

COMP 6651

Algorithm Design Techniques

Lecturer: Thomas Fevens

Department of Computer Science and Software Engineering, Concordia U
thomas.fevens@concordia.ca



COMP 6651

Week 3

Fall 2024

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Problem: Given an array A of n elements, find i th smallest element in it.

Ideas:

- 1 Find smallest, next smallest, etc.
This is the idea behind Heapsort. Here, we would stop when finding the i th smallest value, instead of at the largest value.
Heapsort is an example of a comparison-based sorting algorithm whose run-time is $\Theta(n \log n)$ in the worst case which is not a divide and conquer algorithm.
- 2 Sort elements, take $A[i]$.
- 3 Consider a direct divide and conquer approach for an algorithm.
We'll develop this idea in the next few slides.



Median and Order Statistics

The i th **order statistic** of a set of n elements is the i th smallest element

The **minimum** is the first order statistic ($i = 1$)

The **maximum** is the n th order statistic ($i = n$)

A **median** is the “halfway point” of a set.

n odd: median is unique, at the $(n + 1)/2$ th element

n even: **lower median** is $(n/2)$ th element,
upper median is $(n/2 + 1)$ th element.

We mean lower median when we use the phrase “the median”



Selection Problem

The Selection Problem:

Input: $A[1..n]$ - array of n integers

Output: $x \in A$ larger than exactly $i - 1$ elements in it,
= find i th **order statistic** of A .

Sorting all elements on order to find i th order statistics needs $O(n \log n)$ time.

We will improve on this time complexity. First, we will consider finding the minimum or maximum value.



We can easily obtain an upper bound of $n - 1$ comparisons for finding the minimum of a set of n elements.

- Examine each element in turn and keep track of the smallest one.
- This is the best we can do, because each element, except the minimum, must be compared to a smaller element at least once.

The following pseudocode finds the minimum element in array $A[1..n]$:

Minimum(A, n)

$min \leftarrow A[1]$

for $i \leftarrow 2, n$ **do**

if $min > A[i]$ **then**

$min \leftarrow A[i]$

return min

The maximum can be found in exactly the same way by replacing the $>$ with $<$ in the algorithm.



Simultaneous Minimum and Maximum (§9.1)

Some applications need both the minimum and maximum of a set of elements.

- For example, a graphics program may need to scale a set of (x, y) data to fit onto a rectangular display. To do so, the program must first find the minimum and maximum of each coordinate.

A simple algorithm to find the minimum and maximum is to find each one independently. There will be $n - 1$ comparisons for the minimum and $n - 1$ comparisons for the maximum, for a total of $2n - 2$ comparisons.

This will result in $\Theta(n)$ time.



In fact, at most $3\lfloor n/2 \rfloor$ comparisons suffice to find both the minimum and maximum:

- Maintain the minimum and maximum of elements seen so far.
- Don't compare each element to the minimum and maximum separately.
- Process elements in pairs.
- Compare the elements of a pair to each other.
- Then compare the larger element to the maximum so far, and compare the smaller element to the minimum so far.

This leads to only 3 comparisons for every 2 elements.



Setting up the initial values for the min and max depends on whether n is odd or even.

- If n is even, compare the first two elements and assign the larger to max and the smaller to min. Then process the rest of the elements in pairs.
- If n is odd, set both min and max to the first element. Then process the rest of the elements in pairs.

```

if  $A[i] > A[i + 1]$  then
    if  $max < A[i]$  then
         $max \leftarrow A[i]$ 
    if  $min > A[i + 1]$  then
         $min \leftarrow A[i + 1]$ 
else
    if  $max < A[i + 1]$  then
         $max \leftarrow A[i + 1]$ 
    if  $min > A[i]$  then
         $min \leftarrow A[i]$ 

```



- If n is even, do 1 initial comparison and then $3(n - 2)/2$ more comparisons.

$$\begin{aligned}
 \text{\# of comparisons} &= \frac{3(n - 2)}{2} + 1 \\
 &= \frac{3n - 6}{2} + 1 \\
 &= \frac{3n}{2} - 3 + 1 \\
 &= \frac{3n}{2} - 2.
 \end{aligned}$$

- If n is odd, do $3(n - 1)/2 = 3\lfloor n/2 \rfloor$ comparisons.

In either case, the maximum number of comparisons is $\leq 3\lfloor n/2 \rfloor$.



Selection in Expected Linear Time (§9.2)

There is a linear expected time algorithm for the selection problem. It uses the *divide and conquer* paradigm.

The function **Randomized-Select** uses **Randomized-Partition** from the Quicksort algorithm from last week. **Randomized-Select** differs from Quicksort in that it recurses on only one side of the partition.

Initially, call

Randomized-Select($A, 1, n, i$)

Randomized-Select(A, p, r, i)

\\ Find i th smallest element of $A[p..r]$

if $p = r$ **then**

return $A[p]$

$q \leftarrow$ **Randomized-Partition**(A, p, r)

$k \leftarrow q - p + 1$ \\ number of values in $[p..q]$

if $i = k$ **then**

return $A[q]$

else if $i < k$ **then**

return **Randomized-Select**($A, p, q - 1, i$)

else

return **Randomized-Select**($A, q + 1, r, i - k$)



After the call to **Randomized-Partition**, the array is partitioned into two subarrays $A[p..q - 1]$ and $A[q + 1..r]$, along with the pivot element at $A[q]$.

- The elements of the subarray $A[p..q - 1]$ are all $\leq A[q]$
- The elements of the subarray $A[q + 1..r]$ are all $> A[q]$
- The pivot element is the k th element of the array $A[p..r]$, where $k = q - p + 1$
- If the pivot element is the i th smallest element (i.e., $i = k$), return $A[q]$
- Otherwise, recursively select the appropriate element in **one of the two** partitions



The action of **Randomize-Select** as successive partitionings narrow $A[p..r]$

		p	r	i	partitioning																															
$A^{(0)}$	<table><tr><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td></tr><tr><td>6</td><td>19</td><td>4</td><td>12</td><td>14</td><td>9</td><td>15</td><td>7</td><td>8</td><td>11</td><td>3</td><td>13</td><td>2</td><td>5</td><td>10</td></tr></table>	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	6	19	4	12	14	9	15	7	8	11	3	13	2	5	10	1	15	5		
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The worst-case of **Randomize-Select** is $\Theta(n^2)$.

Theorem

The expected run-time $T(n)$ of **Randomize-Select** is linear, i.e., $T(n) = \Theta(n)$.

Proof

Randomize-Partition returns any value with the same probability as the pivot.

For any k the probability of getting a subarray with k elements, $1 \leq k \leq n$ is $1/n$.

Indicator (Bernoulli) Random variable X_k :

$$X_k = I\{\text{subarray } A[p..q] \text{ has exactly } k \text{ elements}\}$$

$$E[X_k] = 1/n$$

When $X_k = 1$ we recurse either on subarray of size $k - 1$ or $n - k$.

We assume that we have to look in the longer of the two subarrays.

$$T(n) \leq \sum_{k=1}^n X_k \cdot (T(\max(k-1, n-k)) + O(n))$$

$$T(n) \leq \sum_{k=1}^n (X_k \cdot T(\max(k-1, n-k)) + O(n))$$

$$E[T(n)] \leq E\left[\sum_{k=1}^n X_k \cdot T(\max(k-1, n-k)) + O(n)\right]$$

$$E[T(n)] \leq \sum_{k=1}^n E[X_k \cdot T(\max(k-1, n-k))] + O(n)$$

$$E[T(n)] \leq \sum_{k=1}^n E[X_k] \cdot E[T(\max(k-1, n-k))] + O(n)$$



$$E[T(n)] \leq \sum_{k=1}^n \frac{1}{n} \cdot E[T(\max(k-1, n-k))] + O(n)$$

$$k = 1 + i : \max(k-1, n-k) = n-i-1$$

$$k = n - i : \max(k-1, n-k) = n-i-1$$

\Rightarrow max values are same for $k \in [1.. \lfloor n/2 \rfloor - 1]$ and $k \in [\lfloor n/2 \rfloor .. n]$

$$E[T(n)] \leq \frac{2}{n} \sum_{k=\lfloor n/2 \rfloor}^n E[T(k)] + O(n)$$

Solve by substitution: assume $T(n) \leq cn$

$$E[T(n)] \leq \frac{2}{n} \sum_{k=\lfloor n/2 \rfloor}^n ck + an$$



$$E[T(n)] \leq \frac{2c}{n} \left(\sum_{k=1}^n k - \sum_{k=1}^{\lfloor n/2 \rfloor - 1} k \right) + an$$

$$E[T(n)] \leq \frac{2c}{n} ((n-1)n/2 - (\lfloor n/2 \rfloor - 1)\lfloor n/2 \rfloor / 2) + an$$

$$E[T(n)] \leq \frac{2c}{n} ((n-1)n/2 - (n/2 - 2)(n/2 - 1)/2) + an$$

$$E[T(n)] \leq \frac{c}{n} (3n^2/4 + n/2 - 2) + an$$

$$E[T(n)] \leq 3cn/4 + c/2 - 2/n + an$$

$$E[T(n)] \leq cn - (cn/4 - c/2 - an)$$

We need $(cn/4 - c/2 - an) \geq 0$ for sufficiently large n ,

or $n(c/4 - a) \geq c/2$ for sufficiently large n .

Choose $c > 4a$, and we have $n \geq 2c/(c - 4a)$.

All is fine if $T(n) = O(1)$ for small values of n .



Selection in Worst-case Linear Time (§9.3)

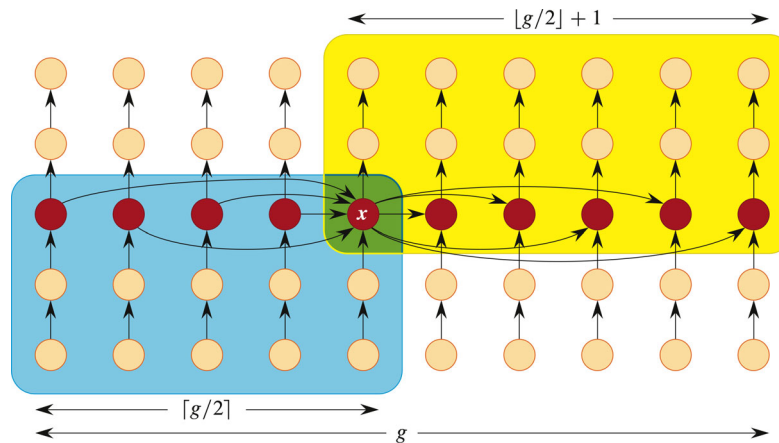
Can we make a **Select** algorithm to be linear in the worst case?

Make the split “good” in all cases by using all the time a provably “good” pivot.

- 1 Divide n elements into $\lfloor n/5 \rfloor$ groups of 5 elements, and one group that can have less than 5 elements.
- 2 Find the median of each group.
- 3 Use **Select** recursively on the medians to find the median x of the $\lceil n/5 \rceil$ median values.
- 4 Partition the entire input $A[p..r]$ around x , with the index for x being q , as before.
- 5 Continue as in the **Select** algorithm recursively.



How good is the partition around x ?



There are at least $3 \left(\lceil \frac{g}{2} \rceil \right) = 3 \left(\lceil \frac{1}{2} \lceil \frac{n}{5} \rceil \rceil \right) \geq 3n/10$ elements greater than x .

There are at least $3n/10$ elements less than x .



Analysis of Select

The code contains three recursive calls, of which at most two execute. The first recursive call to find the median of the medians always executes, taking $T(g) \leq T(\lceil n/2 \rceil)$. At most one of the other two recursive calls executes.

$$T(n) \leq \Theta(1) \text{ if } n \leq c$$

$$T(n) \leq T(\lceil n/5 \rceil) + T(7n/10) + O(n) \text{ if } n > c$$

We can solve the recurrence (by substitution for suitably large constant c) and get that

$$T(n) = cn$$

in the worst case.

Notice that the divide-and-conquer used here breaks **Select** the i th problem into a median problem + smaller **Select** the i th problem.



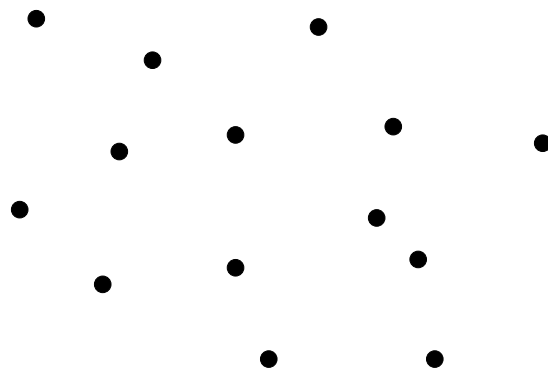
Selection versus Sorting

- Sorting requires $\Omega(n \lg n)$ time in the comparison model
- Sorting algorithms that run in linear time need to make assumptions about their input
- Linear-time *Selection* algorithms do not require any assumptions about their input
- Linear-time selection algorithms solve the selection problem **without** sorting and therefore are not subject to the $\Omega(n \lg n)$ lower bound



Finding a closest pair of points (§33.4 of 3rd Ed. of CLRS; not in 4th Ed.)

Given a set of n points Q in the plane, find a pair of points that is closest.



This is an example of a problem in **Computational Geometry**.

n points form $n(n - 1)/2$ different pairs of points.

An algorithm calculating distances between all pairs needs time $O(n^2)$.
Can we do better using Divide and Conquer?



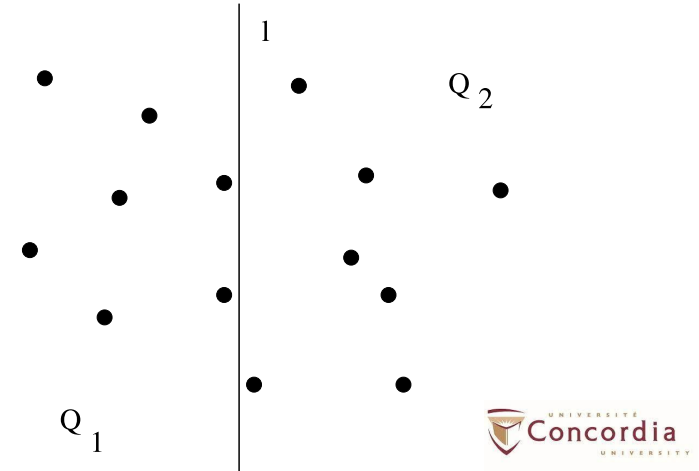
Basic idea:

If there are at most 3 points, solve the problem by calculating all pairs distances, otherwise:

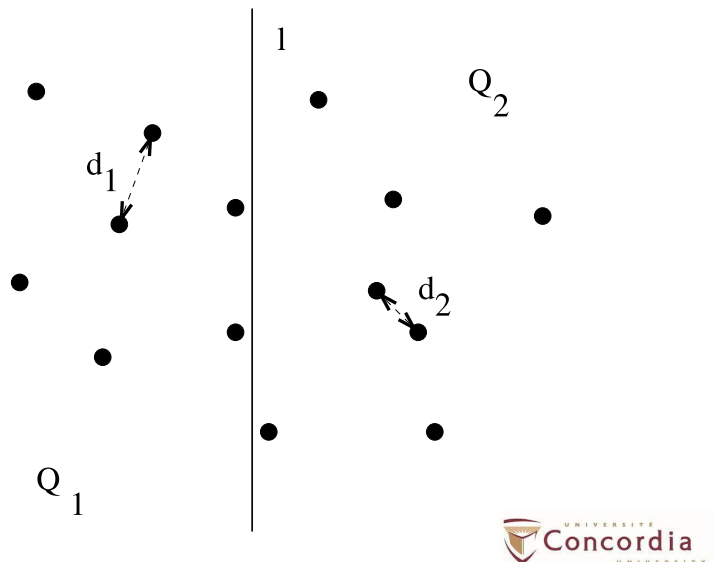
Divide:

Given Q , find a vertical line l that bisects Q into 2 subsets Q_1, Q_2 of the same size.

How? Select median in $O(n)$ time of the x -values.

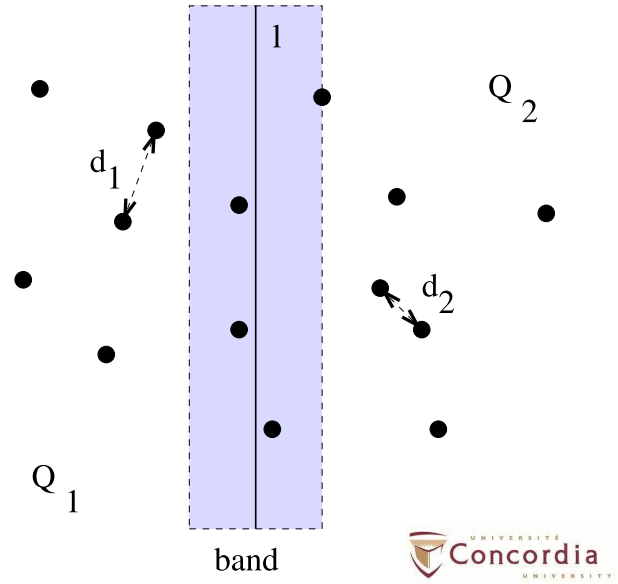
**Conquer (recursively):**

- a) Find the closest pair in Q_1 ,
- b) Find the closest pair in Q_2 ,



Combine:

Let δ be the closest distance in Q_1 and Q_2 .
Inspect the band around l of size 2δ and see
if any pair there is at distance $< \delta$. If yes,
that pair is the solution, otherwise it is a so-
lution of Q_1 or Q_2



We have to investigate whether the idea can be used to give an algorithm that is
better than the trivial $O(n^2)$ algorithm.

We want to show that we can achieve a recurrence

$$T(n) = 2T(n/2) + O(n)$$

which gives $T(n) = O(n \log n)$

We need to show that the *divide* and *combine* are both $O(n)$.

Before we start the algorithm. create from Q arrays

X that is sorted by x coordinate and

Y that is sorted by y coordinate.

X makes bisection very simple, and

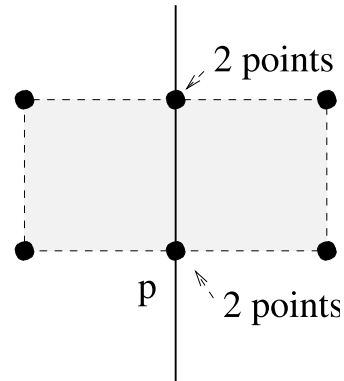
Y is used to make combine $O(n)$.

This adds *additive factor* $O(n \log n)$ to the algorithm.

Calculation of the pair of points at closest distance in the band:

1. Create Y' which contains all points of Y in the 2δ band.
2. For each $p \in Y'$ calculate the distance to the 7 points that follow p .

Why at most 7 points? ($\delta \times \delta$ square can contain at most 4 points at distance at least δ).



3. Keep the smallest distance less than δ distance so far.

This needs at most $O(n)$ time.



Time complexity: $T(n) + O(n \log n)$

$$T(n) = 2T(n/2) + O(n)$$

which gives $T(n) = O(n \log n)$

Thus the time complexity is $O(n \log n)$

If we sort the points after each bisection, we would get

Time complexity: $T(n)$ where

$$T(n) = 2T(n/2) + O(n \log n)$$

which gives $T(n) = \Theta(n \log^2 n)$



How many subproblems to use?

In all examples of divide and conquer algorithms, we have seen so far we used a division of a problem into 2 sub-problems.

This is the most common situation.

Division into three is more complicated in most cases,
division into 4 subproblems is equivalent to applying two steps in division into two subproblems.

We must use what is most convenient from the point of view of the problem.