

# Lecture 2

## Divide & Conquer and Peak Finding

Spring 2023

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# Peak Finder

## One-dimensional Version

Position 2 is a peak if and only if  $b \geq a$  and  $b \geq c$ . Position 9 is a peak if  $i \geq h$ .

1	2	3	4	5	6	7	8	9
a	b	c	d	e	f	g	h	i

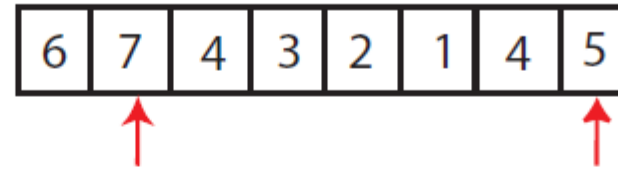
Figure 1: a-i are numbers

Problem: Find a peak if it exists (Does it always exist?)

PS: For the given definition ( $\geq$ ), a peak always exists!  
However, if only  $>$ , a peak does not always exist. E.g.,  $y(x)=c$ .

# Peak Finder

Straightforward Algorithm



Start from left

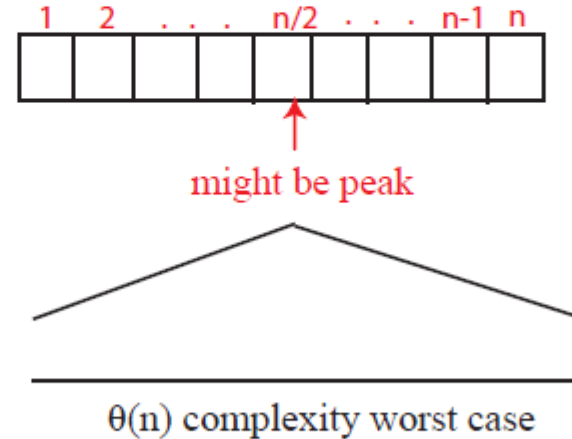


Figure 2: Look at  $n/2$  elements on average, could look at  $n$  elements in the worst case

# Peak Finder

What if we start in the middle? For the configuration below, we would look at  $n/2$  elements. Would we have to ever look at more than  $n/2$  elements if we start in the middle, and choose a direction based on which neighboring element is larger than the middle element?



# Peak Finder

Can we do better?

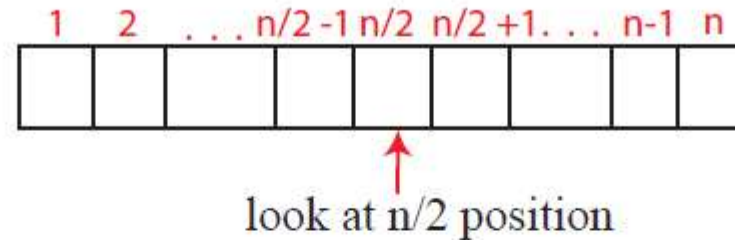


Figure 3: Divide & Conquer

- If  $a[n/2] < a[n/2 - 1]$  then only look at left half  $1 \dots n/2 - 1$  to look for peak
- Else if  $a[n/2] < a[n/2 + 1]$  then only look at right half  $n/2 + 1 \dots n$  to look for peak
- Else  $n/2$  position is a peak: WHY?

$$\begin{array}{lcl} a[n/2] & \geq & a[n/2 - 1] \\ a[n/2] & \geq & a[n/2 + 1] \end{array}$$

# Peak Finder

What is the complexity?

$$T(n) = T(n/2) + \underbrace{\Theta(1)}_{\text{to compare } a[n/2] \text{ to neighbors}} = \Theta(1) + \dots + \Theta(1) \text{ (}\log_2(n) \text{ times)} = \Theta(\log_2(n))$$

In order to sum up the  $\Theta(i)$  as we do here, we need to find a constant that works for all. If  $n = 1000000$ ,  $\Theta(n)$  algo needs 13 sec in python. If algo is  $\Theta(\log n)$  we only need 0.001 sec.

# Peak Finder

## Two-dimensional Version

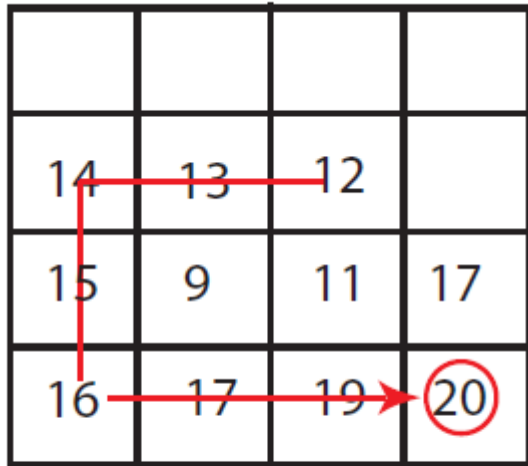


Figure 5: Circled value is peak.

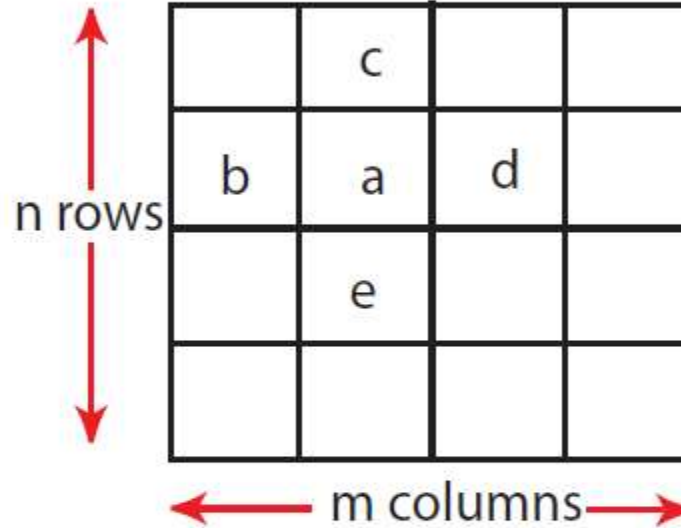
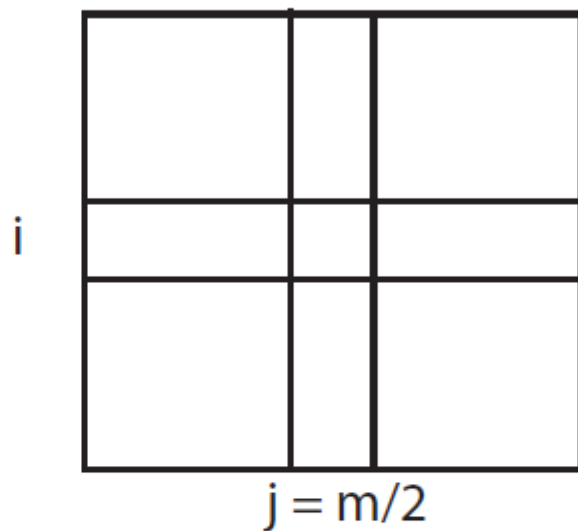


Figure 4: Greedy Ascent Algorithm:  $\Theta(nm)$  complexity,  $\Theta(n^2)$  algorithm if  $m = n$

$a$  is a 2D-peak iff  $a \geq b, a \geq d, a \geq c, a \geq e$

# Peak Finder

Attempt # 1: Extend 1D Divide and Conquer to 2D



- Pick middle column  $j = m/2$ .
- Find a 1D-peak at  $i, j$ .
- Use  $(i, j)$  as a start point on row  $i$  to find 1D-peak on row  $i$ .

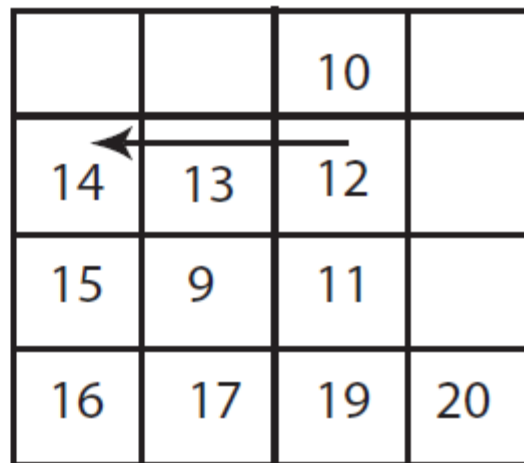


# Peak Finder

Attempt #1 fails

Problem: 2D-peak may not exist on row  $i$

		10	
14	13	12	
15	9	11	
16	17	19	20

A 4x4 grid of numbers. The values are: Row 1: [empty, empty, 10, empty]; Row 2: [14, 13, 12, empty]; Row 3: [15, 9, 11, empty]; Row 4: [16, 17, 19, 20]. A horizontal arrow points from the cell containing 12 to the cell containing 14.

End up with 14 which is not a 2D-peak.

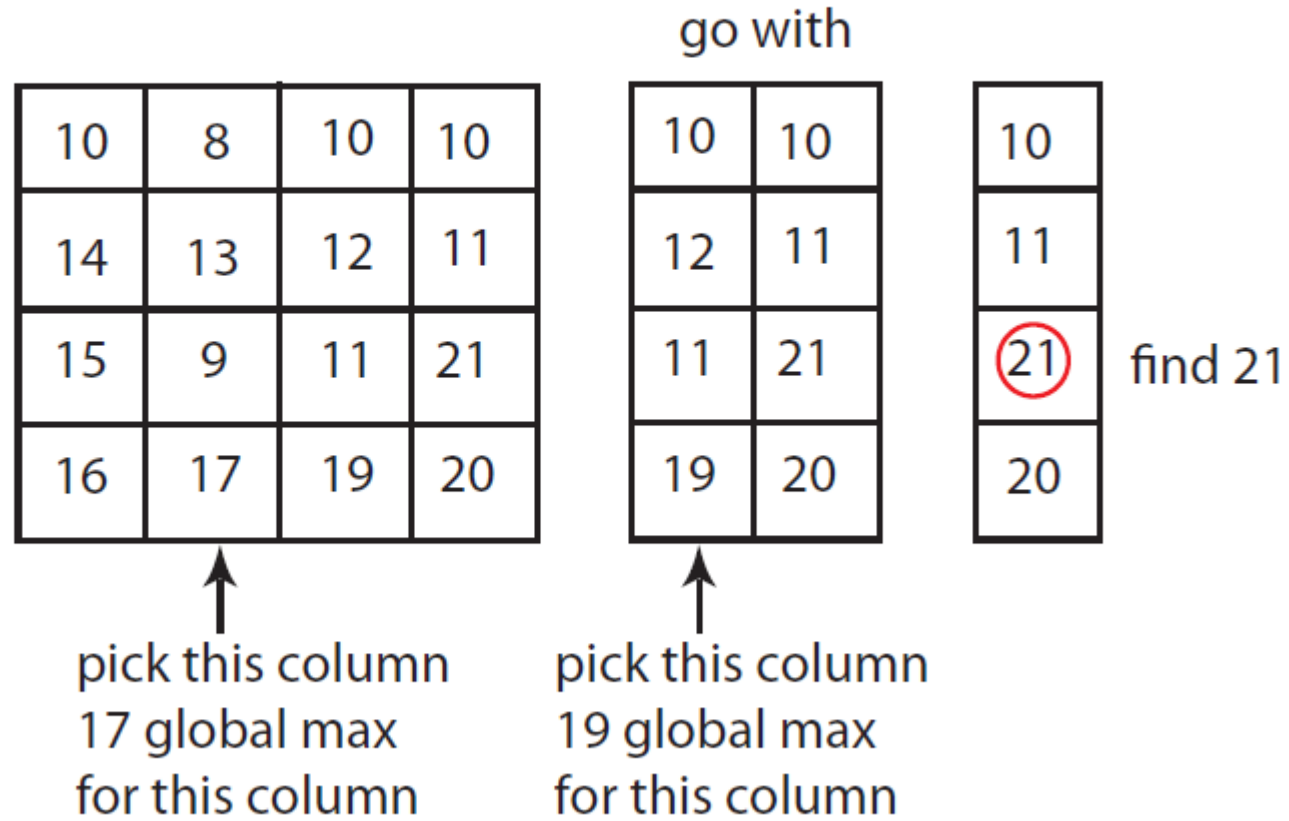
# Peak Finder

## Attempt # 2

- Pick middle column  $j = m/2$
  - Find global maximum on column  $j$  at  $(i, j)$
  - Compare  $(i, j - 1), (i, j), (i, j + 1)$
  - Pick left columns of  $(i, j - 1) > (i, j)$
  - Similarly for right
  - $(i, j)$  is a 2D-peak if neither condition holds ← WHY?
- Solve the new problem with half the number of columns.
  - When you have a single column, find global maximum and you're done.

# Peak Finder

Example of Attempt #2



# Peak Finder

## Complexity of Attempt #2

If  $T(n, m)$  denotes work required to solve problem with  $n$  rows and  $m$  columns

$$T(n, m) = T(n, m/2) + \Theta(n) \text{ (to find global maximum on a column — (n rows))}$$

$$\begin{aligned} T(n, m) &= \underbrace{\Theta(n) + \dots + \Theta(n)}_{\log m} \\ &= \Theta(n \log m) = \Theta(n \log n) \text{ if } m = n \end{aligned}$$

Question: What if we replaced global maximum with 1D-peak in Attempt #2? Would that work?

10	8	10	10
14	13	12	11
15	9	11	21
16	17	19	20

- Divide-and-conquer strategy:
  - Break a problem into subproblems;
  - Recursively solve subproblems;
  - Appropriately combine their answers.

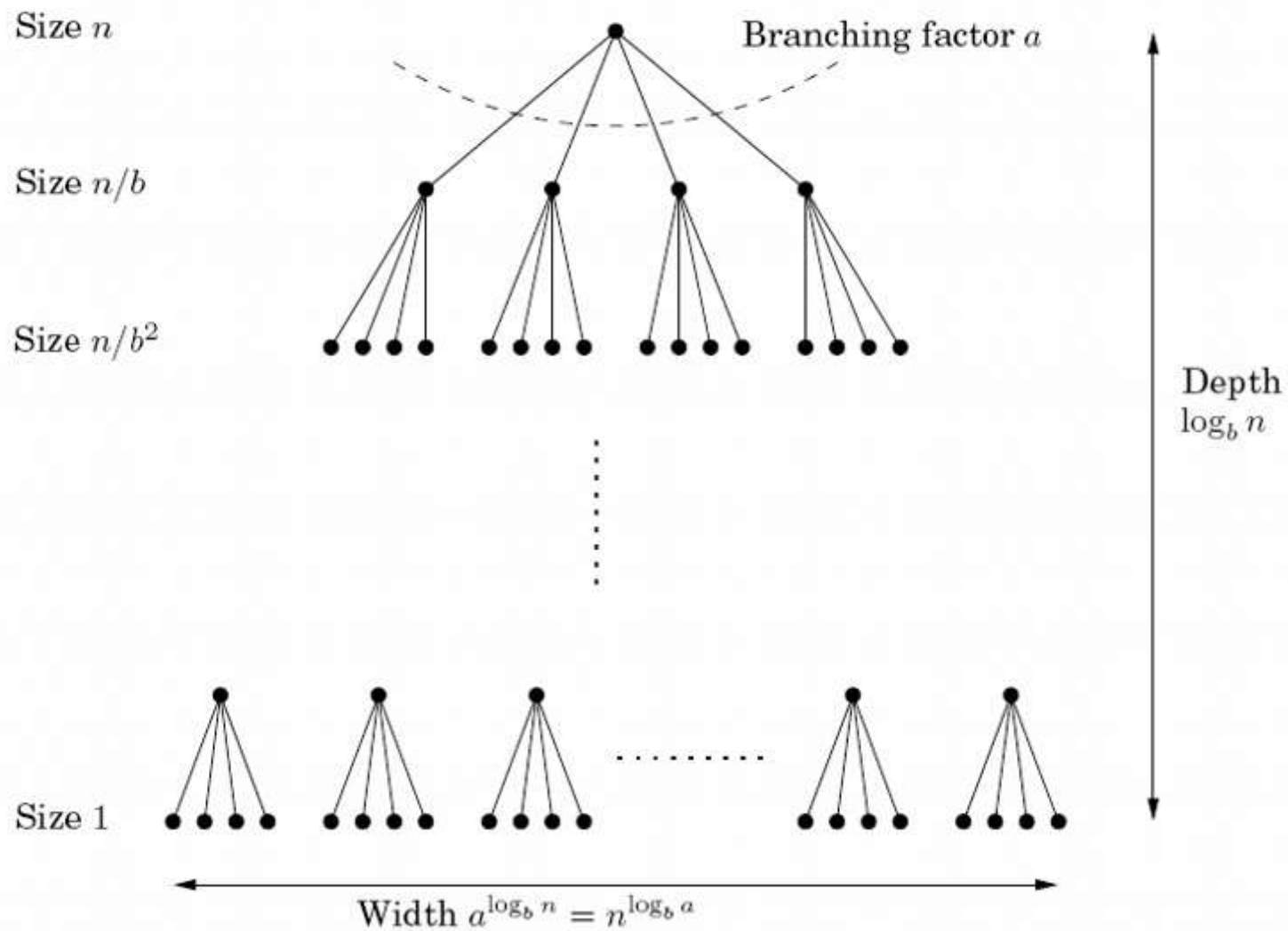
divide and  
conquer

**MERGE-SORT**  $A[1 \dots n]$

1. If  $n = 1$ , done (nothing to sort).
2. Otherwise, recursively sort  $A[1 \dots n/2]$  and  $A[n/2+1 \dots n]$ .
3. “**Merge**” the two sorted sub-arrays.

- Divide-and-conquer algorithms tackle a problem of size  $n$  by recursively solving  $a$  subproblems of size  $n/b$  and then combine these answers in  $O(n^d)$  time
  - Often,  $a \neq b$
  - $O(n^d)$ : polynomial time for all other efforts except for solving subproblems
- **Master theorem** If  $T(n) = aT(\lceil n/b \rceil) + O(n^d)$  for some constants  $a > 0$ ,  $b > 1$ , and  $d \geq 0$ , then
 
$$T(n) = \begin{cases} O(n^d) & \text{if } d > \log_b a \\ O(n^d \log_b n) & \text{if } d = \log_b a \\ O(n^{\log_b a}) & \text{if } d < \log_b a \end{cases}$$

**Figure 2.3** Each problem of size  $n$  is divided into  $a$  subproblems of size  $n/b$ .



*Proof.*

- Assume  $n$  is a power of  $b$
- The total work done at the  $k$ th level

$$a^k \times O\left(\frac{n}{b^k}\right)^d = O(n^d) \times \left(\frac{a}{b^d}\right)^k$$

- As  $k$  goes from 0 to  $\log_b n$ , these numbers form a geometric series with ratio  $a/b^d$ .

1. *The ratio is less than 1.*

Then the series is decreasing, and its sum is just given by its first term,  $O(n^d)$ .

2. *The ratio is greater than 1.*

The series is increasing and its sum is given by its last term,  $O(n^{\log_b a})$ :

$$n^d \left(\frac{a}{b^d}\right)^{\log_b n} = n^d \left(\frac{a^{\log_b n}}{(b^{\log_b n})^d}\right) = a^{\log_b n} = a^{(\log_a n)(\log_b a)} = n^{\log_b a}.$$

3. *The ratio is exactly 1.*

In this case  $O(\log_b n)$  terms of the series are equal to  $O(n^d)$ .



# SOLVING RECURRENCES

- Master theorem
- Substitution method
- Recursion-tree method

## SUBSTITUTION METHOD

- Guess the form of the solution
- Verify by induction
- Solve for constraints of constants

Ex:  $T(n)=4T(n/2)+n$  [ $T(1)=\Theta(1)$ ]

-Guess  $T(n)=O(n^3)$

-Assume  $T(k)\leq ck^3$  for  $k<n$

$$T(n) = 4T(n/2) + n \leq 4c(n/2)^3 + n = \frac{1}{2}cn^3 + n$$

$$= \underbrace{cn^3}_{\text{desired}} - \underbrace{\left(\frac{1}{2}cn^3 - n\right)}_{\text{residual}} \leq cn^3 \quad \text{if } \frac{1}{2}cn^3 - n \geq 0 \text{ i.e. } c \geq \frac{2}{n^2} \Rightarrow c \geq 2, n \geq 1$$

- -Try  $T(n)=O(n^2)$
- -Assume  $T(k) \leq ck^2$  for  $k < n$

$$T(n) = 4T(n/2) + n \leq 4c(n/2)^2 + n = cn^2 + n$$

$$= \underbrace{cn^2}_{desired} - \underbrace{(-n)}_{residual} \text{ (fail)}$$

- -Try  $T(n)=O(n^2)$
- -Assume  $T(k) \leq c_1k^2 - c_2k$  for  $k < n$

$$T(n) = 4T(n/2) + n \leq 4[c_1(n/2)^2 - c_2(n/2)] + n$$

$$= c_1n^2 - 2c_2n + n$$

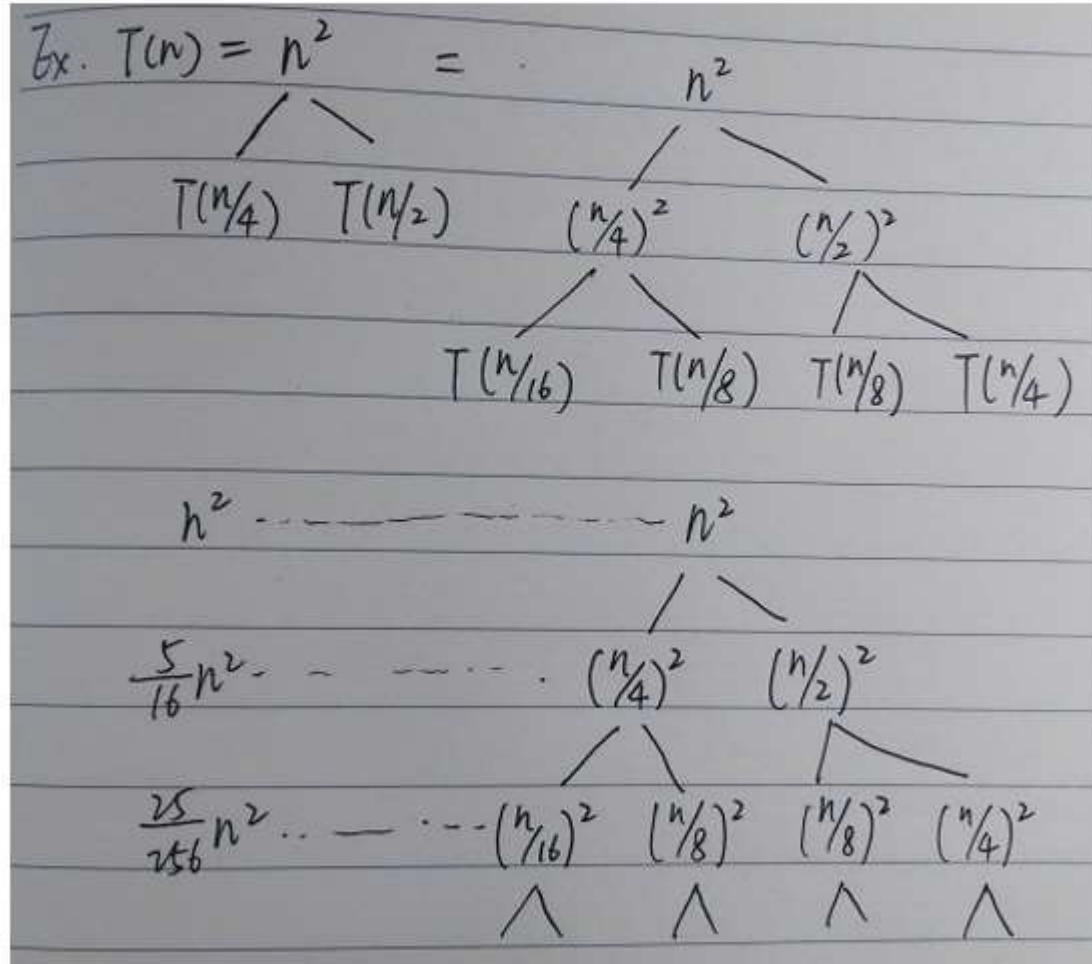
$$= \underbrace{c_1n^2 - c_2n}_{desired} - \underbrace{(c_2n - n)}_{residual} \text{ i.e. } c_2 \geq 1$$

$$T(1) \leq c_1 - c_2 \Rightarrow c_1 \geq T(1) + c_2$$

i.e.  $c_1$  is sufficiently large w.r.t.  $c_2$

## RECURSION-TREE METHOD

- Ex:  $T(n) = T(n/4) + T(n/2) + n^2$



- Total cost (level-by-level)

$$\begin{aligned} &\leq (1 + \frac{5}{16} + (\frac{5}{16})^2 + \dots + (\frac{5}{16})^k + \dots) n^2 \\ &< (1 + \frac{1}{2} + (\frac{1}{2})^2 + \dots + (\frac{1}{2})^k + \dots) n^2 \\ &= 2n^2 = O(n^2) \end{aligned}$$

Ex.  $T(n) = T(n/4) + 2T(n/2) + n^2$

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

$$\begin{array}{cc} & \diagdown \\ & \\ T(n/4) & 2T(n/2) \end{array}$$

=

$$\begin{array}{cc} & \diagdown \\ & n^2 \\ & \diagup \quad \diagdown \\ (n/4)^2 & 2(n/2)^2 \\ \diagup \quad \diagdown & \diagup \quad \diagdown \\ T(n/16) & 2T(n/8) \quad 2T(n/8) & 4T(n/4) \end{array}$$

$$n^2$$

$$\frac{9}{16}n^2 = \left(\frac{n}{4}\right)^2 + 2\left(\frac{n}{2}\right)^2$$

$$\frac{81}{256}n^2 = \left(\frac{n}{16}\right)^2 + 2\left(\frac{n}{8}\right)^2 + 2\left(\frac{n}{8}\right)^2 + 4\left(\frac{n}{4}\right)^2 = \frac{1+2 \times 4+2 \times 4+4 \times 16}{256}n^2$$

# Exercise 1

Section 2.2 describes a method for solving recurrence relations which is based on analyzing the recursion tree and deriving a formula for the work done at each level. Another (closely related) method is to expand out the recurrence a few times, until a pattern emerges. For instance, let's start with the familiar  $T(n) = 2T(n/2) + O(n)$ . Think of  $O(n)$  as being  $\leq cn$  for some constant  $c$ , so:  $T(n) \leq 2T(n/2) + cn$ . By repeatedly applying this rule, we can bound  $T(n)$  in terms of  $T(n/2)$ , then  $T(n/4)$ , then  $T(n/8)$ , and so on, at each step getting closer to the value of  $T(\cdot)$  we do know, namely  $T(1) = O(1)$ .

$$\begin{aligned} T(n) &\leq 2T(n/2) + cn \\ &\leq 2[2T(n/4) + cn/2] + cn = 4T(n/4) + 2cn \\ &\leq 4[2T(n/8) + cn/4] + 2cn = 8T(n/8) + 3cn \\ &\leq 8[2T(n/16) + cn/8] + 3cn = 16T(n/16) + 4cn \\ &\vdots \end{aligned}$$

A pattern is emerging... the general term is

$$T(n) \leq 2^k T(n/2^k) + kcn.$$

Plugging in  $k = \log_2 n$ , we get  $T(n) \leq nT(1) + cn \log_2 n = O(n \log n)$ .

- (a) Do the same thing for the recurrence  $T(n) = 3T(n/2) + O(n)$ . What is the general  $k$ th term in this case? And what value of  $k$  should be plugged in to get the answer?
- (b) Now try the recurrence  $T(n) = T(n-1) + O(1)$ , a case which is not covered by the master theorem. Can you solve this too?

a)

$$\begin{aligned} T(n) &\leq 3T\left(\frac{n}{2}\right) + cn \leq \dots \leq 3^k T\left(\frac{n}{2^k}\right) + cn \sum_{i=0}^{k-1} \left(\frac{3}{2}\right)^i = \\ &= 3^k T\left(\frac{n}{2^k}\right) + 2cn \left( \left(\frac{3}{2}\right)^k - 1 \right) \end{aligned}$$

For  $k = \log_2 n$ ,  $T(\frac{n}{2^k}) = T(1) = d = O(1)$ . Then:

$$T(n) = dn^{\log_2 3} + 2cn \left( \frac{n^{\log_2 3}}{n} - 1 \right) = \Theta(n^{\log_2 3})$$

as predicted by the Master theorem.

b)  $T(n) \leq T(n-1) + c \leq \dots \leq T(n-k) + kc$ . For  $k = n$ ,  $T(n) = T(0) + nc = \Theta(n)$ .

$$T(n) \leq 3[3T(n/4) + cn/2] + cn \leq 3^2 T(n/4) + \frac{3}{2}cn + cn$$

$$\leq 3^2 [3T(n/8) + cn/4] + \frac{3}{2}cn + cn$$

$$\leq 3^3 T(n/8) + \left[ \left(\frac{3}{2}\right)^2 + \frac{3}{2} + 1 \right] cn$$



## Exercise 2

2

- . Suppose you are choosing between the following three algorithms:
- Algorithm *A* solves problems by dividing them into five subproblems of half the size, recursively solving each subproblem, and then combining the solutions in linear time.
  - Algorithm *B* solves problems of size  $n$  by recursively solving two subproblems of size  $n - 1$  and then combining the solutions in constant time.
  - Algorithm *C* solves problems of size  $n$  by dividing them into nine subproblems of size  $n/3$ , recursively solving each subproblem, and then combining the solutions in  $O(n^2)$  time.

What are the running times of each of these algorithms (in big- $O$  notation), and which would you choose?

- a) This is a case of the Master theorem with  $a = 5, b = 2, d = 1$ . As  $a > b^d$ , the running time is  $O(n^{\log_b a}) = O(n^{\log_2 5}) = O(n^{2.33})$ .
- b)  $T(n) = 2T(n-1) + C$ , for some constant  $C$ .  $T(n)$  can then be expanded to  $C \sum_{i=0}^{n-1} 2^i + 2^n T(0) = O(2^n)$ .
- c) This is a case of the Master theorem with  $a = 9, b = 3, d = 2$ . As  $a = b^d$ , the running time is  **$O(n^d \log_3 n) = O(n^2 \log_3 n)$**

$$\begin{aligned} T(n) &= 2T(n-1) + C = 2[2T(n-2) + C] + C \\ &= 2^2 T(n-2) + (2+1)C = 2^2 [2T(n-3) + C] + (2+1)C \\ &= 2^3 T(n-3) + (2^2 + 2 + 1)C \\ &= 2^k T(n-k) + C \sum_{i=0}^{k-1} 2^i \end{aligned}$$

## Exercise 3

Solve the following recurrence relations and give a  $\Theta$  bound for each of them.

(a)  $T(n) = 2T(n/3) + 1$

(b)  $T(n) = 5T(n/4) + n$

(c)  $T(n) = 7T(n/7) + n$

(d)  $T(n) = 9T(n/3) + n^2$

(e)  $T(n) = 8T(n/2) + n^3$

(f)  $T(n) = 49T(n/25) + n^{3/2} \log n$

(g)  $T(n) = T(n-1) + 2$

(h)  $T(n) = T(n-1) + n^c$ , where  $c \geq 1$  is a constant

(i)  $T(n) = T(n-1) + c^n$ , where  $c > 1$  is some constant

(j)  $T(n) = 2T(n-1) + 1$

(k)  $T(n) = T(\sqrt{n}) + 1$

# Exercise 3

- d)  $T(n) = 9T(n/3) + n^2 = \Theta(n^2 \log_3 n)$  by the Master theorem.
- e)  $T(n) = 8T(n/2) + n^3 = \Theta(n^3 \log_2 n)$  by the Master theorem.
- f)  $T(n) = 49T(n/25) + n^{3/2} \log n = \Theta(n^{3/2} \log n)$ . Apply the same reasoning of the proof of the Master Theorem. The contribution of level  $i$  of the recursion is

$$\left(\frac{49}{25^{3/2}}\right)^i n^{3/2} \log\left(\frac{n}{25^{3/2}}\right) = \left(\frac{49}{125}\right)^i O(n^{3/2} \log n)$$

Because the corresponding geometric series is dominated by the contribution of the first level, we obtain  $T(n) = O(n^{3/2} \log n)$ . But,  $T(n)$  is clearly  $\Omega(n^{3/2} \log n)$ . Hence,  $T(n) = \Theta(n^{3/2} \log n)$ .

- g)  $T(n) = T(n-1) + 2 = \Theta(n)$ .

$$h) T(n) = T(n-1) + n^c = T(n-2) + (n-1)^c + n^c$$

$$= T(n-3) + (n-2)^c + (n-1)^c + n^c = \sum_{i=1}^n i^c + T(0) = \Theta(n^{c+1})$$

$$49^i \times \left(\frac{n}{25^i}\right)^{\frac{3}{2}} \log \frac{n}{25^i} = n^{\frac{3}{2}} \times \left(\frac{49}{125}\right)^i \times (\log n - i \log 25) \leq n^{\frac{3}{2}} \times \left(\frac{49}{125}\right)^i \times \log n$$

$$i \leq \log_{25} n \Rightarrow i \log 25 \leq \log n$$

# Exercise

- Solving the following recurrence relations and give a  $\theta$  bound for each of them

(a)  $T(n) = 2T(n/3) + 1$

(b)  $T(n) = 5T(n/4) + n$

(c)  $T(n) = 7T(n/7) + n$

(i)  $T(n) = T(n-1) + c^n$ , where  $c > 1$  is some constant

(j)  $T(n) = 2T(n-1) + 1$

(k)  $T(n) = T(\sqrt{n}) + 1$

a)  $T(n) = 2T(n/3) + 1 = \Theta(n^{\log_3 2})$  by the Master theorem.

b)  $T(n) = 5T(n/4) + n = \Theta(n^{\log_4 5})$  by the Master theorem.

c)  $T(n) = 7T(n/7) + n = \Theta(n \log_7 n)$  by the Master theorem.

$$i) T(n) = T(n-1) + c^n = T(n-2) + c^{n-1} + c^n$$

$$= T(n-3) + c^{n-2} + c^{n-1} + c^n = \sum_{i=1}^n c^i + T(0) = \Theta(c^n)$$

$$j) T(n) = 2T(n-1) + 1 = 2[2T(n-2) + 1] + 1$$

$$= 2^2 T(n-2) + (2+1) = 2^2 [2T(n-3) + 1] + (2+1)$$

$$= 2^3 T(n-3) + (2^2 + 2 + 1) = 2^k T(n-k) + \sum_{i=0}^{k-1} 2^i = 2^n T(0) + \sum_{i=0}^{n-1} 2^i = \Theta(2^n)$$

$$k) T(n) = [T(\sqrt{\sqrt{n}}) + 1] + 1 = [T(\sqrt{\sqrt{\sqrt{n}}}) + 1] + 2$$

$$= k + T(b) \quad s.t. \quad b^{\frac{2*2*\dots*2}{k}} = n$$

$$\Rightarrow b^{2^k} = n \Rightarrow k = \log \log_b n \Rightarrow T(n) = O(\log \log n)$$