Lecture 5: Recursive Algorithms: The Median; Randomized Selection; Deterministic Selection

1 The Median Problem

- How do we find the **median** of a set $S = \{x_1, x_2, \dots, x_n\}$?
 - We could <u>sort</u> the list and then output the $\left[\frac{n}{2}\right]$ th number.
 - Using **Mergesort**, or otherwise, this will take time $O(n \cdot \log n)$.
- Is there a **faster** way to find the median?
 - \circ We only need the median number. Sorting all numbers seems overkill. We cannot do better than O(n) since we need to read n numbers in linear time.

2 The Selection Problem

- How do we find the k^{th} smallest number in $S = \{x_1, x_2, \cdots, x_n\}$?
 - \circ Again, we could **sort** the list and then output the k^{th} number.
 - Using **Mergesort**, this takes time $O(n \cdot \log n)$.
- We can do this much <u>faster</u> using recursion...

The Selection Algorithm

```
Select(S, k)

If |S| = 1 then output x_1

Else

Set S_L = \{x_i \in S : x_i < x_1\}

Set S_R = \{x_i \in S \setminus x_1 : x_i \ge x_1\}

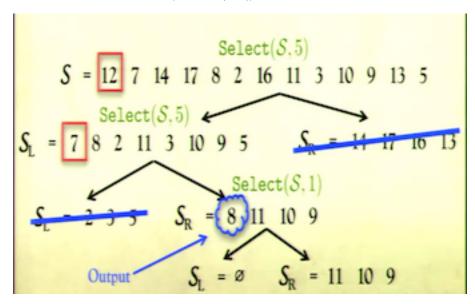
If |S_L| = k - 1 then output x_1

If |S_L| > k - 1 then output Select(S_L, k)

If |S_L| < k - 1 then output Select(S_R, k - 1 - |S_L|)
```

Note:

- 1. If $|S_L| = k 1$, then x_1 is the k^{th} smallest number.
- 2. On the other hand, suppose smallest S_L contains at least (k 1) elements, which means it gets k elements, in other words, k^{th} smallest element is actually in S_L . The k^{th} smallest element of S must also be the k^{th} smallest element of S_L .
- 3. S_L union x_1 has the most (k 1) elements, which means the k^{th} smallest element must be in the set S_R . Since everything in S_R is at least bigger than in x_1 , so that it is also bigger than in S_L , to find the k^{th} smallest element, we need (k 1 $|S_L|$).



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 \bullet How many comparisons T(n) does this recursive selection algorithm make?

```
T(n) = n - 1 + T(\max\{|\mathcal{S}_L|, |\mathcal{S}_R|\}) Select(\mathcal{S}, k) = n - 1 + T(n - 1) If |\mathcal{S}| = 1 then output x_1 Else Set \mathcal{S}_L = \{x_i \in \mathcal{S} : x_i < x_1\} Set \mathcal{S}_R = \{x_i \in \mathcal{S} \setminus x_1 : x_i \geq x_1\} Worst case: |\mathcal{S}_L| or |\mathcal{S}_R| = n - 1 If |\mathcal{S}_L| = k - 1 then output x_1 Worst case: |\mathcal{S}_L| or |\mathcal{S}_R| = n - 1 If |\mathcal{S}_L| > k - 1 then output Select(\mathcal{S}_L, k) If |\mathcal{S}_L| < k - 1 then output Select(\mathcal{S}_R, k - 1 - |\mathcal{S}_L|)
```

• So in the **worst case** we have is:

$$T(n) = (n-1) + T(n-1)$$

$$= (n-1) + (n-2) + T(n-2)$$

$$\vdots$$

$$\vdots$$

$$= (n-1) + (n-2) + (n-3) + \dots + 2 + 1$$

$$= \frac{1}{2}n(n-1)$$

$$= \Omega(n^2)$$

- This is terrible sorting would have been faster!
- How to fix it? Use Balanced Pivots!
 - The problem is the algorithm repeatedly **pivots** on the first number in the current list.
 - \rightarrow But if we are unlucky this pivot could be very **unbalanced**. That is: $\max\{|S_L|, |S_R|\} \approx n$ $\min\{|S_L|, |S_R|\} \approx 0$

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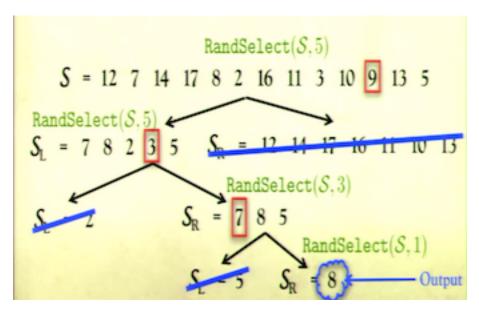
• What we would like is to select a pivot that is **balanced**. That is: $\max\{|S_L|, |S_R|\} \approx \frac{n}{2} \\ \min\{|S_L|, |S_R|\} \approx \frac{n}{2}$

• Randomization

- The current algorithm is **deterministic** in the choice of the pivot.
- To fix the problem we consider a **randomized** implementation.
 - \rightarrow Do not pivot deterministically on x_1 .
 - \rightarrow Instead choose the pivot at <u>random</u> from $S = \{x_1, x_2, \cdots, x_n\}$

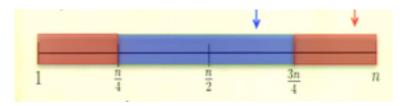
Randomized Selection

```
 \begin{array}{l} \mathbf{RandSelect}(S,\,\mathbf{k}) \\ \mathbf{If}\,\,|S| = 1 \,\,\mathbf{then}\,\,\mathrm{output}\,\,x_1 \\ \mathbf{Else} \\ \quad \text{Pick a random pivot}\,\,x_\tau \in \{x_1,x_2,\cdots,x_n\} \\ \quad \text{Set}\,\,S_L = \{x_i \in S:\, x_i < x_\tau\} \\ \quad \text{Set}\,\,S_R = \{x_i \in S \setminus x_\tau:\, x_i \geq x_\tau\} \\ \quad \mathbf{If}\,\,|S_L| = \mathbf{k} - 1 \,\,\mathbf{then}\,\,\mathrm{output}\,\,x_\tau \\ \quad \mathbf{If}\,\,|S_L| > \mathbf{k} - 1 \,\,\mathbf{then}\,\,\mathrm{output}\,\,\mathbf{RandSelect}(S_L,\,\mathbf{k}) \\ \quad \mathbf{If}\,\,|S_L| < \mathbf{k} - 1 \,\,\mathbf{then}\,\,\mathrm{output}\,\,\mathbf{RandSelect}(S_R,\,\mathbf{k} - 1 - |S_L|) \end{array}
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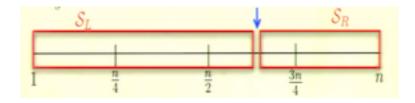


• Good vs Bad Pivots

• Imagine all the numbers in the **sorted** order.



- \circ With probability $\frac{1}{2}$ the pivot x_{τ} lies between the 1st and 3rd quartiles.
 - \rightarrow We say that such a pivot is good.
 - \rightarrow We say that such a pivot is bad.
- **Key Observation**: If the pivot is good then $\max\{|S_L|, |S_R|\} \leq \frac{3}{4} \cdot n$



• Expected Runtime

- In the worst case, the *randomized algorithm* will pick the <u>worst</u> pivot! The probability of its happening is very small.
- \circ So, for randomized algorithms, we are always interested in the **expected** runtime $\bar{T}(n) = E(T(n))$, not the worst case run time.
- Using our observation, we then have that:

$$\bar{T}(n) \le \frac{1}{2} \cdot \bar{T}(\frac{3n}{4}) + \frac{1}{2} \cdot \bar{T}(n) + O(n)$$

Note:

1. The first term: the probability of $\frac{1}{2}$ comes from I make a good pivot. If I make a good pivot, I know both of my subsets will have at most the size of $\frac{3n}{4}$.

2. The second term: If I get a bad pivot, the size of the next problem might be (n - 1), which is $\bar{T}(n)$ in the worst case.

$$\bar{T}(n) \le \frac{1}{2} \cdot \bar{T}(\frac{3n}{4}) + \frac{1}{2} \cdot \bar{T}(n) + O(n)$$

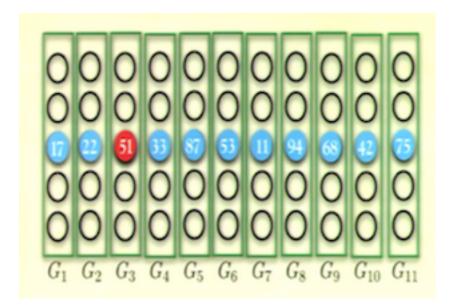
$$\Rightarrow \frac{1}{2} \cdot \bar{T}(n) \le \frac{1}{2} \cdot \bar{T}(\frac{3n}{4}) + O(n)$$

$$\Rightarrow \bar{T}(n) \le \bar{T}(\frac{3n}{4}) + O(n)$$

- Apply the Master Theorem
 - \rightarrow a = 1, b = $\frac{4}{3}$, and d = 1
 - \rightarrow This is Case 1 of the Master Theorem.
 - \rightarrow Runtime = $O(n^d) = O(n)$

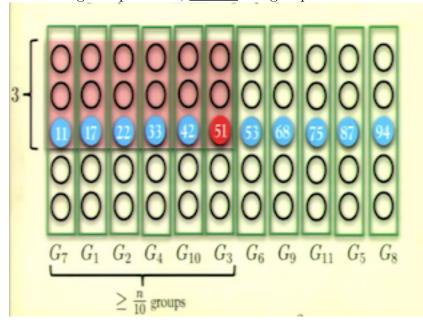
3 Deterministic Selection

- So we have a **linear time** <u>randomized</u> algorithm for the selection problem.
- Is there a linear time <u>deterministic</u> algorithm?
- To do this, what we need is a deterministic method to find a **good pivot**.
- The idea is to find "the median of the medians."
- Divide $S = \{x_1, x_2, \dots, x_n\}$ into groups of cardinality five: $G_1 = \{x_1, \dots, x_5\}, G_2 = \{x_6, \dots, x_{10}\}, \dots, G_{\frac{n}{5}} = \{x_{n-4}, \dots, x_n\}$
- Now sort each group and let z_i be the median of the froup G_i



• Let $\underline{\mathbf{m}}$ be the **median** of $Z = \{z_1, z_2, \cdot \cdot \cdot, z_{\frac{n}{5}}\}$

• As a thought experiment, <u>reorder</u> the groups their median values:



ullet The median of the medians is greater than at least $\frac{3n}{10}-1$ numbers in S

$$\Rightarrow |S_R| = |\{x_i \in S \setminus m : x_i \ge m\}| \le \frac{7}{10} \cdot n$$

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• There are at least $\frac{3n}{10} - 1$ numbers in S that are at least as big as m.

$$\Rightarrow |S_L| = |\{x_i \in S : x_i < m\}| \le \frac{7}{10} \cdot n$$



• Thus, using m as a **pivot** we have:

$$\Rightarrow max\{|S_L|, |S_R|\} \leq \frac{7}{10} \cdot n$$

- Thus the median of the medians is a **good** pivot.
- But how actually do we find the median of the medians?
 - \circ Using the same deterministic recursive algorithm!

;)

Deterministic Selection

```
DetSelect(S, k)

If |S| = 1 then output x_1

Else

Partition S into \left[\frac{n}{5}\right] groups of 5.

For j = \{1, 2, \dots, \frac{n}{5}\}

Let z_j be the median of group G_j

Let Z = \{z_1, z_2, \dots, z_{\left[\frac{n}{5}\right]}\}

Set m \leftarrow \text{DetSelect}(Z, \left[\frac{n}{10}\right])

Set S_L = \{x_i \in S : x_i < m\}

Set S_R = \{x_i \in S \setminus \{m\} : x_i \ge m\}

If |S_L| = k - 1 then output m

If |S_L| > k - 1 then output m

If |S_L| > k - 1 then output m

If |S_L| < k - 1 then output m

PetSelect(S_R, s_R)
```

• Thus, using m as a **pivot** we have:

$$\Rightarrow max\{|S_L|, |S_R|\} \leq \frac{7}{10} \cdot n$$

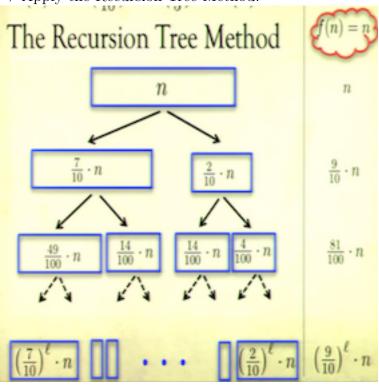
• The recursive formula for the running time is then:

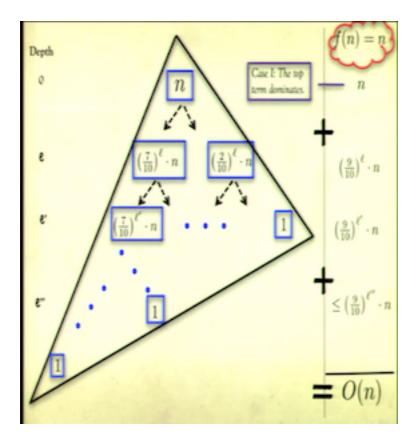
$$\Rightarrow T(n) \le T(\frac{7n}{10}) + T(\frac{n}{5}) + O(n)$$

Note:

- 1. $T(\frac{n}{5})$ term comes from finding the median of the medians.
- 2. $T(\frac{7n}{10})$ comes from that pivoting on the median of the medians gives a significantly smaller sub-problem.
- 3. O(n) comes from breaking in groups of size 5, finding the median of each group, and pivoting on the median of medians.
- But this does **not** fit with the Master Theorem!
 - The problem is not broken into the same sized sub-problems. One is $\frac{7n}{10}$, the other is $\frac{n}{5}$.

 \bullet This does not matter as we understand the proof of the Master Theorem, \Rightarrow Apply the Recursion Tree Method!





- Runtime: T(n) = O(n)
- Thus, we have a deterministic **linear time** algorithm to solve the selection problem (and, specifically, to find the median).
 - The reason why finding the selection problem is useful is that we try to find the median, but when we break it into two sub-problems, we are not finding the medians in the sub-problems since things would be shifted, and we might be finding the n over 10th problem.
 - This works a lot in induction. When you do induction proof, here we are using a stronger algorithm as our sub-routines, using kth selection problem, rather than median problem, which assumes that you have a stronger induction hypothesis. Often we use induction, it is hard to prove an easy result, since we can prove a general result, using induction.