

# Randomized Algorithm II

## Randomized QuickSort

# Randomized Quicksort

- Recall *deterministic* Quicksort
- Depending on the choice pivot, could be  $O(n^2)$
- What if we pick the pivot uniformly at random?
  - We saw in randomized selection that this leads to good pivots [half of the time](#)

## **Quicksort( $A$ ):**

If  $|A| < 3$  : Sort( $A$ ) directly

Else: choose a pivot element  $p \leftarrow A$

$A_{<p}, A_{>p} \leftarrow$  Partition around  $p$

Quicksort( $A_{<p}$ )

Quicksort( $A_{>p}$ )

# Randomized Quicksort

- Intuitively half the pivots will be good, half bad
- We will analyze quick sort using another accounting trick (see the textbook for example similar to selection's approach of analyzing "phases")
- Total work done can be split into two types:
  - Work done making recursive calls (this is a lower order term, it turns out)
  - Work partitioning the elements
- How many recursive calls in the worst case?
  - Imagine worst pivot being chosen each time
  - $O(n)$

# Randomized Quicksort

- We thus need to bound the work partitioning elements
- Partitioning an array of size  $n$  around a pivot  $p$  takes exactly  $n - 1$  comparisons
- We won't look at partitions made in each recursive call, which depend on the choice of random pivot
- **Idea:** Instead, account for the total work done by the partition step by summing up the total number of comparisons made
- Two ways to count total comparisons:
  - Look at the size of arrays across recursive calls and sum
  - Look at all pairs of elements and count total # of times they are compared (this is easier to do in this case)

# Aside: Randomized Analysis

- Often multiple ways to determine a randomized algorithm's cost
- We can split into phases, or count the cost directly. We can calculate each probability, or use linearity of expectation
- Intrinsically some “cleverness” involved in choosing the way that gets you a clean answer
- We'll focus on problems where there's a clear path to finding the solution (either it follows directly from the question, or we'll revisit problems you've seen before). More complex problems abound if you look!
- That said, here's a very clever way to calculate Quicksort's running time

# Counting Total Comparisons

- Just for analysis, let  $B$  denote the sorted version of input array  $A$ , that is,  $B[i]$  is the  $i^{\text{th}}$  smallest element in  $A$
- Define random variable  $X_{ij}$  as the number of times Quicksort compares  $B[i]$  and  $B[j]$
- **Observation:**  $X_{ij} = 0$  or  $X_{ij} = 1$ , why?
  - $B[i], B[j]$  only compared when one of them is the current pivot; pivots are excluded from future recursive calls

- Let  $T = \sum_{i=1}^n \sum_{j=i+1}^n X_{ij}$  be the total number of comparisons made

by randomized Quicksort



# Expected Running Time

- **Goal:**  $E[T] = E \left[ \sum_{i=1}^n \sum_{j=i+1}^n X_{ij} \right] = \sum_{i=1}^n \sum_{j=i+1}^n E[X_{ij}]$
- $E[X_{ij}] = \Pr[X_{ij} = 1]$
- When is  $X_{ij} = 1$ ? That is, when are  $B[i]$  and  $B[j]$  compared?
- Consider a particular recursive call. Let rank of pivot  $p$  be  $r$ .
  - Let's think about where  $B[i], B[j]$  lie with respect to  $p$

# Expected Running Time

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- $E[X_{ij}] = \Pr[X_{ij} = 1]$
- When is  $X_{ij} = 1$ ? That is, when are  $B[i]$  and  $B[j]$  compared?
- Consider a particular recursive call. Let rank of pivot  $p$  be  $r$ .
  - Case 1. One of them is the pivot:  $r = i$  or  $r = j$
  - Case 2. Pivot is between them:  $r > i$  and  $r < j$
  - Case 3. Both less than the pivot:  $r > i, j$
  - Case 4. Both greater than the pivot:  $r < i, j$



# Comparisons for Each Case

- **Case 1.**  $r = i$  or  $r = j$ 
  - $B[i]$  and  $B[j]$  are compared once and one of them is excluded from all future calls
- **Case 2.**  $r > i$  and  $r < j$ 
  - $B[i]$  and  $B[j]$  are both compared to the pivot but not to each other, after which they are in different recursive calls: will never be compared again
- **Case 3.**  $r > i, j$  and **Case 4.**  $r < i, j$ 
  - $B[i]$  and  $B[j]$  are not compared to each other, they are both in the same subarray and may be compared in the future
- **Takeaway:**  $B[i], B[j]$  are compared for the 1st time when one of them is chosen as pivot from  $B[i], B[i + 1], \dots, B[j]$  & never again

# Expected Running Time

- $\Pr[X_{ij} = 1] = \Pr(\text{one of them is picked as pivot from } B[i], B[i + 1], \dots, B[j])$

- $\Pr[X_{ij} = 1] = \frac{2}{j - i + 1}$

- $E[T] = \sum_{i=1}^n \sum_{j=i+1}^n E[X_{ij}] = 2 \sum_{i=1}^n \sum_{j=i+1}^n \frac{1}{j - i + 1}$

# Expected Running Time

- $B[i]$  and  $B[j]$  are compared iff one of them is the first pivot chosen from the range  $B[i], B[i + 1], \dots, B[j]$

- $$\Pr[X_{ij} = 1] = \frac{2}{j - i + 1}$$

At each round, the probability that  $X_{ij} = 1$  conditioned on the event that we are in Case 1 or Case 2. (In Cases 3 and 4, we “kick the can” until another round)

- $$E[T] = \sum_{i=1}^n \sum_{j=i+1}^n E[X_{ij}] = 2 \sum_{i=1}^n \sum_{j=i+1}^n \frac{1}{j - i + 1}$$

- For fixed  $i$ , inner sum is  $\frac{1}{2} + \frac{1}{3} + \frac{1}{4} + \dots + \frac{1}{n - i + 1} \leq \sum_{\ell=2}^n \frac{1}{\ell} = O(\log n)$

- Thus, expected number of comparisons is:  
$$E[T] = O(n \log n)$$

# Quick Sort Summary

- Las Vegas algorithms like Quicksort and Selection are always correct and their running time guarantees hold *in expectation*
- We can actually prove that the number of comparisons made by Quicksort is  $O(n \log n)$  **with high probability**
  - W.H.P. means that the the probability that the running time of quicksort **is more than a constant  $c$  factor away from its expectation** is very small (polynomially small: less than  $1/n^c$  for  $c \geq 1$ )
  - Whp bounds are called **concentration bounds**
  - Whp: ideal guarantees possible for a randomized algorithm

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  - Kleinberg Tardos Slides by Kevin Wayne (<https://www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/04GreedyAlgorithmsI.pdf>)
  - Jeff Erickson's Algorithms Book (<http://jeffe.cs.illinois.edu/teaching/algorithms/book/Algorithms-JeffE.pdf>)