Lecture 3

Recurrence Relations and how to solve them!

Announcements!

- **HW1** is due Friday!

- I messed up the section times last week!
  - Sorry for the confusion!!!
  - Check the website for accurate times/location ☺

Not really an announcement

You can ignore this if you aren't interested…

- **Last time:** In the definition of big-Oh, why $c > 0$?
- It doesn't matter if everything in sight is positive
  (which is the case for us, when f, g in "$f(n) = O\big(g(n)\big)$" are running times)
- It does matter when things might be negative.
  - Example: $f(n) = n, g(n) = -n$
  - Then $f(n)$ is **NOT** $O(g(n))$ with our definition, but it would be with a definition that allowed negative "c"
  - Note: Sources disagree on the definition when g is negative. It won't matter for us.

Ed Heroes!

As of Monday evening

Top askers

Name	Questions
Lucio M	4
Henry H	2
Liam C	2
Armeen Al	2
Britney B	2
Juan P.	2
Peter B Cl	2
Mario D. P	2
Angelina M C	2
Carole S D	2

Top answerers

Name	Answers
Anisha Palaparthi STAFF	9
Sophia Amelie Barnes STAFF	6
Thanawan Atchariyachanvanit STAFF	5
Bradley Moon STAFF	5
Henry H	4
	4
	4
	4
	3
	3

Top hearted

Name	Hearts
Anisha Palaparthi STAFF	32
Thanawan Atchariyachanvanit STAFF	14
Mary Wootters STAFF	12
Bradley Moon STAFF	8
Henry H	7
Sophia Amelie Barnes STAFF	4
Angela N	3
Janina T	3
Xiao Mao STAFF	3
Lucio M	2

Last time….

- Sorting: InsertionSort and MergeSort
- What does it mean to work and be fast?
  - Worst-Case Analysis
  - Big-Oh Notation
- Analyzing correctness of iterative + recursive algs
  - Induction!
- Analyzing running time of recursive algorithms
  - By writing out a tree and adding up all the work done.

Today

- Recurrence Relations!
  - How do we calculate the runtime a recursive algorithm?
- The Master Method
  - A useful theorem so we don’t have to answer this question from scratch each time.
- The Substitution Method
  - A different way to solve recurrence relations, more general than the Master Method.

Running time of MergeSort

- Let T(n) be the running time of MergeSort on a length n array.

- We know that T(n) = O(nlog(n)).

- We also know that T(n) satisfies:

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + O(n)$$

```
MERGESORT(A):
  n = length(A)
  if n ≤ 1:
    return A
  L = MERGESORT(A[:n/2])
  R = MERGESORT(A[n/2:])
  return MERGE(L,R)
```

Running time of MergeSort

- Let T(n) be the running time of MergeSort on a length n array.
- We know that T(n) = O(nlog(n)).
- We also know that T(n) satisfies:

$$T(n) \leq 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$$

Last time we showed that the time to run MERGE on a problem of size n is O(n). For concreteness, let's say that it's at most 11n operations.

```
MERGESORT(A):
   n = length(A)
   if n ≤ 1:
      return A
   L = MERGESORT(A[:n/2])
   R = MERGESORT(A[n/2:])
   return MERGE(L,R)
```

Recurrence Relations

- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$ is a **recurrence relation.**
- It gives us a formula for T(n) in terms of T(less than n)

- The challenge:

Given a recurrence relation for T(n), find a closed form expression for T(n).

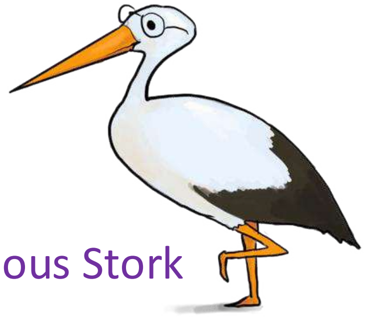
- For example, T(n) = O(nlog(n))

Note that
$T(n) \leq 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$
(with a $\leq$) is also a recurrence relation! Does it matter for a conclusion like T(n) = O(n log(n))?

Technicalities I
Base Cases

- Formally, we should always have base cases with recurrence relations.
- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$ with $T(1) = 1$

  is not the same function as
- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$ with $T(1) = 1000000000$
- However, no matter what T is, T(1) is O(1), so sometimes we'll just omit it.



On your pre-lecture exercise

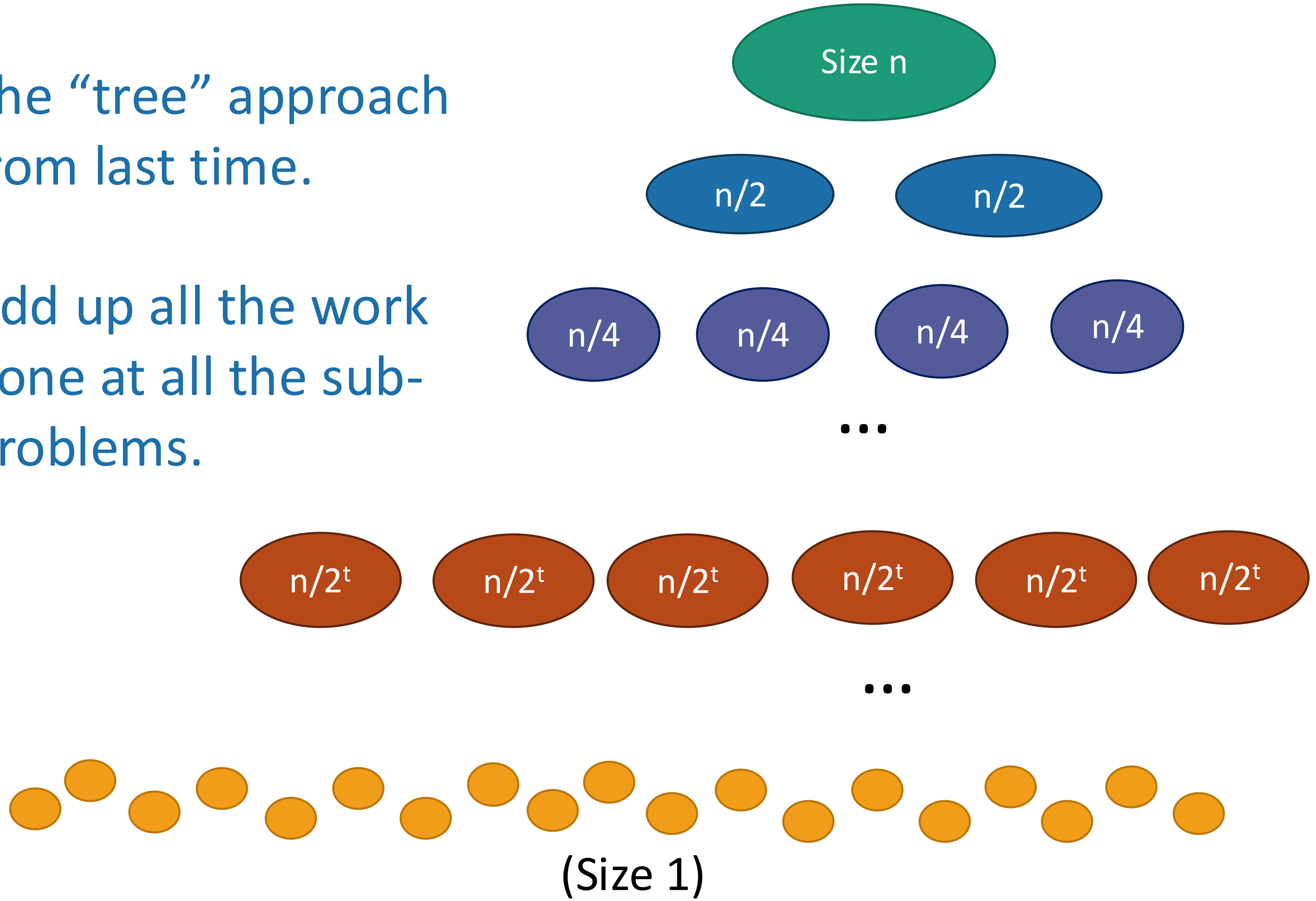
- You played around with these examples (when n is a power of 2):

1. $T_1(n) = T_1\left(\frac{n}{2}\right) + n, \qquad T(1) = 1$
2. $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n, \qquad T(1) = 1$
3. $T_2(n) = 4 \cdot T_2\left(\frac{n}{2}\right) + n, \qquad T(1) = 1$

The pre-lecture exercise showed you two ways to do this one!

One approach for all of these

- The “tree” approach from last time.
- Add up all the work done at all the sub-problems.

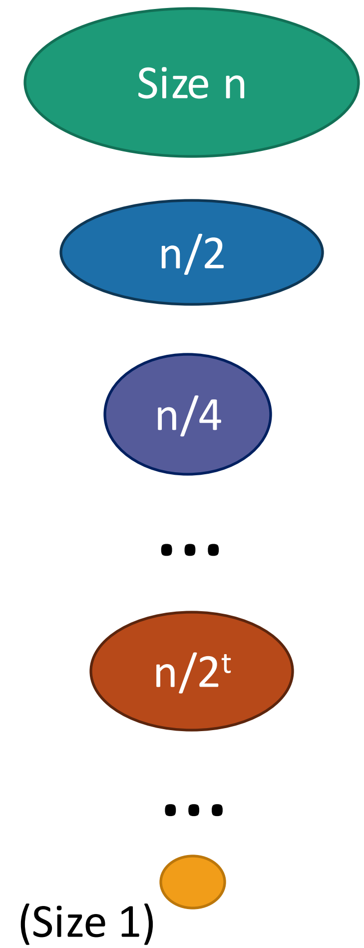


Solutions to pre-lecture exercise (1)

- $T_1(n) = T_1\left(\frac{n}{2}\right) + n, \quad T_1(1) = 1.$
- Adding up over all layers:

$$\sum_{i=0}^{\log(n)} \frac{n}{2^i} = 2n - 1$$

- So $T_1(n) = O(n).$



Contribution at this layer:

n

n/2

n/4

n/2^t

1

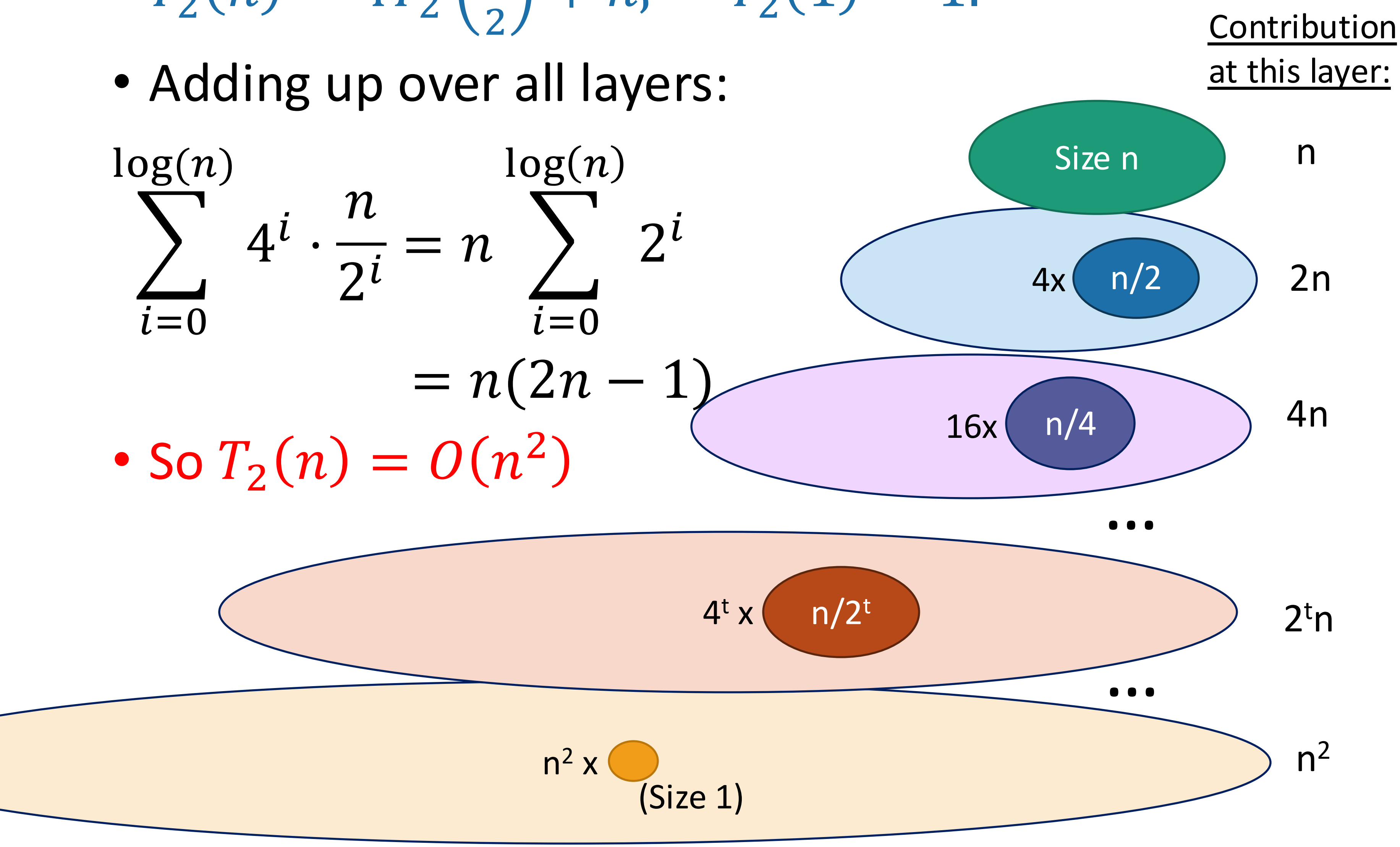
Solutions to pre-lecture exercise (2)

- $T_2(n) = 4T_2\left(\frac{n}{2}\right) + n, \quad T_2(1) = 1.$
- Adding up over all layers:

$$\sum_{i=0}^{\log(n)} 4^i \cdot \frac{n}{2^i} = n \sum_{i=0}^{\log(n)} 2^i$$

$$= n(2n-1)$$

- So $T_2(n) = O(n^2)$



More examples

T(n) = time to solve a problem of size n.

- Needlessly recursive integer multiplication
- $T(n) = 4\,T(n/2) + O(n)$
- $T(n) = O(n^2)$

This is similar to T_2 from the pre-lecture exercise.

- Karatsuba integer multiplication
- $T(n) = 3\,T(n/2) + O(n)$
- $T(n) = O\left(n^{\log_2(3)} \approx n^{1.6}\right)$

- MergeSort
- $T(n) = 2T(n/2) + O(n)$
- $T(n) = O(n\log(n))$

What's the pattern?!?!?!?!

The master theorem

- A formula for many recurrence relations.
    - We'll see an example Wednesday when it won't work.

- Proof: "Generalized" tree method.

A useful
formula it is.
Know why it works
you should.

Jedi master Yoda

The master theorem

We can also take n/b to mean either $\left\lfloor \frac{n}{b} \right\rfloor$ or $\left\lceil \frac{n}{b} \right\rceil$ and the theorem is still true.

- Suppose that $a \geq 1, b > 1,$ and d are constants (independent of n).
- Suppose $T(n) = a \cdot T\left(\frac{n}{b}\right) + O\left(n^d\right)$. Then

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

Three parameters:

a : number of subproblems

b : factor by which input size shrinks

d : need to do n^d work to create all the subproblems and combine their solutions.

Many symbols those are….

Technicalities II

Integer division

Plucky the Pedantic Penguin

- If n is odd, I can't break it up into two problems of size n/2.

$$T(n) = T\left(\left\lfloor\frac{n}{2}\right\rfloor\right) + T\left(\left\lceil\frac{n}{2}\right\rceil\right) + O(n)$$

- However (see CLRS, Section 4.6.2 for details), one can show that the Master theorem works fine if you pretend that what you have is:

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + \ O(n)$$

- From now on we'll mostly **ignore floors and ceilings** in recurrence relations.

Examples
(details on board)

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + O(n^d).$$

$$T(n) = \begin{cases} O(n^d \log(n)) & \text{if } a = b^d \\ O(n^d) & \text{if } a < b^d \\ O(n^{\log_b(a)}) & \text{if } a > b^d \end{cases}$$

- Needlessly recursive integer mult.
  - T(n) = 4 T(n/2) + O(n)
  - T(n) = O(n^2)

$a = 4$
$b = 2$
$d = 1$

$a > b^d$ ✓

- Karatsuba integer multiplication
  - T(n) = 3 T(n/2) + O(n)
  - T(n) = O($n^{\text{log\_2(3)}} \approx n^{1.6}$)

$a = 3$
$b = 2$
$d = 1$

$a > b^d$ ✓

- MergeSort
  - T(n) = 2T(n/2) + O(n)
  - T(n) = O(nlog(n))

$a = 2$
$b = 2$
$d = 1$

$a = b^d$ ✓

- That other one
  - T(n) = T(n/2) + O(n)
  - T(n) = O(n)

$a = 1$
$b = 2$
$d = 1$

$a < b^d$ ✓

Proof of the master theorem

- We'll do the same recursion tree thing we did for MergeSort, but be more careful.
- Suppose that $T(n) \leq a \cdot T\left(\frac{n}{b}\right) + c \cdot n^d$.

Hang on! The hypothesis of the Master Theorem was that the extra work at each level was $O(n^d)$, but we're writing $\leq cn^d$...

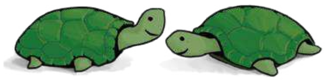
Plucky the Pedantic Penguin

That's true … the hypothesis should be that $T(n) = a \cdot T\left(\frac{n}{b}\right) + O(n^d)$. For simplicity, today we are essentially we are assuming the $n_0 = 1$ in the definition of big-Oh. It's a good exercise to verify that the proof works for $n_0 > 1$ too.

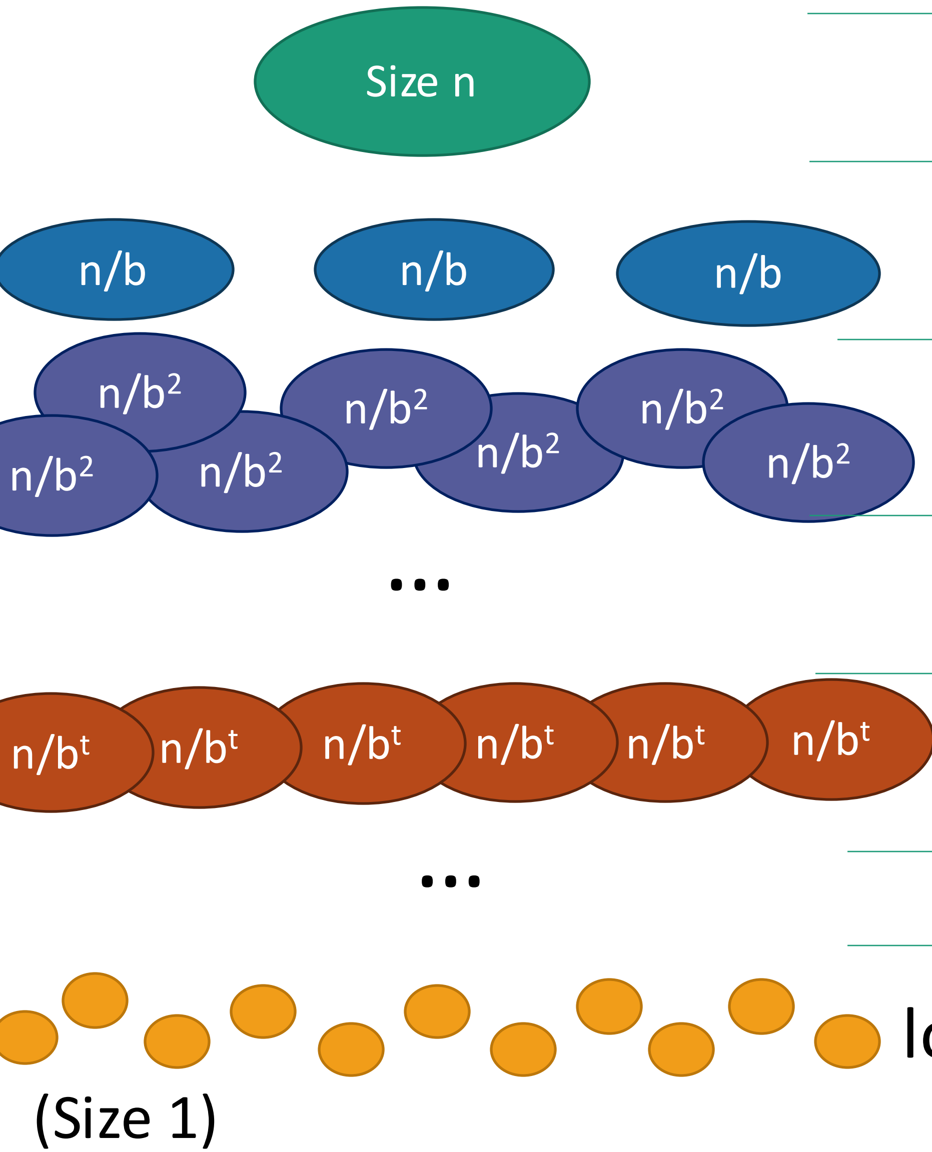
Siggi the Studious Stork

Recursion tree

$$T(n) \leq a \cdot T\left(\frac{n}{b}\right) + c \cdot n^d$$



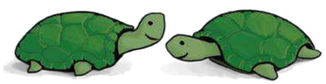
Fill this in! (Say T(1) = c)



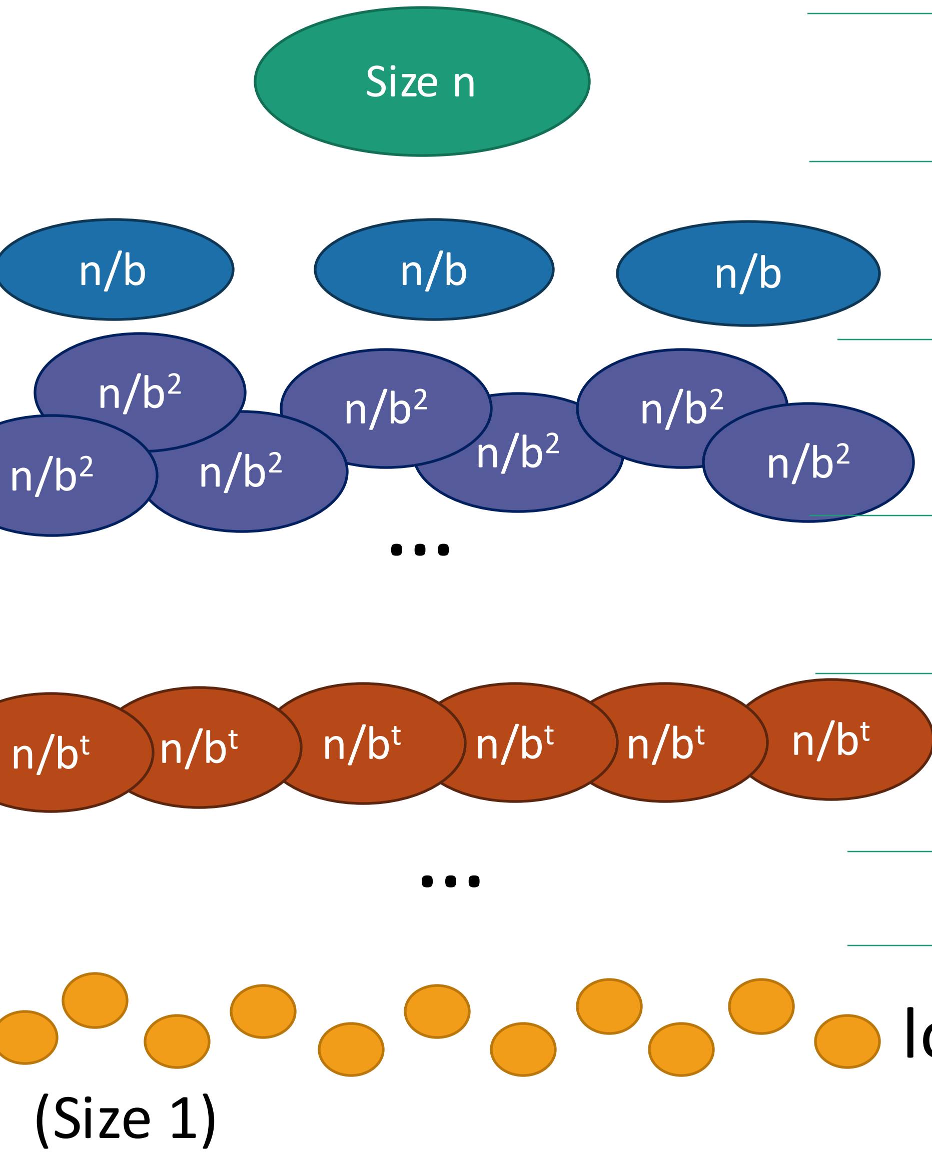
Level	# problems	Size of each problem	Amount of work at this level
0	1	n	
1	a	n/b	
2	a^2	n/b^2	
t	a^t	n/b^t	
…			
$\log_b(n)$	$a^{\log_b(n)}$	1	

Recursion tree

$$T(n) \le a \cdot T\left(\frac{n}{b}\right) + c \cdot n^d$$



Fill this in! (Say T(1) = c)

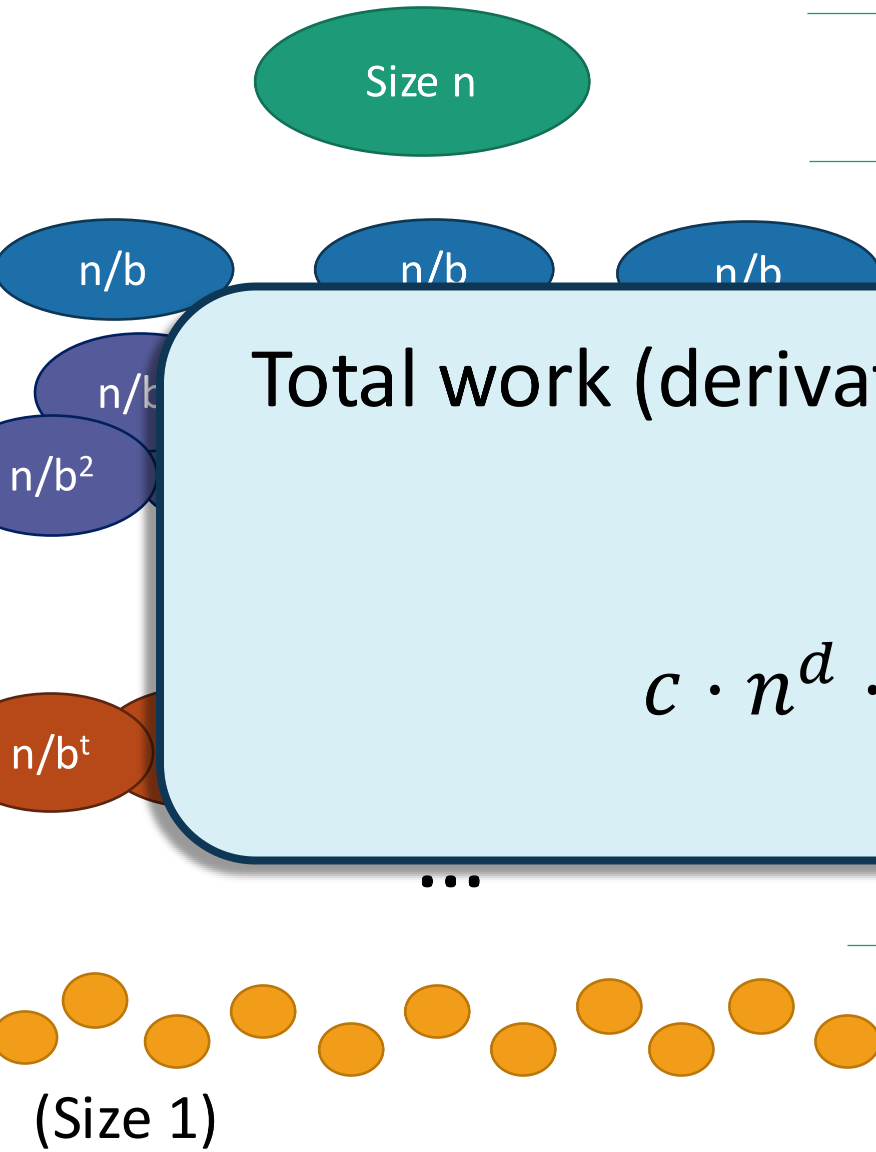


Level	# problems	Size of each problem	Amount of work at this level
0	1	n	$c \cdot n^d$
1	a	n/b	$ac\left(\frac{n}{b}\right)^d$
2	a^2	n/b^2	$a^2c\left(\frac{n}{b^2}\right)^d$
t	a^t	n/b^t	$a^tc\left(\frac{n}{b^t}\right)^d$
…			
$\log_b(n)$	$a^{\log_b(n)}$	1	$a^{\log_b(n)}c$

(Let's pretend that the base case is T(1) = c for convenience).

Recursion tree

$T(n) \le a \cdot T\left(\frac{n}{b}\right) + c \cdot n^d$



Level	# problems	Size of each problem	Amount of work at this level
0	1	n	$c \cdot n^d$
1	a	n/b	$ac\left(\frac{n}{b}\right)^d$
...			
$\log_b(n)$	$a^{\log_b(n)}$	1	$a^{\log_b(n)} c$

(Let's pretend that the base case is T(1) = c for convenience).

Total work (derivation on board) is at most:

$$c \cdot n^d \cdot \sum_{t=0}^{\log_b(n)} \left(\frac{a}{b^d}\right)^t$$

Now let's check all the cases

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

Case 1: $a = b^d$

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

- $T(n) \leq c \cdot n^d \cdot \sum_{t=0}^{log_b(n)} \left(\frac{a}{b^d}\right)^t$ Equal to 1!

$$= c \cdot n^d \cdot \sum_{t=0}^{log_b(n)} 1$$

$$= c \cdot n^d \cdot (\log_b(n) + 1)$$

$$= c \cdot n^d \cdot \left(\frac{\log(n)}{\log(b)} + 1\right)$$

$$= \Theta\left(n^d \log(n)\right)$$

Case 2: $a < b^d$

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

- $T(n) \leq \; c \cdot n^d \cdot \sum_{t=0}^{log_b(n)} \left(\frac{a}{b^d}\right)^t$ Less than 1!

*Assume that x is constant and N is growing.

Aside: Geometric sums

- What is $\sum_{t=0}^{N} x^t$?
- You may remember that $\sum_{t=0}^{N} x^t = \frac{x^{N+1}-1}{x-1}$ for $x \neq 1$.
- Morally:

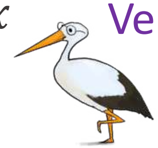
$$x^0 + x^1 + x^2 + x^3 + \cdots + x^N$$

If $0 < x < 1$, this term dominates, and the whole sum is $\Theta(1)$

(If $x = 1$, all terms the same)

If $x > 1$, this term dominates, and the whole sum is $\Theta(x^N)$.

$$1 \leq \frac{1 - x^{N+1}}{1 - x} \leq \frac{1}{1 - x}$$



Verify this!

This too!

$$x^N \leq \frac{x^{N+1}-1}{x - 1} \leq x^N \cdot \left(\frac{x}{x-1}\right)$$

Case 2: $a < b^d$

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

- $T(n) \leq \; c \cdot n^d \cdot \sum_{t=0}^{log_b(n)} \left(\frac{a}{b^d}\right)^t$ Less than 1!

  $= c \cdot n^d \cdot [\text{some constant}]$

  $= \Theta\left(n^d\right)$

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

Case 3: $a > b^d$

- $T(n) \leq c \cdot n^d \cdot \sum_{t=0}^{\log_b(n)} \left(\frac{a}{b^d}\right)^t$

Larger than 1!

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

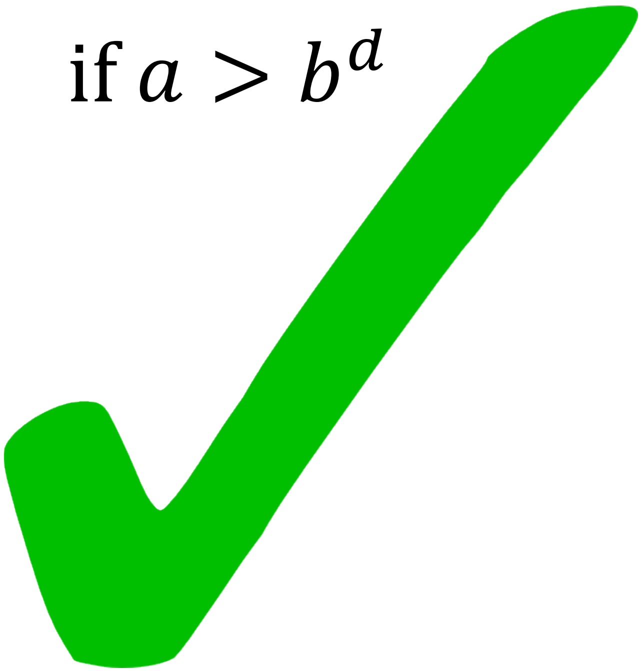
Convice yourself that this step is legit!

$$= \Theta\left(n^{\log_b(a)}\right)$$

We'll do this step on the board!

Now let’s check all the cases

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$



Understanding the Master Theorem

- Let $a \geq 1, b > 1,$ and d be constants.
- Suppose $T(n) = a \cdot T\left(\frac{n}{b}\right) + O\left(n^d\right)$. Then

$$T(n) = \begin{cases} O\left(n^d \log(n)\right) & \text{if } a = b^d \\ O\left(n^d\right) & \text{if } a < b^d \\ O\left(n^{\log_b(a)}\right) & \text{if } a > b^d \end{cases}$$

- What do these three cases mean?

The eternal struggle

Branching causes the number of problems to explode!
The most work is at the bottom of the tree!

The problems lower in the tree are smaller!
The most work is at the top of the tree!

Consider our three warm-ups

1. $T(n) = T\left(\frac{n}{2}\right) + n$
2. $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n$
3. $T(n) = 4 \cdot T\left(\frac{n}{2}\right) + n$

First example: tall and skinny tree

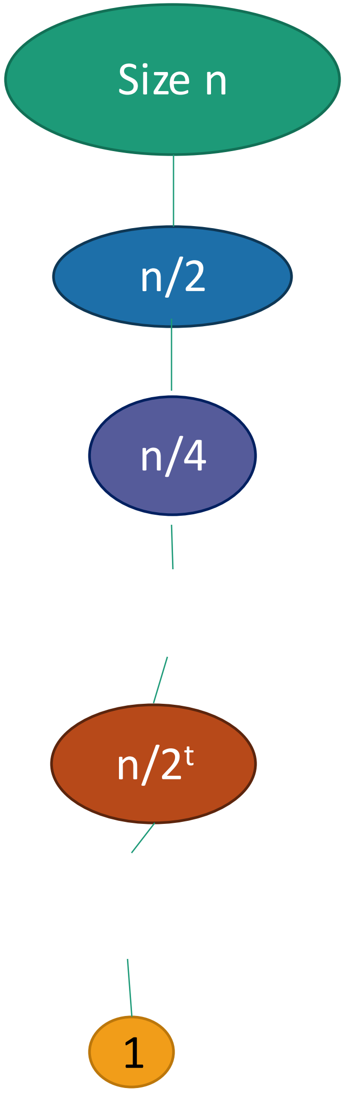
1. $T(n) = T\left(\frac{n}{2}\right) + n, \qquad \left(a < b^d\right)$

- The amount of work done at the top (the biggest problem) swamps the amount of work done anywhere else.

- T(n) = O(work at top) = O(n)

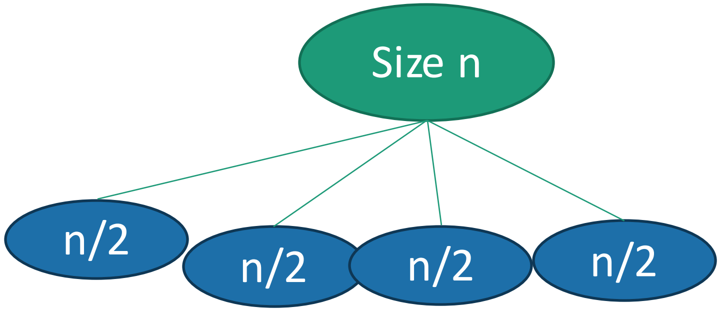
WINNER

Most work at the top of the tree!



Third example: bushy tree

3. $T(n) = 4 \cdot T\left(\frac{n}{2}\right) + n, \qquad \left(a > b^d\right)$

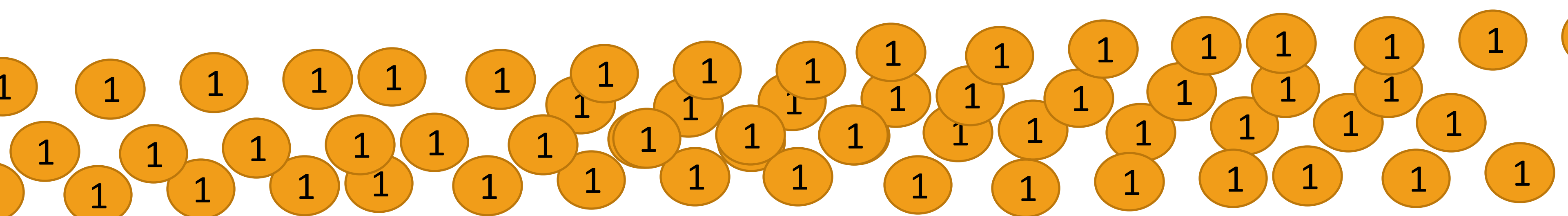


WINNER

Most work at the bottom of the tree!

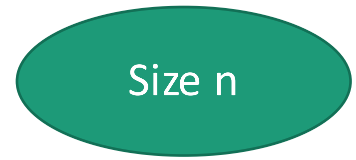
- There are a HUGE number of leaves, and the total work is dominated by the time to do work at these leaves.

- T(n) = O(work at bottom) = O($4^{\text{depth of tree}}$) = O(n^2)

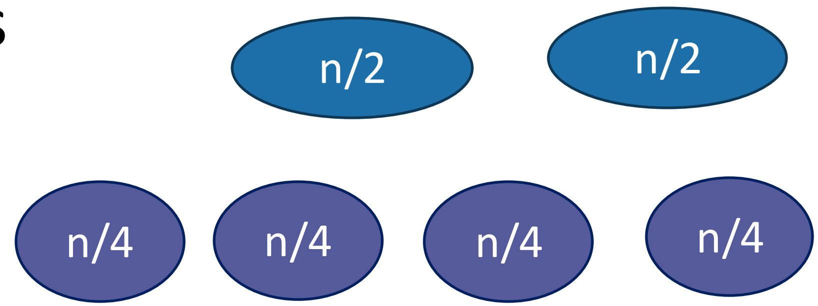


Second example: just right

2. $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n, \qquad \left(a = b^d\right)$



- The branching **just** balances out the amount of work.



- The same amount of work is done at every level.
- T(n) = (number of levels) * (work per level)
- = log(n) * O(n) = O(nlog(n))

What have we learned?

- The "Master Method" makes our lives easier.
- But it's basically just codifying a calculation we could do from scratch if we wanted to.

The Substitution Method

- Another way to solve recurrence relations.
- More general than the master method.

- Step 1: Generate a guess at the correct answer.
- Step 2: Try to prove that your guess is correct.
- (Step 3: Profit.)

The Substitution Method

first example

- Let's return to:

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n\text{, with } T(1) = 1.$$

  - (assuming n is a power of 2…)
- The Master Method says $T(n) = O(n\log(n))$.
- We will prove this via the Substitution Method.

$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n$, with $T(1) = 1$.

Step 1: Guess the answer

- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n$
- $T(n) = 2 \cdot \left(2 \cdot T\left(\frac{n}{4}\right) + \frac{n}{2}\right) + n$
- $T(n) = 4 \cdot T\left(\frac{n}{4}\right) + 2n$
- $T(n) = 4 \cdot \left(2 \cdot T\left(\frac{n}{8}\right) + \frac{n}{4}\right) + 2n$
- $T(n) = 8 \cdot T\left(\frac{n}{8}\right) + 3n$
- …

Expand $T\left(\frac{n}{2}\right)$

Simplify

Expand $T\left(\frac{n}{4}\right)$

Simplify

You can guess the answer however you want: meta-reasoning, a little bird told you, wishful thinking, etc. One useful way is to try to "unroll" the recursion, like we're doing here.

Guessing the pattern: $T(n) = 2^j \cdot T\left(\frac{n}{2^j}\right) + j \cdot n$

Plug in $j = \log(n)$, and get

$$T(n) = n \cdot T(1) + \log(n) \cdot n = n(\log(n) + 1)$$

$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n$, with $T(1) = 1$.

Step 2: Prove the guess is correct.

- Inductive Hyp.: $T(n) = n(\log(n) + 1)$.
- Base Case (n=1): $T(1) = 1 = 1 \cdot (\log(1) + 1)$
- Inductive Step:
  - Assume Inductive Hyp. for $1 \leq n < k$:
    - Suppose that $T(n) = n(\log(n) + 1)$ for all $1 \leq n < k$.
  - Prove Inductive Hyp. for n=k:
    - $T(k) = 2 \cdot T\left(\frac{k}{2}\right) + k$ by definition
    - $T(k) = 2 \cdot \left(\frac{k}{2}\left(\log\left(\frac{k}{2}\right) + 1\right)\right) + k$ by induction.
    - $T(k) = k(\log(k) + 1)$ by simplifying.
    - So Inductive Hyp. holds for n=k.
- Conclusion: For all $n \geq 1, T(n) = n(\log(n) + 1)$

We're assuming the n is a power of 2, so we're not worried about floors and ceilings. What would you need to change if n wasn't a power of 2?

Step 3: Profit

- Pretend like you never did Step 1, and just write down:

- *Theorem:* $T(n) = O(n \log(n))$
- *Proof:* *[Whatever you wrote in Step 2]*

What have we learned?

- The substitution method is a different way of solving recurrence relations.

- Step 1: Guess the answer.
- Step 2: Prove your guess is correct.
- Step 3: Profit.

- We'll get more practice with the substitution method next lecture!

Another example (if time)

(If not time, that's okay; we'll see these ideas in Lecture 4)

- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 32 \cdot n$
- $T(2) = 2$

- Step 1: Guess: $O(n \log(n))$ (divine inspiration).
- But I don't have such a precise guess about the form for the $O(n \log(n))$ …
  - That is, what's the leading constant?
- Can I still do Step 2?

Aside: What’s wrong with this?

This is NOT CORRECT!!!

Plucky the Pedantic Penguin

- Inductive Hypothesis: $T(n) = O(n\log(n))$
- Base case: $T(2) = 2 = O(1) = O(2\log(2))$
- Inductive Step:
  - Suppose that $T(n) = O(n\log(n))$ for n < k.
  - Then $T(k) = 2 \cdot T\left(\frac{k}{2}\right) + 32 \cdot k$ by definition
  - So $T(k) = 2 \cdot O\left(\frac{k}{2}\log\left(\frac{k}{2}\right)\right) + 32 \cdot k$ by induction
  - But that’s $T(k) = O(k\log(k))$, so the I.H. holds for n=k.
- Conclusion:
  - By induction, $T(n) = O(n\log(n))$ for all n.

Figure out what’s wrong here!!!

Siggi the Studious Stork

Red flag: We can use the same reasoning to prove that T(n) = O(n), which is not true!

This slide skipped in class

Aside: What's wrong with this?

This is NOT CORRECT!!!

Plucky the Pedantic Penguin

- Inductive Hypothesis: $T(n) = O(n)$
- Base case: $T(2) = 2 = O(1) = O(2)$
- Inductive Step:
  - Suppose that $T(n) = O(n)$ for n < k.
  - Then $T(k) = 2 \cdot T\left(\frac{k}{2}\right) + 32 \cdot k$ by definition
  - So $T(k) = 2 \cdot O\left(\frac{k}{2}\right) + 32 \cdot k$ by induction
  - But that's $T(k) = O(k)$, so the I.H. holds for n=k.
- Conclusion:
  - By induction, $T(n) = O(n)$ for all n.

Red flag: We can use the same reasoning to prove that T(n) = O(n), which is not true!

This slide skipped in class

This is NOT CORRECT!!!

Aside: What’s wrong with this?

Plucky the Pedantic Penguin

- Inductive Hypothesis: $T(n) = O(n)$
- Base case: $T(2) = 2 = O(1) = O(2)$
- Inductive Step:
  - Suppose that $T(n) = O(n)$ for n < k.
  - Then $T(k) = 2 \cdot T\left(\frac{k}{2}\right) + 32 \cdot k$ by definition
  - So $T(k) = 2 \cdot O\left(\frac{k}{2}\right) + 32 \cdot k$ by induction
  - But that’s $T(k) = O(k)$, so the I.H. holds for n=k.
- Conclusion:
  - By induction, $T(n) = O(n)$ for all n.

The problem is that this doesn’t make any sense. We can’t have “T(n) = O(n) for n < k,” since the def. of big-Oh needs to hold for all n.

Another example (if time)

(If not time, that's okay; we'll see these ideas in Lecture 4)

- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 32 \cdot n$
- $T(2) = 2$

- Step 1: Guess: $O(n\log(n))$ (divine inspiration).
- But I don't have such a precise guess about the form for the $O(n\log(n))$ …
  - That is, what's the leading constant?
- Can I still do Step 2?

Step 2: Prove it, working backwards to figure out the constant

- Guess: $T(n) \leq C \cdot n\log(n)$ for some constant C TBD.
- Inductive Hypothesis (for $n \geq 2$) : $T(n) \leq C \cdot n\log(n)$
- Base case: $T(2) = 2 \leq C \cdot 2\log(2)$ as long as $C \geq 1$
- Inductive Step:

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 32 \cdot n$$
$$T(2) = 2$$

Inductive step

- Assume that the inductive hypothesis holds for n<k.
- $T(k) = 2T\left(\frac{k}{2}\right) + 32k$
- $\leq 2C\frac{k}{2}\log\left(\frac{k}{2}\right) + 32k$
- $= k(C \cdot \log(k) + 32 - C)$
- $\leq k(C \cdot \log(k))$ as long as $C \geq 32$.
- Then the inductive hypothesis holds for n=k.

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 32 \cdot n$$
$$T(2) = 2$$

Step 2: Prove it, working backwards to figure out the constant

- Guess: $T(n) \leq C \cdot n \log(n)$ for some constant C TBD.
- Inductive Hypothesis (for $n \geq 2$): $T(n) \leq C \cdot n \log(n)$
- Base case: $T(2) = 2 \leq C \cdot 2 \log(2)$ as long as $C \geq 1$
- Inductive step: Works as long as $C \geq 32$
  - So choose $C = 32$.
- Conclusion: $T(n) \leq 32 \cdot n \log(n)$

$$T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 32 \cdot n$$
$$T(2) = 2$$

Step 3: Profit.

Technically this proof isn't quite correct since we assumed n was a power of 2, but the theorem statement is about all large enough n.

Plucky the Pedantic Penguin

- *Theorem:* $T(n) = O(n \log(n))$
- *Proof:*
  - Inductive Hypothesis: $T(n) \leq 32 \cdot n \log(n)$
  - Base case: $T(2) = 2 \leq 32 \cdot 2 \log(2)$ is true.
  - Inductive step:
    - Assume Inductive Hyp. for n<k.
    - $T(k) = 2T\left(\frac{k}{2}\right) + 32k$ By the def. of T(k)
    - $\leq 2 \cdot 32 \cdot \frac{k}{2} \log\left(\frac{k}{2}\right) + 32k$ By induction
    - $= k(32 \cdot \log(k) + 32 - 32)$
    - $= 32 \cdot k \log(k)$
    - This establishes inductive hyp. for n=k.
  - Conclusion: $T(n) \leq 32 \cdot n \log(n)$ for all $n \geq 2$.
    - By the definition of big-Oh, with $n_0 = 2$ and $c = 32$, this implies that $T(n) = O(n \log(n))$

Why two methods?

- Sometimes the Substitution Method works where the Master Method does not.
- More on this next time!

Next Time

- What happens if the sub-problems are different sizes?
- And when might that happen?

BEFORE Next Time

- Pre-Lecture Exercise 4!
- Get started on HW1 if you haven't already!