



Lecture 19

Recap part A

CS 161 Design and Analysis of Algorithms

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Divide and conquer method

- Steps of method:
 - **Divide** input into parts (**smaller problems**)
 - **Conquer** (solve) each part recursively
 - **Combine** results to obtain solution of original

$$\begin{aligned} T(n) = & \text{divide time} \\ & + T(n_1) + T(n_2) + \dots + T(n_k) \\ & + \text{combine time} \end{aligned}$$

Mergesort - A fast sorting recursive Algorithm

- Key idea:
 - Divide** input into two parts of equal size
 - Sort** each part recursively
 - Merge** the two sorted parts to obtain the solution.

Example: Sort the following 11 numbers

9 3 4 220 1 3 10 5 8 7 2

Divide

Recursion

Merge

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9 3 4 220 1 3 10 5 8 7 2

9 3 4 220 1

3 10 5 8 7 2

Divide

1 3 4 9 220

2 3 5 7 8 10

Recursion

Merge

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 - Divide** input into two parts of equal size
 - Sort** each part recursively
 - Merge** the two sorted parts to obtain the solution.

Example: Sort the following 11 numbers

9 3 4 220 1 3 10 5 8 7 2

9 3 4 220 1

3 10 5 8 7 2

Divide

1 3 4 9 220

2 3 5 7 8 10

Recursion

1 2 3 3 4 5 7 8 9 10 220

Merge

Mergesort - A fast sorting recursive Algorithm

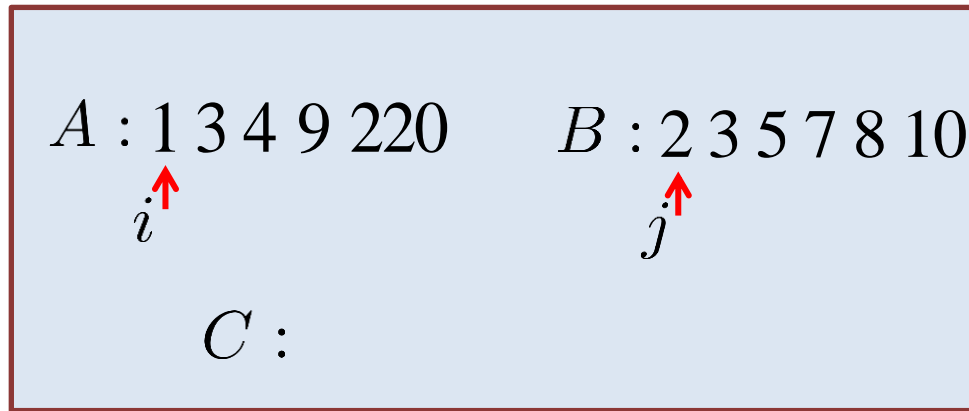
- Tricky part: Merge

Problem: Given two sorted arrays A , B , merge them to a sorted array C .

Mergesort - A fast sorting recursive Algorithm

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Mergesort - A fast sorting recursive Algorithm

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$A : 1\ 3\ 4\ 9\ 220$

$i \uparrow$

$B : 2\ 3\ 5\ 7\ 8\ 10$

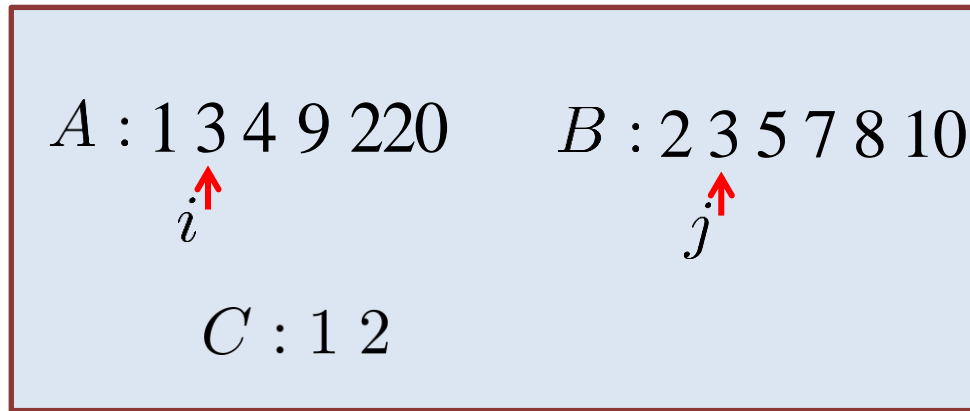
$j \uparrow$

$C : 1$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: **Merge**

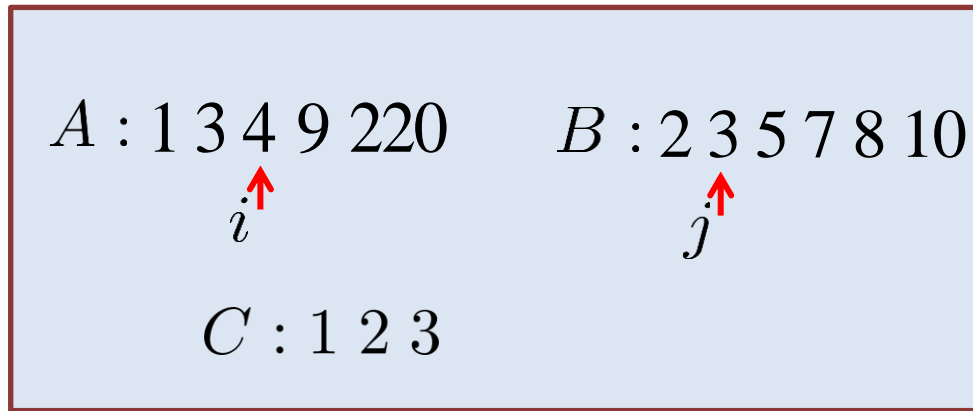
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Mergesort - A fast sorting recursive Algorithm

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Mergesort - A fast sorting recursive Algorithm

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Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1\ 3\ 4\ 9\ 220$

$i \uparrow$

$B : 2\ 3\ 5\ 7\ 8\ 10$

$j \uparrow$

$C : 1\ 2\ 3\ 3$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: Merge

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1\ 3\ 4\ 9\ 220$

 i
$$B : 2 \ 3 \ 5 \ 7 \ 8 \ 10$$
 j^{\uparrow}
$$C : 1 \ 2 \ 3 \ 3 \ 4$$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: **Merge**

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1\ 3\ 4\ 9\ 22\ 0$ $B : 2\ 3\ 5\ 7\ 8\ 10$

i j

$C : 1\ 2\ 3\ 3\ 4\ 5$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: **Merge**

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1\ 3\ 4\ 9\ 22\ 0$ $B : 2\ 3\ 5\ 7\ 8\ 10$

i j

$C : 1\ 2\ 3\ 3\ 4\ 5\ 7$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: Merge

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1 \ 3 \ 4 \ 9 \ 220$ $B : 2 \ 3 \ 5 \ 7 \ 8 \ 10$

$i \uparrow$ $j \uparrow$

$C : 1 \ 2 \ 3 \ 3 \ 4 \ 5 \ 7 \ 8$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: Merge

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$$A : 1 \ 3 \ 4 \ 9 \ 220 \qquad B : 2 \ 3 \ 5 \ 7 \ 8 \ 10$$

$i \uparrow \qquad \qquad \qquad j \uparrow$

$$C : 1 \ 2 \ 3 \ 3 \ 4 \ 5 \ 7 \ 8 \ 9$$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: **Merge**

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

$A : 1\ 3\ 4\ 9\ 22\ 0$ $B : 2\ 3\ 5\ 7\ 8\ 10$

i j

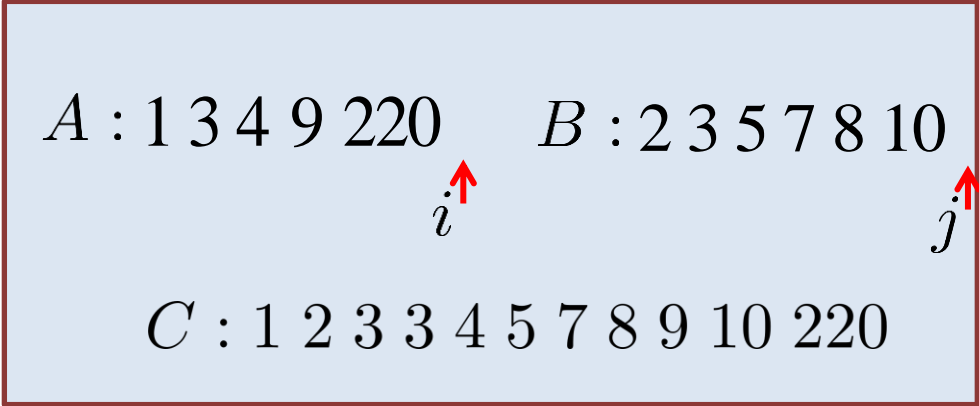
$C : 1\ 2\ 3\ 3\ 4\ 5\ 7\ 8\ 9\ 10$

Mergesort - A fast sorting recursive Algorithm

- Tricky part: **Merge**

Problem: Given two sorted arrays A, B , merge them to a sorted array C .

Running time: $\Theta(n)$



$A : 1\ 3\ 4\ 9\ 220$ $B : 2\ 3\ 5\ 7\ 8\ 10$

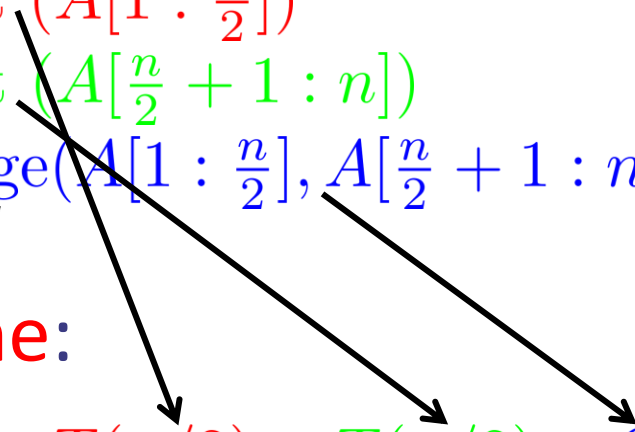
i j

$C : 1\ 2\ 3\ 3\ 4\ 5\ 7\ 8\ 9\ 10\ 220$

Mergesort

- Pseudocode:

```
Mergesort( $A[1 : n]$ )  
  If  $n == 1$  then  
    return  $A$   
  Mergesort( $A[1 : \frac{n}{2}]$ )  
  Mergesort( $A[\frac{n}{2} + 1 : n]$ )  
   $C \leftarrow \text{Merge}(A[1 : \frac{n}{2}], A[\frac{n}{2} + 1 : n])$   
  return  $C$ 
```



- Running time:

$$\begin{aligned} T(n) &= T(n/2) + T(n/2) + \Theta(n) + \Theta(1) \\ &= 2T(n/2) + \Theta(n) \end{aligned}$$

How to analyze?

Master theorem

$$T(n) = \begin{cases} T(1) = \Theta(1) \\ aT(n/b) + f(n) \end{cases}$$

- The Master Theorem can find the order of $T(n)$ which is defined recursively.

Master theorem

$$T(n) = \begin{cases} T(1) = \Theta(1) \\ aT(n/b) + f(n) \end{cases}$$

- The **Master Theorem** can find the order of $T(n)$ which is defined **recursively**.
- **Key idea**: The answer depends on the comparison between $f(n)$ and $n^{\log_b a}$. So, there are **3** cases!

Master theorem

$$T(n) = \begin{cases} T(1) = \Theta(1) \\ aT(n/b) + f(n) \end{cases}$$

1. **If** $f(n)$ **is** $O(n^{\log_b a - \epsilon})$, **then** $T(n)$ **is** $\Theta(n^{\log_b a})$
2. If $f(n)$ is $\Theta(n^{\log_b a} \log^k n)$, then $T(n)$ is $\Theta(n^{\log_b a} \log^{k+1} n)$
3. If $f(n)$ is $\Omega(n^{\log_b a + \epsilon})$, then $T(n)$ is $\Theta(f(n))$,
need to check $af(n/b) < f(n)$.

Case 1: $n^{\log_b a}$ **dominates** $f(n)$

Master theorem

$$T(n) = \begin{cases} T(1) = \Theta(1) \\ aT(n/b) + f(n) \end{cases}$$

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3. If $f(n)$ is $\Omega(n^{\log_b a + \epsilon})$, then $T(n)$ is $\Theta(f(n))$,
need to check $af(n/b) < f(n)$.

Case 2: $n^{\log_b a}$ **have same order as** $f(n)$ (up to $\log^k n$)

Master theorem

$$T(n) = \begin{cases} T(1) = \Theta(1) \\ aT(n/b) + f(n) \end{cases}$$

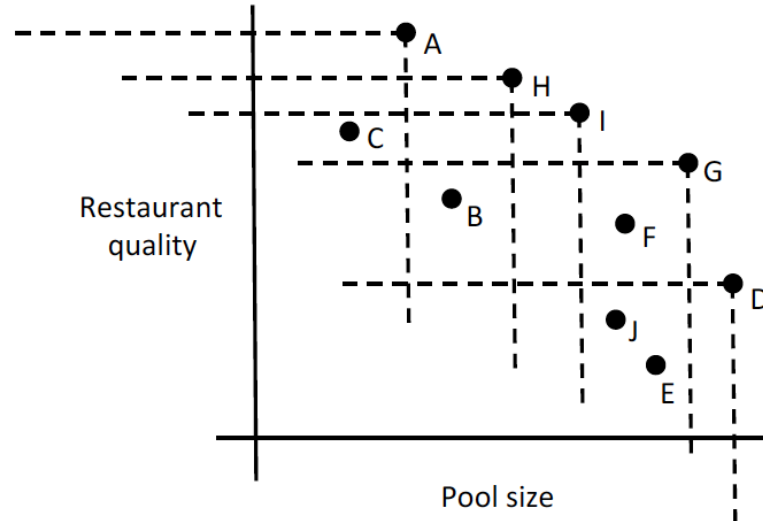
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3. **If $f(n)$ is $\Omega(n^{\log_b a + \epsilon})$, then $T(n)$ is $\Theta(f(n))$,
need to check $a f(n/b) < f(n)$.**

Case 3: $n^{\log_b a}$ **is dominated by $f(n)$** (+ another condition)

Case study: Maxima Set

Problem: We are given n points $(x_1, y_1), \dots, (x_n, y_n)$ on the plane. A point (x_i, y_i) is called a **maximum point** if there is no other point (x_j, y_j) that $x_i \leq x_j$ and $y_i \leq y_j$.

Example: x captures pool size and y restaurant quality. 10 hotels



Case study: Maxima Set

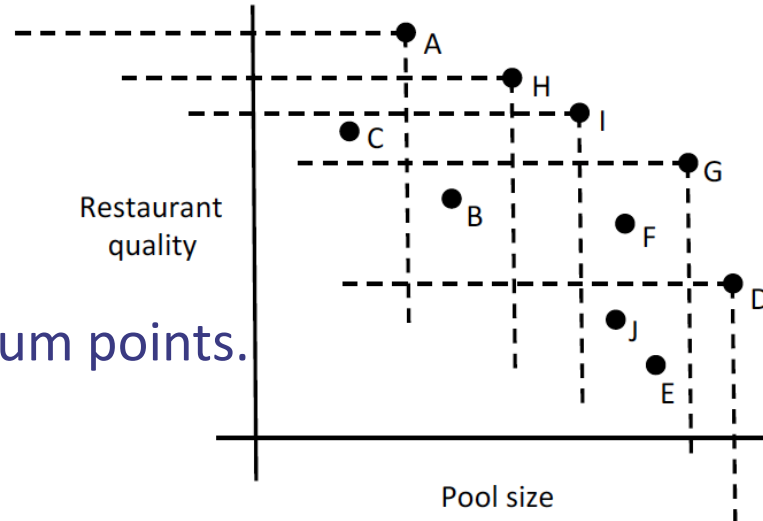
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Example: x captures pool size and y restaurant quality. 10 hotels

Explanation:

A, H, I, G, D are maximum points.

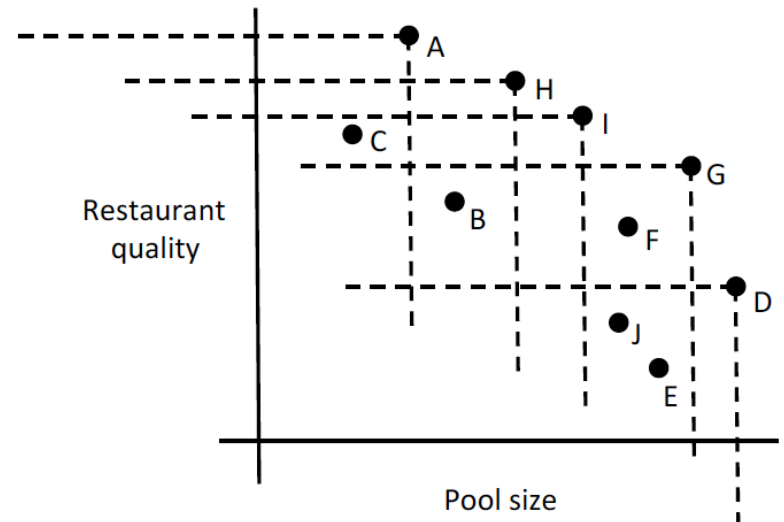
C, B, F, J, E are not.



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Idea: Divide and conquer. **Divide** step and **Combine** step is challenging.



Case study: Maxima Set

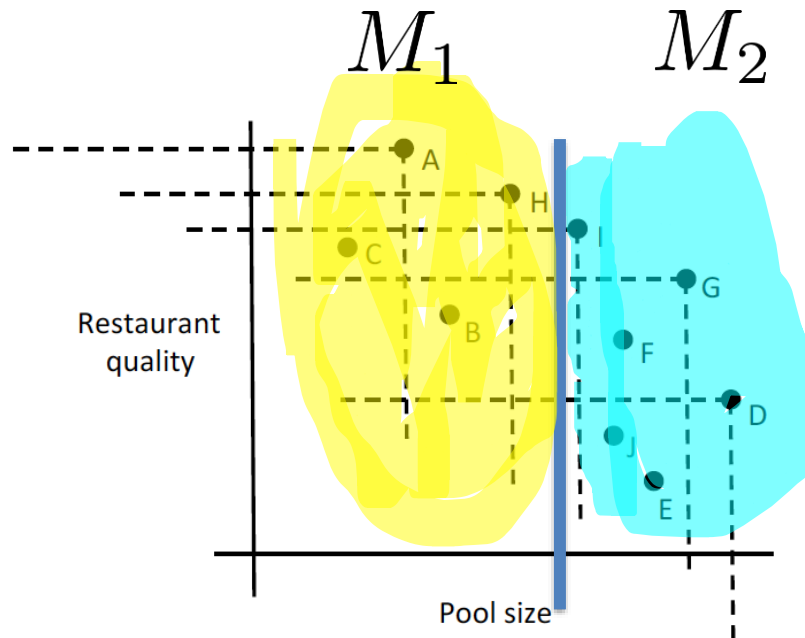
Divide step: It should split the points in two parts of equal size.

How?

Case study: Maxima Set

Divide step: It should split the points in two parts of equal size.

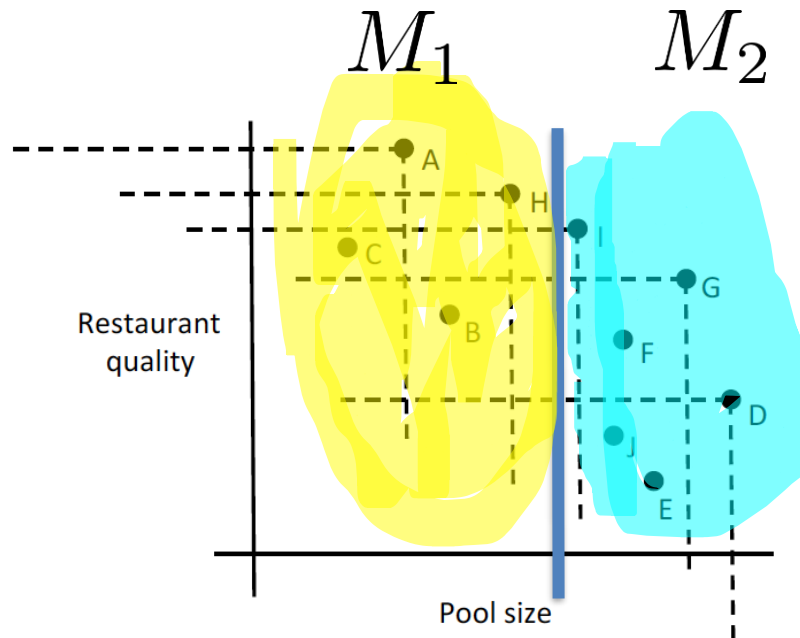
How? Choose the middle (median) point with respect to x coordinates.



Case study: Maxima Set

Divide step: It should split the points in two parts of equal size.

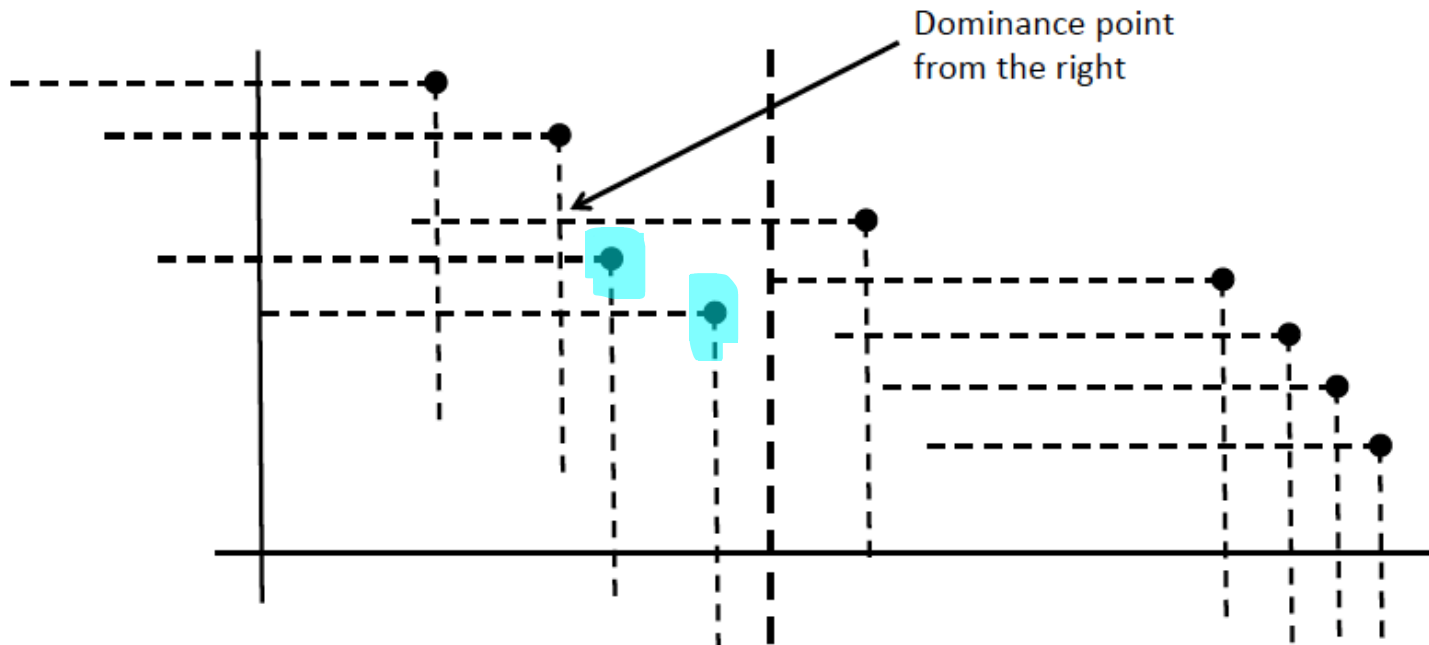
How? Choose the middle (median) point with respect to x coordinates.



Combine step: Return $M_1 \cup M_2$?

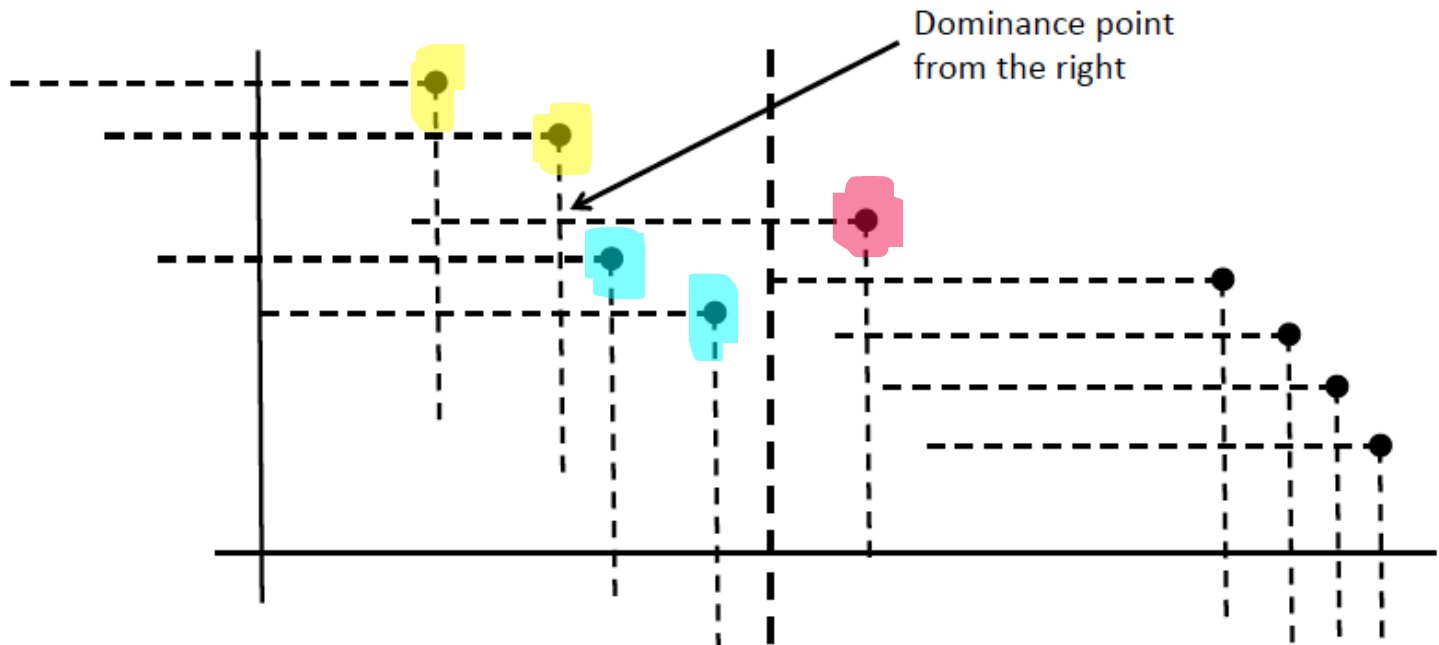
Case study: Maxima Set

Combine step: Return $M_1 \cup M_2$? **Wrong:** blue points below of M_1 are not part of the solution



Case study: Maxima Set

Combine step idea: M_2 points should part of the solution. From M_1 , the points that are maximum should not be dominated by smallest with respect to x coordinates in M_2



Case study: Maxima Set

Pseudocode:

MaximaSet(S, n):

if $n = 1$ **then**

return S

 Let p be the median point in S , by x -coordinates

 Let L be the set of points less than p in S by x -coordinates

 Let G be the set of points greater than or equal to p in S by x -coordinates

$M_1 \leftarrow \text{MaximaSet}(L)$

$M_2 \leftarrow \text{MaximaSet}(G)$

 Let q be the smallest point in M_2

for each point, r , in M_1 **do** by x -coordinates

if $x(r) \leq x(q)$ **and** $y(r) \leq y(q)$ **then**

 Remove r from M_1

return $M_1 \cup M_2$

Running time??



Running time is $T(n) = 2T(n/2) + T_{\text{media}}(n) + T_{\text{min}}(n) + \Theta(n)$
 $= 2T(n/2) + T_{\text{media}}(n) + \Theta(n)$

Dynamic Programming

Technique for solving optimization problems.

Solve problem by solving **sub**-problems and combine:

This is called **Optimal substructure** property.

Dynamic Programming

Technique for solving optimization problems.

Solve problem by solving **sub**-problems and combine:

This is called **Optimal substructure** property.

- **Similar** to divide-and-conquer: **recursion** (for solving sub-problems)
- Sub-problems **overlap**: solve them only **once**!

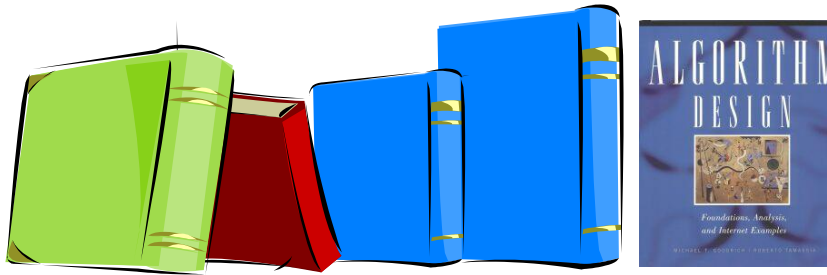
DP = recursion + re-use (**Memoization**)

Case study II: 0/1 Knapsack

Problem: A set of n items, with each item i having positive weight w_i and positive benefit v_i . You are asked to choose items with **maximum total benefit** so that the **total weight** is **at most W**

Example:

Items:



Weight:	4 lbs	2 lbs	2 lbs	6 lbs	2 lbs
Benefit:	\$20	\$3	\$6	\$25	\$80

“knapsack” with 9 lbs capacity



Solution:

- item 5 (\$80, 2 lbs)
- item 3 (\$6, 2lbs)
- item 1 (\$20, 4lbs)

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (first attempt).

Step 1: Define the problem and subproblems.

Answer: Let $DP[k]$ be the **maximum value** I can get from items $\{1, \dots, k\}$ without exceeding W .

Step 2: Define the goal/output given Step 1.
It is $DP[n]$.

Step 3: Define the base cases
It is $DP[0] = 0$.

Step 4: Define the recurrence

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (first attempt).

Step 4: Define the recurrence

Item k will be used or not.

$$DP[k] = \max(DP[k-1], DP[k-1] + v_k)$$

But how do we know that $DP[k-1]$ does **not exceed** $W - w_k$ in weight so we can use k ?

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 1: Define the problem and subproblems.

Answer: Let $DP[k, j]$ be the **maximum value** I can get from items $\{1, \dots, k\}$ without exceeding j .

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 1: Define the problem and subproblems.

Answer: Let $DP[k, j]$ be the **maximum value** I can get from items $\{1, \dots, k\}$ without exceeding j .

Step 2: Define the goal/output given Step 1.

It is $DP[n, W]$.

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 1: Define the problem and subproblems.

Answer: Let $DP[k, j]$ be the **maximum value** I can get from items $\{1, \dots, k\}$ without exceeding j .

Step 2: Define the goal/output given Step 1.

It is $DP[n, W]$.

Step 3: Define the base cases

It is $DP[0, j] = 0$ for all j and $DP[i, 0] = 0$ for all i .

Step 4: Define the recurrence

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 4: Define the recurrence

Item k will be **used** or **not**.

$$DP[k][j] = \max(DP[k-1][j-w_k] + v_k, DP[k-1][j])$$

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 4: Define the recurrence

Item k will be **used** or **not**.

$$DP[k][j] = \max(DP[k-1][j-w_k] + v_k, DP[k-1][j])$$

Question: How do we know that item k does not have weight more than j ?

Case study II: 0/1 Knapsack

Idea: Dynamic Programming (correct attempt).

Step 4: Define the recurrence

Item k will be **used** or **not**.

$$DP[k][j] = \begin{array}{ll} \text{if } w_k \leq j & \max(DP[k-1][j-w_k] + v_k, DP[k-1][j]) \\ \text{If } w_k > j & DP[k-1][j] \end{array}$$

Answer: Add an if statement in the recurrence.

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

Initialization:

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0				
2	0				
3	0				

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0 ($j < w_1$)			
2	0	0 ($j < w_2$)			
3	0	0 ($j < w_3$)			

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	$\max(0, v_1 + 0)$		
2	0	0			
3	0	0			

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1		
2	0	0	$\max(1, v_2+0)$		
3	0	0			

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1		
2	0	0	1		
3	0	0	1 ($j < w_3$)		

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	$\max(0, v_1 + 0)$	
2	0	0	1		
3	0	0	1		

The table represents the dynamic programming table for the 0/1 Knapsack problem. The rows represent items (0 to 3) and the columns represent the knapsack capacity (0 to 4). The values in the table are the maximum value that can be achieved with a given capacity and a subset of items. The red arrow indicates the optimal solution for capacity 1, which is achieved by not taking any items (i=0, j=1). The green arrow indicates the optimal solution for capacity 2, which is achieved by taking item 1 (i=1, j=2).

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	
2	0	0	1	$\max(1, v_2+0)$	
3	0	0	1		

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	
2	0	0	1	1	
3	0	0	1	$\max(1, v_3+0)$	

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	$\max(0, v_1+0)$
2	0	0	1	1	
3	0	0	1	5	

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	1
2	0	0	1	1	$\max(1, v_2+1)$
3	0	0	1	5	

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	1
2	0	0	1	1	2
3	0	0	1	5	$\max(2, 0+v_3)$

Case study II: 0/1 Knapsack

Example: 3 items, $W = 4$
 $w_1 = 2, v_1 = 1, w_2 = 2, v_2 = 1, w_3 = 3, v_3 = 5$

	j=0	1	2	3	4
i=0	0	0	0	0	0
1	0	0	1	1	1
2	0	0	1	1	2
3	0	0	1	5	5

Case study II: 0/1 Knapsack

Pseudocode:

Array $DP[][]$

For $i = 0$ to n **do**

$DP[i, 0] \leftarrow 0$

For $j = 1$ to W **do**

$DP[0, j] \leftarrow 0$

For $i = 1$ to n **do**

For $j = 1$ to W **do**

If $j < w_i$ **then**

$DP[i][j] \leftarrow DP[i - 1][j]$

else $DP[i][j] \leftarrow \max(DP[i - 1][j], DP[i - 1][j - w_i] + v_i)$

return $DP[n][W]$

Initialization

Bottom up filling DP

Goal

Case study II: 0/1 Knapsack

Pseudocode:

```
Array DP[][]
For  $i = 0$  to  $n$  do
     $DP[i, 0] \leftarrow 0$ 
For  $j = 1$  to  $W$  do
     $DP[0, j] \leftarrow 0$ 
For  $i = 1$  to  $n$  do
    For  $j = 1$  to  $W$  do
        If  $j < w_i$  then
             $DP[i][j] \leftarrow DP[i - 1][j]$ 
        else  $DP[i][j] \leftarrow \max(DP[i - 1][j], DP[i - 1][j - w_i] + v_i)$ 
return  $DP[n][W]$ 
```

Initialization

Bottom up filling DP

Goal

Running time: $\Theta(nW)$