Algorithm and Data Structure Analysis (ADSA)

Lecture 6: Order Statistics

Review: Sorting Algorithms Comparison Sorts

- Comparison sorts: O(n lg n) at best (decision tree with n! leaves → O(n lg n) height)
- Counting sort: O(n+k) =O(n) for n inputs in the range
 1..k (k=O(n))
- Radix sort: O(dn+dk)=O(n) for n numbers on d digits that range from 1..k (constant d, k=O(n))
- Bucket sort:
 - Use n buckets (linked lists) to divide interval [0,1) (range k=O(n)) into subintervals of size 1/n (k/n)
 - Uniform input distribution → O(1) bucket size → expected total time O(n)

- The *i*th *order statistic* in a set of *n* elements is the *i*th smallest element
- The minimum is thus the 1st order statistic
- The maximum is (duh) the nth order statistic
- The *median* is the n/2 order statistic
 - If n is even, there are 2 medians
- How can we calculate order statistics?
- What is the running time?

 How many comparisons are needed to find the minimum element in a set? The maximum?

```
MINIMUM(A, n)

1 min = A[1]

2 for i = 2 to n

3 if min > A[i]

4 min = A[i]

5 return min
```

There is a lower bound of n-1 comparisons for this problem

- How many comparisons are needed to find the minimum element in a set? The maximum?
- Can we simultaneously find the minimum and maximum with less than twice the cost?

- How many comparisons are needed to find the minimum element in a set? The maximum?
- Can we simultaneously find the minimum and maximum with less than twice the cost?
- Yes:
 - Walk through elements by pairs
 - Compare each element in pair to the other
 - Compare the largest to maximum, smallest to minimum
 - Total cost: 3 comparisons per 2 elements = O(3n/2)

Finding Order Statistics: The Selection Problem

 A more interesting problem is selection: finding the ith smallest element of a set

Finding Order Statistics: The Selection Problem

- A more interesting problem is selection: finding the ith smallest element of a set
- We will show:
 - A practical randomized algorithm with O(n) expected running time
 - A cool algorithm of theoretical interest only with
 O(n) worst-case running time

- Key idea: use partition() from quicksort
 - But, only need to examine one subarray
 - This savings shows up in running time: O(n)
- We will again use a slightly different partition than the book:

Array q = RandomizedPartition(A, p, r a segment of the array $\leq A[q]$ $\geq A[q]$ p r David Luebke

```
start end
RandomizedSelect(A, p, r, i)smallest segment among all the segments
    if (p == r) then return A[p];
    q = RandomizedPartition(A, p, r)
    k = q - p + 1;
    if (i == k) then return A[q]; // not in book
    if (i < k) then
         return RandomizedSelect(A, p, q-1, i);
    else
         return RandomizedSelect(A, q+1, r, i-k);
             \leq A[q]
                                          \geq A[q]
    p
                        David Luebke<sup>Q</sup>
```

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- Analyzing RandomizedSelect()
 - Worst case: partition always 0:n-1

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= $O(n^2)$

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```

- Better than sorting!
- What if this had been a 99:1 split? still linear time

- Average case
 - For upper bound, assume ith element always falls in larger side of partition:

when k = 0:

$$T(n-1)+$$

 $T(n-2)+$
 $T(n-3)+$
 $T(n-4)+$
...
 $T(n-4)+$
 $T(n-3)+$
 $T(n-3)+$
 $T(n-2)+$
 $T(n-2)+$
 $T(n-1)-$
Let's show that $T(n) = O(n)$ by substitution

David Luebke

• Assume $T(n) \le cn$ for sufficiently large c:

$$T(n) \leq \frac{2}{n} \sum_{k=n/2}^{n-1} T(k) + \Theta(n) \qquad The recurrence we started with$$

$$\leq \frac{2}{n} \sum_{k=n/2}^{n-1} ck + \Theta(n) \qquad Substitute T(n) \leq cn \text{ for } T(k)$$

$$= \frac{2c}{n} \left(\sum_{k=1}^{n-1} k - \sum_{k=1}^{n/2-1} k \right) + \Theta(n) \qquad \text{"Split" the recurrence}$$

$$= \frac{2c}{n} \left(\frac{1}{2} (n-1)n - \frac{1}{2} \left(\frac{n}{2} - 1 \right) \frac{n}{2} \right) + \Theta(n) \qquad Expand \text{ arithmetic series}$$

$$= c(n-1) - \frac{c}{2} \left(\frac{n}{2} - 1 \right) + \Theta(n) \qquad Multiply \text{ it out}$$

• Assume $T(n) \le cn$ for sufficiently large c:

$$T(n) \leq c(n-1) - \frac{c}{2} \left(\frac{n}{2} - 1\right) + \Theta(n) \qquad \text{The recurrence so far}$$

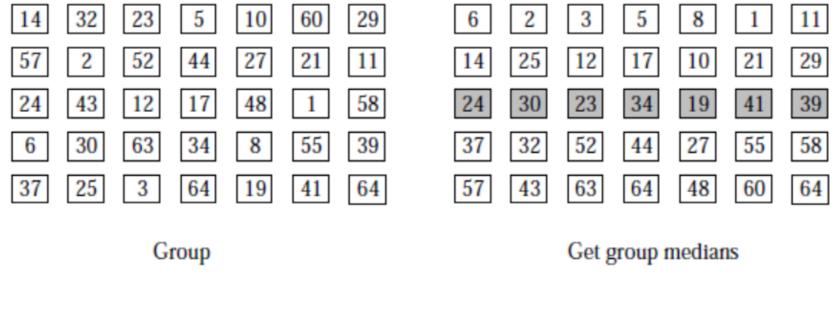
$$= cn - c - \frac{cn}{4} + \frac{c}{2} + \Theta(n) \qquad \text{Multiply it out}$$

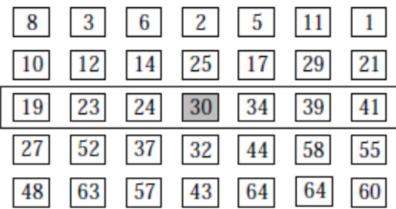
$$= cn - \frac{cn}{4} - \frac{c}{2} + \Theta(n) \qquad \text{Subtract c/2}$$

$$= cn - \left(\frac{cn}{4} + \frac{c}{2} - \Theta(n)\right) \qquad \text{Rearrange the arithmetic}$$

$$\leq cn \quad \text{(if c is big enough)} \qquad \text{What we set out to prove}$$

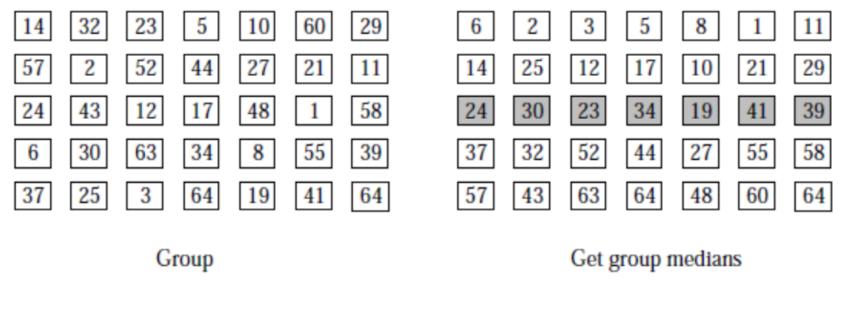
- Randomized algorithm works well in practice
- What follows is a worst-case linear time algorithm, really of theoretical interest only
- Basic idea:
 - Generate a good partitioning element
 - Call this element x





Get median of medians (Sorting of group medians is not really performed)

Figure 8: Choosing the Pivot. 30 is the final pivot.





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Figure 8: Choosing the Pivot. 30 is the final pivot.

The algorithm in words:

- 1. Divide *n* elements into groups of 5
- 2. Find median of each group (*How? How long?*)
- 3. Use Select() recursively to find median *x* of the [n/5] medians
- 4. Partition the *n* elements around *x*. Let k = rank(x)
- 5. **if** (i == k) **then** return x
 - if (i < k) then use Select() recursively to find ith smallest element in first partition
 - **else** (i > k) use Select() recursively to find (i-k)th smallest element in last partition

- (Sketch situation on the board)
- How many of the 5-element medians are $\leq x$?
 - At least 1/2 of the medians = $\lfloor \lfloor n/5 \rfloor / 2 \rfloor = \lfloor n/10 \rfloor$
- How many elements are $\leq x$?
 - At least 3 [n/10] elements
- For large n, $3 \lfloor n/10 \rfloor \ge n/4$ (How large?)
- So at least n/4 elements $\leq x$
- Similarly: at least n/4 elements $\geq x$

- Thus after partitioning around x, step 5 will call Select() on at most 3n/4 elements
- The recurrence is therefore:

$$T(n) \leq T(\lfloor n/5 \rfloor) + T(3n/4) + \Theta(n)$$

$$\leq T(n/5) + T(3n/4) + \Theta(n) \qquad [n/5] \leq n/5$$

$$\leq cn/5 + 3cn/4 + \Theta(n) \qquad Substitute \ T(n) = cn$$

$$= 19cn/20 + \Theta(n) \qquad Combine \ fractions$$

$$= cn - (cn/20 - \Theta(n)) \qquad Express \ in \ desired \ form$$

$$\leq cn \quad \text{if } c \text{ is big enough } What \ we \ set \ out \ to \ prove$$

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- Intuitively:
 - Work at each level is a constant fraction (19/20)
 smaller
 - Geometric progression!
 - Thus the O(n) work at the root dominates

Linear-Time Median Selection

- Given a "black box" O(n) median algorithm, what can we do?
 - ith order statistic:
 - Find median x
 - Partition input around x
 - if $(i \le (n+1)/2)$ recursively find ith element of first half
 - else find (i (n+1)/2)th element in second half
 - T(n) = T(n/2) + O(n) = O(n)
 - Can you think of an application to sorting?

Linear-Time Median Selection

- Worst-case O(n lg n) quicksort
 - Find median x and partition around it
 - Recursively quicksort two halves
 - $-T(n) = 2T(n/2) + O(n) = O(n \lg n)$

The End