

# **DESIGN AND ANALYSIS OF ALGORITHMS**

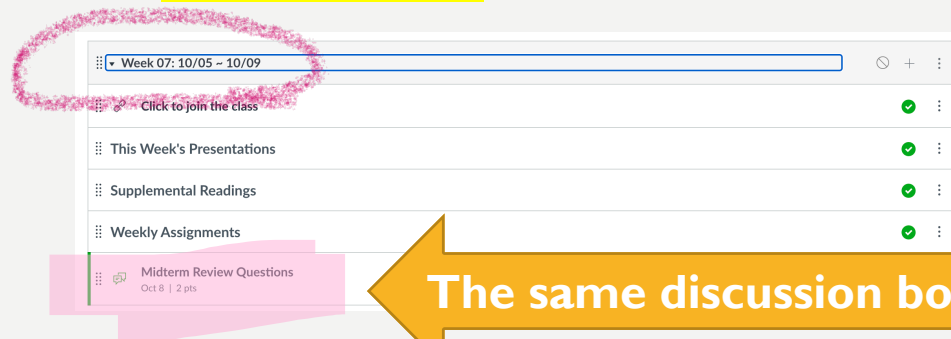
**CS 4120/5120  
PRUNE AND SEARCH**

# MIDTERM

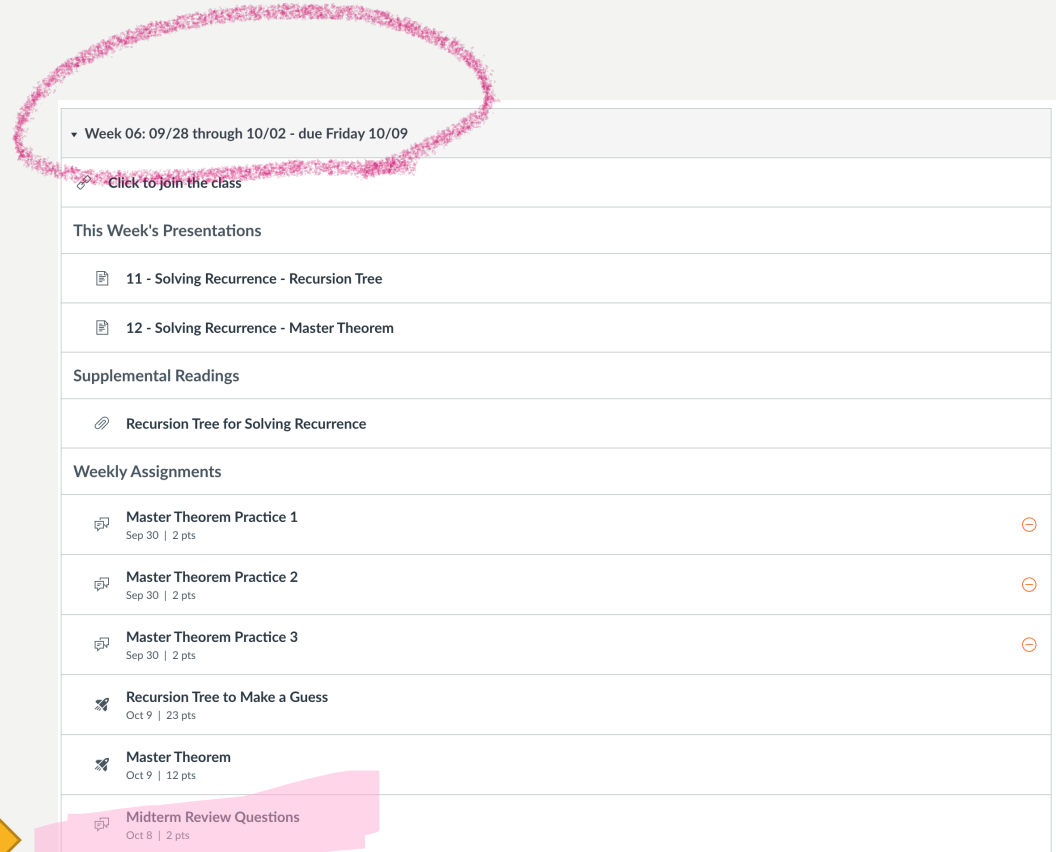
- Exam will be open on Monday Oct 12 and closed at 11:59pm Friday Oct 16 (8th week)
- Topics
  - Analyze algorithm
    - Correctness (loop invariant)
    - Efficiency (cost-time columns)
  - Asymptotic notations
  - Divide and conquer
  - Solving recurrence (substitution, recursion tree, master theorem)

# MIDTERM REVIEW

- A review of homework assignments will be arranged **next Friday Oct 9th**.
- I will be reviewing homework questions based on demands.
  - Please leave the question number in the discussion board



The same discussion board!



# AGENDA

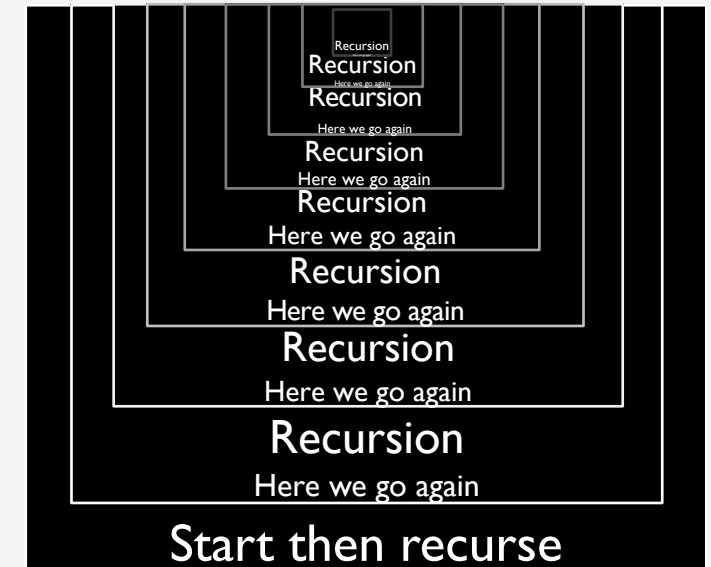
- **The topics moving forward will be assessed in the final exam.**
- Order statistic
- Prune and search steps
- Selection algorithm

# ORDER STATISTIC

- The  $i$ th order statistic of a set of  $n$  elements is the  $i$ th smallest element.
- The median of  $A[1..n]$ .
  - The “halfway point” of the set.
    - Regardless of the parity of  $n$ .
  - Medians occur at  $i = \left\lfloor \frac{n+1}{2} \right\rfloor$  and  $i = \left\lceil \frac{n+1}{2} \right\rceil$ .
    - Names: lower median and upper median, respectively.
    - By convention, we use the lower median.
  - We often use  $i = \left\lfloor \frac{n+1}{2} \right\rfloor$  (the lower mid) as the *halfway point* (*midpoint*) of an array  $A[1..n]$ .

# PRUNE AND SEARCH

- Decrease and conquer
  - **Divide** the problem into a number of subproblems that are smaller instances of the same problem.
  - **Prune** the subproblems and eliminate some instances based on certain criteria.
  - **Conquer** the original problem by solving remaining subproblem recursively.
    - As the problem gets smaller, a straight-forward method can be used.
- Example: Binary search, Selection



# SELECTION PROBLEM

- Problem
  - Input: An array  $A[1..n]$  that contains  $n$  distinct numbers, and an integer  $i \in [1, n]$ .
  - Output: An element  $x \in A$  that  $x$  is greater than exactly  $i - 1$  other elements of  $A$ .  $\Leftrightarrow$   **$i$ th statistic**
- Example
  - Input: Array  $A = \{8, 25, 3, 37, 12, 16, 7, 22\}$ , and  $i = 4$ .
  - Output:  $x = 12$
- **Algorithm?**

# SELECTION PROBLEM

## BRAIN STORMING

- Problem
  - Input: An array  $A[1..n]$  that contains  $n$  distinct numbers, and an integer  $i \in [1, n]$ .
  - Output: An element  $x \in A$  that  $x$  is greater than exactly  $i - 1$  other elements of  $A$ .
- How many ways to find the  **$i$ th statistic** of  $A[1..n]$ ?
- What is their complexities?



# SELECTION PROBLEM

## SOLUTION 1

- Sort the numbers in array  $A$  in increasing order **Fastest  $O(n \cdot \log n)$**
- Return  $A[i]$ .  **$\Theta(1)$**

# SELECTION PROBLEM

## SOLUTION 2

- Perform  $i$  scans. Each scan finds the min of the array excluding the min found in previous scans.

SELECT-BY-SCAN ( $A, n, i$ )		Cost	Time (Worst-case Scenario)
1	<b>for</b> $j = 1$ <b>to</b> $i$	$\Theta(1)$	$i + 1$
2	$k = j$	$\Theta(1)$	$i$
3	$MIN = A[k]$	$\Theta(1)$	$i$
4	<b>for</b> $k = j$ <b>to</b> $n$	$\Theta(1)$	$\sum_{j=1}^i t_j$
5	<b>if</b> $A[k] < MIN$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
6	$MIN = A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
7	Swap $A[j]$ and $A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$

# SELECTION PROBLEM

## SOLUTION 2 (CONT'D)

- Perform  $i$  scans. Each scan finds the min of the array excluding the min found in previous scans.

- Running time  

$$T(n) = \Theta(i) + \Theta(1) + \Theta\left(\sum_{j=1}^i t_j\right) +$$

$$\Theta\left(\sum_{j=1}^i (t_j - 1)\right)$$

, where  $t_j$  denotes the # of exe of line 4 for a value of  $j$ .

SELECT-BY-SCAN ( $A, n, i$ )		Cost	Time (Worst-case Scenario)
1	<b>for</b> $j = 1$ <b>to</b> $i$	$\Theta(1)$	$i + 1$
2	$k = j$	$\Theta(1)$	$i$
3	$MIN = A[k]$	$\Theta(1)$	$i$
4	<b>for</b> $k = j$ <b>to</b> $n$	$\Theta(1)$	$\sum_{j=1}^i t_j$
5	<b>if</b> $A[k] < MIN$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
6	$MIN = A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
7	Swap $A[j]$ and $A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$

# SELECTION PROBLEM

## SOLUTION 2 (CONT'D)

- Perform  $i$  scans. Each scan finds the min of the array excluding the min found in previous scans.
- Obviously, for a value of  $j$ , the **for**-statement (line 4) will execute  $n - j + 1 + 1 = \mathbf{n - j + 2}$  times.

- Running time

$$T(n) = \Theta(i) + \Theta(1) + \Theta\left(\sum_{j=1}^i (\mathbf{n - j + 2})\right) + \Theta\left(\sum_{j=1}^i (\mathbf{n - j + 1})\right)$$

SELECT-BY-SCAN ( $A, n, i$ )		Cost	Time (Worst-case Scenario)
1	<b>for</b> $j = 1$ <b>to</b> $i$	$\Theta(1)$	$i + 1$
2	$k = j$	$\Theta(1)$	$i$
3	$MIN = A[k]$	$\Theta(1)$	$i$
4	<b>for</b> $k = j$ <b>to</b> $n$	$\Theta(1)$	$\sum_{j=1}^i t_j$
5	<b>if</b> $A[k] < MIN$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
6	$MIN = A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
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# SELECTION PROBLEM

## SOLUTION 2 (CONT'D)

- Perform  $i$  scans. Each scan finds the min of the array excluding the min found in previous scans.
- Obviously, for a value of  $j$ , the **for**-statement (line 4) will execute  $n - j + 1 + 1 = \mathbf{n - j + 2}$  times.

- Running time

$$T(n) = \Theta(i) + \Theta(1) +$$

$$\Theta\left(\mathbf{i}n - \frac{i(1+i)}{2} + \mathbf{2}i\right) +$$

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SELECT-BY-SCAN ( $A, n, i$ )		Cost	Time (Worst-case Scenario)
1	<b>for</b> $j = 1$ <b>to</b> $i$	$\Theta(1)$	$i + 1$
2	$k = j$	$\Theta(1)$	$i$
3	$MIN = A[k]$	$\Theta(1)$	$i$
4	<b>for</b> $k = j$ <b>to</b> $n$	$\Theta(1)$	$\sum_{j=1}^i t_j$
5	<b>if</b> $A[k] < MIN$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
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# SELECTION PROBLEM

## SOLUTION 2 (CONT'D)

- Perform  $i$  scans. Each scan finds the min of the array excluding the min found in previous scans.
- Obviously, for a value of  $j$ , the **for**-statement (line 4) will execute  $n - j + 1 + 1 = n - j + 2$  times.

- Running time

$$T(n) = \Theta(i) + \Theta(1) +$$

$$O(i^2) +$$

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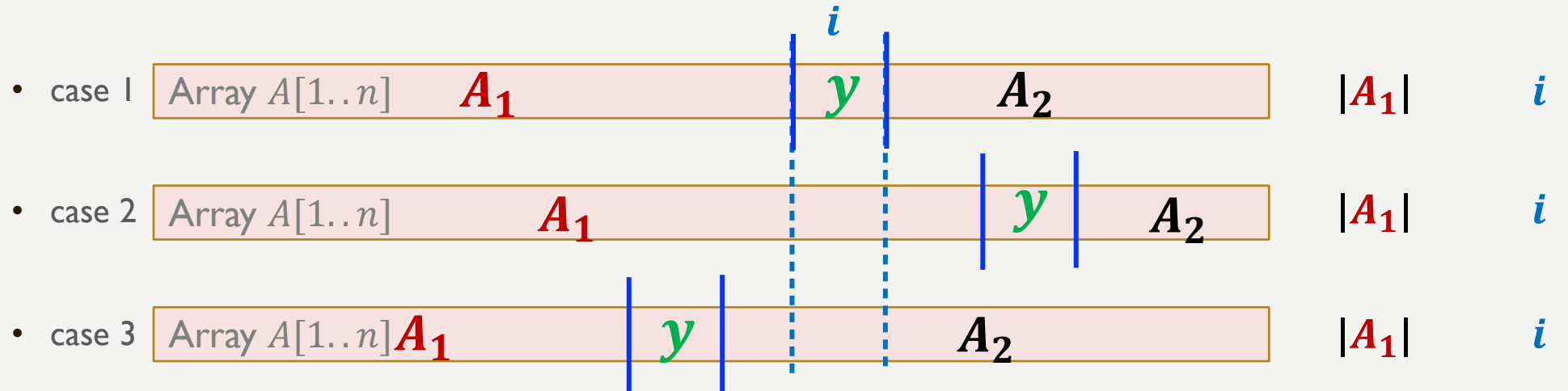
$$= O(i^2)$$

SELECT-BY-SCAN ( $A, n, i$ )		Cost	Time (Worst-case Scenario)
1	<b>for</b> $j = 1$ <b>to</b> $i$	$\Theta(1)$	$i + 1$
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6	$MIN = A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$
7	Swap $A[j]$ and $A[k]$	$\Theta(1)$	$\sum_{j=1}^i (t_j - 1)$

# SELECTION PROBLEM

## SOLUTION 3

- **Step 1:** Randomly pick a number  $y$  in  $A$ . **Divide**  $A$  into two subarrays  $A_1$  and  $A_2$ , such that
  - All the numbers in  $A_1$  are  $< y$ ; all the numbers in  $A_2$  are  $> y$
  - What the relationship between  $|A_1|$  and  $i$ ?





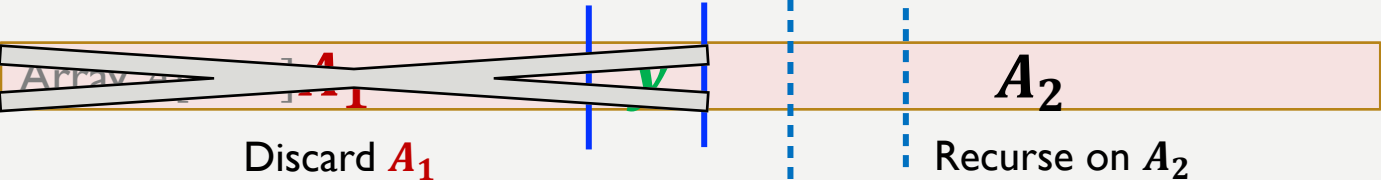
# SELECTION PROBLEM

## SOLUTION 3

- **Step 2: Prune** the subarrays based on the relation between  $|A_1|$  and  $i$ .



return

- case 1   $|A_1| = i - 1$
- case 2   $|A_1| > i - 1$
- case 3   $|A_1| < i - 1$



# RANDOMIZED SELECT ALGORITHM

## SOLUTION 3

- Let the input be  $(A, p, r, i)$ 
  - $A$  is the array
  - $p$  is the low index
  - $r$  is the high index
  - $i$  is the  $i$ th order statistic of  $A$  that we wish to find

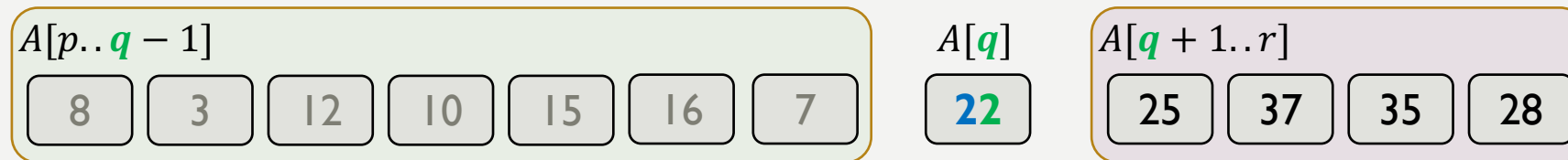
RANDOMIZED-SELECT ( $A, p, r, i$ )	
Bottoms-out case	1 <b>if</b> $p == r$
	2 <b>return</b> $A[p]$
Partition	3 $q = \text{RANDOMIZED-PARTITION}(A, p, r)$
	4 $k = q - p + 1$
Prune (5, 7)- and- search (8,9)	5 <b>if</b> $i == k$
	6 <b>return</b> $A[q]$
	7 <b>elseif</b> $i < k$
	8 <b>return</b> RANDOMIZED-SELECT( $A, p, q - 1, i$ )
	9 <b>else return</b> RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )

# RANDOMIZED SELECT ALGORITHM

## WORKING PROCESS CASE 1

- After RANDOMIZED-PARTITIONing the input  $A[p..r]$ , use  $q$  to denote the **pivot** index.
- Use the instance  $A = \{8, 25, 3, 37, 12, 10, 35, 15, 28, 16, 7, \mathbf{22}\}$ ,  $i = 8$ .
- **Compare** the length of  $A[p..q] = k$  with  $i$ .

– **Case I**



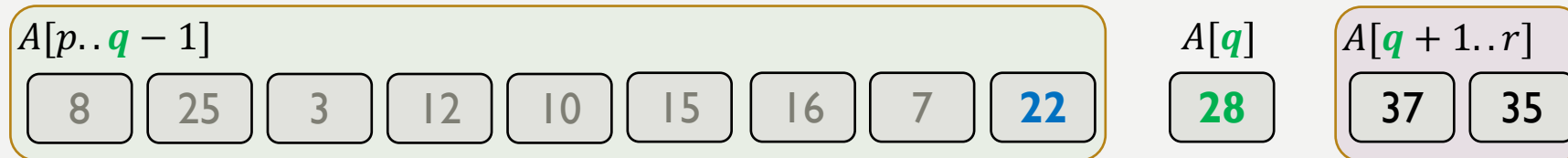
- $q =$  \_\_\_\_\_; the length of  $A[p..q] = k =$  \_\_\_\_\_;
- $i$  \_\_\_\_\_  $k$ , the  $i$ th order statistic of  $A$  is \_\_\_\_\_.

# RANDOMIZED SELECT ALGORITHM

## WORKING PROCESS CASE 2

- After RANDOMIZED-PARTITIONing the input  $A[p..r]$ , use  $q$  to denote the **pivot** index.
- Use the instance  $A = \{8, 25, 3, 37, 12, 10, 35, 15, 28, 16, 7, 22\}$ ,  $i = 8$ .
- **Compare** the length of  $A[p..q] = k$  with  $i$ .

### – Case 2



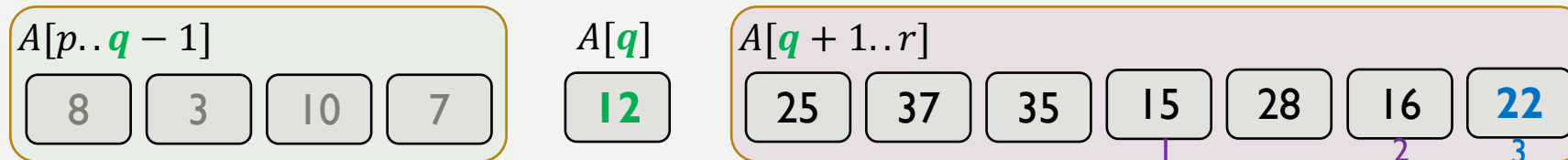
- $q =$  \_\_\_\_\_; the length of  $A[p..q] = k =$  \_\_\_\_\_;
- $i$  \_\_\_\_\_  $k$ , the  $i$ th order statistic of  $A$  lies in subarray \_\_\_\_\_.

**Recurse** on  $A[ \text{_____} ]$ . Find the \_\_\_\_\_ th order statistic of  $A[ \text{_____} ]$ .

# RANDOMIZED SELECT ALGORITHM

## WORKING PROCESS CASE 3

- After RANDOMIZED-PARTITIONing the input  $A[p..r]$ , use  $q$  to denote the **pivot** index.
- Use the instance  $A = \{8, 25, 3, 37, 12, 10, 35, 15, 28, 16, 7, \mathbf{22}\}$ ,  $i = 8$ .
- **Compare** the length of  $A[p..q] = k$  with  $i$ .
  - **Case 3**



- $q =$  \_\_\_\_\_; the length of  $A[p..q] = k =$  \_\_\_\_\_;
- $i$  \_\_\_\_\_  $k$ , the  $i$ th order statistic of  $A$  lies in subarray \_\_\_\_\_.

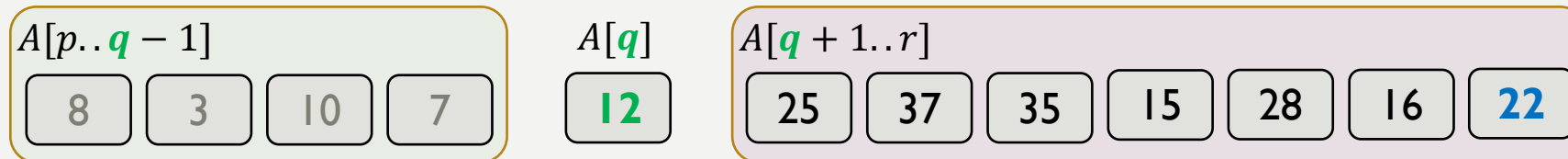
Is 22 still the 8th order statistic of  $A[q+1..r]$ ? What is the next step and what is the new goal?

# RANDOMIZED SELECT ALGORITHM

## WORKING PROCESS CASE 3

- After RANDOMIZED-PARTITIONing the input  $A[p..r]$ , use  $q$  to denote the **pivot** index.
- Use the instance  $A = \{8, 25, 3, 37, 12, 10, 35, 15, 28, 16, 7, 22\}$ ,  $i = 8$ .
- **Compare** the length of  $A[p..q] = k$  with  $i$ .

### – Case 3



- $q =$  \_\_\_\_\_; the length of  $A[p..q] = k =$  \_\_\_\_\_;
- $i$  \_\_\_\_\_  $k$ , the  $i$ th order statistic of  $A$  lies in subarray \_\_\_\_\_.

**Recurse** on  $A[ \text{_____} ]$ . Find the \_\_\_\_\_th order statistic of  $A[ \text{_____} ]$ .

# RANDOMIZED SELECT ALGORITHM

## COST-TIME COLUMNS

- Complete the **cost-time** columns of the RANDOMIZED-SELECT ( $A, p, r, i$ ) on input  $A[p..r]$ .
  - Use function  $f(r - p + 1)$  to denote the cost of RANDOMIZED-PARTITION ( $A, p, r$ )

RANDOMIZED-SELECT ( $A, p, r, i$ )		Cost	Time (Best)	Time (Worst)
1	if $p == r$			
2	return $A[p]$			
3	$q = \text{RANDOMIZED-PARTITION}(A, p, r)$			
4	$k = q - p + 1$			
5	if $i == k$			
6	return $A[q]$			
7	elseif $i < k$			
8	return RANDOMIZED-SELECT( $A, p, q - 1, i$ )			
9	else return RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )			

# RANDOMIZED SELECT ALGORITHM

## COST-TIME COLUMNS

- Complete the **cost-time** columns of the RANDOMIZED-SELECT ( $A, p, r, i$ ) on input  $A[p..r]$ .
  - Use function  $f(r - p + 1)$  to denote the cost of RANDOMIZED-PARTITION ( $A, p, r$ )

RANDOMIZED-SELECT ( $A, p, r, i$ )		Cost	Time (Best)	Time (Norm.)
1	if $p == r$	$\Theta(1)$	base	base
2	return $A[p]$	$\Theta(1)$	base	base
3	$q = \text{RANDOMIZED-PARTITION}(A, p, r)$	$f(r - p + 1)$	1	1
4	$k = q - p + 1$	$\Theta(1)$	1	1
5	if $i == k$	$\Theta(1)$	1	1
6	return $A[q]$	$\Theta(1)$	1	0
7	elseif $i < k$	$\Theta(1)$	0	1
8	return RANDOMIZED-SELECT( $A, p, q - 1, i$ )	$T(q - p)$	0	0/1
9	else return RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )	$T(r - q)$	0	1/0

# RANDOMIZED SELECT ALGORITHM

## RUNNING TIME FUNCTION

- **Best**-of-all scenario
  - $x =$  \_\_\_\_\_.
- **Normal** scenario
  - $x$  lies in \_\_\_\_\_.
- The running time of the normal scenario  
 $T(r - p + 1)$   
 $= \Theta(1) +$   
 $f(r - p + 1) + \max\{T(q - p), T(r - q)\}$

RANDOMIZED-SELECT ( $A, p, r, i$ )		Cost	Time (Best)	Time (Norm.)
1	if $p == r$	$\Theta(1)$	base	base
2	return $A[p]$	$\Theta(1)$	base	base
3	$q = \text{RANDOMIZED-PARTITION}(A, p, r)$	$f(r - p + 1)$	1	1
4	$k = q - p + 1$	$\Theta(1)$	1	1
5	if $i == k$	$\Theta(1)$	1	1
6	return $A[q]$	$\Theta(1)$	1	0
7	elseif $i < k$	$\Theta(1)$	0	1
8	return RANDOMIZED-SELECT( $A, p, q - 1, i$ )	$T(q - p)$	0	0/1
9	else return RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )	$T(r - q)$	0	1/0



# RANDOMIZED PARTITION ALGORITHM

- The algorithm uses a random number generator to generate a value  $i \in [p, r]$ .
- Then it moves  $A[i]$  to **the tail of (sub)array  $A[p..r]$** .
- Lastly, it applies normal partition on  $A[p..r]$ .

RANDOMIZED-PARTITION ( $A, p, r$ )	
1	$i = \text{RANDOM}(p, r)$
2	exchange $A[r]$ with $A[i]$
3	return PARTITION ( $A, p, r$ )

# RANDOMIZED PARTITION ALGORITHM

## RUNNING TIME

- Complete the **cost** and **time** columns.
  - Use  $f'(r - p + 1)$  to denote the cost of partitioning  $A[p..r]$  around  $A[r]$ .
- The running time of the algorithm on (sub)array  $A[p..r]$ 

$$f(r - p + 1)$$

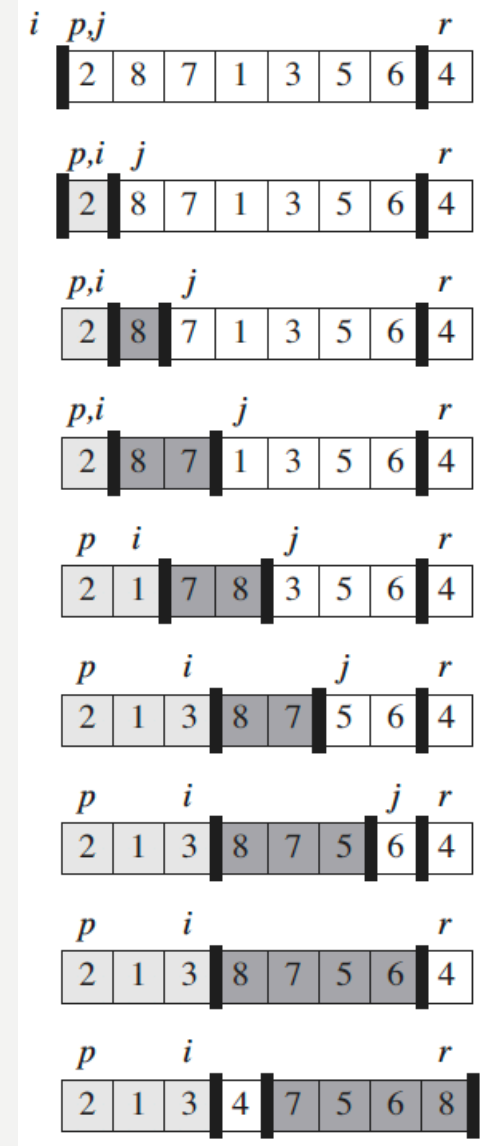
$$= \Theta(1) + f'(r - p + 1)$$

RANDOMIZED-PARTITION ( $A, p, r$ )		Cost	Time (Best)	Time (Norm.)
1	$i = \text{RANDOM}(p, r)$	$\Theta(1)$	1	1
2	exchange $A[r]$ with $A[i]$	$\Theta(1)$	1	1
3	return PARTITION ( $A, p, r$ )	$f'(r - p + 1)$	1	1

# THE PARTITION PROCEDURE

- The **PARTITION** procedure uses **the tail of (sub)array  $A[p..r]$**  as the **pivot** to partition  $A[p..r]$  in to three parts.
  - Subarray  $A[p..i]$  that contains the elements  $<$  pivot
  - $A[i + 1]$  the pivot
  - Subarray  $A[i + 2..r]$  that contains the elements  $>$  pivot.

<b>PARTITION</b> ( $A, p, r$ )	
1	$x = A[r]$
2	$i = p - 1$
3	<b>for</b> $j = p$ <b>to</b> $r - 1$
4	<b>if</b> $A[j] \leq x$
5	$i = i + 1$
6	exchange $A[i]$ with $A[j]$
7	exchange $A[i + 1]$ with $A[r]$
8	<b>return</b> $i + 1$



# THE PARTITION PROCEDURE

## RUNNING TIME

- Best-case scenario
  - \_\_\_\_\_.
- Worst-case scenario
  - \_\_\_\_\_.
- The running time of **PARTITION**ing (sub)array  $A[p..r]$  in the **worst**-case  
 $f'(r - p + 1)$   
 $= \Theta(1) + \Theta(r - p) + \Theta(r - p - 1)$   
 $= \Theta(1) + \Theta(r - p)$

<b>PARTITION</b> ( $A, p, r$ )	Cost	Time ( <b>Best</b> )	Time ( <b>Worst</b> )
1 $x = A[r]$	$\Theta(1)$	1	1
2 $i = p - 1$	$\Theta(1)$	1	1
3 <b>for</b> $j = p$ <b>to</b> $r - 1$	$\Theta(1)$	$r - p$	$r - p$
4 <b>if</b> $A[j] \leq x$	$\Theta(1)$	$r - p - 1$	$r - p - 1$
5 $i = i + 1$	$\Theta(1)$	<b>0</b>	<b><math>r - p - 1</math></b>
6             exchange $A[i]$ with $A[j]$	$\Theta(1)$	<b>0</b>	<b><math>r - p - 1</math></b>
7 exchange $A[i + 1]$ with $A[r]$	$\Theta(1)$	1	1
8 <b>return</b> $i + 1$	$\Theta(1)$	1	1

# RANDOMIZED PARTITION ALGORITHM

## RUNNING TIME (COMING BACK)

- The running time of the algorithm on (sub)array  $A[p..r]$

$$f(r - p + 1)$$

$$= \Theta(1) + f'(r - p + 1)$$

, where  $f'(r - p + 1)$  is the running time of the **PARTITION** procedure.

- $f'(r - p + 1) = \Theta(1) + \Theta(r - p)$
- $f(r - p + 1) = \Theta(1) + \Theta(1) + \Theta(r - p) = \Theta(1) + \Theta(r - p)$

RANDOMIZED-PARTITION ( $A, p, r$ )		Cost	Time (Best)	Time (Norm.)
1	$i = \text{RANDOM}(p, r)$	$\Theta(1)$	1	1
2	exchange $A[r]$ with $A[i]$	$\Theta(1)$	1	1
3	return <b>PARTITION</b> ( $A, p, r$ )	$f'(r - p + 1)$	1	1

# RANDOMIZED SELECT ALGORITHM

## RUNNING TIME FUNCTION (BACK)

- The running time of the normal scenario  
 $T(r - p + 1)$

$$= \Theta(1) +$$

$$\Theta(1) + \Theta(r - p) +$$

$$\max\{T(q - p), T(r - q)\}$$

$$= \Theta(1) + \Theta(r - p) +$$

$$\max\{T(q - p), T(r - q)\}$$

RANDOMIZED-SELECT ( $A, p, r, i$ )		Cost	Time (Best)	Time (Norm)
1	if $p == r$	$\Theta(1)$	base	base
2	return $A[p]$	$\Theta(1)$	base	base
3	$q = \text{RANDOMIZED-PARTITION}(A, p, r)$	$f(r - p + 1)$	1	1
4	$k = q - p + 1$	$\Theta(1)$	1	1
5	if $i == k$	$\Theta(1)$	1	1
6	return $A[q]$	$\Theta(1)$	1	0
7	elseif $i < k$	$\Theta(1)$	0	1
8	return RANDOMIZED-SELECT( $A, p, q - 1, i$ )	$T(q - p)$	0	0/1
9	else return RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )	$T(r - q)$	0	1/0

# APPLY RANDOMIZED-SELECT ON $A[1..n]$

- Call RANDOMIZED-SELECT ( $A, \_, \_, i$ )  
–  $n = \underline{\hspace{2cm}}$ .

- The running time of the worst-case scenario

$$T(r - p + 1)$$

$$= \Theta(1) + \Theta(r - p) + \max\{T(q - p), T(r - q)\}$$

$$= \Theta(1) + \Theta(n - 1) + \max\{T(q - 1), T(n - q)\} = T(n)$$

RANDOMIZED-SELECT ( $A, p, r, i$ )		Cost	Time (Best)	Time (Norm.)
1	if $p == r$	$\Theta(1)$	base	base
2	return $A[p]$	$\Theta(1)$	base	base
3	$q = \text{RANDOMIZED-PARTITION}(A, p, r)$	$f(r - p + 1)$	1	1
4	$k = q - p + 1$	$\Theta(1)$	1	1
5	if $i == k$	$\Theta(1)$	1	1
6	return $A[q]$	$\Theta(1)$	1	0
7	elseif $i < k$	$\Theta(1)$	0	1
8	return RANDOMIZED-SELECT( $A, p, q - 1, i$ )	$T(q - p)$	0	0/1
9	else return RANDOMIZED-SELECT( $A, q + 1, r, i - k$ )	$T(r - q)$	0	1/0

# APPLY RANDOMIZED-SELECT ON $A[1..n]$ **BEST CASE**

- Simplify the running time function of the normal scenario

$$T(n) = \Theta(n) + \textcolor{red}{max} \{T(\textcolor{green}{q} - 1), T(n - \textcolor{green}{q})\}$$

- The **best-case** scenario of the normal case

- $\textcolor{green}{q} = \underline{\hspace{2cm}}$
- yielding  $T(n) = \underline{\hspace{2cm}}$ .
- $T(n) = O(\underline{\hspace{2cm}})$ .



# APPLY RANDOMIZED-SELECT ON $A[1..n]$ **WORST** CASE

- Simplify the running time function of the normal scenario

$$T(n) = \Theta(n) + \text{max} \{T(q - 1), T(n - q)\}$$

- The **worst**-of-all scenario

- $q = \underline{\hspace{2cm}}$
- yielding  $T(n) = \underline{\hspace{2cm}}$ .
- $T(n) = O(\underline{\hspace{2cm}})$ .

# RANDOMIZED-SELECT

## TIME COMPLEXITY

- The **best-case** scenario of the normal case  $T(n) = \underline{\Theta(n) + T(n/2)} = O(\underline{n})$ .
- The **worst-case** scenario of the normal case  $T(n) = \underline{\Theta(n) + T(n-1)} = O(\underline{n^2})$ .
- The **expected** time complexity
  - We can find any order statistic in **expected** linear time, assuming that the elements are distinct.
$$E[T(n)] = O(n)$$
  - See textbook page 217 – 219 for proof.

- **Improvement?**

# **NEXT UP**

## **SELECT IN WORST-CASE LINEAR TIME**

# REFERENCE