n) = n^2$ .
- If  $g(n) \in O(f(n))$ , then
  - There are  $c, n_0$  such that
  - $g(n) \leq c f(n)$  for all  $n \geq n_0$ .
- But, for any  $c$ , suppose  $n > 100,000c$ .
  - Then  $g(n) = n^2 > 100,000c n = c f(n)$
- So  $g(n) \notin O(f(n))$ .

# Big Oh Example 2



# Big Oh Facts

- Big Oh allows us to ignore constant factors:
  - For any constant  $c$ ,  $c f(n) \in O(f(n))$
- Big Oh allows us to ignore lower order terms:
  - If  $f(n) \in O(g(n))$ , then  $g(n) + f(n) \in O(g(n))$

# Big Oh Facts

- If  $a \leq b$ , then  $n^a \in O(n^b)$ 
  - Proof:  $n^a \leq n^b$  for all  $n \geq 1$ .
- If  $1 < a \leq b$ , then  $a^n \in O(b^n)$ 
  - Proof:  $a^n \leq b^n$  for all  $n > 0$ .
- For any  $a, b$ ,  $\log_a(n) \in O(\log_b(n))$ 
  - Proof:  $\log_a(n) = \log_b(n) \log_a(b)$  for all  $n > 0$ .

We can usually ignore the base for logarithms.

We will use  $\log(n)$  to denote  $\log_2(n)$

# Big Oh Facts

- For any  $a > 0$ ,  $b > 1$ ,  $n^a \in O(b^n)$ 
  - We'll see a proof in a bit
- For any  $a > 0$ ,  $\log n \in O(n^a)$ 
  - We'll see a proof in a bit

# Big Oh Facts

- If  $f(n) \in O(g(n))$ , and  $g(n) \in O(h(n))$ , then  
 $f(n) \in O(h(n))$ 
  - Proof: There are  $c, n_0$  such that  $f(n) \leq c g(n)$  for  $n \geq n_0$ .
  - There are  $c', n_0'$  such that  $g(n) \leq c' h(n)$  for  $n \geq n_0'$ .
  - Let  $c'' = c c', n_0'' = \text{Max}(n_0, n_0')$ .
  - If  $n \geq n_0''$ , then  $f(n) \leq c g(n) \leq c c' h(n) = c'' h(n)$ .
- $f(n) \in O(f(n))$ : let  $c=1, n_0=1$ .

Big Oh inclusion is a sort of “ $\leq$ ” on functions

# Big Omega

$$\Omega(f(n)) =$$

$$\{g(n) : \exists c, n_0 \text{ such that } g(n) \geq c f(n) \forall n \geq n_0\}$$

- So  $g(n) \in \Omega(f(n))$  if
  - There are  $c$  and  $n_0$  such that
  - $g(n) \geq c f(n)$  for all  $n \geq n_0$ .
- Sometimes write  $g(n) = \Omega(f(n))$ .

# Big Omega

- $g(n) \in \Omega(f(n))$  is equivalent to  $f(n) \in O(g(n))$ 
  - Proof:  $f(n) \in O(g(n))$  means there is  $c, n_0$  such that
$$f(n) \leq c g(n) \text{ for } n \geq n_0.$$
  - Then  $g(n) \geq (1/c) f(n)$  for  $n \geq n_0$ .
  - Similar proof for other direction.

Big Omega inclusion is a sort of “ $\geq$ ” on functions



# Big Theta

- $g(n) \in \Theta(f(n))$  if:
  - $g(n) \in O(f(n))$  and
  - $g(n) \in \Omega(f(n))$  (or equivalently  $f(n) \in O(g(n))$  )
- Note: the constants  $c, n_0$  may be different for showing  $g(n) \in O(f(n))$  and  $g(n) \in \Omega(f(n))$
- $g(n) \in \Theta(f(n))$  is equivalent to  $f(n) \in \Theta(g(n))$

Big Theta inclusion is a sort of “=” on functions

# Little o, omega

- $f(n) \in o(g(n))$  if, for all  $c$ , there is an  $n_0$ :  
 $f(n) < c g(n)$  for all  $n \geq n_0$ .
- $f(n) \in \omega(g(n))$  if, for all  $c$ , there is an  $n_0$ :  
 $f(n) > c g(n)$  for all  $n \geq n_0$ .
- $f(n) \in o(g(n))$  is equivalent to  $g(n) \in \omega(f(n))$

Little o and omega are a sort of “<” and “>”  
for functions

# Big Oh Is Not Total!

- It is not true that  $f(n) \in O(g(n))$  or  $g(n) \in O(f(n))$ 
  - $f(n) = n^{1+\cos(\pi n)}$ ,  $g(n) = n$
- Similarly,  $f(n) \notin O(g(n))$  does not imply that  $f(n) \in \omega(g(n))$

# Limit Test

- Let  $c = \lim_{n \rightarrow \infty} f(n)/g(n)$ 
  - If  $c = 0$ , then  $f(n) \in o(g(n))$
  - If  $0 < c < \infty$ , then  $f(n) \in \Theta(g(n))$ .
  - If  $c = \infty$ , then  $f(n) \in \omega(g(n))$

# Limit Test

- For any  $a > 0$ ,  $\log n \in o(n^a)$ 
  - Proof: Let  $c = \lim_{n \rightarrow \infty} \log n / n^a$
  - L'Hôpital's rule:  
$$c = \lim_{n \rightarrow \infty} (1/n) / (a n^{a-1}) = \lim_{n \rightarrow \infty} 1 / (a n^a) = 0.$$

# Limit Test

- For any  $a > 0$ ,  $b > 1$ ,  $n^a \in o(b^n)$ 
  - Proof: Let  $c = \lim_{n \rightarrow \infty} n^a/b^n$
  - L'Hôpital's rule:
$$c = \lim_{n \rightarrow \infty} (a n^{a-1})/(b^n \ln b) = (a/\ln b) \lim_{n \rightarrow \infty} n^{a-1}/b^n$$
  - Repeat until  $a \leq 0$
  - We have that  $c = \text{const} \times \lim_{n \rightarrow \infty} n^{a'}/b^n$  for  $a' \leq 0$ 
    - Numerator goes to 0, denominator goes to infinity
    - Thus  $c = 0$ .

# Other Notation

- $f(n) \in g(n)+o(h(n))$  means  $f(n)-g(n) \in o(h(n))$ 
  - Common example:  $f(n) \in g(n)+o(1)$  means  $f(n)$  converges to  $g(n)$ .
- $f(n) \in g(n)^{O(h(n))}$  means there is some function  $h'(n) \in O(h(n))$  such that  $f(n)=g(n)^{h'(n)}$ .
  - Common example:  $f(n) \in n^{O(1)}$  means  $f(n) \in O(n^a)$  for some  $a$ .

# Course Information

- Lectures: WMF 2:15-3:30
- Text: *Algorithm Design* by Kleinberg and Tardos
- Webpage: <http://cs161.stanford.edu>
- Piazza: <http://piazza.com/class#summer2012/cs161>
- Staff Email: [cs161-summer2012-staff@lists.stanford.edu](mailto:cs161-summer2012-staff@lists.stanford.edu)



# Grading

- Homeworks: 50%
  - Five weekly homeworks
- Midterm: 20%
  - Wednesday, July 25<sup>th</sup> in class
- Final: 30%
  - Friday, August 17<sup>th</sup>, Location: TBA

# Homework

- Assigned each Wednesday, due following Friday
  - Exceptions: no homework due week of midterm or final
  - Due at **beginning** of class (2:15PM)
- May work in groups of up to three
  - Write up solutions individually
- One 72-hour extension
- Can submit digitally to [cs161-summer2012-submissions@lists.stanford.edu](mailto:cs161-summer2012-submissions@lists.stanford.edu)
- See website for policies