

Lecture 3

Recurrence Relations and the Master Theorem!

Announcements!

- **HW1** is posted!
 - Due Friday.
- **Sections** will be Tuesdays 4:30-5:20 , room 380-381U!
 - They are optional.
 - But valuable!
- Sign up for **Piazza**!
 - There's a link on the course website.
 - Course announcements will be posted on Piazza.

More announcements



2017 STANFORD LOCAL PROGRAMMING CONTEST

October 7th (SAT) 9:00AM

Gates B08/B12/B30

Register at:

<http://cs.stanford.edu/group/acm/SLPC>



Sponsored by: 

Last time....

- Sorting: InsertionSort and MergeSort
- Analyzing correctness of iterative + recursive algs
 - Via “loop invariant” and induction
- Analyzing running time of recursive algorithms
 - By writing out a tree and adding up all the work done.
- How do we measure the runtime of an algorithm?
 - Worst-Case Analysis
 - Big-Oh Notation

Today

- Recurrence Relations!
 - How do we measure the runtime a recursive algorithm?
 - Like **Integer Multiplication** and **MergeSort**?
- The ***Master Method***
 - A useful theorem so we don't have to answer this question from scratch each time.

Running time of MergeSort

- Let's call this running time $T(n)$.
 - when the input has length n .
- We know that $T(n) = O(n \log(n))$.
- But if we didn't know that...

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

From last time



```
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 $T(\text{less than } n)$
- The challenge:
Given a recurrence relation for $T(n)$, find a closed form expression for $T(n)$.
- For example, $T(n) = O(n \log(n))$

Technicalities I

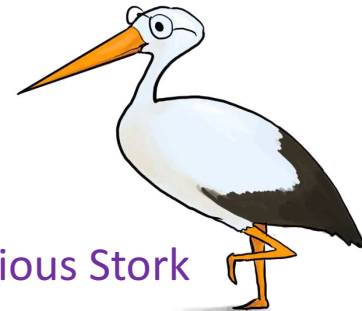
Base Cases



Plucky the
Pedantic Penguin

- 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 as
- $T(n) = 2 \cdot T\left(\frac{n}{2}\right) + 11 \cdot n$ with $T(1) = 10000000000$
- However, $T(1) = O(1)$, so sometimes we'll just omit it.

Why does $T(1) = O(1)$?



Siggi the Studios Stork

On your pre-lecture exercise

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

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

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

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

- What are the closed forms?

[on board]

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

- $T(n) = 2 \cdot \left(2 \cdot T\left(\frac{n}{4}\right) + \frac{11 \cdot n}{2}\right) + 11 \cdot n$

- $T(n) = 4 \cdot T\left(\frac{n}{4}\right) + 22 \cdot n$

- $T(n) = 4 \cdot \left(2 \cdot T\left(\frac{n}{8}\right) + \frac{11 \cdot n}{4}\right) + 22 \cdot n$

- $T(n) = 8 \cdot T\left(\frac{n}{8}\right) + 33 \cdot n$

- Following the pattern...

- $T(n) = n \cdot T(1) + 11 \cdot \log(n) \cdot n = O(n \cdot \log(n))$

Another approach:

Recursively apply the relationship a bunch until you see a pattern.

Formally, this should be accompanied with a proof that the pattern holds!

More next time.

This slide skipped in class, provided here in case this way makes more sense to you.

More examples

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

- Needlessly recursive integer multiplication

- $T(n) = 4 T(n/2) + O(n)$

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

- Karatsuba integer multiplication

- $T(n) = 3 T(n/2) + O(n)$

- $T(n) = O(n^{\log_2(3)} \approx n^{1.6})$

- MergeSort

- $T(n) = 2T(n/2) + O(n)$

- $T(n) = O(n \log(n))$

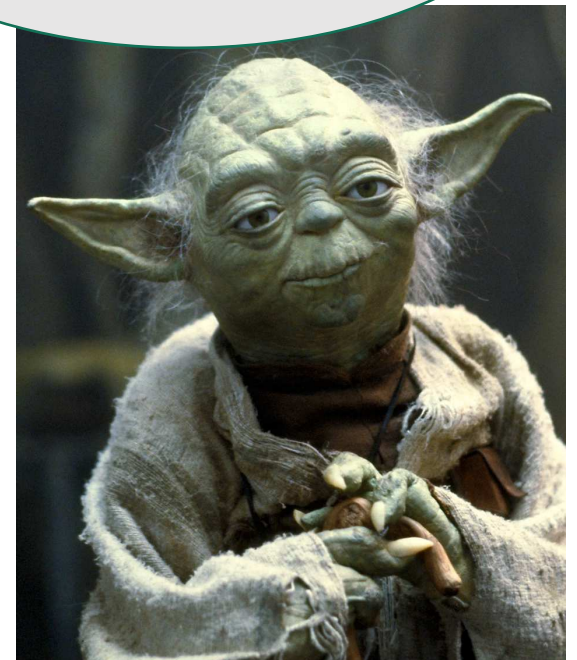
These two are the same as the ones on your pre-lecture exercise.

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

The master theorem

- A **formula** that solves recurrences when all of the sub-problems are the same size.
 - We'll see an example Wednesday when not all problems are the same size.
- "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 $\lfloor \frac{n}{b} \rfloor$ or $\lceil \frac{n}{b} \rceil$ and the theorem is still true.

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

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

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

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- 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), 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.

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

$$\begin{aligned} a &= 4 \\ b &= 2 \\ d &= 1 \end{aligned}$$

$$a > b^d$$



- Karatsuba integer multiplication

- $T(n) = 3 T(n/2) + O(n)$
- $T(n) = O(n^{\log_2(3)} \approx n^{1.6})$

$$\begin{aligned} a &= 3 \\ b &= 2 \\ d &= 1 \end{aligned}$$

$$a > b^d$$



- MergeSort

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

$$\begin{aligned} a &= 2 \\ b &= 2 \\ d &= 1 \end{aligned}$$

$$a = b^d$$



- That other one

- $T(n) = T(n/2) + O(n)$
- $T(n) = O(n)$

$$\begin{aligned} a &= 1 \\ b &= 2 \\ d &= 1 \end{aligned}$$

$$a < b^d$$



Proof of the master theorem

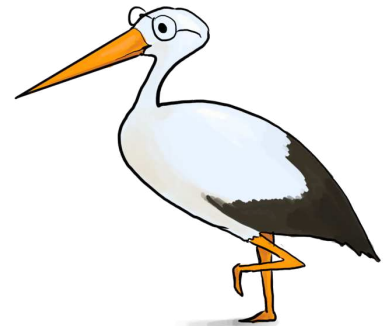
- We'll do the same recursion tree thing we did for MergeSort, but be more careful.
- Suppose that $T(n) = a \cdot T\left(\frac{n}{b}\right) + c \cdot n^d$.

Hang on! The hypothesis of the Master Theorem was the the extra work at each level was $O(n^d)$. That's NOT the same as $\text{work} \leq cn^d$ for some constant c .



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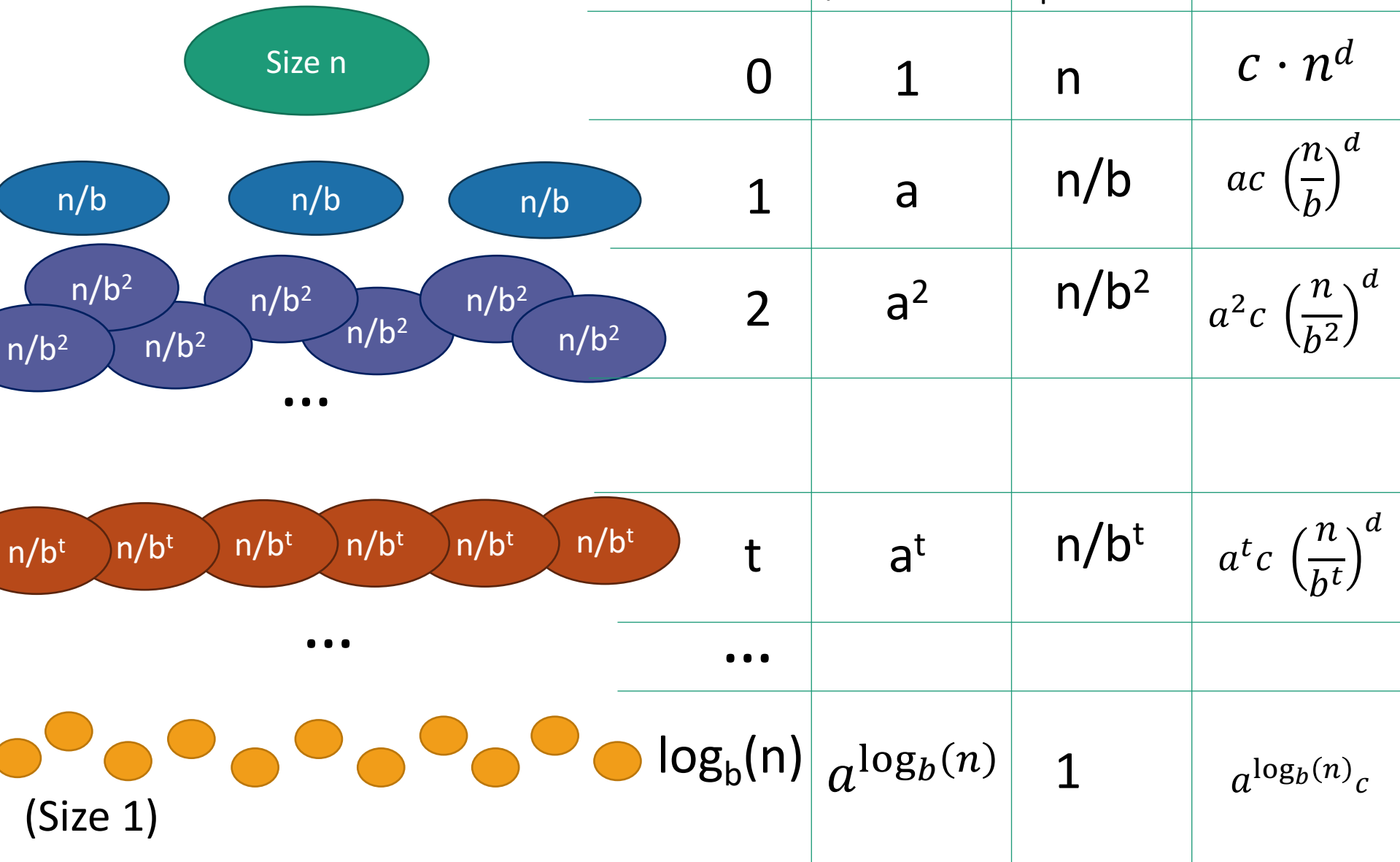
That's true ... we'll actually prove a weaker statement that uses this hypothesis instead of the hypothesis that $T(n) = a \cdot T\left(\frac{n}{b}\right) + O(n^d)$. It's a good exercise to make this proof work rigorously with the $O()$ notation.



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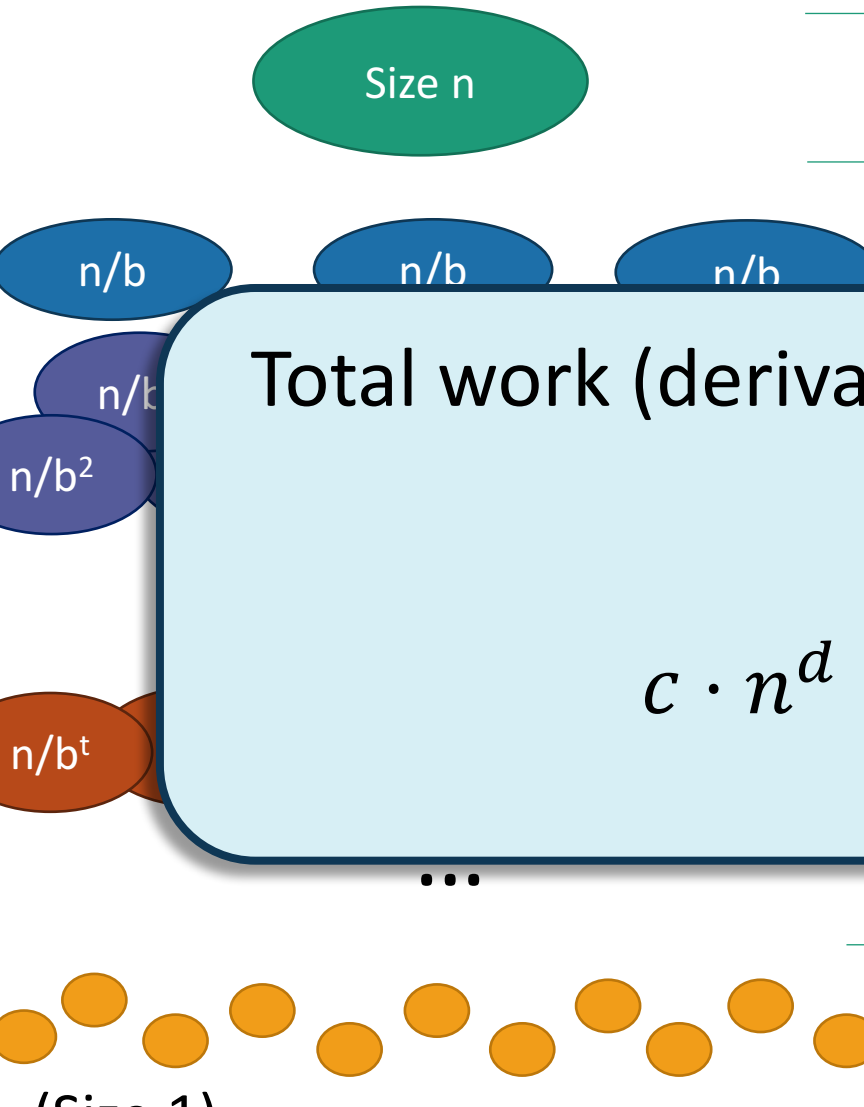
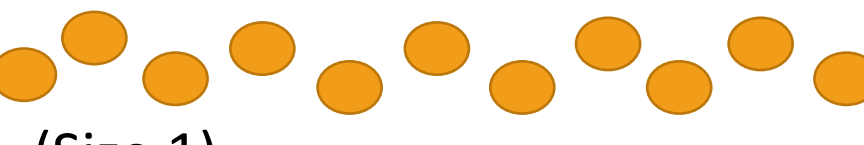
Recursion tree

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



Recursion tree

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

				Level	# problems	Size of each problem	Amount of work at this level
					0	n	$c \cdot n^d$
					1	n/b	$a c \left(\frac{n}{b}\right)^d$
<div> <p>Total work (derivation on board) is at most:</p> $c \cdot n^d \cdot \sum_{t=0}^{\log_b(n)} \left(\frac{a}{b^d}\right)^t$ </div>							
...					...		
 (Size 1)					$\log_b(n)$	1	$a^{\log_b(n)} c$

Now let's check all the cases
(on board)

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

Even more generally, for $T(n) = aT(n/b) + f(n)$...

Theorem 3.2 (Master Theorem). *Let $T(n) = a \cdot T\left(\frac{n}{b}\right) + f(n)$ be a recurrence where $a \geq 1$, $b > 1$. Then,*

- *If $f(n) = O(n^{\log_b a - \epsilon})$ for some constant $\epsilon > 0$, $T(n) = \Theta(n^{\log_b a})$.*
- *If $f(n) = \Theta(n^{\log_b a})$, $T(n) = \Theta(n^{\log_b a} \log n)$.*
- *If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for some constant $\epsilon > 0$ and if $af(n/b) \leq cf(n)$ for $c < 1$ and all sufficiently large n , then $T(n) = \Theta(f(n))$.*



Figure out how to adapt
the proof we gave to prove
this more general version!

[From CLRS]



LIFE IS SO GOOD

**BUT I WILL NOT BECOME COMPLACENT AND I CAN
TOTALLY SOLVE RECURRENCES FROM SCRATCH IF I WANT TO**

Understanding the Master Theorem

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

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

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

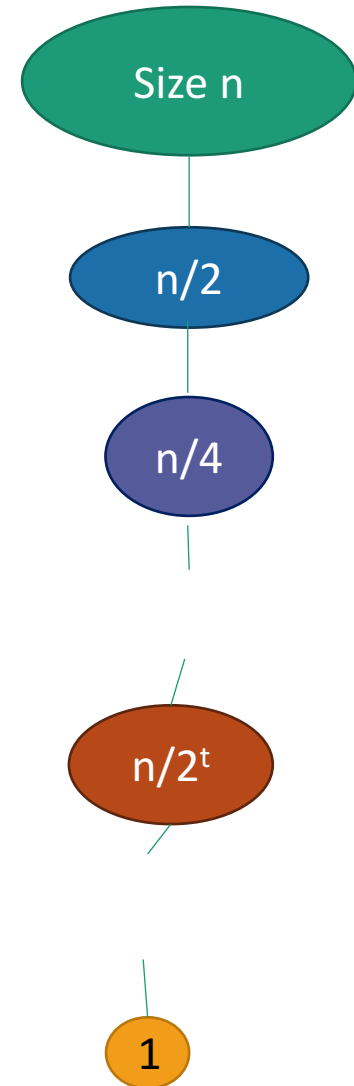
3. $T(n) = 4 \cdot T\left(\frac{n}{2}\right) + n$

First example: tall and skinny tree

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

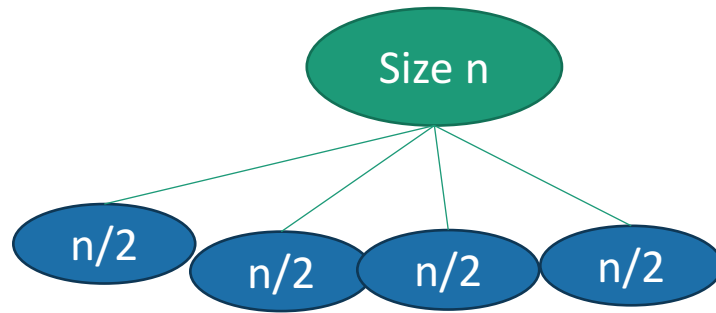
- The amount of work done at the top (the biggest problem) swamps the amount of work done anywhere else.

- $T(n) = O(\text{work at top}) = O(n)$



Third example: bushy tree

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

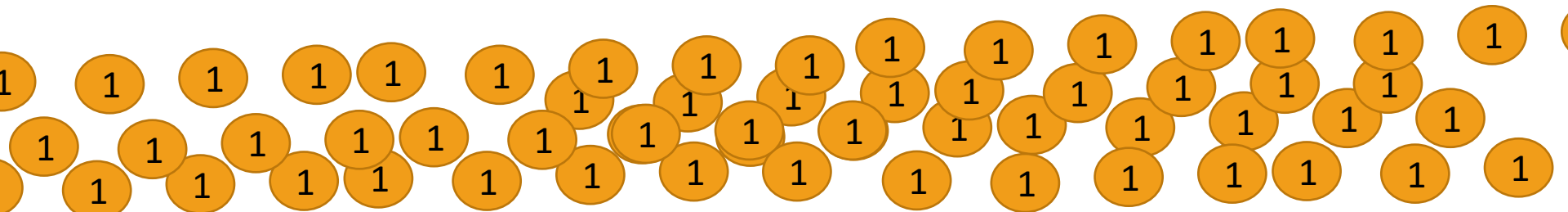


WINNER



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



Second example: just right

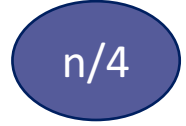
$$2. \quad T(n) = 2 \cdot T\left(\frac{n}{2}\right) + n, \quad (a = b^d)$$



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



- The same amount of work is done at every level.



- $T(n) = (\text{number of levels}) * (\text{work per level})$
- $= \log(n) * O(n) = O(n \log(n))$



Recap

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

Next Time

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

BEFORE Next Time

- Pre-Lecture Exercise 4!
 - Which should be easier if you did Pre-Lecture Exercise 3...