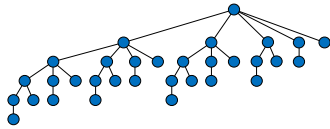


Lecture 6. Randomized Analysis

CpSc 8400: Algorithms and Data Structures
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Recall: Priority Queue Implementations

- There are *many* simple ways to implement the abstract notion of a priority queue as a concrete data structure:

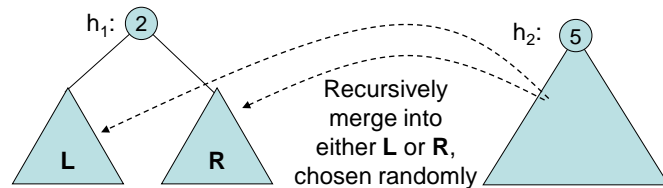
	<i>insert</i>	<i>remove-min</i>
Unsorted array or linked list	$O(1)$	$O(n)$
Sorted array or linked list	$O(n)$	$O(1)$
Binary heap	$O(\log n)$	$O(\log n)$
Balanced binary search tree	$O(\log n)$	$O(\log n)$
Skew heap	$O(\log n)$ am.	$O(\log n)$ am.
Randomized mergeable binary heap	$O(\log n)$ whp.	$O(\log n)$ whp.
Binomial heap	$O(1)$ am.	$O(\log n)$
Fibonacci heap	$O(1)$ am.	$O(\log n)$ am.

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Recall: The Randomized Mergeable Binary Heap

- Merges any two heaps in $O(\log n)$ time with high probability!



- Equivalent outlook: random null path down any tree has length $O(\log n)$ with high probability.

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Definition : “With High Probability”

- We say an algorithm with input size n runs in $O(\log n)$ time **with high probability** if, for any constant c , we can find another constant k such that

$$\Pr[\text{running time} > k \log n] \leq 1 / n^c.$$

- That is, the probability we fail to run in $O(\log n)$ time is at most $1 / n^c$, for any constant c of our choosing (as long as we choose a sufficiently large hidden constant in the $O(\log n)$ notation).

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An Easy Starting Point

- Suppose we have an algorithm for which:
 - We start with a problem of size n .
 - In every iteration, the effective size of the problem is reduced to a constant fraction of its original size
- Then, our algorithm performs only $O(\log n)$ iterations

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The Randomized Reduction Lemma

- Suppose we have an algorithm for which:
 - We start with a problem of size n .
 - In every iteration, the effective size of the problem is reduced to a constant fraction of its original size **with some constant probability**.
- Then, our algorithm performs only $O(\log n)$ iterations **with high probability**.

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Example: Randomized Binary Search

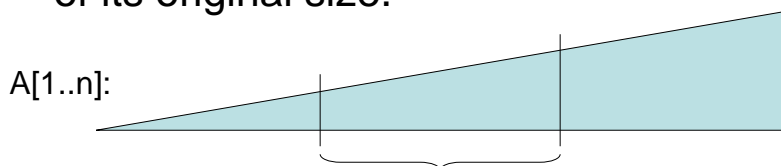
- Suppose we're searching a sorted array $A[1..n]$ for an element of value X .
- In a standard binary search, we compare $A[n/2]$ and X , then recursively search either $A[1..n/2]$ or $A[n/2..n]$.
- Suppose instead of $A[n/2]$, we compare X against a random element and then recursively search left or right as before...

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Example: Randomized Binary Search

- **Claim:** Randomized binary search runs in $O(\log n)$ time with high probability.
- **Simple proof:** If we happen to choose a "pivot" element $A[j]$ where $n/3 \leq j \leq 2n/3$ (and this happens with probability $\geq 1/3$), then our problem will be reduced to $\leq 2/3$ of its original size.



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Applying the Randomized Reduction Lemma to Mergeable Heaps

- Suppose we build a null path in an arbitrary heap-ordered binary tree by walking downward at random from the root.
- In each step (say, at element e), one of e 's left or right subtrees must contain fewer than $\frac{1}{2}$ of the total number of elements in e 's subtree.
 - So with probability $\frac{1}{2}$, each step reduces the number of nodes in our current subtree by a factor of at least 2.
 - Hence, a randomly-built null path has length $O(\log n)$ with high probability.
- On a randomized mergeable binary heap, *merge* and all other priority queue operations therefore run in $O(\log n)$ time with high probability.

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Randomized Reduction Exercise

- Suppose we build an n -element binary heap by inserting n elements in random order.
- How many times do we change the root?

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Randomized Reduction Exercise

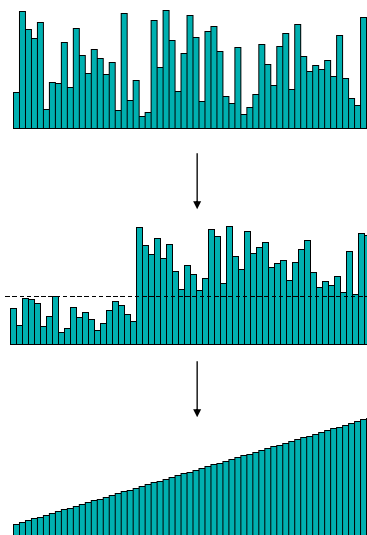
- Suppose we build an n -element binary heap by inserting n elements in random order.
- How many times do we change the root?
- Equivalently, if you scan through a random permutation of n elements while keeping a running minimum, how many times will you see this minimum being reset?

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Quicksort

- In linear time, **partition** array based on the value of some **pivot** element.
- Then recursively sort left side (all elements \leq pivot) and right side (\geq pivot).
- How to partition?
 - Ideally “in place”
 - Careful if equal elements...



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Quicksort Variants

- **Simple quicksort.** Choose pivot using a simple deterministic rule; e.g., first element, last element, median($A[1]$, $A[n]$, $A[n/2]$).
 - $\Theta(n \log n)$ time if “lucky”, but $\Theta(n^2)$ worst-case.
- **Deterministic quicksort.** Pivot on median (we’ll see shortly how to find the median in linear time).
 - $\Theta(n \log n)$ time, but not the best in practice.
- **Randomized quicksort.** Choose pivot uniformly at random.
 - $\Theta(n \log n)$ time with high probability, and fast / popular in practice

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Randomized Reduction and Randomized Quicksort

Randomized binary search for 7

1 2 3 7 8 9 12 13 14 15

1 2 3 7 8 9

3 7 8 9

3 7

 = random choices of “pivots”

Randomized quicksort

3 7 9 2 8 1 12 14 15 13

1 2 8 7 9 3 13 14 15

1 7 3 8 9 13 15

3 7 9

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 = random choices of pivots

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The Union Bound

- Recall that $\Pr[A \cup B] = \Pr[A] + \Pr[B] - \Pr[A \cap B]$.
- It typically suffices just to use the rough upper bound $\Pr[A \cup B] \leq \Pr[A] + \Pr[B]$.
- For multiple events $E_1 \dots E_k$, this gives us what is known as the **union bound** or **Boole's inequality**:
 $\Pr[E_1 \cup E_2 \cup \dots \cup E_k] \leq \Pr[E_1] + \dots + \Pr[E_k]$.
- For example:
 - Suppose each of 50 parts in a complex machine fails with probability $\leq 1/100$
 - Then $\Pr[\text{entire machine fails}] \leq 50(1/100) = 1/2$.

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The Union Bound

- If there are n bad events that can happen, and each happens with probability $\leq p$, then the probability **any** bad event happens is at most np .
I.e, for events $E_1 \dots E_n$, $\Pr[\cup_i E_i] \leq \sum_i \Pr[E_i]$
- This meshes particularly well with our definition of “with high probability”: If some property holds for a generic input element w.h.p., then it also holds for each of our n input elements w.h.p.
- **Example:** If randomized quicksort spends only $O(\log n)$ on a generic input element w.h.p, then its total running time is $O(n \log n)$ w.h.p.

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A Prototypical “High Probability” Analysis...

- **Step 1:** Consider some generic input element e . Show that randomized quicksort spends $O(\log n)$ work on e w.h.p.
 - Usually easy with the randomized reduction lemma.
- **Step 2:** The union bound automatically allows us to extend this result to show that randomized quicksort spends $O(\log n)$ work on **each** of its input elements w.h.p.
- So total running time is $O(n \log n)$ w.h.p.

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More Randomized Reduction Practice

- Throw N balls into N bins, each one independently at random. How full is the fullest bin?

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More Randomized Reduction Practice

- Throw N balls into N bins, each one independently at random. How full is the fullest bin? $O(\log N)$ balls whp!

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More Randomized Reduction Practice

- Throw N balls into N bins, each one independently at random. How full is the fullest bin? $O(\log N)$ balls whp!
- Coupon collecting: Each time you open a box of cereal, you receive one of N coupon types (independently at random). How many boxes of cereal must you open to collect at least one of each coupon type?

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More Randomized Reduction Practice

- Throw N balls into N bins, each one independently at random. How full is the fullest bin? $O(\log N)$ balls whp!
- Coupon collecting: Each time you open a box of cereal, you receive one of N coupon types (independently at random). How many boxes of cereal must you open to collect at least one of each coupon type? $O(N \log N)$ whp!
 - Many related questions; e.g., cover time of a complete graph.

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