

# CSE100: Design and Analysis of Algorithms

## Lecture 11 – Randomized Algorithms

**Feb 22<sup>nd</sup> 2022**

Randomized Algorithms, QuickSort



# Randomized algorithms (review)

- We make some random choices during the algorithm.
- We hope the algorithm works.
- We hope the algorithm is fast.

For today we will look at algorithms that always work and are probably fast.

e.g., **Select** with a random pivot is a randomized algorithm.

- Always works (aka, is correct).
- Probably fast.



# How do we measure the runtime of a randomized algorithm? (review)

## Scenario 1

1. You publish your algorithm.
2. Bad guy picks the input.
3. You run your randomized algorithm.




- In **Scenario 1**, the running time is a **random variable**.
  - It makes sense to talk about **expected running time**.
- In **Scenario 2**, the running time is **not random**.
  - We call this the **worst-case running time** of the randomized algorithm.

## Scenario 2

1. You publish your algorithm.
2. Bad guy picks the input.
3. Bad guy chooses the randomness (fixes the dice) and runs your algorithm.



# Today

- How do we analyze randomized algorithms?
- A few randomized algorithms for sorting.
  - **BogoSort** 
  - QuickSort
- **BogoSort** is a pedagogical tool.
- **QuickSort** is important to know. (in contrast with BogoSort...)



# BogoSort (review)

Suppose that you can draw a random integer in  $\{1, \dots, n\}$  in time  $O(1)$ . How would you randomly permute an array in-place in time  $O(n)$ ?



Ollie the over-achieving ostrich

- **BogoSort(A)**
  - **While** true:
    - Randomly permute A.
    - Check if A is sorted.
    - **If** A is sorted, **return** A.

- Let  $X_i = \begin{cases} 1 & \text{if A is sorted after iteration } i \\ 0 & \text{otherwise} \end{cases}$

- $E[X_i] = \frac{1}{n!}$

- $E[\text{number of iterations until A is sorted}] = n!$



# MATH 32 Refresher

1. Let  $X$  be a random variable which is 1 with probability  $1/100$  and 0 with probability  $99/100$ .

a)  $E[X] = 1/100$

- b) If  $X_1, X_2, \dots, X_n$  are iid copies of  $X$ , by linearity of expectation,

$$E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i] = \frac{n}{100}$$

iid: independent  
and identically  
distributed

- c) Let  $N$  be the index of the first 1. Then  $E[N] = 100$ .



To see part (c), either:

- You saw in MATH 32 that  $N$  is a geometric random variable, and you know a formula for that.
- Suppose you do the first trial. If it comes up 1 (with probability  $1/100$ ), then  $N=1$ . Otherwise, you start again except you've already used one trial. Thus:

$$E[N] = \frac{1}{100} \cdot 1 + \left(1 - \frac{1}{100}\right) \cdot (1 + E[N]) = 1 + \left(1 - \frac{1}{100}\right) E[N]$$

Solving for  $E[N]$  we see  $E[N] = 100$ .

- (There are other derivations too).



# MATH 32 Refresher 2

2. Let  $X_i$  be 1 iff A is sorted on iteration i.

- a)  $E[X_i] = 1/n!$  since there are  $n!$  possible orderings of A and only one is sorted. (Suppose A has distinct entries).
- b) Let N be the index of the first 1. Then  $E[N] = n!$ .

Part (b) is similar to part (c) in previous slide:

- You saw in MATH 32 that N is a geometric random variable, and you know a formula for that. Or,
- Suppose you do the first trial. If it comes up 1 (with probability  $1/n!$ ), then  $N=1$ . Otherwise, you start again except you've already used one trial. Thus:

$$E[N] = \frac{1}{n!} \cdot 1 + \left(1 - \frac{1}{n!}\right) \cdot (1 + E[N]) = 1 + \left(1 - \frac{1}{n!}\right) E[N]$$

Solving for  $E[N]$  we see  $E[N] = n!$

- (There are other derivations too).



From your MATH 32 refresher exercise:

# BogoSort

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# Expected Running time of BogoSort

This isn't random, so we can pull it out of the expectation.

$$E[\text{running time on a list of length } n] \\ = E[(\text{number of iterations}) * (\text{time per iteration})]$$

$$= (\text{time per iteration}) * E[\text{number of iterations}]$$

$$= O(n \cdot n!)$$

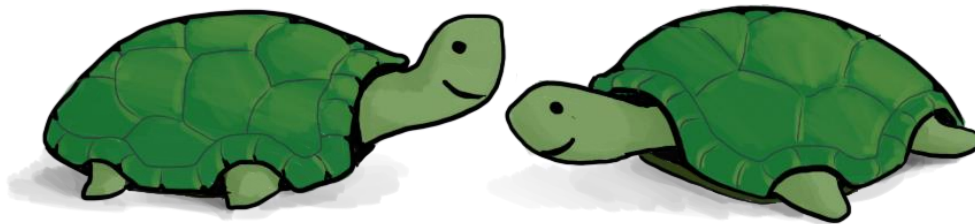
This is  $O(n)$  (to permute and then check if sorted)

We just computed this. It's  $n!$ .

= **REALLY REALLY BIG.**



# Worst-case running time of BogoSort?

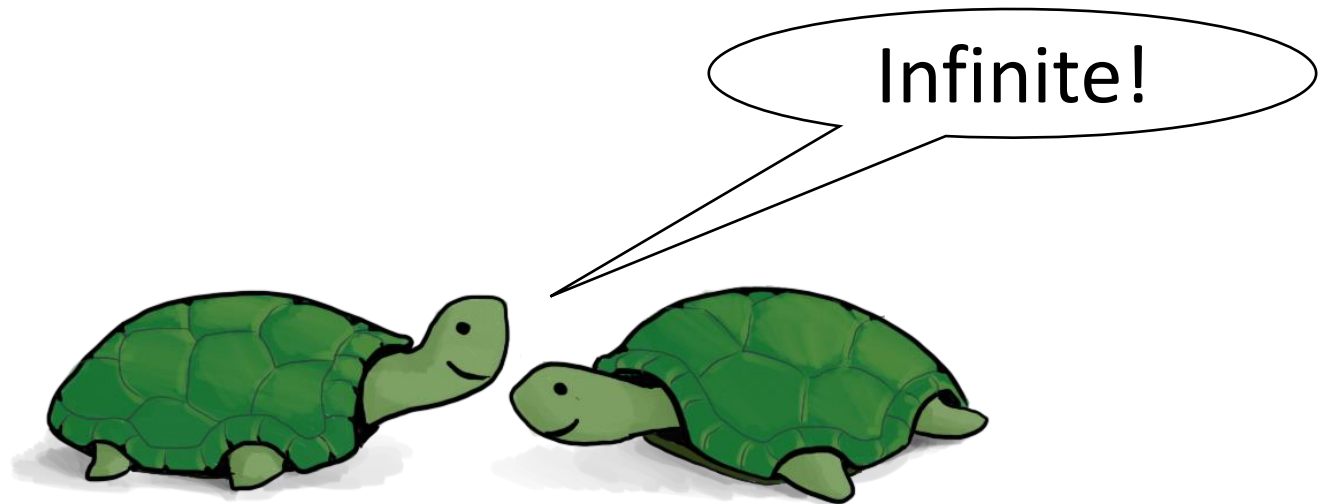


Think-Pair-Share Terrapins!

- **BogoSort(A)**
  - **While** true:
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# Worst-case running time of BogoSort?



Think-Pair-Share Terrapins!

- **BogoSort(A)**
  - **While** true:
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# What have we learned?

- Expected running time:
  1. You publish your randomized algorithm.
  2. Bad guy picks an input.
  3. You get to roll the dice.
- Worst-case running time:
  1. You publish your randomized algorithm.
  2. Bad guy picks an input.
  3. Bad guy gets to “roll” the dice.
- Don't use bogoSort.



# Today

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- A few randomized algorithms for sorting.
  - **BogoSort**
  - **QuickSort** 
- **BogoSort** is a pedagogical tool.
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# a better randomized algorithm:

## QuickSort

- Expected runtime  $O(n \log(n))$ .
- Worst-case runtime  $O(n^2)$ .
- In practice works great!
  - (More later)



# Quicksort

We want to sort  
this array.

For the rest of the lecture, assume all  
elements of A are distinct.



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First, pick a “pivot.”  
**Do it at random.**



random pivot!



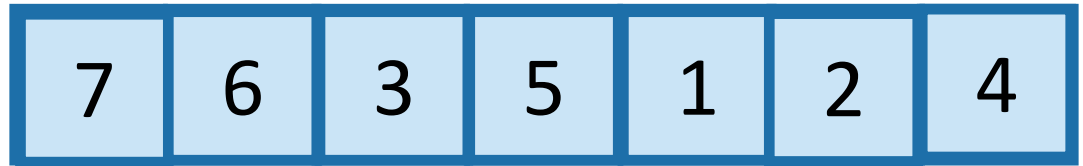


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“bigger than 5” or “less than 5”



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Next, partition the array into  
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L = array with things  
smaller than A[pivot]

R = array with things  
larger than A[pivot]



# Quicksort

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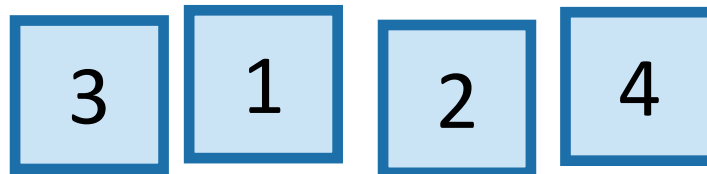
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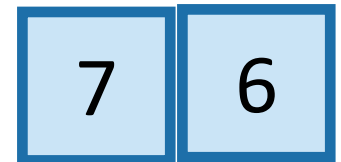
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random pivot!

This PARTITION step takes time  $O(n)$ .  
(Notice that we don't sort each half).  
[same as in SELECT]



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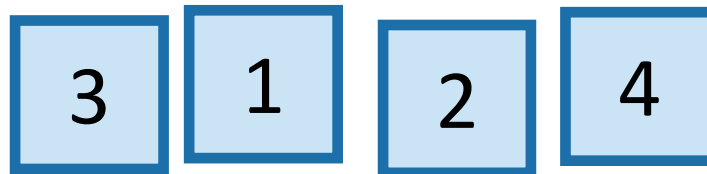


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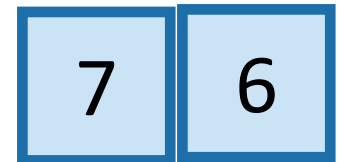
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This PARTITION step takes time  $O(n)$ .  
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Arrange them like so:



L = array with things smaller than A[pivot]



R = array with things larger than A[pivot]



# Quicksort

We want to sort this array.

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First, pick a “pivot.”  
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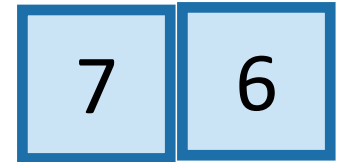
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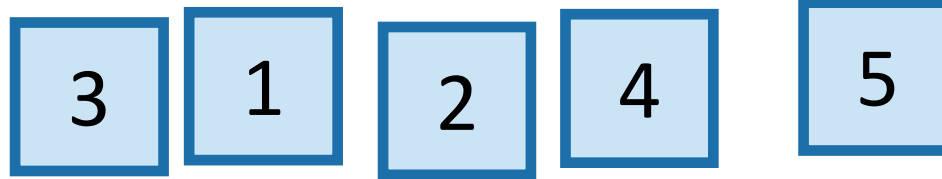


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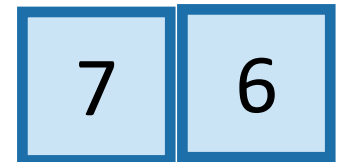
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Recurse on  
L and R:



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For the rest of the lecture, assume all elements of A are distinct.

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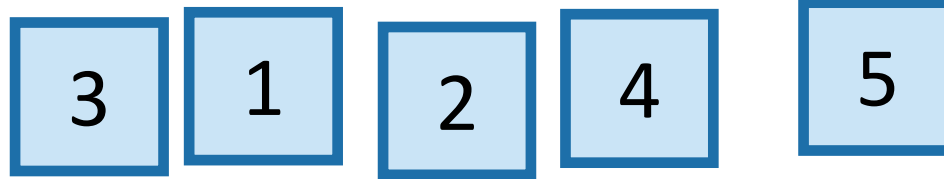


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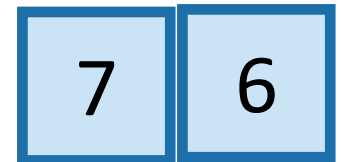
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This PARTITION step takes time  $O(n)$ .  
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Arrange them like so:



L = array with things smaller than A[pivot]



R = array with things larger than A[pivot]

Recurse on L and R:



# PseudoPseudoCode for what we just saw

Lab 05 asks for an  
implementation  
of this algorithm.

- QuickSort(A):
  - **If**  $\text{len}(A) \leq 1$ :
    - **return**
  - Pick some  $x = A[i]$  at random. Call this the **pivot**.
  - **PARTITION** the rest of A into:
    - L (less than x) and
    - R (greater than x)
  - Replace A with [L, x, R] (that is, rearrange A in this order)
  - QuickSort(L)
  - QuickSort(R)

Assume that all elements  
of A are distinct. How  
would you change this if  
that's not the case?



How would you do all this in-place?  
Without hurting the running time?  
(We'll see later...)





# Running time?

- $T(n) = T(|L|) + T(|R|) + O(n)$
- In an ideal world...
  - if the pivot splits the array exactly in half...

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

- We've seen that a bunch:

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



# The expected running time of QuickSort is $O(n \log(n))$ .

**Proof:**\*

- $E[|L|] = E[|R|] = \frac{n-1}{2}$ .
  - The expected number of items on each side of the pivot is half of the things.



# Aside

why is  $E[|L|] = \frac{n-1}{2}$  ?

- $E[|L|] = E[|R|]$ 
  - by symmetry
- $E[|L| + |R|] = n - 1$ 
  - because L and R make up everything except the pivot.
- $E[|L|] + E[|R|] = n - 1$ 
  - By linearity of expectation
- $2E[|L|] = n - 1$ 
  - Plugging in the first bullet point.
- $E[|L|] = \frac{n-1}{2}$ 
  - Solving for  $E[|L|]$ .



# The expected running time of QuickSort is $O(n \log(n))$ .

## Proof:<sup>\*</sup>

- $E[|L|] = E[|R|] = \frac{n-1}{2}$ .
  - The expected number of items on each side of the pivot is half of the things.
- If that occurs, the running time is  $T(n) = O(n \log(n))$ .
  - Since the relevant recurrence relation is  $T(n) = 2T\left(\frac{n-1}{2}\right) + O(n)$
- Therefore, the expected running time is  $O(n \log(n))$ .





# Red flag

- **Slow** Sort(A):
  - If  $\text{len}(A) \leq 1$ :
  - return

We can use the same argument to prove something false.

- **Pick the pivot x to be either max(A) or min(A), randomly**
  - \\ We can find the max and min in  $O(n)$  time

- PARTITION the rest of A into:
  - L (less than x) and
  - R (greater than x)
- Replace A with [L, x, R] (that is, rearrange A in this order)
- **Slow** Sort(L)
- **Slow** Sort(R)

- Same recurrence relation:

$$T(n) = T(|L|) + T(|R|) + O(n)$$

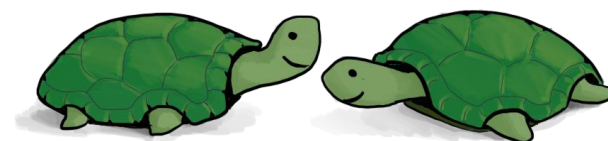
- We still have  $E[|L|] = E[|R|] = \frac{n-1}{2}$
- But now, one of |L| or |R| is always  $n-1$ .
- You check: Running time is  $\Theta(n^2)$ , with probability 1.



# The expected running time of SlowSort is $O(n \log(n))$ .

**Proof:**\*

What's wrong???



- $E[|L|] = E[|R|] = \frac{n-1}{2}$ .
  - The expected number of items on each side of the pivot is half of the things.
- If that occurs, the running time is  $T(n) = O(n \log(n))$ .
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# What's wrong?

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  - Since the relevant recurrence relation is  $T(n) = 2T\left(\frac{n-1}{2}\right) + O(n)$
- Therefore, the expected running time is  $O(n \log(n))$ .

This argument says:

*That's not how  
expectations work!*

$T(n) =$  some function of  $|L|$  and  $|R|$



$E[T(n)] = E[\text{some function of } |L| \text{ and } |R|]$



$E[T(n)] =$  some function of  $E[|L|]$  and  $E[|R|]$



Plucky the Pedantic Penguin