

# Analysis of Algorithms

V. Adamchik

CSCI 570

Lecture 5

University of Southern California

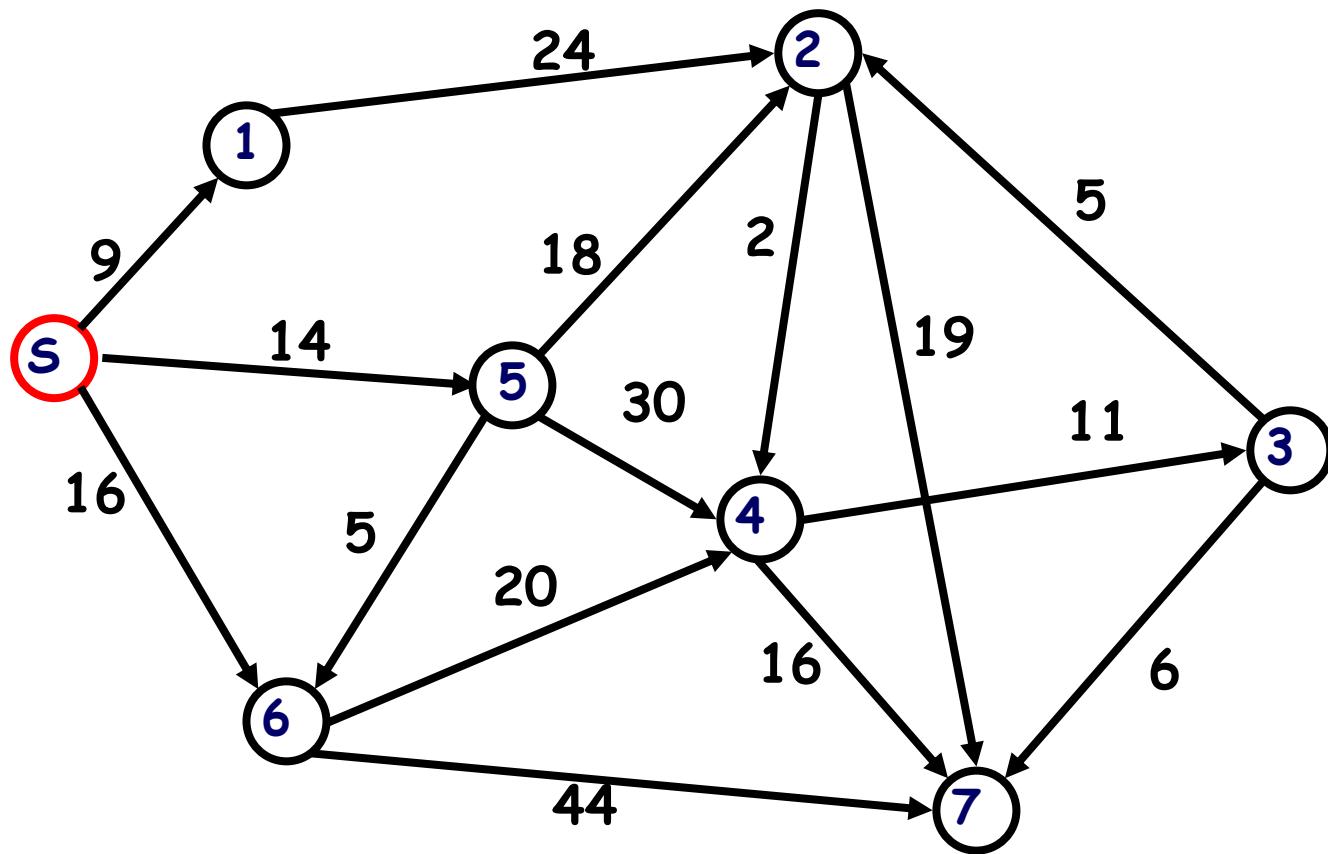
Fall 2023

## Dijkstra's Algorithm Divide and Conquer Algorithms

Reading: chapters 4 & 5

# The Shortest Path Problem

Given a positively weighted graph  $G$  with a source vertex  $s$ , find the shortest path from  $s$  to all other vertices in the graph.

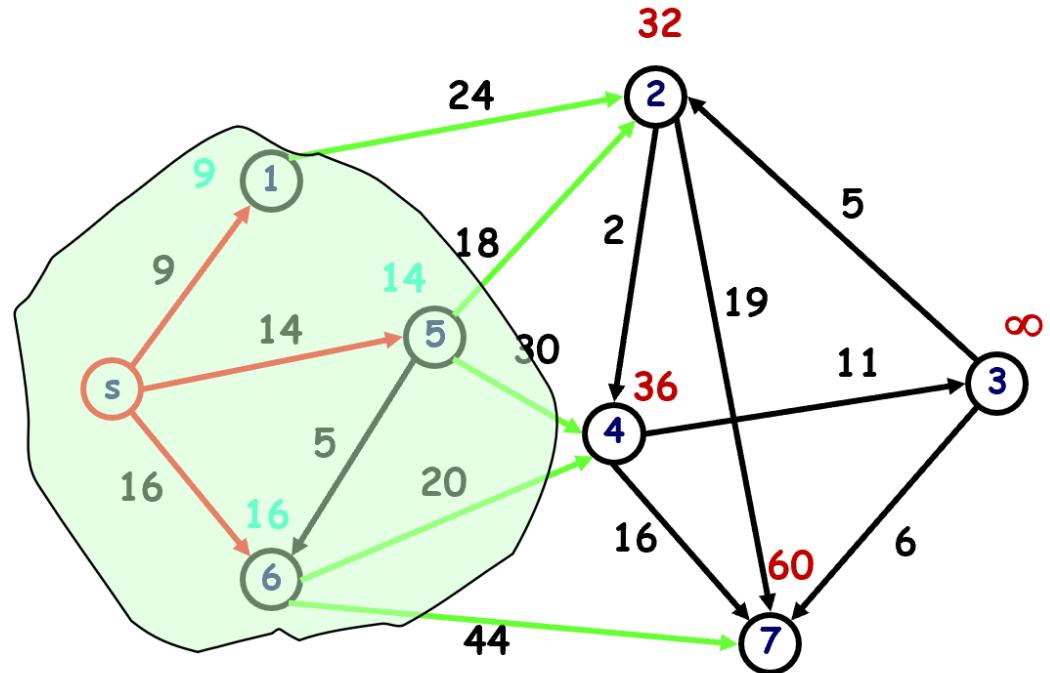


# Greedy Approach

When algorithm proceeds all vertices are divided into two groups:  
vertices whose shortest path from the source **s**

- is known
- is NOT discovered yet

Move vertices one at a time from the undiscovered set of vertices to the known set of the shortest distances, based on the shortest distance from the source.

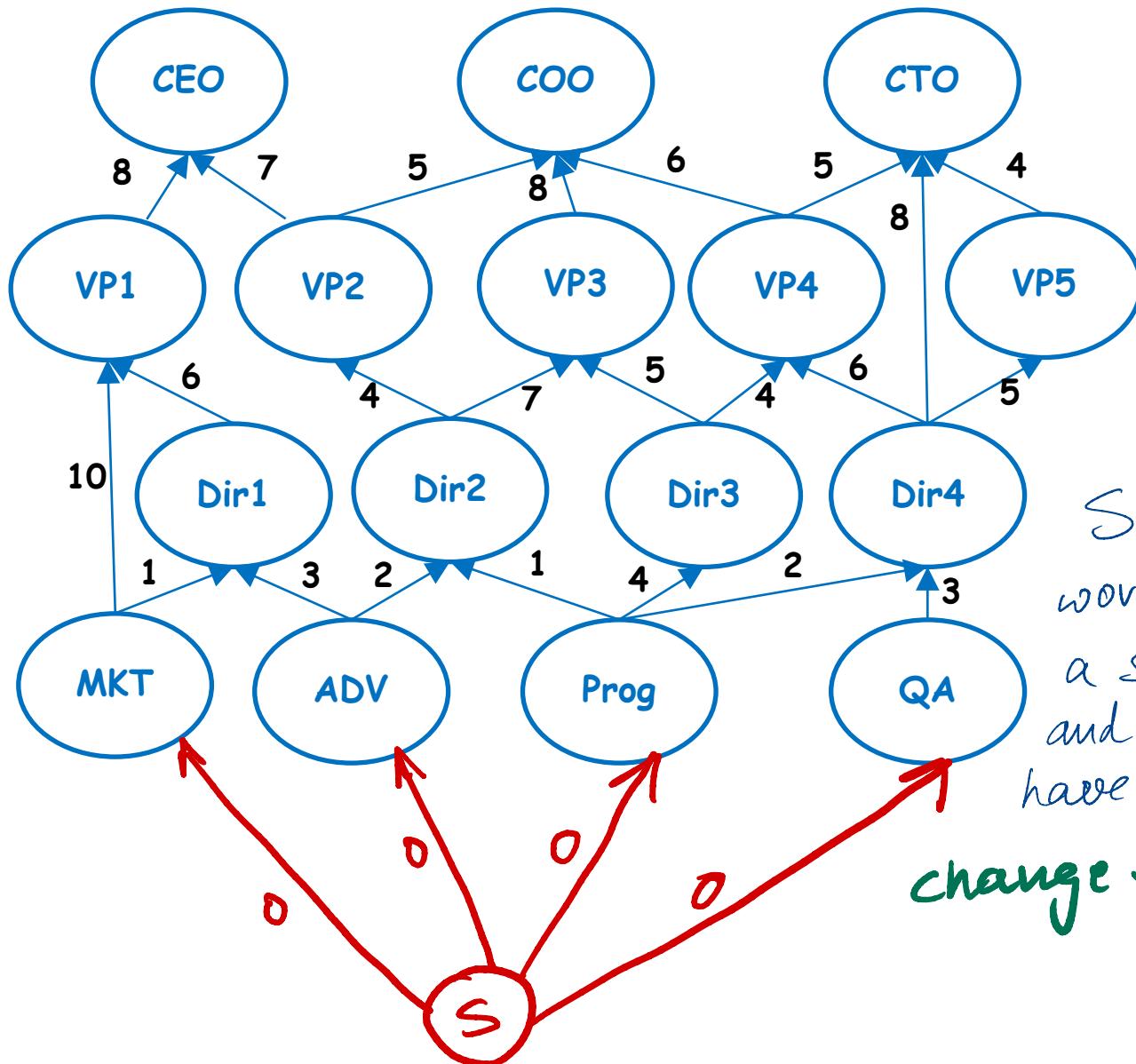


solution tree = { s, 1, 5, 6 }

heap = {2, 3, 4, 7}

# Discussion Problem 1

You are given a graph representing the several career paths available in industry. Each node represents a position and there is an edge from node v to node u if and only if v is a pre-requisite for u. Top positions are the ones which are not pre-requisites for any positions. Start positions are the ones which have no pre-requisites. The cost of an edge  $(v,u)$  is the effort required to go from one position v to position u. Salma wants to start a career and achieve a top position with minimum effort. Using the given graph can you provide an algorithm with the same run time complexity as Dijkstra's algorithm?

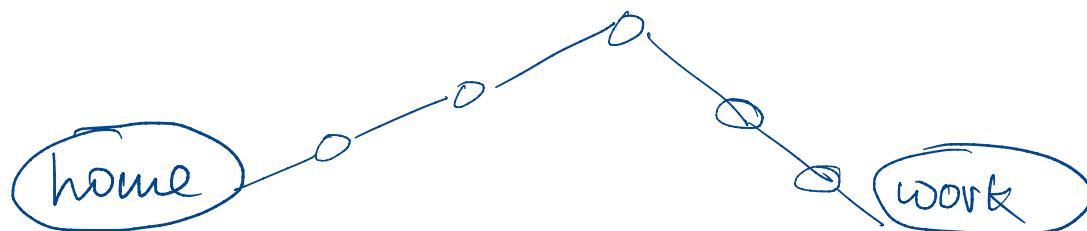


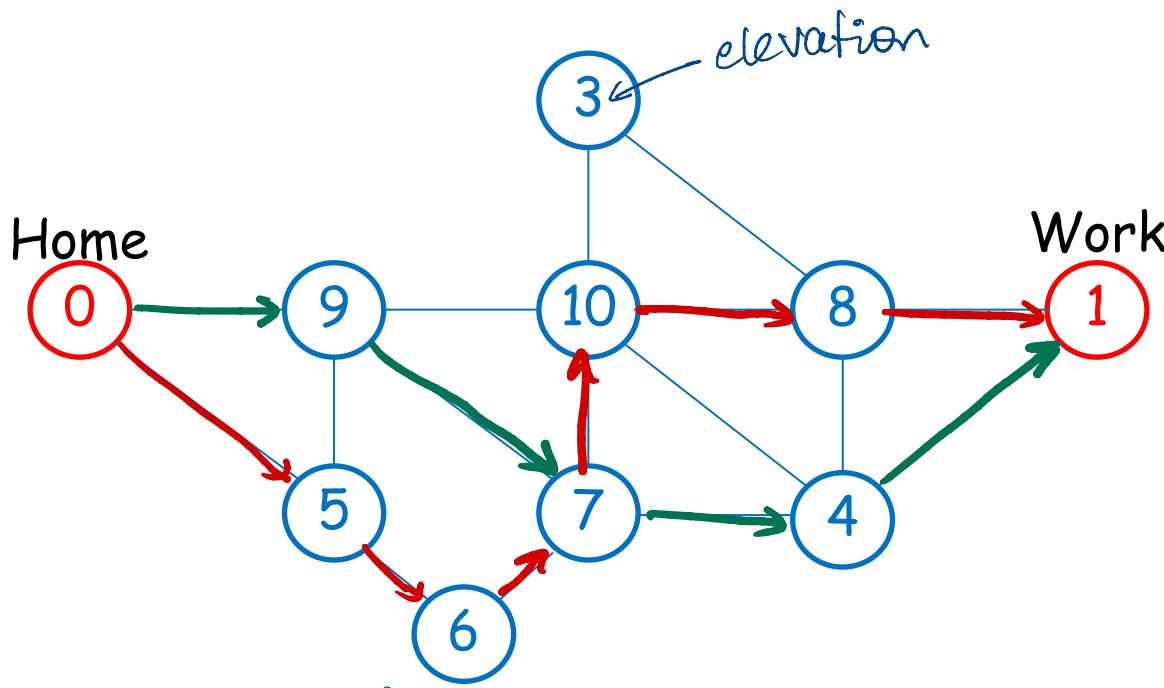
Since dijkstra  
works only when  
a single source,  
and here we  
have 4 sources

change the input

## Discussion Problem 2

Hardy decides to start running to work in San Francisco to get in shape. He prefers a route to work that goes first entirely uphill and then entirely downhill. To guide his run, he prints out a detailed map of the roads between home and work. Each road segment has a positive length, and each intersection has a distinct elevation. Assuming that every road segment is either fully uphill or fully downhill, give an efficient algorithm to find the shortest path that meets Hardy's specifications.



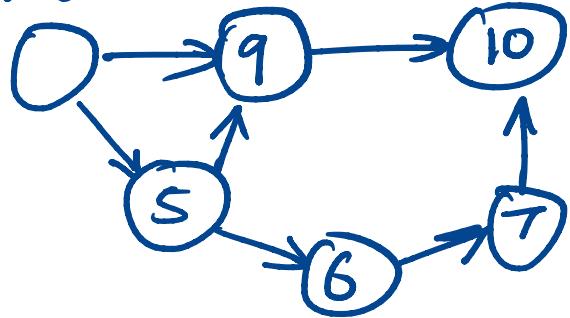


*change the input*

- ① create a new graph of uphill vertices starting from home
- ② create a uphill graph from work.  
↳ which is the same as downhill from work

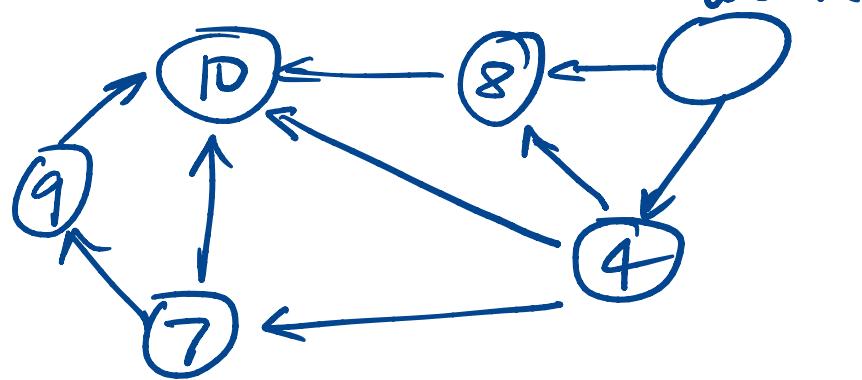
Uphill

Home



~~Downhill~~ Uphill

work



Run Dijkstra from  
Home

Run Dijkstras from  
work

③ Find common vertices

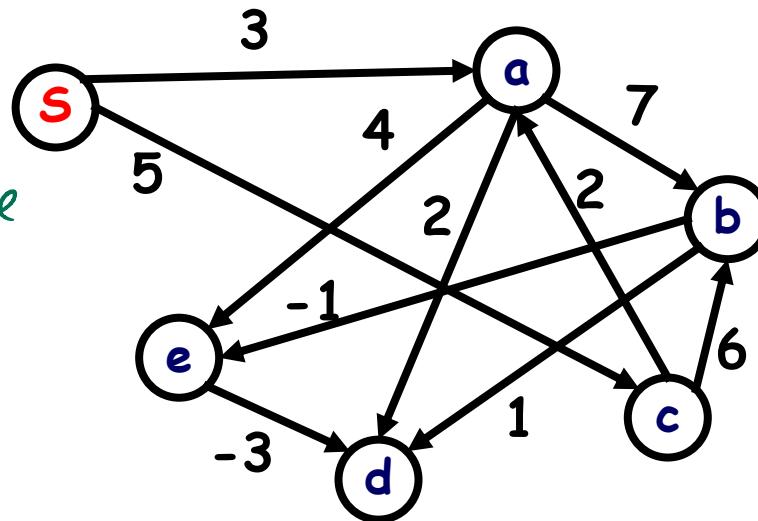
④ Check all common vertices & those distances .

No Dijkstra

## Discussion Problem 3

Design a **linear time** algorithm to find **shortest** distances in a DAG.

how can topological sort help us solve this problem?



- a) traversal
- b) topological sort

s	a	b	c	d	e	
0	3	-	5	-	-	s
		5+b				s,c
		3+7		3+2	3+4	s,c,a
3	10	5	5	7		s,c,a,b
3	10	5	4	7		s,c,a,b,e

Runtime: topological sort +  $O(E)$



# Discussion Problem 4

Why doesn't Dijkstra's greedy algorithm work on graphs with negative weights?

Run Dijkstra's:

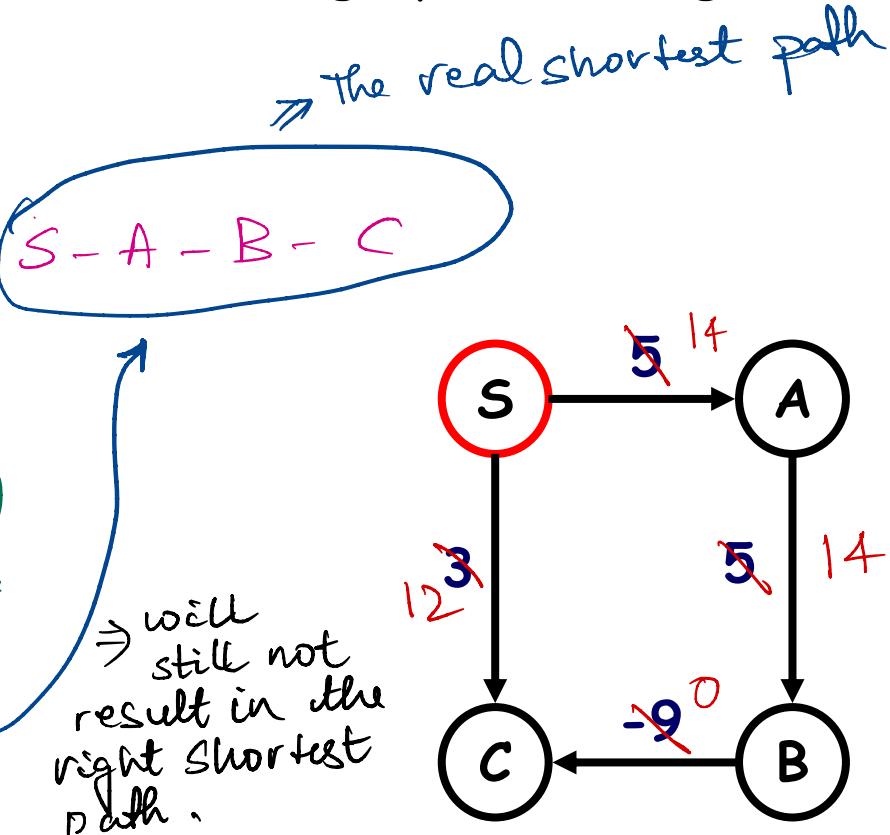
$$d(A) = 0, d(C) = 3$$

$$d(A) = 5, d(B) = 10$$

How do you fix Dijkstra?

a) reweight the graph

$$\text{Reweighted Dijkstra: } S-C = 12$$



- b) another approach can be to use a regular queue instead of a priority queue & let it run  $V-1$  times.
- c) use a table & do dynamic programming

# Divide and Conquer Algorithms



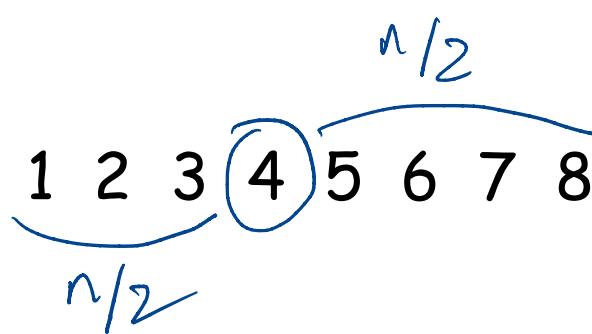
A divide-and-conquer algorithm consists of

- dividing a problem into smaller subproblems
- solving (recursively) each subproblem
- then combining solutions to subproblems to get solution to original problem

# Binary Search

Given a sorted array of size  $n$ :

- compare the search item with the middle
- if it's less, search in the lower half
- if it's greater, search in the upper half
- if it's equal or the entire array has been searched, terminate.



linear	Binary
$n$	$n$
$n-1$	$n/2$
$n-2$	$n/2$
	$\Omega(n)$

# Mergesort

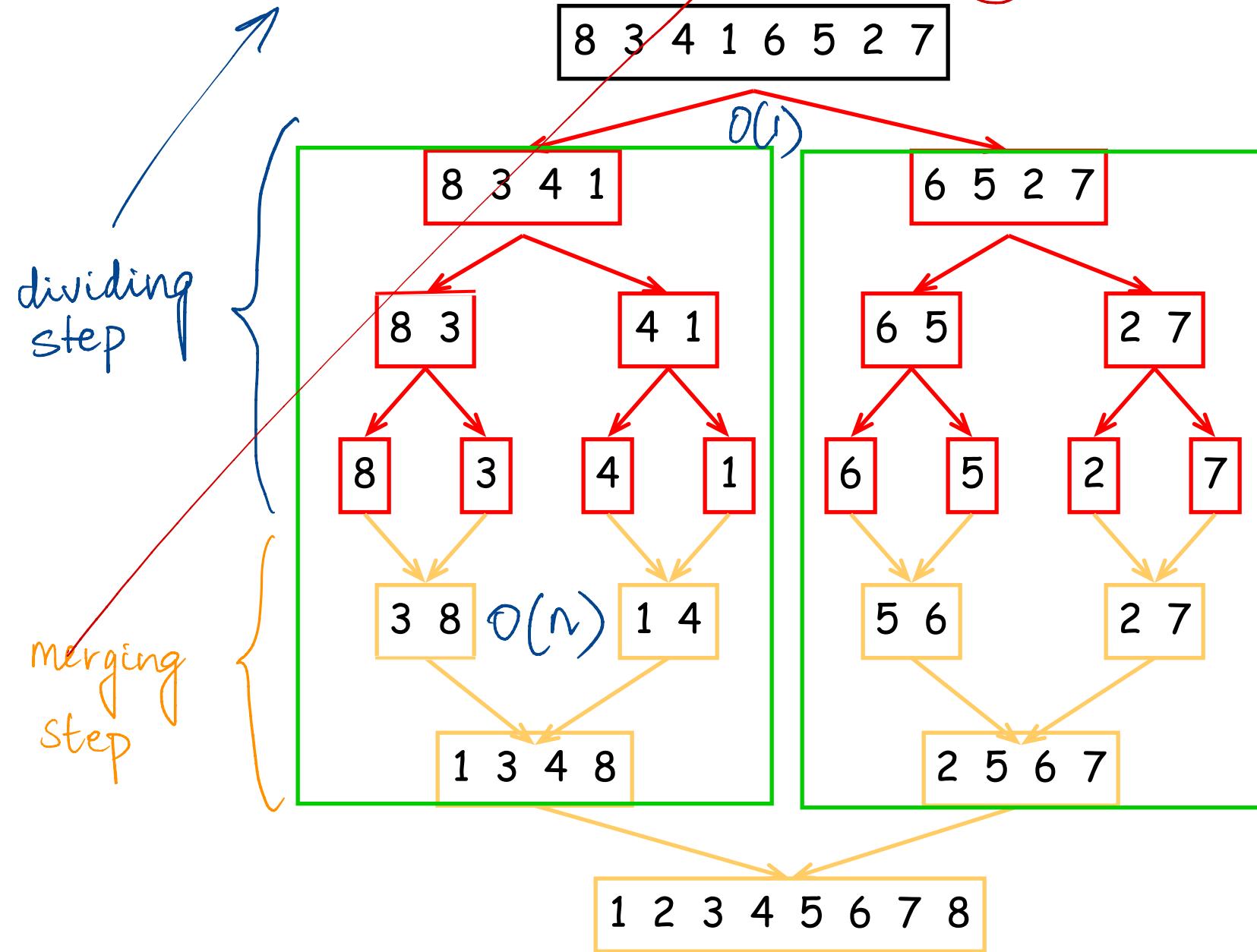
divides an unsorted list into two equal or nearly equal sub lists

sorts each of the sub lists by calling itself recursively, and then

merges the two sub lists together to form a sorted list

$$T(n) = 2 \cdot T(n/2) + O(n) + O(1)$$

Split



# D&C Recurrences

Suppose  $T(n)$  is the number of steps in the worst case needed to solve the problem of size  $n$ .

We define the runtime complexity  $T(n)$  by a recurrence equation.

Binary Search:  $T(n) = T(n/2) + O(1)$

MergeSort:  $T(n) = 2T(n/2) + O(n)$

# D&C Recurrences

Suppose  $T(n)$  is the number of steps in the worst case needed to solve the problem of size  $n$ .

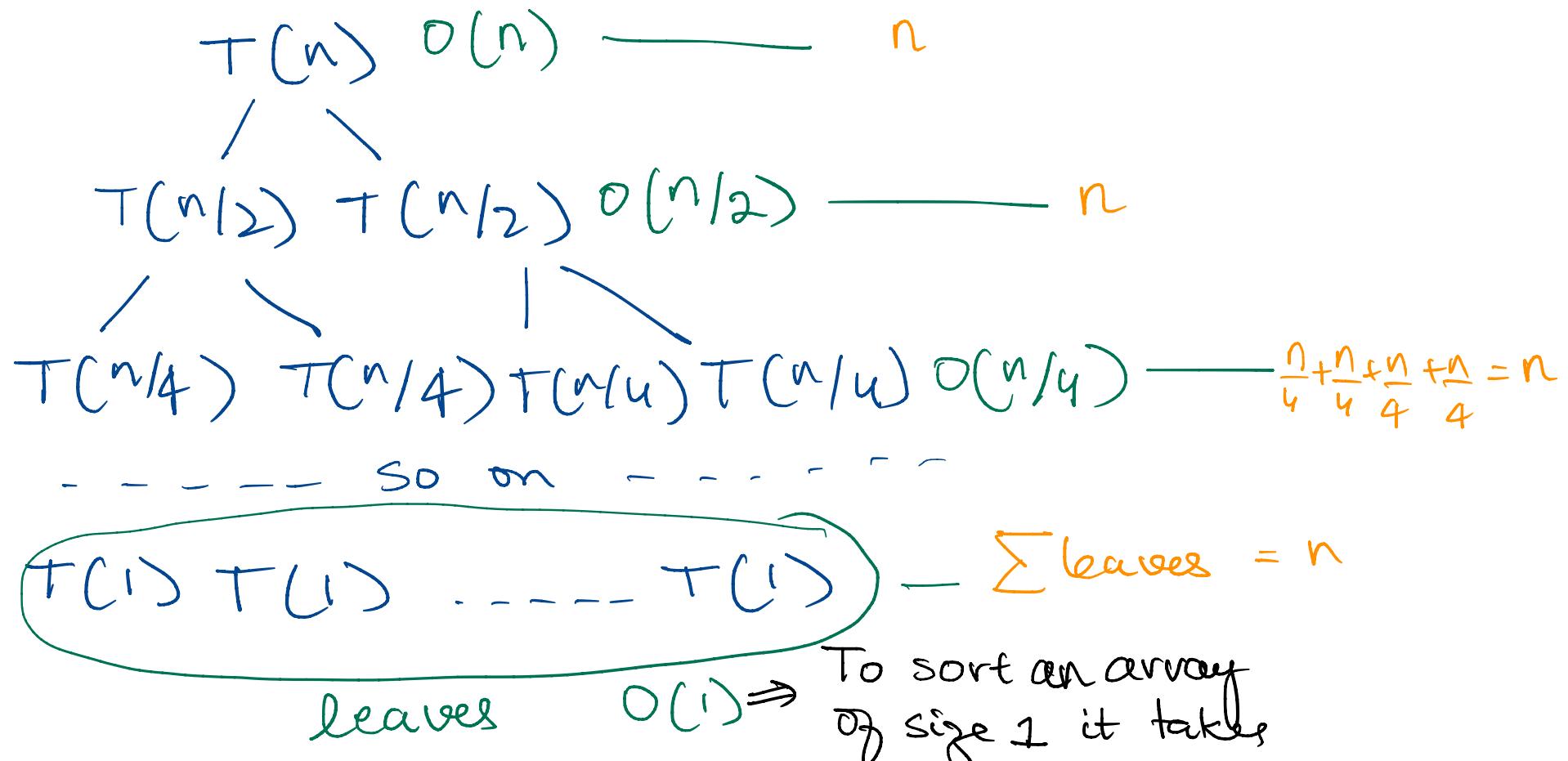
Let us divide a problem into  $a \geq 1$  subproblems, each of which is of the input size  $n/b$  where  $b > 1$ .

The total complexity  $T(n)$  is obtained by

$$T(n) = a \cdot T(n/b) + f(n)$$

Here  $f(n)$  is a complexity of combining subproblem solutions (including complexity of dividing step).

# Mergesort: tree of recursive calls



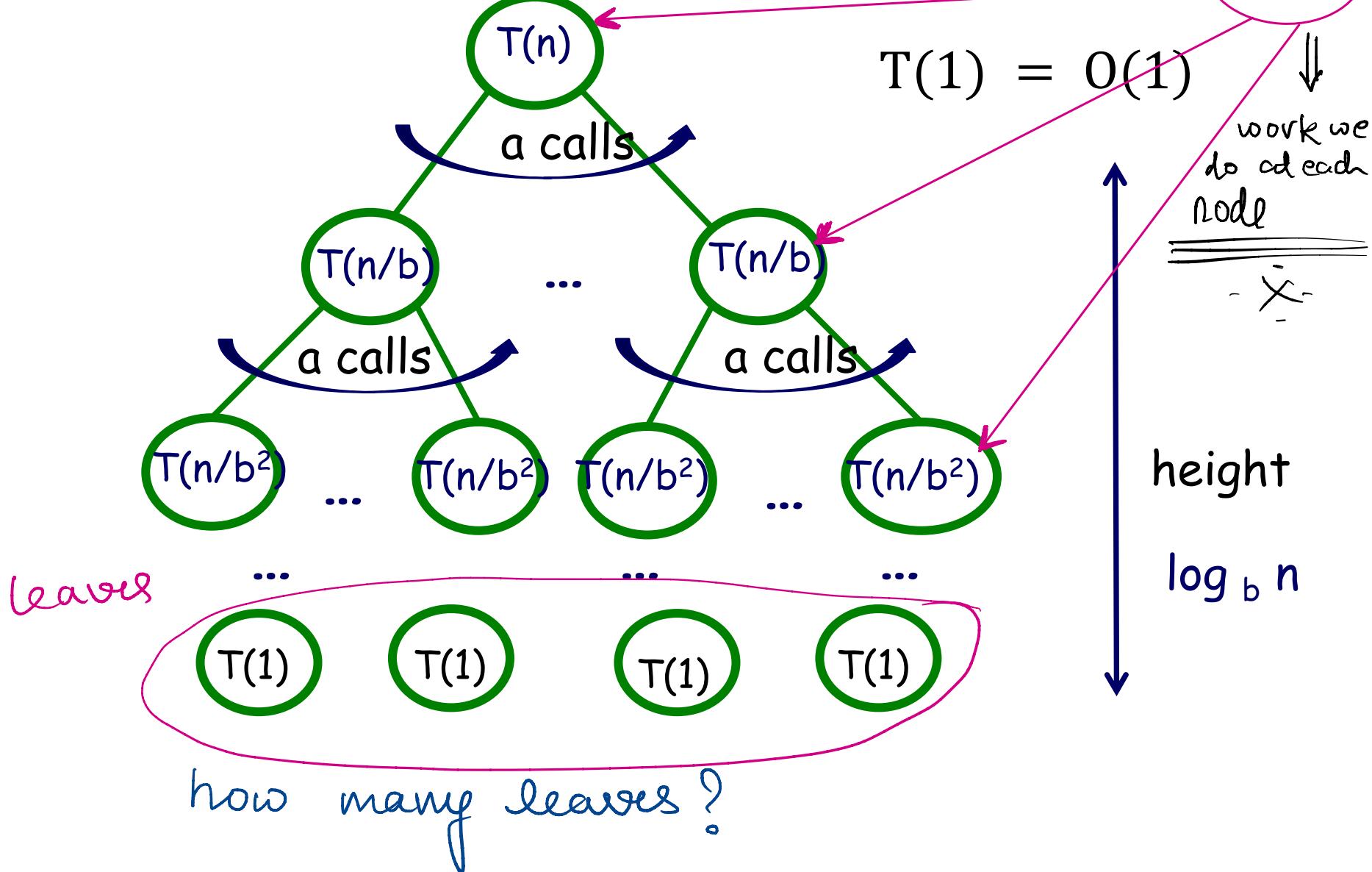
Each level the work is linear  $O(n)$

$\therefore$  TOTAL Work  $\Rightarrow n \cdot \text{height} = O(n \cdot \log n)$

# Tree of recursive calls

$$T(n) = a \cdot T(n/b) + f(n)$$

$$T(1) = O(1)$$



# Counting leaves

Let  $h = \text{height}$

$$\# \text{ of leaves} = a^h \quad T(n) = a \cdot T(n/b) + f(n)$$

$$a^h = a^{\log_b n} = \left(a^{\log_a n}\right)^{1/\log_a b} = n^{\log_b a}$$

$$\frac{1}{\log_a b} = \log_b a$$

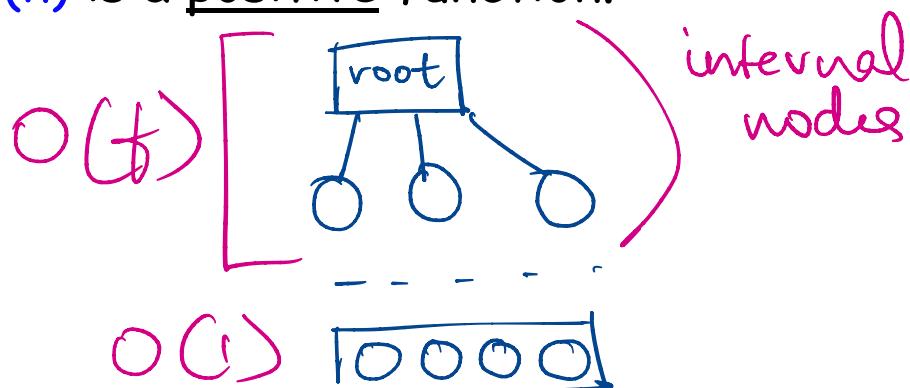
$$\log_b n = \frac{\log_a n}{\log_a b}$$

# The Master Theorem

The master method provides a straightforward ("cookbook") method for solving recurrences of the form

$$T(n) = a \cdot T(n/b) + f(n)$$

where  $a \geq 1$  and  $b > 1$  are constants (not necessarily integers) and  $f(n)$  is a positive function.



$$T(n) = \sum_{\text{internal nodes}} O(t) + \sum_{\text{leaves}} O(1)$$

# The Master Theorem

$$T(n) = a \cdot T(n/b) + f(n), \quad \begin{matrix} \geq 0 \\ \end{matrix} \quad \begin{matrix} a \geq 1 \text{ and } b > 1 \\ \text{any} \end{matrix}$$

Let  $c = \log_b a$ .

**Case 1:** (only leaves)

if  $f(n)=O(n^{c-\varepsilon})$ , then  $T(n) = \Theta(n^c)$  for some  $\varepsilon>0$ .

**Case 2:** (all nodes) Merge Sort

if  $f(n)=\Theta(n^c \log^k n)$ ,  $k \geq 0$ , then  $T(n) = \Theta(n^c \log^{k+1} n)$

**Case 3:** (only internal nodes)

if  $f(n)=\Omega(n^{c+\varepsilon})$ , then  $T(n) = \Theta(f(n))$  for some  $\varepsilon>0$ .

# Discussion Problem 5

Solve the recurrence by the Master Theorem:

$$T(n) = \boxed{16}^a T(n/b) + \boxed{5n^3}^b \rightarrow f(n)$$

$$a = 16$$

$$b = 4$$

$$c = \log_b a = 2 \rightarrow \# \text{ of leaves} = O(n^2)$$

$$\log_{\frac{1}{4}} 16 = 2$$

$$T(n) = a \cdot T(n/b) + f(n)$$

Case 1: if  $f(n) = O(n^{c-\varepsilon})$ , then  $T(n) = \Theta(n^c)$

Case 2: if  $f(n) = \Theta(n^c \log^k n)$ , then  $T(n) = \Theta(n^c \log^{k+1} n)$

**Case 3:** if  $f(n) = \Omega(n^{c+\varepsilon})$ , then  $T(n) = \Theta(f(n))$

$$T(n) = \Theta(n^3)$$

where  $c = \log_b a$ .

# Discussion Problem 6

Solve the recurrence by the Master Theorem:

$$1. A(n) = 3A(n/3) + 15$$

$a=3, b=3, \log_b^a = 1, f(n) = O(1), \#_{\text{leaves}} = n^1 = O(n)$   
Case 1  $T(n) = \Theta(n)$

$$2. B(n) = 4B(n/2) + n^3$$

$a=4, b=2, \log_b^a = 2, f(n) = O(n^3), \#_{\text{leaves}} = O(n^2)$   
Case 3  $T(n) = \Theta(n^3)$

$$3. C(n) = 4C(n/2) + n^2$$

$a=4, b=2, \log_b^a = 2, f(n) = O(n^2), \#_{\text{leaves}} = O(n^2)$   
Case 2  $T(n) = \Theta(n^2 \log n)$

$$4. D(n) = 4D(n/2) + n$$

$a=4, b=2, \log_b^a = 2, f(n) = O(n), \#_{\text{leaves}} = O(n)$   
Case 1  $T(n) = \Theta(n^2)$

$$5. E(n) = 4E(n/2) + n^2 \log n$$

$\uparrow k=1$   $a=4, b=2, \log_b^a = 2, f(n) = O(n^2 \log n)$   
Case 2,  $k=1 \therefore T(n) = \Theta(n^2 \log^{1+1} n)$  Case 2  $T(n) = \Theta(n^2 \log^2 n)$

# Integer Multiplication

✗

Given two n-digit integers  $a$  and  $b$ , compute  $a \times b$ .

Brute force solution:  $O(n^2)$  bit operations.

Even though the divide and conquer method time complexity is same as brute force. The advantage is that it can be done in parallel

$$1545 \cdot 17766 = \underline{1545} \times 10^4 + \underline{7766}$$

$n$  bits

$$a \times b = (x_1 \cdot 10^{n/2} + x_0) \cdot (y_1 \cdot 10^{n/2} + y_0)$$

$$= x_1 y_1 \cdot 10^n + (x_1 y_0 + x_0 y_1) 10^{n/2} + x_0 y_0$$

$\underset{O(1)}{-} \quad \underset{O(n)}{-}$

$$+ (n) = 4 \cdot T(n/2) + O(1) + O(n)$$

$$T(n) = \Theta(n^2)$$

$$\begin{array}{r} 1234 \\ \times 1111 \\ \hline 1234 \\ 1234 \\ 1234 \\ + 1234 \\ \hline 1370974 \end{array}$$

Complexity for addition

Complexity for multiplying  
4 multiplication by 10s  
operations marked in red.

# Karatsuba's algorithm

Divide-and-conquer algorithm. Split each integer in two parts and consider their product:

$$a \times b = (x_1 \cdot 10^{n/2} + x_0) \cdot (y_1 \cdot 10^{n/2} + y_0)$$

$$(x_1^{\circ} y_0 + x_0^{\circ} y_1) = \underbrace{(x_0 + x_1)^{\circ} (y_0 + y_1)}_{\text{hashtable}} - x_0 y_0 - x_1 y_1$$
$$a \times b = x_1^{\circ} y_1 \cdot 10^n + [ \quad ] \cdot 10^{n/2} + x_0^{\circ} y_0$$

$$T(n) = 3T(n/2) + O(n), T(n) = \Theta(n^{\log 3})$$

$$= \Theta(n^{1.58})$$

## Discussion Problem 7

Consider another divide and conquer algorithm for integer multiplication. The key idea is to divide a large integer into 3 parts (rather than 2) of size approximately  $n/3$  and then multiply those parts. What would be the runtime complexity of this multiplication?

$$154517766 = 154 \cdot 10^6 + 517 \cdot 10^3 + 766$$

3 parts & 3 multiplications = 9

$$T(n) = 9 \cdot T\left(\frac{n}{3}\right) + O(n), T(1) = \Theta(n^2)$$

< \log 3

To be better than Karatsuba's we will need to do 5 multiplications.

$$T(n) = 5 \cdot T\left(\frac{n}{3}\right) + O(n), T(n) = \underline{\Theta\left(n^{\frac{\log 5}{\log 3}}\right)}$$

# Matrix Multiplication

A

$$n \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

B

$$= \begin{pmatrix} a_{11}b_{11} + a_{12}b_{21} & a_{11}b_{12} + a_{12}b_{22} \\ a_{21}b_{11} + a_{22}b_{21} & a_{21}b_{12} + a_{22}b_{22} \end{pmatrix}$$

C = AxB

CPU - integers

GPU - matrix

TPU - tensor, 3D matrix

$$\text{Runtime} = O(n \cdot n^2) = O(n^3)$$

In a matrix you will need to split into 4 parts  
not 2 parts.

# Matrix Multiplication

The usual rules of matrix multiplication holds for  
block matrices

$$\begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} = \begin{pmatrix} A_{11}^{\textcircled{0}} B_{11} + A_{12}^{\textcircled{0}} B_{21} & A_{11}^{\textcircled{0}} B_{12} + A_{12}^{\textcircled{0}} B_{22} \\ A_{21}^{\textcircled{0}} B_{11} + A_{22}^{\textcircled{0}} B_{21} & A_{21}^{\textcircled{0}} B_{12} + A_{22}^{\textcircled{0}} B_{22} \end{pmatrix}$$

If the letter is lowercase then it is a matrix element. If it is capital, it means that it is a matrix itself

$\cdot X \cdot$

$\searrow$   
8 multiplications

# D&C Algorithm

Let  $n = 2^k$  and  $M(A, B)$  denote the matrix product

1. if  $A$  is  $1 \times 1$  matrix, return  $a_{11} * b_{11}$ .

2. write

$$A = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \quad B = \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix}$$

where  $A_{ij}$  and  $B_{ij}$  are  $n/2 \times n/2$  matrices.

3. Compute  $C_{ij} = M(A_{i1}, B_{1j}) + M(A_{i2}, B_{2j})$

4. Return

$$\begin{pmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{pmatrix}$$

$$\text{Runtime} = T(n) = 8T(n/2) + O(n^2)$$

$$\# \text{recs} = O(n^3) \quad f(n) = O(n^2)$$

$$\therefore T(n) = \Theta(n^3)$$

# Strassen's Algorithm

$$\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} = \begin{pmatrix} s_1 + s_2 - s_4 + s_6 & s_4 - s_5 \\ s_6 + s_7 & s_2 - s_3 + s_5 - s_7 \end{pmatrix}$$

$$s_1 = (a_{12} - a_{22})(b_{21} + b_{22})$$

$$s_2 = (a_{11} + a_{22})(b_{11} + b_{22})$$

$$s_3 = (a_{11} - a_{21})(b_{11} + b_{12})$$

$$s_4 = (a_{11} + a_{12})b_{22}$$

$$s_5 = a_{11}(b_{12} - b_{22})$$

$$s_6 = a_{22}(b_{21} - b_{11})$$

$$s_7 = (a_{21} + a_{22})b_{11}$$

It takes 7 multiplications

$$T(n) = 7 \cdot T(n/2) + O(n^2)$$

$$T(n) = O(n^{\log 7})$$

$$= O(n^{2.8})$$

There are 18 additions, count all the signs in the matrix & the  $s_i$  elements.

# Fast Matrix Multiplication

1969, Strassen  $O(n^{2.808})$ .

1978, Pan  $O(n^{2.796})$

1979, Bini  $O(n^{2.78})$

1981, Schonhage  $O(n^{2.548})$

1981, Pan  $O(n^{2.522})$

1982, Romani  $O(n^{2.517})$

1982, Coppersmith and Winograd  $O(n^{2.496})$

1986, Strassen  $O(n^{2.479})$

1989, Coppersmith and Winograd  $O(n^{2.376})$

2010, Stothers  $O(n^{2.374})$

2011, Williams  $O(n^{2.3728642})$

2014, Le Gall  $O(n^{2.3728639})$

# Finding the Maximum Subsequence Sum

Given an array  $A[0, \dots, n-1]$  of integers, design a D&C algorithm that finds a subarray  $A[i, \dots, j]$  such that

$$A[i] + A[i + 1] + \dots + A[j]$$

is the maximum.

For example,

$$A = \{3, -4, 5, -2, -2, 6, -3, 5, -3, 2\}$$

Output:  $\{5, -2, -2, 6, -3, 5\}$

Sum =  $5-2-2+6-3+5 = 9$

# Finding the Maximum Subsequence Sum (MSS)

3, -4, 5, -2, -2, | 6, -3, 5, -3, 2  
A<sub>1</sub>                                    A<sub>2</sub>

[l<sub>1</sub>, r<sub>1</sub>, max<sub>1</sub>] = MSS(A<sub>1</sub>) recursive

[l<sub>2</sub>, r<sub>2</sub>, max<sub>2</sub>] = MSS(A<sub>2</sub>) recursive

[l<sub>3</sub>, r<sub>3</sub>, max<sub>3</sub>] = Span(A<sub>1</sub>, A<sub>2</sub>) iterative

return MAX(max<sub>1</sub>, max<sub>2</sub>, max<sub>3</sub>)

# Finding the Maximum Subsequence Sum (MSS)

3, -4, 5, -2, -2, 6, -3, 5, -3, 2  
A<sub>1</sub>                    A<sub>2</sub>

Implementation of span

Contradictions

- ② must be a part of span, if -2 is not part of span then max is in the right part of the array
- ⑥ must be a part of span, if 6 is not part of span then max is in the left part of the array

Compute partial sums

0, -3, 1, -4, -2 | 6, 3, 8, 5, 7  
l<sub>3</sub>                    r<sub>3</sub>

2 recursive calls

Cost of span

$$\text{Runtime : } T(n) = 2 \cdot T(n/2) + O(n) = \Theta(n \log n)$$

# Review

## Master Theorem Limitations

We have already seen various examples of analysing time complexity using the master theorem, but can we use it for any function in the given form? - No.

You may be wondering when can we then?

Here are the conditions where we cannot use the master theorem:

- If  $T(n)$  is not monotone, like  $\sin n$ . By this, we mean that  $T(n)$  should be a monotonically increasing function.
- If  $f(n)$  is not a polynomial. For example, if  $T(n) = 2T(n/2) + 2n$ ,  $f(n)$  is an exponent. So, we cannot use the master's theorem here.
- If  $a$  is not a constant. For example, if  $T(n) = 2n.T(n/3) + n.\log n$ , here  $a = 2n$  which is not a constant. So,  $T(n)$  cannot be analysed using the master's theorem.

For each of the following recurrences, give an expression for the runtime  $T(n)$  if the recurrence can be solved with the Master Theorem. Otherwise, indicate that the Master Theorem does not apply.

$$1. T(n) = 16 T(n/4) + 5 n^3 + \log n = \Theta(n^3)$$

$$2. T(n) = 4 T(n/2) + n^2 \log n + n^2 = \Theta(n^2 \log^2 n)$$

$$3. T(n) = 4 T(n/8) - n^2 \text{ negative} = \text{NOT APPLICABLE}$$

$$4. T(n) = 2^n T(n/2) + n \text{ } \xrightarrow{\text{not a number,}} \text{ its a function} = \text{NOT APPLICABLE}$$

$$5. T(n) = 0.2 T(n/2) + n \log n \geq 1 = \text{NOT APPLICABLE}$$

# Review

Design a new Mergesort algorithm in which instead of splitting the input array in half we split it in **the ratio 1:3**.

Write down the recurrence relation for the number of comparisons.

What is the runtime complexity of this algorithm?

$$T(n) = T(n/4) + T(3n/4) + O(n)$$

$$T(n) = \Theta(n \log n)$$

we know this because

In 1st lecture, the above recurrence relation has nothing to do w/  
it.