

CS 170

# Efficient Algorithms and Intractable Problems

## Lecture 3: Divide and Conquer II

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# Announcements

**Discussion sections** (yesterday and Tuesday).

- Feeling you need a slower-paced section? Go to LOST section on Fridays.
- **Starting next week:** Tuesday 3-4pm and Thursday 10-11am discussion

**Homework party:**

- Tomorrow (Friday) and ~~Monday~~ (labor day!). **HW1 due on Tuesday.**

Short break:

- Seemed to work. Let's give it a second try today.
- Remember: at break time, please help close the lecture hall doors.

# Recap of last time

- Karatsuba's algorithm with  $O(n^{1.6})$   
→ Using divide and conquer with fewer subproblems!
- Reviewed  $O(\cdot)$  and  $\Omega(\cdot)$  notation formally.
- Recurrence relations and the Master theorem!

# Recap: Master Theorem

## The Master Theorem

Suppose that  $a \geq 1$ ,  $b > 1$ , and  $d \geq 0$  are constants (independent of  $n$ ).

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

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

$a$ : Number of sub-problems

$b$ : Factor by which the problem size shrinks at each layer

$n^d$ : Amount of computation per node, before/after subproblems are done.

# Recap: Master Theorem's Interpretation

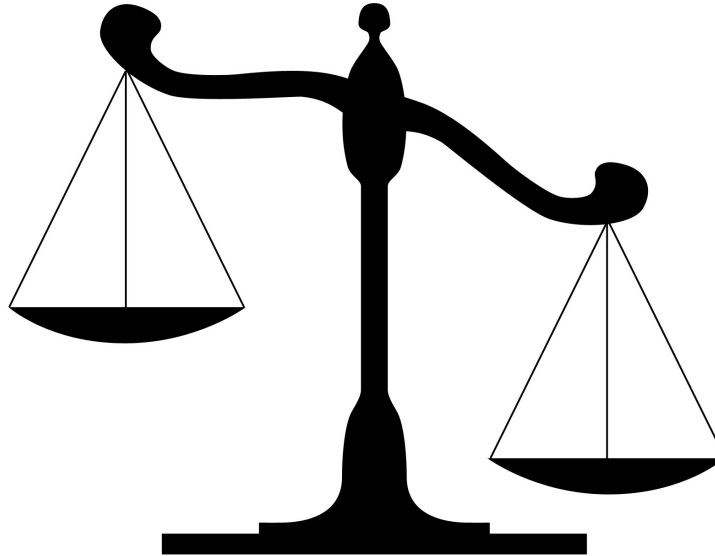
$a$  vs.  $b^d$

Wide tree  
 $a > b^d$

Branching causes the number  
of problems to explode!

**Most work is at the  
bottom of the tree!**

$$O(n^{\log_b(a)})$$



Tall and narrow  
 $a < b^d$

Problem size shrinks fast,  
so **most work is at the  
top of the tree!**

$$O(n^d)$$

$$a = b^d$$

Branching perfectly balances  
total amount of work per layer.  
**All layers contribute equally.**

$$O(n^d \log(n))$$

# This lecture

Two awesome uses of Divide and conquer

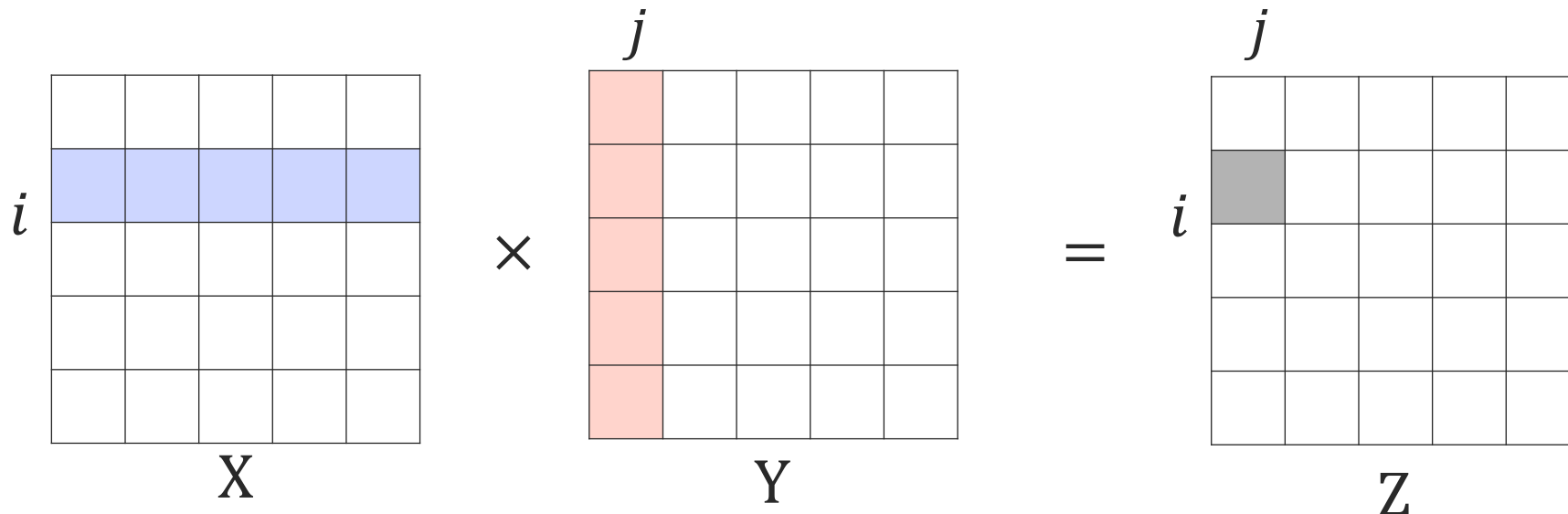
- Matrix Multiplication
- Median Selection

# Matrix Operations

We showed that integer multiplication can be done faster than the grade school algorithm.

→ Why stop there? Can we multiply Matrices faster than we did in high school?

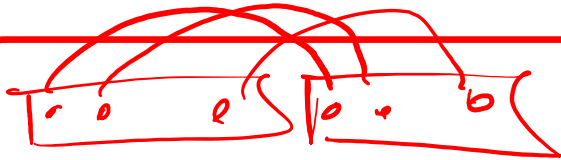
Product of two  $n \times n$  matrices  $X$  and  $Y$ , is a  $n \times n$  matrix  $Z$ : Entry  $z_{i,j}$  is dot-product of  $X$ (row  $i$ ) and  $Y$ (col  $j$ ).



# Matrix Operations

- For integer multiplication, “problem size” was the number of digits
- For matrix multiplication, it is the dimensionality.
  - But we assume the integers have small number of bits, say 32-64.
  - So, we can multiply/add two elements of the matrices in  $O(1)$ .
  - Huge matrices in practice?

## Discuss



### Dot-product

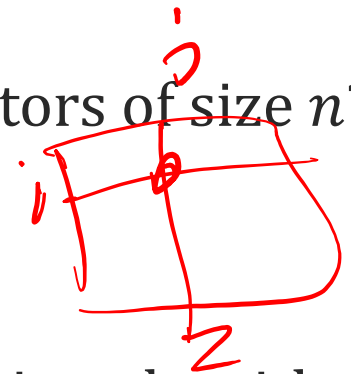
$O(n)$

- What is the runtime of computing the dot-product of two vectors of size  $n$ ?

$$n^2 \times O(n) = O(n^3)$$

### Matrix Multiplication

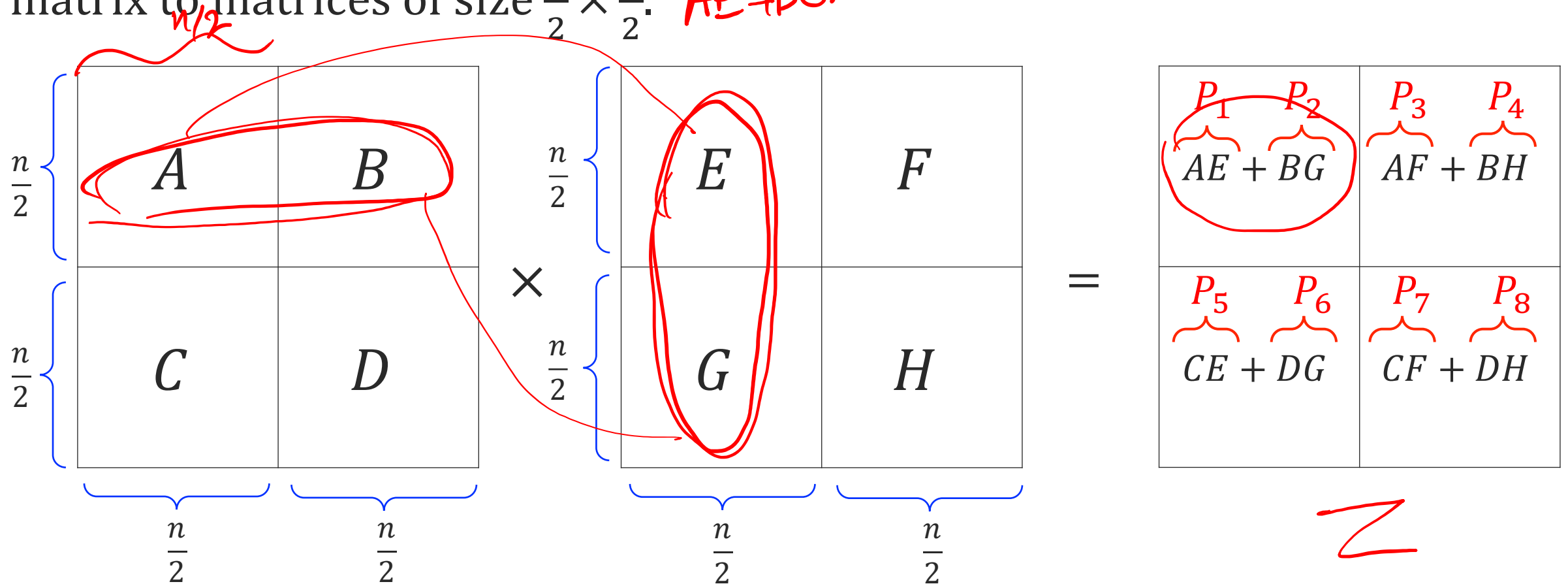
- What is the runtime of the high-school  $n \times n$  matrix multiplication algorithm?





# Breaking Matrix Multiplication to Subproblems

Let's try the same trick we used in integer multiplication: Break the matrix to matrices of size  $\frac{n}{2} \times \frac{n}{2}$ . *AE + BG*



Each subproblem  $P_i$  is a matrix multiplication of two  $\frac{n}{2} \times \frac{n}{2}$  matrices

# Recurrence Relationship

- At each layer, we have 8 problems
- Each problem of size  $\frac{n}{2}$ .

We have to do a bunch of other operations

- Finding A, B, ..., H by shifting  $n$ -digit arrays.
- Adding  $\frac{n}{2} \times \frac{n}{2}$  matrices.
- Appending matrices to make one  $n \times n$  matrix

## The Master Theorem

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

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

$$O(n^2)$$

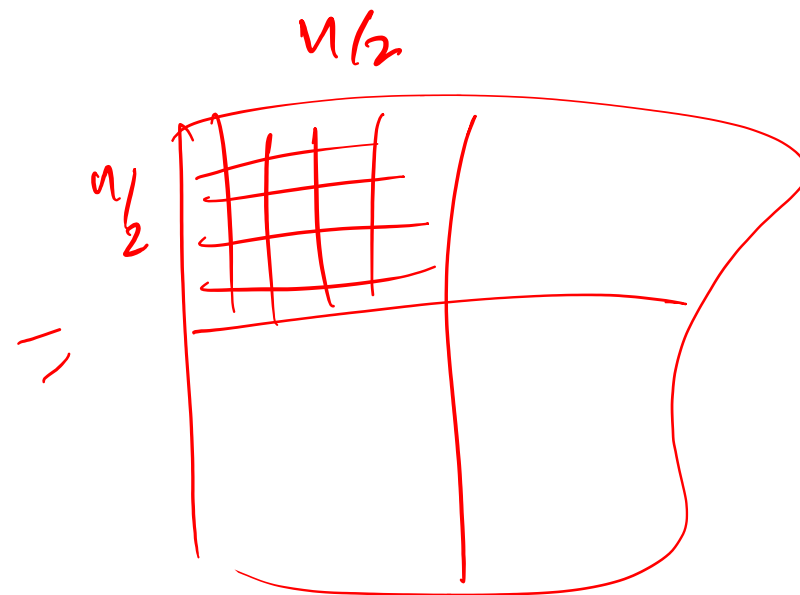
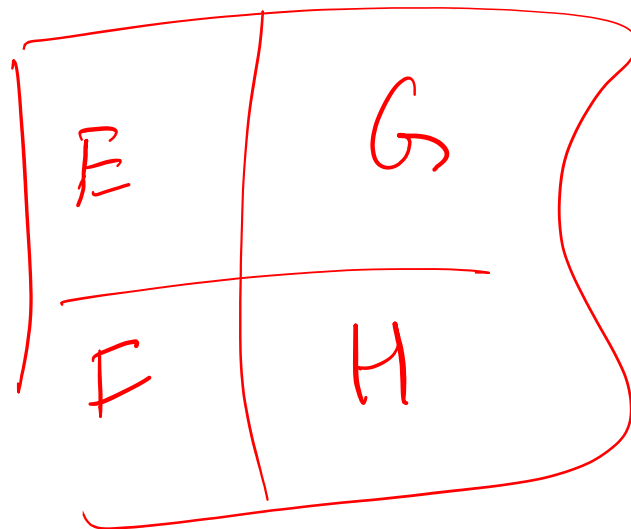
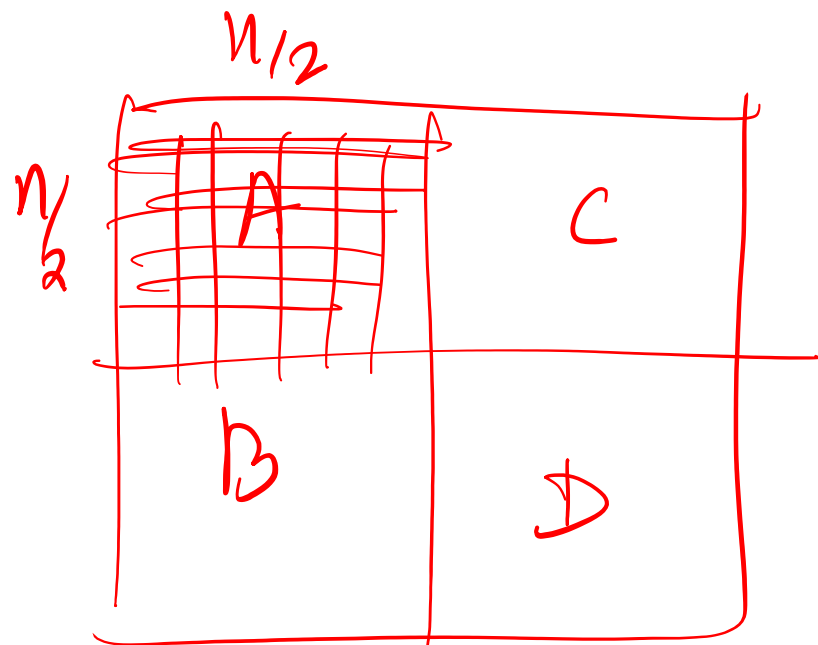
$\underbrace{P_5}_{CE + DG}$	$\underbrace{P_6}_{CF + DH}$

Recurrence  $T(n) = ?$

Runtime  $T(n) = ?$

Handwritten notes:  $a = 8$ ,  $b = 2$ ,  $d = 2$ ,  $8 > 2^2$

$$8 > 2^2$$



# Strassen's Algorithm



Like Karatsuba's algorithm, but this time for matrices.

No need to  
memorize this!

Express the answer with fewer than **8 subproblems** of size  $\frac{n}{2} \times \frac{n}{2}$ .

→ Subtlety: Matrix multiplication is not “commutative” → order matters!

$$\underbrace{(AF - AH)}_{2 \text{ multiplications}} = A \times \underbrace{(F - H)}_{1 \text{ multiplication}}$$

Strassen's trick:

$$\left. \begin{aligned} Q_1 &= A(F - H) \\ Q_2 &= (A + B)H \end{aligned} \right\} AF + BH$$

$$Q_3 = (C + D)E$$

$$Q_4 = D(G - E)$$

$$Q_5 = (A + D)(E + H)$$

$$Q_6 = (B - D)(G + H)$$

$$Q_7 = (A - C)(E + F)$$

$X \times Y =$

$Q_5 + Q_4 - Q_2 + Q_6$	<u><math>Q_1 + Q_2</math></u>
$Q_3 + Q_4$	$Q_1 + Q_5 - Q_3 - Q_7$

# Recurrence Relationship

- At each layer, we have **7 problems**  
→ Each problem of size  $\frac{n}{2}$ .

All other extra operations, additions, subtractions, ...

- At most  $O(n^2)$

$\underbrace{P_1}_{AE} + \underbrace{P_2}_{BG}$	$\underbrace{P_3}_{AF} + \underbrace{P_4}_{BH}$
$\underbrace{P_5}_{CE} + \underbrace{P_6}_{DG}$	$\underbrace{P_7}_{CF} + \underbrace{P_8}_{DH}$

Runtime  $T(n) = 7T\left(\frac{n}{2}\right) + O(n^2)$

# Recurrence Relationship

- At each layer, we have **7 problems**  
→ Each problem of size  $\frac{n}{2}$ .

All other extra operations, additions, subtract

- At most  $O(n^2)$

## The Master Theorem

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

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

$\underbrace{P_5}_{CE + DG}$	$\underbrace{P_6}_{CF + DH}$

$$7 > 2^2$$

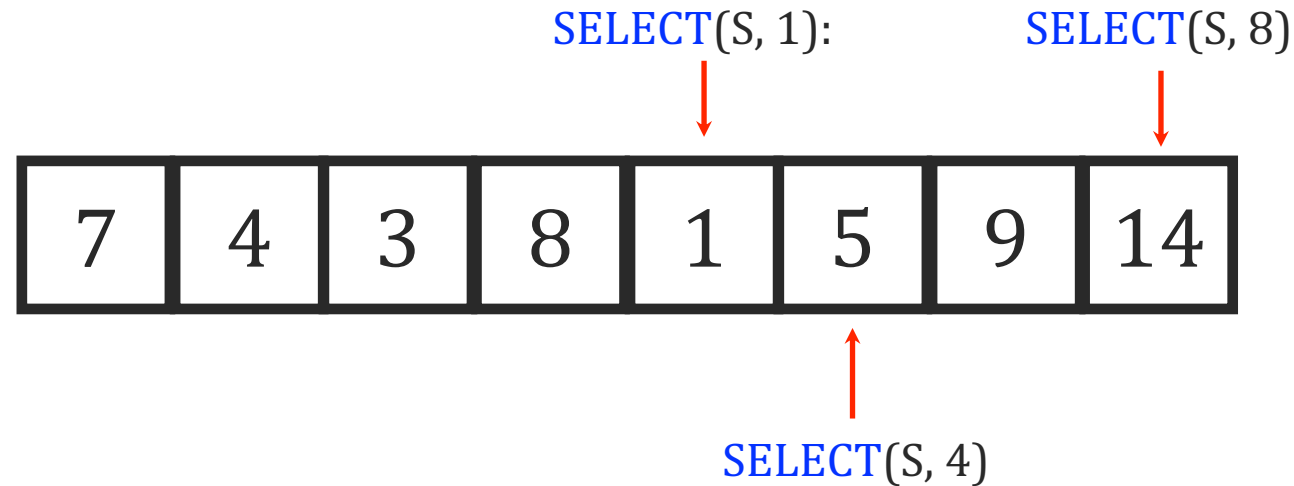
Runtime  $T(n) = 7 T\left(\frac{n}{2}\right) + O(n^2)$

Using the master theorem  $T(n) = ?$   $O\left(n^{\log_2(7)}\right) \approx O\left(n^{2.8}\right)$

(Median) Selection

# The $k$ -select Problem

Given an array  $S$  of  $n$  numbers and  $k \in \{1, 2, \dots, n\}$ , find the  $k$ th smallest element of it.



Some special cases:

$\text{SELECT}(S, 1)$ : Minimum element of the array

$\text{SELECT}(S, n)$ : Maximum element of the array

$\text{SELECT}(S, \lceil \frac{n}{2} \rceil)$ : Median element of the array



# Simple Algorithms for $k$ -Select

An  $O(n \log(n))$  algorithm

- Sort the array, using merge-sort (or another  $O(n \log(n))$  sort).
- Then go through the array and return the  $k$ -th element.

**Technicality:** Arrays are **0-index**, so you should return  $S[k - 1]$  after sorting!

Remainder of the lecture  
Can we do better than  $O(n \log(n))$ ?  
Can we do  $O(n)$ ?

# Simple Algorithms for $k$ -Select

Can you think of  $O(n)$  algorithm for **SELECT**( $S$ , 1)?

- FOR loop through the array. **Store the minimum so far**: If the current element is less than the stored value, store the current value as min instead.

Can you think of  $O(n)$  algorithm for **SELECT**( $S$ , 2)?

- Run **SELECT**( $S$ , 1) and let  $S \leftarrow S \setminus \text{SELECT}(S, 1)$ . (remove that element)  $O(n)$
- Return **SELECT**( $S$ , 1)  $O(n)$
- Total of  $O(n)$  runtime.

Does this trick produce an  $O(n)$  algorithm for **SELECT**( $S$ ,  $n/2$ )?

- No. We would be running  $\frac{n}{2}$  **SELECT**s each  $O(n)$ .

**Technically**: Array  $S$  is shrinking, so **SELECT**( $S$ , 1) is getting faster, but not that much faster  $\text{len}(S) > \frac{n}{2}$ .

# Big Question

Can we perform Median selection  
(or any other  $k$ -select generally)  
in  $O(n)$ ?

# Idea: Divide and Conquer

We want to divide the problem to subproblems. How?

- Imagine we are given a **“pivot”**  $v$ . Split the array into three pieces

→  $S_L$ : Elements less than the pivot

→  $S_v$ : Elements equal to the pivot

→  $S_R$ : Elements larger than the pivot

2	36	5	21	8	13	11	20	5	4	1
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Given “pivot”

$S_L$

$S_L$

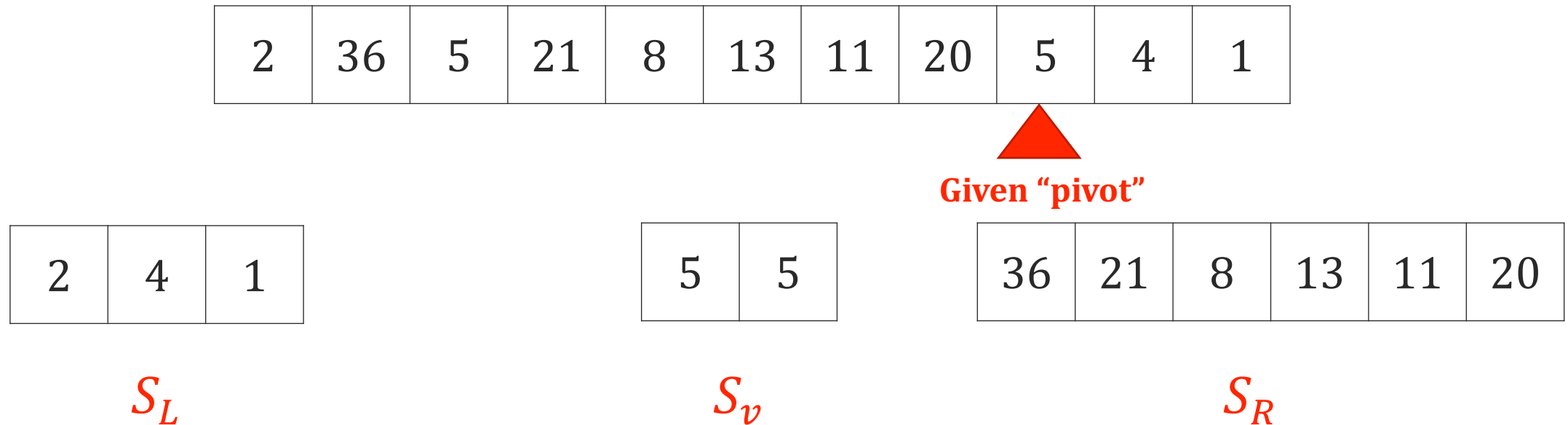
$S_v$

$S_v$

$S_R$

$S_R$

# The subproblems



We want to compute **SELECT**( $S, k$ ):

- If  $k \leq \text{len}(S_L)$ : We should return **SELECT**( $S_L, k$ )
- If  $\text{len}(S_L) < k \leq \text{len}(S_L) + \text{len}(S_v)$ : We should return  $v$ .
- If  $\text{len}(S_L) + \text{len}(S_v) < k$ : We should return **SELECT**( $S_R, k - \text{len}(S_L) - \text{len}(S_v)$ )

# The Recurrence Relation

We want to compute **SELECT**( $S, k$ ):

- If  $k \leq \text{len}(S_L)$ : We should return **SELECT**( $S_L, k$ )
- If  $\text{len}(S_L) < k \leq \text{len}(S_L) + \text{len}(S_v)$ : We should return  $v$ .
- If  $\text{len}(S_L) + \text{len}(S_v) < k$ : We should return **SELECT**( $S_R, k - \text{len}(S_L) - \text{len}(S_v)$ )

$$T(n) = \begin{cases} T(\text{len}(S_L)) + O(n) & \text{if } k \leq \text{len}(S_L) \\ T(\text{len}(S_R)) + O(n) & \text{if } \text{len}(S_L) + \text{len}(S_v) < k \\ O(n) & \text{if } \text{len}(S_L) < k \leq \text{len}(S_L) + \text{len}(S_v) \end{cases}$$

The lengths of  $S_L$  and  $S_R$  depend on the choice of the pivot.

# What are good/bad choices of pivot

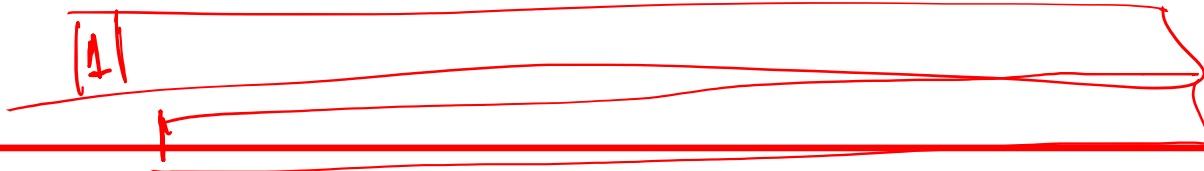
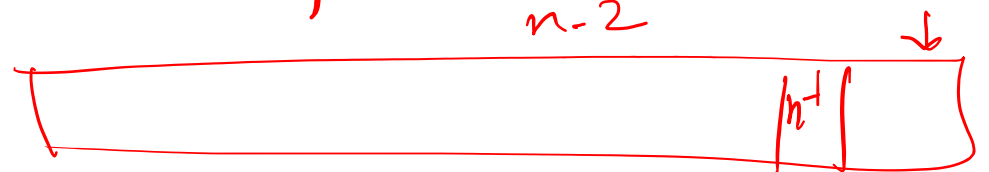
Intuitively, we want a pivot such that  $\max(\text{len}(S_L), \text{len}(S_R))$  is small.

## Discuss

Order the following pivots from worst pivot to the best pivot. For intuition, imagine **no element is repeated**.

1. smallest element (min)
2.  $n/4$  th smallest element
3.  $n/2$  th smallest element (median)
4.  $3n/4$  th smallest element
5.  $(n - 1)$ th smallest element

1 → 5 → 2 → 3  
4



# Runtime, given the ideal pivot

Let's pretend that the pivot we picked is indeed the median!



Then  $\text{len}(S_L) \leq n/2$  and  $\text{len}(S_R) \leq n/2$ .

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

What's the runtime?

$a = 1, b = 2, d = 1$ , so  $a < b^d$   
 $O(n)$  runtime.

Uhhh! Wasn't the whole point that we don't know how to find the median in  $O(n)$ ?

Yes! This is just a thought exercise to know the ideal situation.

## The Master Theorem

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

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



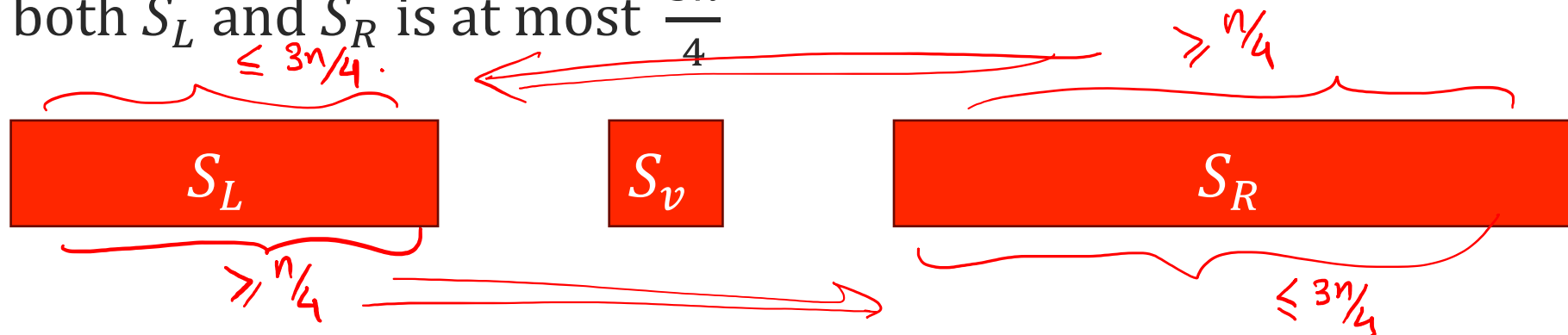
# “Good” pivots

I still don't know how to find such a pivot, but ok for now ....



Any pivot **between the  $\frac{n}{4}$ th smallest and  $\frac{3n}{4}$ th smallest element** is good enough!

Length of both  $S_L$  and  $S_R$  is at most  $\frac{3n}{4}$



What's the runtime if pivot is between the  $\frac{n}{4}$ th and  $\frac{3n}{4}$ th smallest element?

## The Master Theorem

$$T(n) \leq T\left(\frac{3n}{4}\right) + O(n)$$

What's the runtime?

- $a = 1, b = 4/3, d = 1, a < b^d$
- $O(n)$  runtime.

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

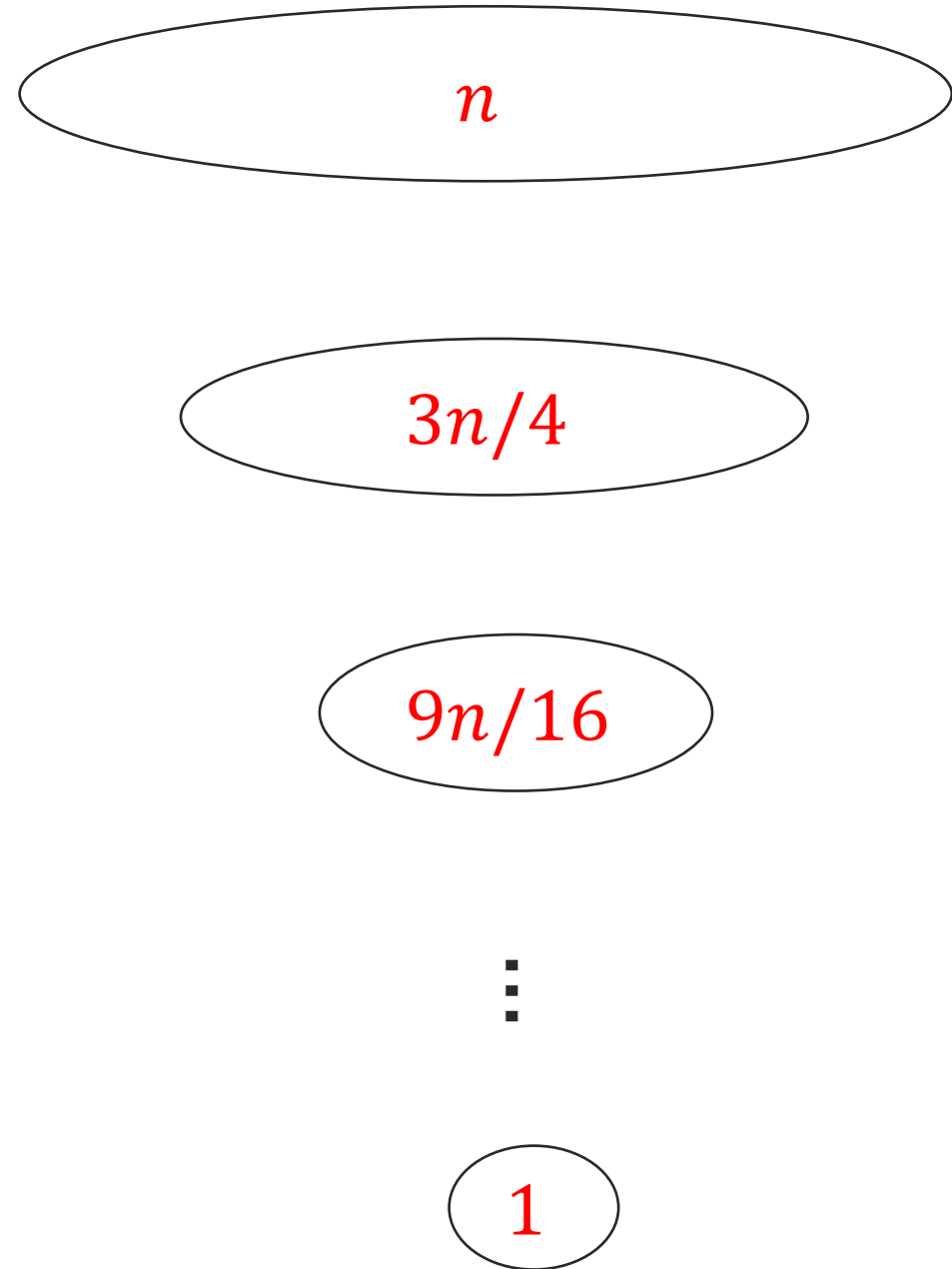
$$T(n) = \begin{cases} O(n^d) & \text{if } a < b^d \\ O(n^d \log(n)) & \text{if } a = b^d \\ O(n^{\log_b(a)}) & \text{if } a > b^d \end{cases}$$

# Trees Revisited

Imagine: At every round we got a “good” pivot.  
So we multiply the size by  $\leq 3/4$ .

Single node at layer  $i$  of size  $n \left(\frac{3}{4}\right)^i$ . Total  
contribution at layer  $i$  is  $\leq c \cdot n \left(\frac{3}{4}\right)^i$ .

What is the total amount of work in all layers?



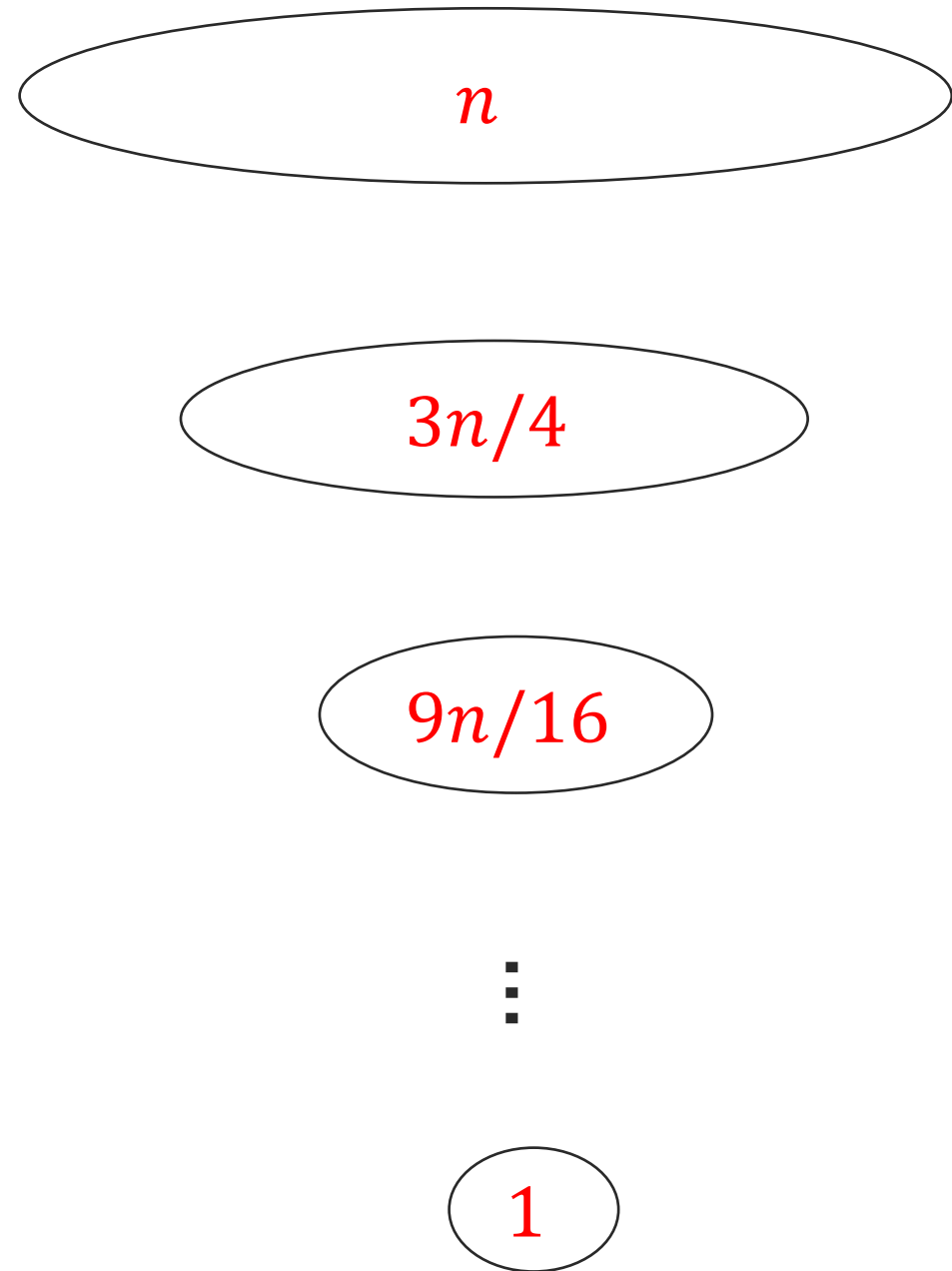
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contribution at layer  $i$  is  $\leq c \cdot n \left(\frac{3}{4}\right)^i$ .

What is the total amount of work in all layers?

$$T(n) \leq \sum_{i=0}^{\log_{4/3}(n)} c n \left(\frac{3}{4}\right)^i \in O(n)$$



# How do we pick a “good” pivot?

Two ideas:

1. Pick it uniformly at random from array  $S$ .
  - We get a “good” pivot in the  $n/4$ - $3n/4$  range with probability  $1/2$ .
  - Show that the algorithm runs in  $O(n)$  in expectation.

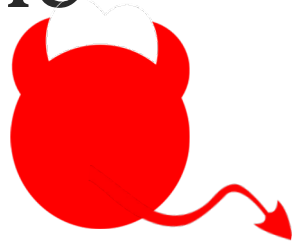
We will do this one.

2. Find a good enough pivot deterministically.
  - It always runs in  $O(n)$ .
  - Much harder analysis and in practice it is slower than the random pivot.

We will post readings for this.

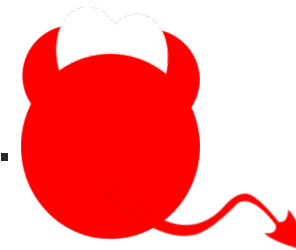
# Randomized Algorithms and Expected Runtime

We typically think about runtime of an Alg on the **worst possible** problem instance.



Randomized Algorithms:

1. Write down the algorithm description.
2. Adversary sees the description and picks a bad instance.
3. Run the algorithm and throw the dice.



The adversary (choice of bad problem instance) doesn't depend on the randomness.

The running time is a **random variable**.

- It makes sense to talk about **expected running time**.

# Expected Running Time and Divide and Conquer

We are interested in **expected runtime**.

$$\mathbb{E}[T(n)]$$

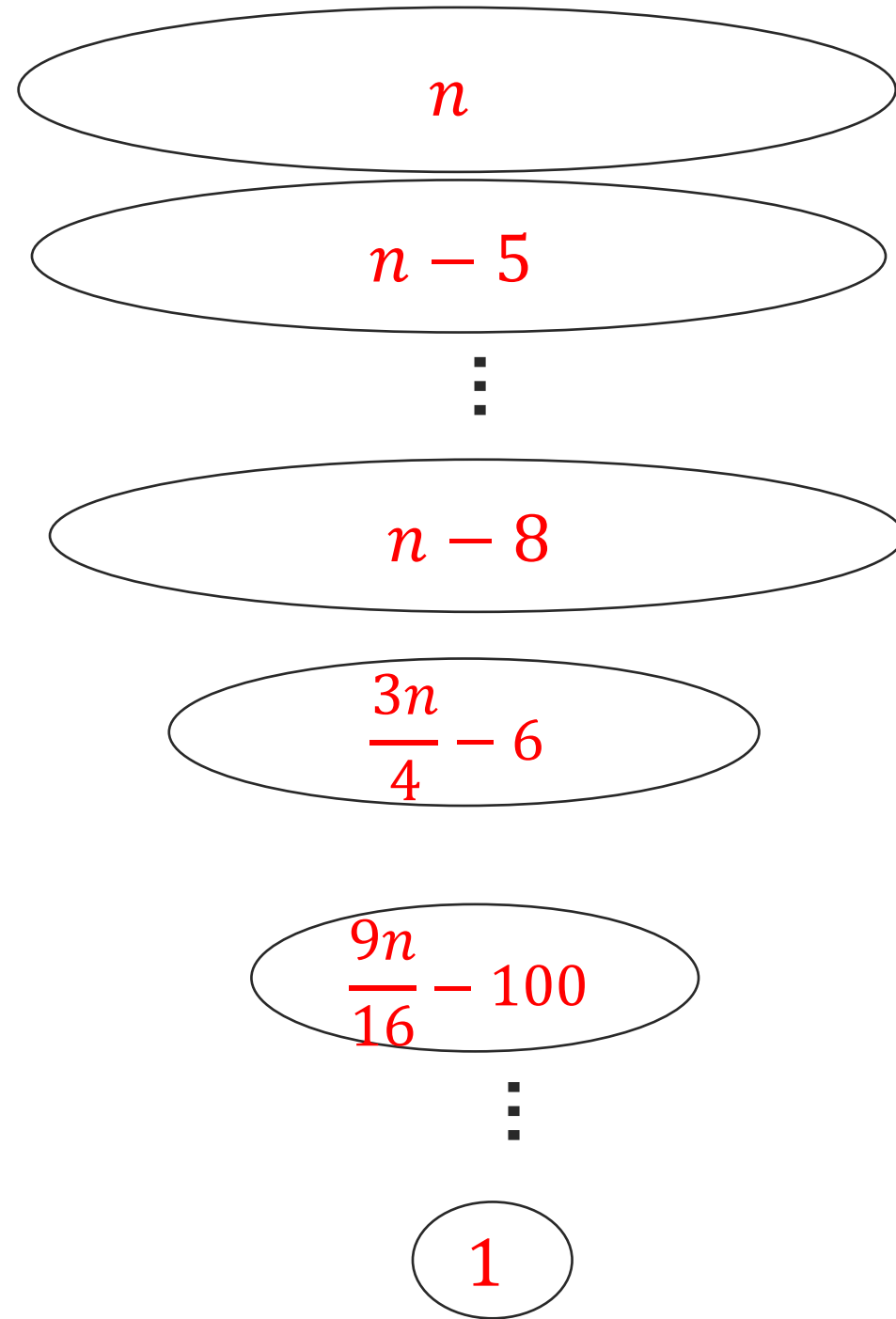
averages over runtimes  $T(i)$  based on the probability of getting a subproblem of size  $i$ .

$\mathbb{E}[T(n)]$  is small when large size  $i$  has very low probability of happening

# Trees Revisited

If every time we got a “good” pivot, we multiply the size by  $\leq 3/4$ .

In reality, in some rounds we are using bad pivots and in some rounds we are using good pivots.



# Trees Revisited

Partition layers to “phases”, when the size drops to  $\frac{3}{4}$  or less of the original array size. **Phase 0**

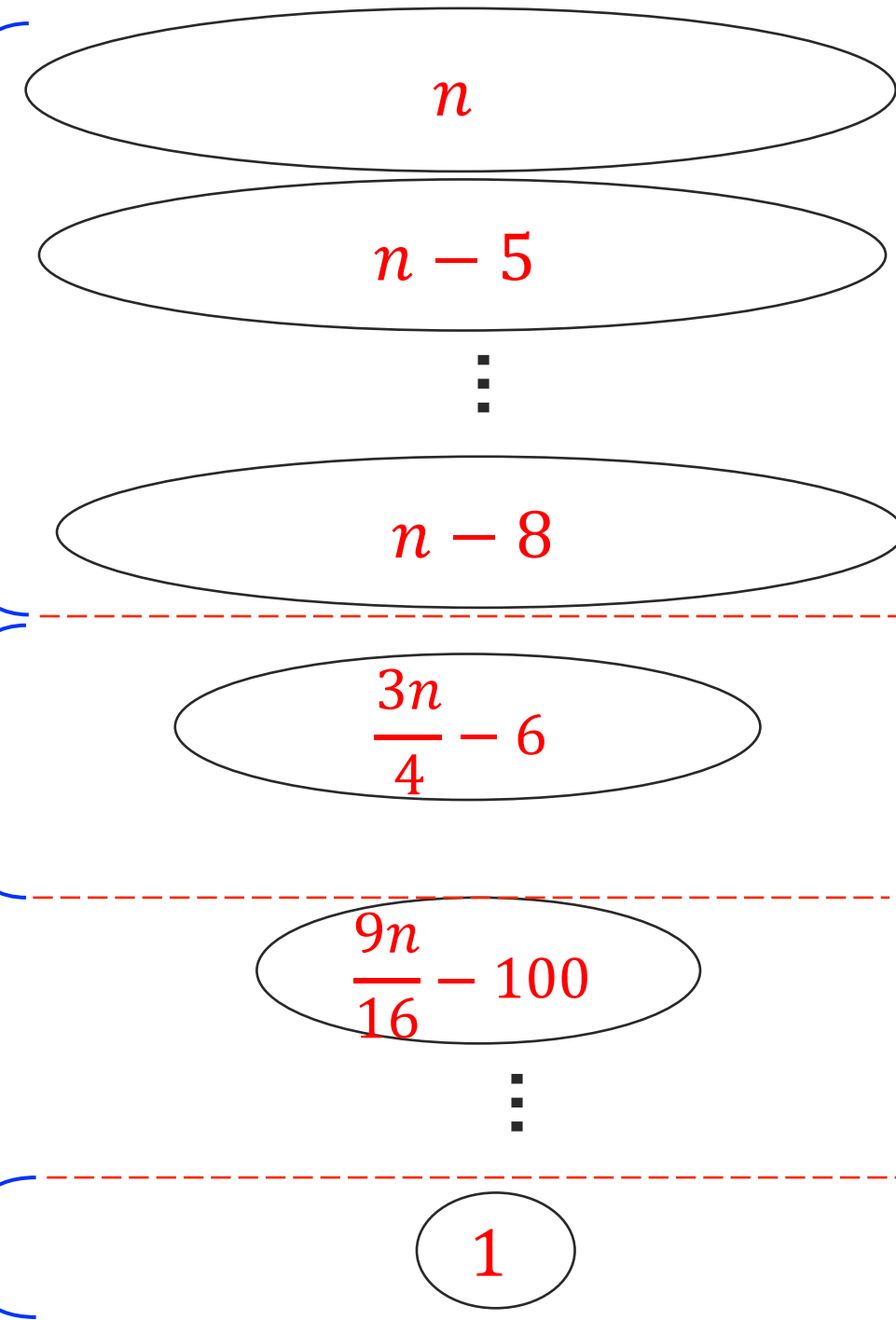
- In **phase  $i$** , problem size  $\leq \left(\frac{3}{4}\right)^i n$ .
- $X_i$  : random variable for length of **phase  $i$** .  
Equiv, # tries until we choose a good pivot.

What is the contribution of phase  $i$ ?

Total runtime:

$$\mathbb{E}[T(n)] \leq \sum_{i=0}^{\log_{4/3}(n)} \mathbb{E}[X_i] \cdot c \cdot n \left(\frac{3}{4}\right)^i$$

**Phase**  
 $\leq \log_{4/3}(n)$





# Trees Revisited

Partition layers to “phases”, when the size drops to  $\frac{3}{4}$  or less of the original array size. **Phase 0**

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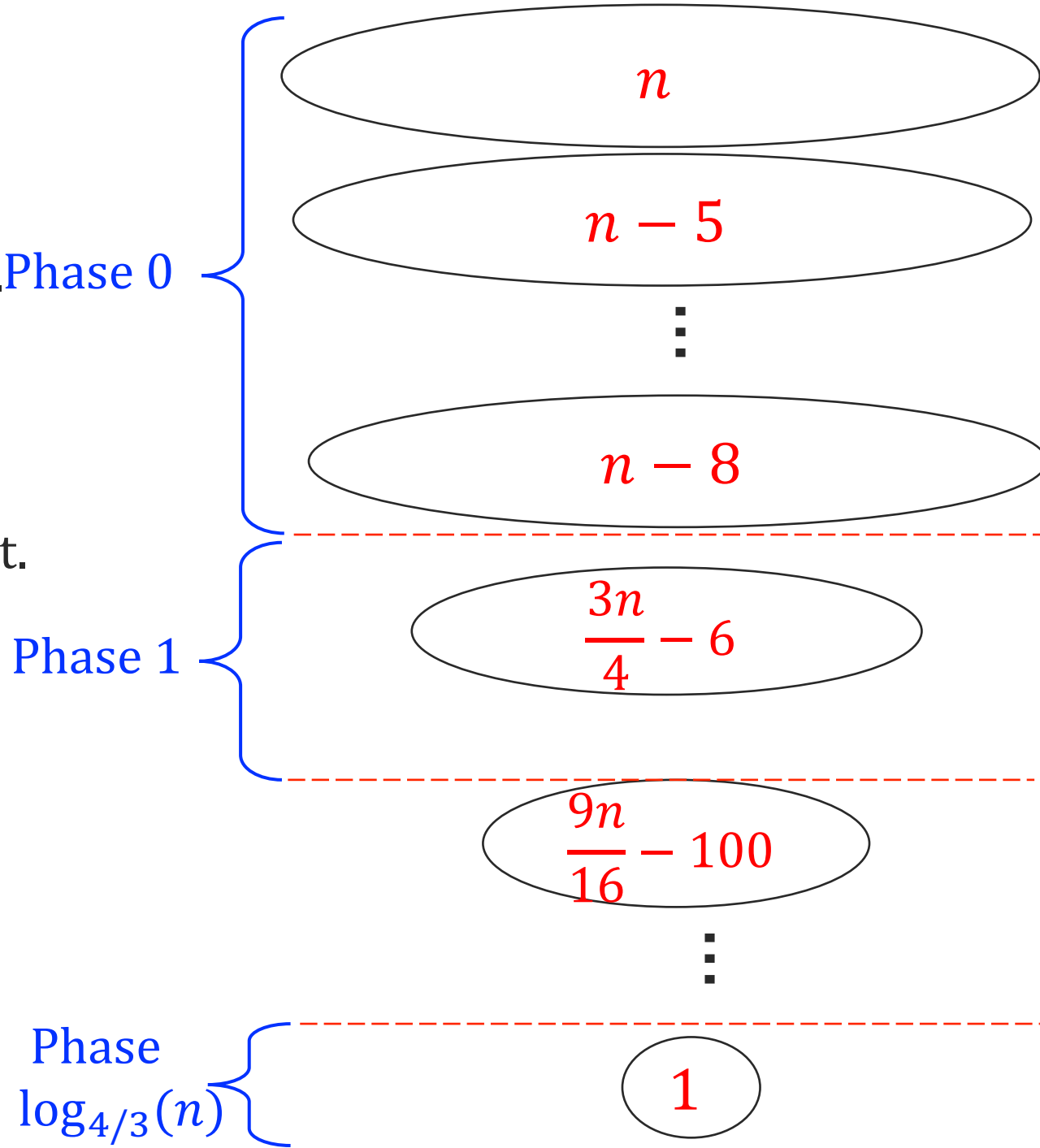
What is the contribution of phase  $i$ ?

$$\leq X_i \cdot c \left(\frac{3}{4}\right)^i n$$

Total runtime:

$$\mathbb{E}[T(n)] \leq \sum_{i=0}^{\log_{4/3}(n)} \mathbb{E}[X_i] c n \left(\frac{3}{4}\right)^i$$

**Phase**  
 $\leq \log_{4/3}(n)$



# Expected Phase Length

We want to compute the expected phase length  $X_i$ .

$$\mathbb{E}[X_i] = \sum_{s=1}^{\infty} s \Pr[X_i = s]$$

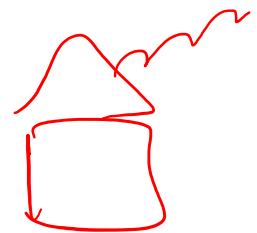
Recall,  $X_i$  is the number of times we choose a pivot in phase  $i$ .

Same as the number of pivots chosen until one falls in the middle 50% of the elements.

## Discuss

What is  $\Pr[X_i = s]$ ?  $(\frac{1}{2})^{s-1} \cdot (\frac{1}{2}) = (\frac{1}{2})^s$

And what is  $\mathbb{E}[X_i]$ ?  $\sum_{s=1}^{\infty} s \frac{1}{2^s} \leq 2$



# Expected Phase Length

We want to compute the expected phase length  $X_i$ .

$$\mathbb{E}[X_i] = \sum_{s=1}^{\infty} s \Pr[X_i = s]$$

Recall,  $X_i$  is the number of times we choose a pivot in phase  $i$ . Same as the number of pivots chosen until one falls in the middle 50% of the elements.

## Discuss

What is  $\Pr[X_i = s]$ ?  $= \left(\frac{1}{2}\right)^{s-1} \times \frac{1}{2} = \left(\frac{1}{2}\right)^s$

Explanation:  $X_i = s$  means that the first  $s - 1$  pivots were bad (happens with prob  $\frac{1}{2}^{s-1}$ ) and the last pivot was good (happens with prob  $\frac{1}{2}$ ).

And what is  $\mathbb{E}[X_i]$ ?  $\sum_{s=1}^{\infty} \frac{s}{2^s} \leq 2$

# Computing the Expected Runtime

There are at most  $\log_{4/3}(n)$  phases and each contributes  $\leq X_i \cdot c \left(\frac{3}{4}\right)^i n$

- Total expected runtime

$$\begin{aligned}\mathbb{E}[T(n)] &\leq \mathbb{E}\left[\sum_{i=0}^{\log_{4/3}(n)} X_i \cdot c \cdot n \left(\frac{3}{4}\right)^i\right] \\ &= \sum_{i=0}^{\log_{4/3}(n)} \mathbb{E}[X_i] \cdot c \cdot n \left(\frac{3}{4}\right)^i \\ &= \sum_{i=0}^{\log_{4/3}(n)} 2 \cdot c \cdot n \left(\frac{3}{4}\right)^i \in O(n)\end{aligned}$$

Yes! There is **randomized algorithm** that solves **SELECT**( $S, k$ ) in **expected runtime** of  $O(n)$ !

This algorithm is called QuickSelect.

# Wrap up

Matrix Multiplication:

Strassen's algorithm

Similar to Karatsuba, we reduce the number of subproblems from 8 to 7.

$k$ -Select

There is a randomized alg, with expected  $O(n)$  runtime.

There is also a really cool **deterministic algorithm**, whose runtime is always  $O(n)$ .

Master theorem in action:

Matrix multiplication and selection

**Next time**

- Multiplying polynomials!
- Fast Fourier Transform