# Lecture 4: Analyzing **Complexity** via **Recurrences**



1 *These slides include material originally prepared by Dr.Ron Cytron, Dr. Jeremy Buhler, and Dr. Steve Cole.*

### **Announcements: Lab 3**

- Pre-lab due **Tuesday** (tonight!) at 11:59 PM
- Code and Post-lab due **Friday** at 11:59 pm
	- Pre- and post-labs via Gradescope (usual writeup standards)
	- Code in your Bitbucket repo
	- Please **verify that your work has been checked in** by looking at your repo via the browser, and double-checking Gradescope
		- Avoid pull-before-push failure
- Academic Integrity (the other AI)
	- Many, many legitimate resources
	- Don't panic, even at last minute—reach out instead
		- Zero credit w/explanation is much, much better than an AI case
	- Previous semesters  $\Rightarrow$  many cases from Lab 3 reported to Dean's office
	- This semester  $==$  can we go for zero??

### **Announcements: Exam 1**

- **Wednesday 2/20 6:30-8:30 PM – rooms TBA (Piazza)**
- Please see Piazza for details (forthcoming), especially if you must reschedule for religious or other acceptable reasons
- Covers **Lectures** and **Studios 0-4**
- Exam review Sunday, Feb. 17, 2-5 pm Louderman 458 (instead of recitation)
- A practice exam will be posted this week

### **Last Time: Cost of heapify**

- We gave a recursive procedure for heapify
- We defined its running time to be **T(n)** on a heap of size n
- We derived a *recursive formula (recurrence)* for T(n)

**T(n) = T(2n/3) + k**

*We magically solved this recurrence:* T(n) = Θ(log n)



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# **But how did we get it?**

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### **Strategies We Will Consider**

• Problem: given a recurrence for T(n), find a closed**form asymptotic complexity function that satisfies the recurrence.**

#### • Possible strategies

- Guess and check (a.k.a. substitution)
- Recursion tree accounting (for certain kinds of recurrence)
- Master Method (next time)

#### **Guess and Check**

- Guess an **exact** (not asymptotic) function  $f(n)$  for  $T(n)$
- Prove that  $f(n)$  satisfies the recurrence for all  $n > 0$
- Proof is inductive on n
- [Requires that we know a base case for the recurrence]

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- $\bullet$  Let's say T(1) = k

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- **What solution should we guess?**

- $T(n) = T(n-1) + k$
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- $\bullet$  Intuitively, we add k every time n goes up by 1, so  $T(n)$  is something like nk.

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- $\bullet$   $T(n) = T(n-1) + k = (n-1)k + k$

By IH, we can **algebraically substitute T(m) by** proposed **f(m)** for m < n on the RHS

- **Claim: T(n) = nk**
- **By induction on n**
- Bas  $(n=1)$ :  $T(1) = k = 1*k$   $\leftarrow$  claim holds!
- $\bullet$  Ind (n > 1): assume true for m < n.
- $T(n) = T(n-1) + k = (n-1)k + k = nk$   $\leftarrow$  claim holds!
- Conclude that  $T(n)$  indeed = nk =  $\Theta(n)$

### **A Slightly More Interesting Example**

- **Binary search**: an algorithm for finding a value in a sorted array
- **Problem**: Given sorted array A of size n, and a *query value* x…
- If x occurs in A, return an index  $\mathbf{j}$  s.t. A[j] = x
- If x does not occur in A, return special value "**notFound**"

**3 5 6 17 22 23 30 48** 0 1 2 3 4 5 6 7

### Algorithm Idea

- Divide the array in half, and look at the middle element A[mid]
- If  $A[\text{mid}] < x$ , x must be in the \_\_\_\_\_\_\_\_\_ half of A if it appears at all.

### Algorithm Idea

- $\bullet$  Divide the array in half, and look at the middle element A[mid]
- If A[mid] < x, x must be in the **upper** half of A if it appears at all.
- If  $A[\text{mid}] > x$ , x must be in the  $\_\_\_\_\_\$  half of A if it appears at all.

### Algorithm Idea

- Divide the array in half, and look at the middle element A[mid]
- If A[mid] < x, x must be in the **upper** half of A if it appears at all.
- If A[mid] > x, x must be in the **lower** half of A if it appears at all.
- In either case, recursively look for x in the appropriate half of A.

#### Binary search

#### ● Looking for 3

- Try a middle element
- $\circ$  From there, discard  $\frac{1}{2}$
- Repeat



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#### Binary search

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- Repeat

#### ● Found it!



#### Binary Search

- You'll study the code and correctness of binary search more deeply in Studio 5.
- For today, let's focus on a rough running time analysis.

### Binary Search

• We start with an array of size n.

- At each step, we
	- $\circ$  do constant work (compare midpoint of A to x)
	- cut the problem size in half
	- recur on the appropriate half

### Binary Search

• We start with an array of size n. **T(n)** 



- At each step, we
	- do constant work (compare midpoint of A to x) **c**
	- cut the problem size in half
	- recur on the appropriate half **T(n/2)**

### Binary Search Recurrence

- $T(n) = T(n/2) + c$
- What's the base case?
- If not specified, assume it is *some* constant for  $T(1)$
- *Which* constant doesn't affect asymptotic solution  $\rightarrow$  pick for convenience
- *(More on this in Studio 4)* 35

### Guessing Running Time

- $\bullet$  Is T(n) constant-time?
- Let's guess  $T(n) = c$
- Pick  $T(1) = c$  to make base case match [constant for  $T(1)$  doesn't matter!]
- $\bullet$   $T(n) = T(n/2) + c = ?$ ?? [what does substitution yield?]
## Guessing Running Time

- $\bullet$  Is T(n) constant-time?
- Let's guess  $T(n) = c$
- Pick  $T(1) = c$  to make base case match [constant for  $T(1)$  doesn't matter!]
- $T(n) = T(n/2) + c = c + c = 2c$
- $\bullet$  But we are trying to prove that  $T(n) = c$ , so proof failed!

## Guessing Running Time

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- $T(n) = T(n/2) + c = c + c = 2c$
- $\bullet$  But we are trying to prove that  $T(n) = c$ , so proof failed!
- *(And indeed, can see that no other constant > 0 would work either)*

- $\bullet$  Is T(n) linear-time?
- Let's guess  $T(n) = cn$
- Pick  $T(1) = c$  to make base case match [constant for  $T(1)$  doesn't matter!]
- $T(n) = T(n/2) + c = ?$ ??

- $\bullet$  Is T(n) linear-time?
- Let's guess  $T(n) = cn$
- Pick  $T(1) = c$  to make base case match [constant for  $T(1)$  doesn't matter!]
- $\bullet$   $T(n) = T(n/2) + c = cn/2 + c$   $\leftarrow$  not cn as desired! Proof fails, *but*...

- $\bullet$  Is T(n) linear-time?
- Let's guess  $T(n) = cn$
- Pick  $T(1) = c$  to make base case match [constant for  $T(1)$  doesn't matter!]
- T(n) = T(n/2) + c = cn/2 + c *= c(n/2 + 1) ≤ cn for n ≥ 2*

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- *Conclude that T(n) ≤ cn for all n.*
- *Therefore, T(n) = ??? [asymptotically]*

- Is T(n) linear-time?
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- T(n) = T(n/2) + c = cn/2 + c *= c(n/2 + 1) ≤ cn for n ≥ 2*
- *Conclude that T(n) ≤ cn for all n.*
- *Therefore, T(n) = O(n) proving ≤ implies upper bound*

- $Is T(n)$  linear-time?
- Let's guess  $T(n) = cn$



- Is T(n) logarithmic-time?
- Let's guess  $T(n) = c \log_2 n$
- If  $T(1) = c... c log<sub>2</sub> 1 = 0 \neq c.$  Whoops.

- Is T(n) logarithmic-time?
- Let's guess  $T(n) = c \log_2 n$
- $\bullet$  T(1) = c log<sub>2</sub> 1 = 0  $\neq$  c. Whoops.

- $\bullet$  Is T(n) logarithmic-time?
- Let's guess  $T(n) = c \log_2 n$
- $T(2) = c \log_2 2 = c$ . So induction will start at  $n = 2$  (fine for asymptotic!)
- $T(n) = T(n/2) + c$  $= c \log_2(n/2) + c$  $= c(\log_2 n - \log_2 2) + c$  $= c$  log<sub>2</sub> n – c + c  $= c \log_2 n$   $\leftarrow$  Yay, it worked! So T(n) =Θ(log n)





#### Pros and Cons of Guess and Check

- + For **any recurrence**, given right guess, can prove that it is correct.
- + Can use separate upper-, lower-bound proofs to prove Θ result.

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#### **Can we take the guess-work out of solving recurrences?**

Pros and Cons of G

- + For **any recurrence, THI GENETAL, NO.** that it is correct.
- + Can use separate upper- bound prove Θ result.
- **You must start**
- 

**Example 1** Finding values and the make the induction work for *c* and *n\_0* in Can we take the guess-work or only of solving recurrences? (It's a bit like a Big-Oh proof )

**In general, no.**

Pros and Cons of G

- + For **any recurrence in grandral notably that it is correct.**
- 
- **You must start from a correct guess**
- Guessing the right constants and lower-order terms to make the induction work

+ Can use separate up prove Can use Separate up prove Θ result. **In general, no.**

*But for certain common cases, there's a way.*

Can we take the guide of the solution of solving recurrences?

- You have an algorithm FOO that runs on an input of size n.
- FOO does some *local* work.
- FOO makes some recursive calls on inputs whose size is a fraction of n.

```
FOO(A[1..n])
FOO(A[1..n/2])
Print(A)
FOO(A[n/2+1..n])
```
- FOO takes time **T(n) on input of size n**.
- FOO does some *local* work taking time **f(n)**.
- FOO makes **a** recursive calls on inputs of size **n/b.**

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**FOO(A[1..n]) FOO(A[1..n/2]) Print(A) FOO(A[n/2+1..n])**  $a = 2$   $b = 2$ **f(n) = cn**

- FOO takes time **T(n) on input of size n**.
- FOO does some *local* work taking time **f(n)**.
- FOO makes **a** recursive calls on inputs of size **n/b.**

# **T(n) = aT(n/b) + f(n)**

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- FOO does some *local* work taking time **f(n)**.
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# **T(n) = aT(n/b) + f(n)**

*Assumes T(n) = constant for small enough n – see Studio 4 for more on this*

#### Examples That Fit the Paradigm

- Binary search:  $T(n) = T(n/2) + c$
- Merge sort:  $T(n) = 2T(n/2) + cn$
- Strassen's matrix multiply:  $T(n) = 7T(n/2) + cn^2$
- [Maximum subarray:](http://www.utdallas.edu/~daescu/maxsa.pdf)  $T(n) = 2T(n/2) + c$

#### New Strategy

- We could, in principle, expand the recurrence to a sum of terms (as we sketched for heapify) and add them up
- E.g.,  $T(n) = T(n/2) + c = (T(n/4) + c) + c = ((T(n/8) + c) + c) + c = ...$

$$
= C + C + C + \dots + C
$$

**How many times?**

#### New Strategy

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- E.g.,  $T(n) = T(n/2) + c = (T(n/4) + c) + c = ((T(n/8) + c) + c) + c = ...$

$$
= c + c + c + \dots + c
$$

= **Θ(log n) About log<sup>2</sup> n times**



#### Idea: Draw a Picture!

- We'll draw a tree showing all the terms in the recurrence.
- It's called a recursion tree.

- Each node records work of one term in expansion of recurrence.
- Add up work over all nodes to get total work.

● Root contains first term of expansion



● Root contains first term of expansion



● Expand once to get second term



• Now repeat...







- What's *the last term*?
- (Assume n is power of 2)
- What is the last term?



- What's *the last term*?
- (Assume n is power of 2)
- We stop at  $T(1)$
- What is  $T(1)$ ?


### **Example: T(n) = T(n/2) + c**

- What's *the last term*? • (Assume n is power of 2) • We stop at  $T(1)$ • What is  $T(1)$ ?
	- We assumed  $T(1) = c$





### **Accounting**  $T(n) = T(n/2) + c$



**Accounting**  $T(n) = T(n/2) + c$ 

Max depth  $=$ # of divisions by 2 needed to get from n down to 1.



**Accounting**  $T(n) = T(n/2) + c$ 

> Total work is sum of local work in each row





#### **Recursion Tree Methodology**

- Given recurrence...
- Sketch the tree (figure out its height!)
- Figure out problem size and local work/node at each level
- Sum local work over whole tree

● Root contains first term of expansion



• There are two subproblems at next level



• How much work in each node?



• How much work in each node?



- cn/2 [but it doesn't fit in the circles]
- Let's just draw the tree…

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- $\bullet$  # of nodes doubles at each level  $(a = 2)$



- Let's just draw the tree…
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- After j steps, we have **2 <sup>j</sup>** nodes at level j



- Let's just draw the tree…
- $\bullet$  # of nodes doubles at each level  $(a = 2)$
- After j steps, we have **2 <sup>j</sup>** nodes at level j
- Bottom out at  $T(1)$ again























#### **T(n) = 2T(n/2) + cn**

Multiply across each level to get its work



(Simplification isn't always this nice)

### **T(n) = 2T(n/2) + cn**





#### **Recursion Tree Methodology (Again)**

- Given recurrence…
- Sketch the tree (figure out its height!)
- Figure out problem size, # nodes, and local work/node at each level
- Sum local work at each level, then across levels

## **Example:**  $T(n) = 3T(n/4) + cn^2$   $[T(1) = d]$

• [This one is worked in your text as well  $-$  see p. 89]

### **Example:**  $T(n) = 3T(n/4) + cn^2$   $[T(1) = d]$

• This time,  $a = 3$ , so each node branches 3 ways!





### **Example:**  $T(n) = 3T(n/4) + cn^2$   $[T(1) = d]$

• This time,  $a = 3$ , so each node branches 3 ways!

• This time,  $b = 4$ , so problem size goes down by factor of 4 per level.
































#### **A Brief Diversion**

 $a^{\log_b n} = a$ by change of base  $\log_b n = \log_a n \log_b a$  $= n^{\log_b a}$ 

$$
a^{\log_b n}=n^{\log_b a}
$$





























## $T(n) = 3T(n/4) + cn^2$



## $T(n) = 3T(n/4) + cn^2$



## $T(n) = 3T(n/4) + cn^2$





#### *Switch to separate PDF for algebraic resolution of this formula into an asymptotic complexity*

#### **End of Lecture 4**