



Greedy (1)
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Algorithm Design and Analysis

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Slides credited from Hsueh-I Lu, Hsu-Chun Hsiao, & Michael Tsai



Outline



- Greedy Algorithms
- Greedy #1: Activity-Selection / Interval Scheduling
- Greedy #2: Coin Changing
- Greedy #3: Fractional Knapsack Problem
- Greedy #4: Breakpoint Selection
- Greedy #5: Huffman Codes
- Greedy #6: Task-Scheduling
- Greedy #7: Scheduling to Minimize Lateness

Algorithm Design Strategy

- Do not focus on “specific algorithms”
- But “some strategies” to “design” algorithms

- First Skill: Divide-and-Conquer (各個擊破)
- Second Skill: Dynamic Programming (動態規劃)
- Third Skill: Greedy (貪婪法則)



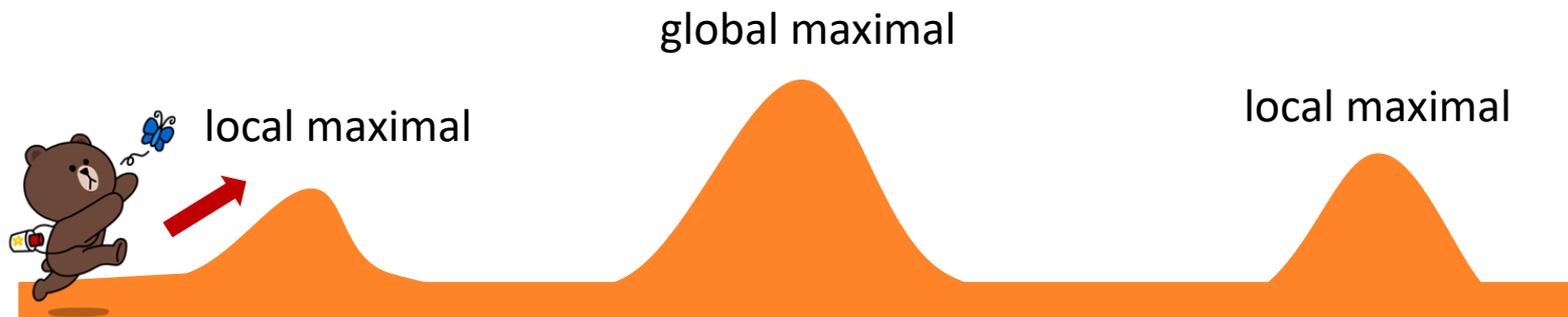
Greedy Algorithms

Textbook Chapter 16 – Greedy Algorithms

Textbook Chapter 16.2 – Elements of the greedy strategy

What is Greedy Algorithms?

- always makes the choice that looks best at the moment
- makes a **locally optimal** choice in the hope that this choice will lead to a **globally optimal** solution
 - not always yield optimal solution; may end up at local optimal

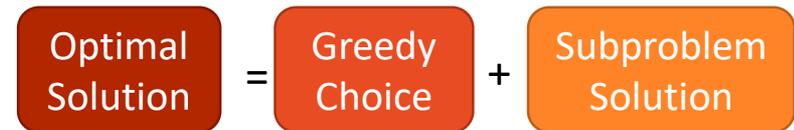
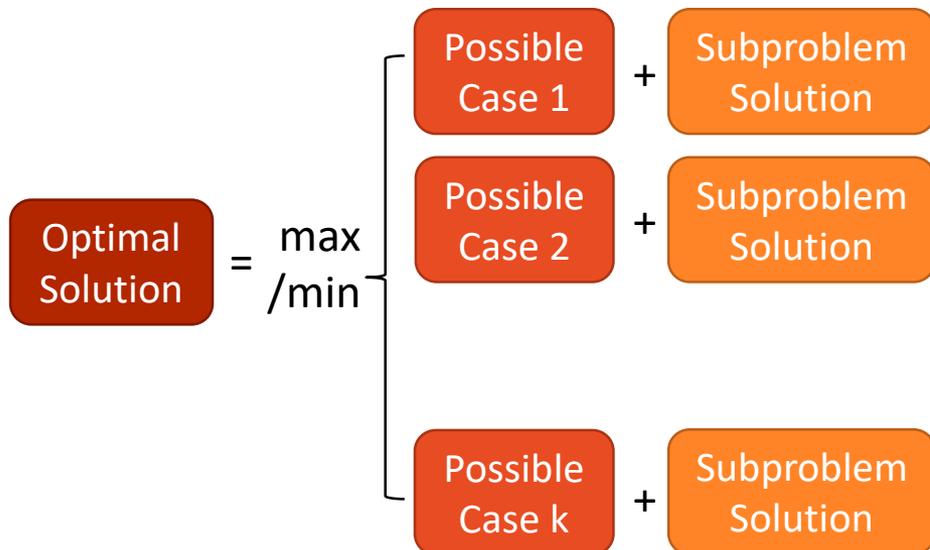


Greedy: move towards max gradient and hope it is global maximum

Algorithm Design Paradigms

- Dynamic Programming
 - has **optimal substructure**
 - make an informed choice after getting optimal solutions to subproblems
 - **dependent** or **overlapping** subproblems

- Greedy Algorithms
 - has **optimal substructure**
 - make a greedy choice before solving the subproblem
 - **no overlapping** subproblems
 - ✓ Each round selects only one subproblem
 - ✓ The subproblem size decreases



Greedy Procedure

1. **Cast the optimization problem** as one in which we make a choice and remain one subproblem to solve
2. **Demonstrate the optimal substructure**
 - ✓ Combining an optimal solution to the subproblem via greedy can arrive an optimal solution to the original problem
3. **Prove** that there is always an optimal solution to the original problem that makes the **greedy choice**

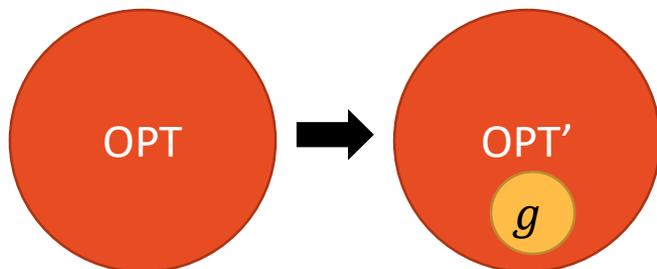
Greedy Algorithms

To yield an optimal solution, the problem should exhibit

1. **Optimal Substructure** : an optimal solution to the problem contains within it optimal solutions to subproblems
2. **Greedy-Choice Property** : making locally optimal (greedy) choices leads to a globally optimal solution

Proof of Correctness Skills

- **Optimal Substructure** : an optimal solution to the problem contains within it optimal solutions to subproblems
- **Greedy-Choice Property** : making locally optimal (greedy) choices leads to a globally optimal solution
 - Show that it exists an optimal solution that “contains” the greedy choice using **exchange argument**
 - For any optimal solution OPT, the greedy choice g has two cases
 - g is in OPT: done
 - g not in OPT: modify OPT into OPT' s.t. OPT' contains g and is at least as good as OPT



- ✓ If OPT' is better than OPT, the property is proved by contradiction
- ✓ If OPT' is as good as OPT, then we showed that there exists an optimal solution containing g by construction

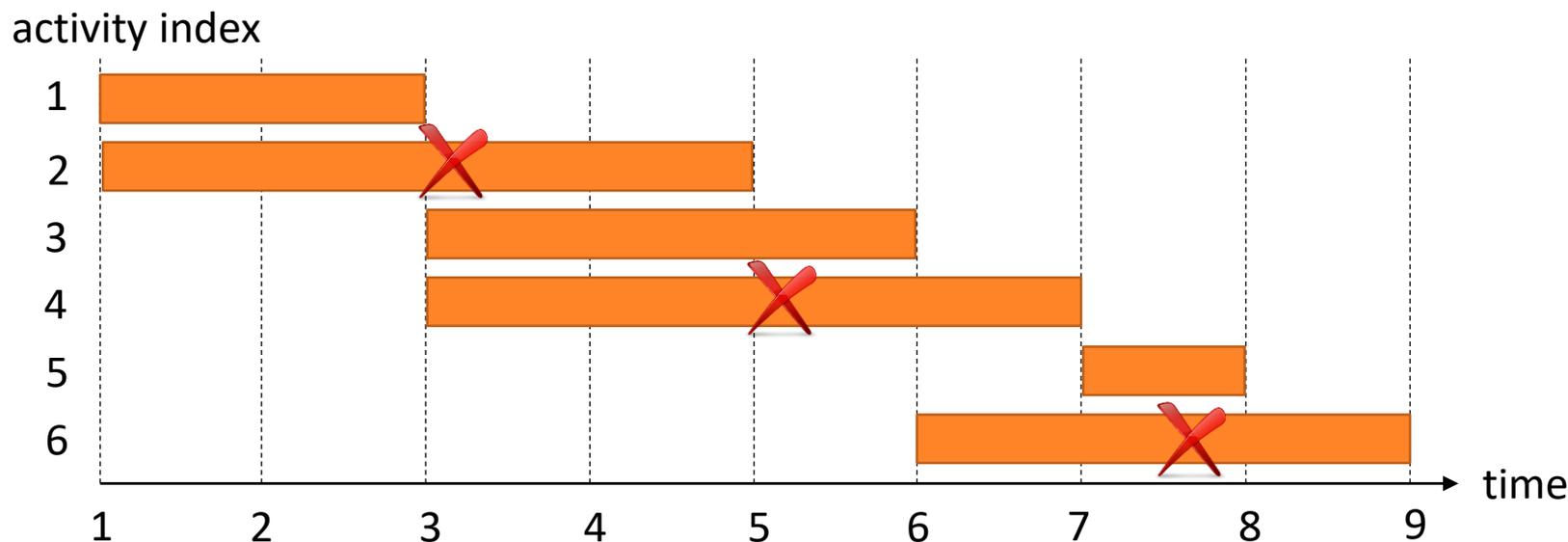


Activity-Selection / Interval Scheduling

Textbook Chapter 16.1 – An activity-selection problem

Activity-Selection/ Interval Scheduling

- Input: n activities with start times s_i and finish times f_i (the activities are sorted in monotonically increasing order of finish time $f_1 \leq f_2 \leq \dots \leq f_n$)
- Output: the maximum number of compatible activities
- Without loss of generality: $s_1 < s_2 < \dots < s_n$ and $f_1 < f_2 < \dots < f_n$
 - 大的包小的則不考慮大的 \rightarrow 用小的取代大的一定不會變差





Weighted Interval Scheduling

Weighted Interval Scheduling Problem

Input: n jobs with $\langle s_i, f_i, v_i \rangle$, $p(j) =$ largest index $i < j$ s.t. jobs i and j are compatible

Output: the maximum total value obtainable from compatible

- Subproblems
 - $WIS(i)$: weighted interval scheduling for the first i jobs
 - Goal: $WIS(n)$
- Dynamic programming algorithm

$$M_i = \begin{cases} 0 & \text{if } i = 0 \\ \max(v_i + M_{p(i)}, M_{i-1}) & \text{otherwise} \end{cases}$$

i	0	1	2	3	4	5	...	n	
$M[i]$			→						

$$T(n) = \Theta(n)$$

Set $v_i = 1$ for all i to formulate it into the activity-selection problem

Activity-Selection Problem

Activity-Selection Problem

Input: n activities with $\langle s_i, f_i \rangle$, $p(j) =$ largest index $i < j$ s.t. i and j are compatible

Output: the maximum number of activities

- Dynamic programming

$$M_i = \begin{cases} 0 & \text{if } i = 0 \\ \max(1 + M_{p(i)}, M_{i-1}) & \text{otherwise} \end{cases}$$

- Optimal substructure** is already proved

- Greedy algorithm

$$M_i = \begin{cases} 0 & \text{if } i = 0 \\ 1 + M_{p(i)} & \text{otherwise} \end{cases}$$

select the i -th activity

Why does the i -th activity must appear in an OPT?



Greedy-Choice Property

- Goal: $1 + M_{p(i)} \geq M_{i-1}$

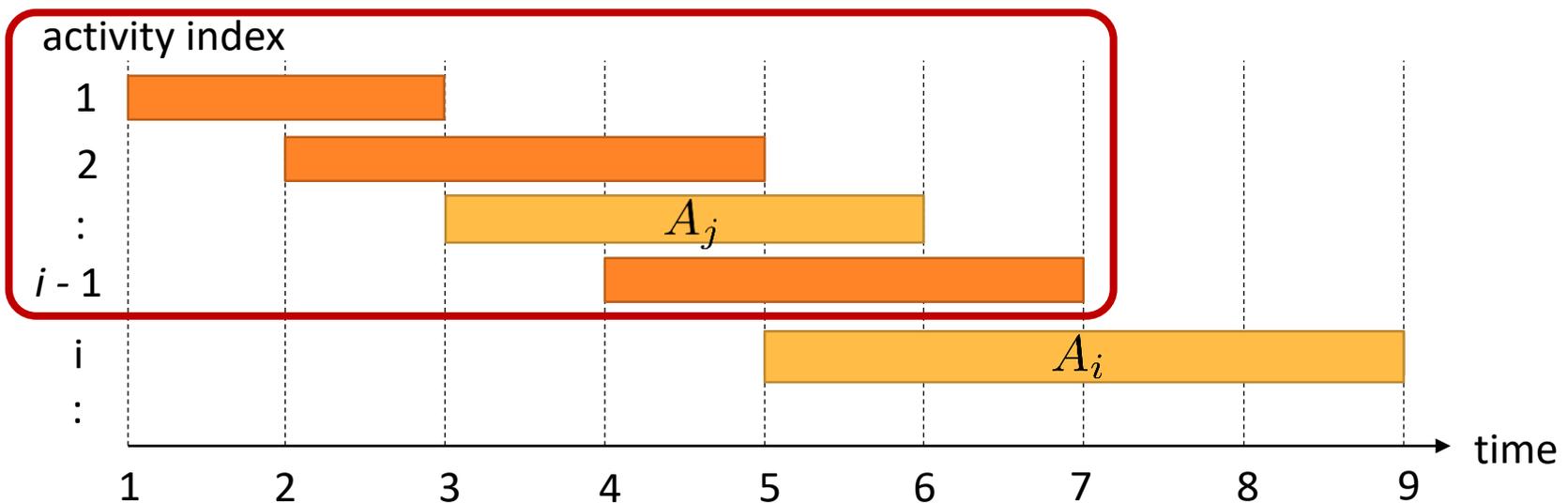
- Proof

- Assume there is an OPT solution for the first $i - 1$ activities (M_{i-1})

- A_j is the last activity in the OPT solution $\rightarrow M_{i-1} = 1 + M_{p(j)}$

- Replacing A_j with A_i does not make the OPT worse

$$1 + M_{p(i)} \geq 1 + M_{p(j)} = M_{i-1}$$



Pseudo Code

Activity-Selection Problem

Input: n activities with $\langle s_i, f_i \rangle$, $p(j)$ = largest index $i < j$ s.t. i and j are compatible

Output: the maximum number of activities

```
Act-Select( $n, s, f, v, p$ )
```

```
  M[0] = 0
```

```
  for  $i = 1$  to  $n$ 
```

```
    if  $p[i] \geq 0$ 
```

```
      M[i] = 1 + M[p[i]]
```

```
  return M[n]
```

$$T(n) = \Theta(n)$$

```
Find-Solution(M,  $n$ )
```

```
  if  $n = 0$ 
```

```
    return {}
```

```
  return { $n$ }  $\cup$  Find-Solution(p[n])
```

$$T(n) = \Theta(n)$$

Select the **last** compatible one (\leftarrow) = Select the **first** compatible one (\rightarrow)



Coin Changing



Textbook Exercise 16.1

Coin Changing Problem

- Input: n dollars and unlimited coins with values $\{v_i\}$ (1, 5, 10, 50)
- Output: the minimum number of coins with the total value n
- **Cashier's algorithm:** at each iteration, add the coin with the largest value no more than the current total

Does this algorithm return the OPT?



Step 1: Cast Optimization Problem

Coin Changing Problem

Input: n dollars and unlimited coins with values $\{v_i\}$ (1, 5, 10, 50)

Output: the minimum number of coins with the total value n

- Subproblems
 - $C(i)$: minimal number of coins for the total value i
 - Goal: $C(n)$

Step 2: Prove Optimal Substructure

Coin Changing Problem

Input: n dollars and unlimited coins with values $\{v_i\}$ (1, 5, 10, 50)

Output: the minimum number of coins with the total value n

- Suppose OPT is an optimal solution to $C(i)$, there are 4 cases:
 - Case 1: coin 1 in OPT
 - $\text{OPT} \setminus \text{coin1}$ is an optimal solution of $C(i - v_1)$
 - Case 2: coin 2 in OPT
 - $\text{OPT} \setminus \text{coin2}$ is an optimal solution of $C(i - v_2)$
 - Case 3: coin 3 in OPT
 - $\text{OPT} \setminus \text{coin3}$ is an optimal solution of $C(i - v_3)$
 - Case 4: coin 4 in OPT
 - $\text{OPT} \setminus \text{coin4}$ is an optimal solution of $C(i - v_4)$

$$C_i = \min_j (1 + C_{i-v_j})$$

Step 3: Prove Greedy-Choice Property

Coin Changing Problem

Input: n dollars and unlimited coins with values $\{v_i\}$ (1, 5, 10, 50)

Output: the minimum number of coins with the total value n

- **Greedy choice: select the coin with the largest value no more than the current total**
- Proof via contradiction (use the case $10 \leq i < 50$ for demo)
 - Assume that there is no OPT including this greedy choice (choose 10)
 - all OPT use 1, 5, 50 to pay i
 - 50 cannot be used
 - #coins with value 5 < 2 → otherwise we can use a 10 to have a better output
 - #coins with value 1 < 5 → otherwise we can use a 5 to have a better output
 - We cannot pay i with the constraints (at most $5 + 4 = 9$)



To Be Continued...



Question?

Important announcement will be sent to @ntu.edu.tw mailbox
& post to the course website

Course Website: <http://ada.miulab.tw>

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