

CS4311  
Design and Analysis of  
Algorithms

Lecture 9: Dynamic Programming I

# About this lecture

- **Divide-and-conquer** strategy allows us to solve a big problem by handling only smaller sub-problems
- Some problems may be solved using a stronger strategy: **dynamic programming**
- We will see some examples today

# Assembly Line Scheduling

- You are the **boss** of a company which assembles Gundam models to customers



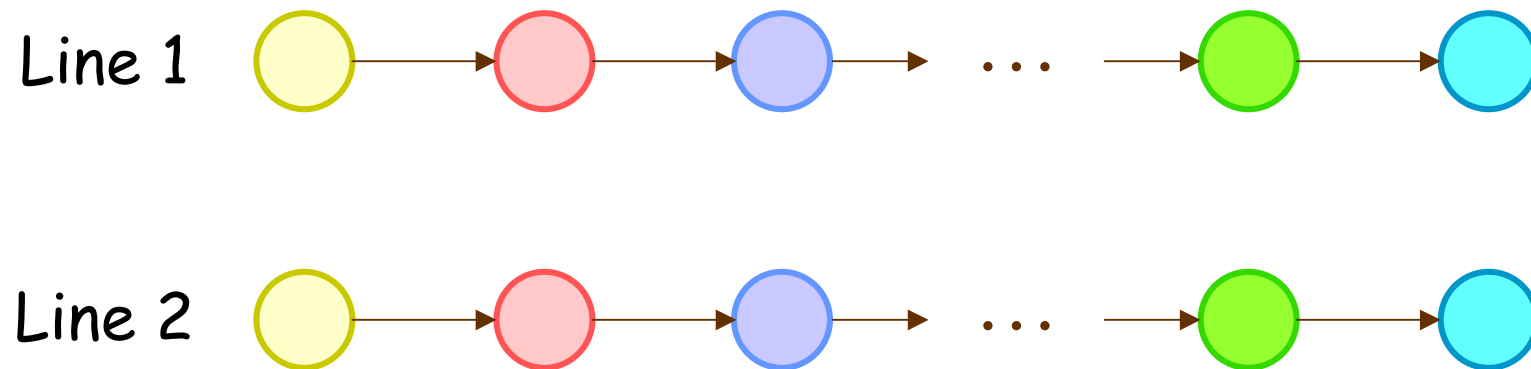
# Assembly Line Scheduling

- Normally, to assemble a Gundam model, there are  $n$  sequential steps



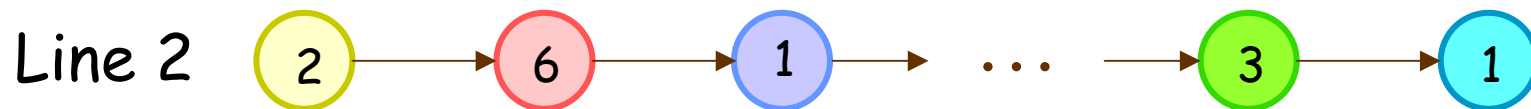
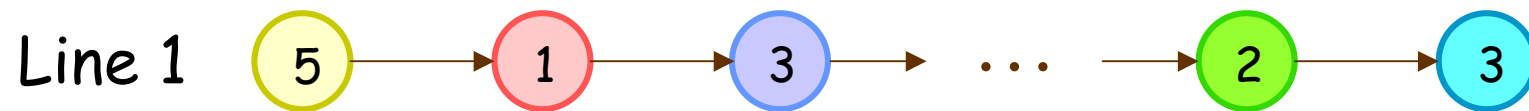
# Assembly Line Scheduling

- To improve efficiency, there are two separate assembly lines:



# Assembly Line Scheduling

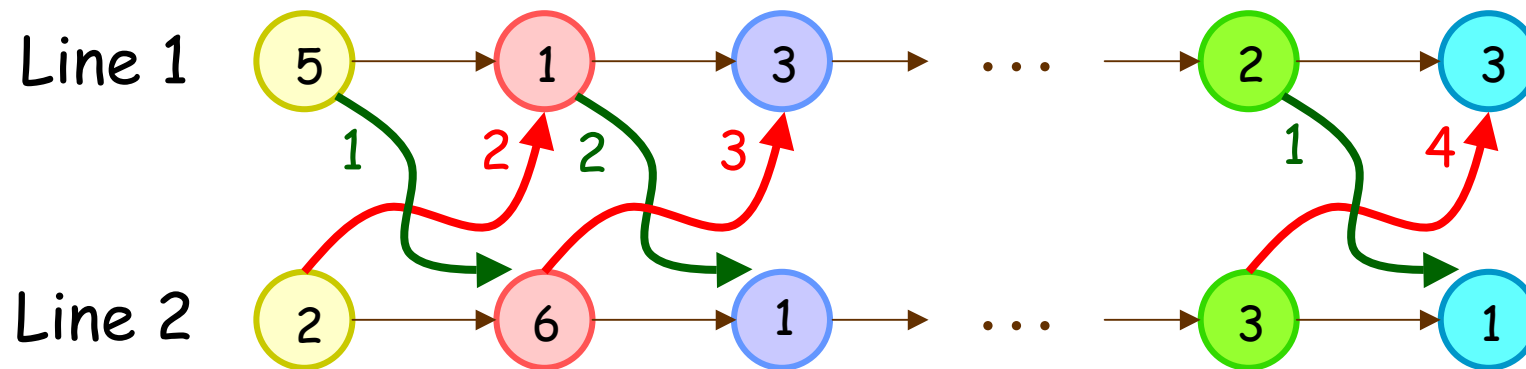
- Since different lines hire different people, processing speed is not the same:



E.g., Line 1 may need 34 mins, and Line 2 may need 38 mins

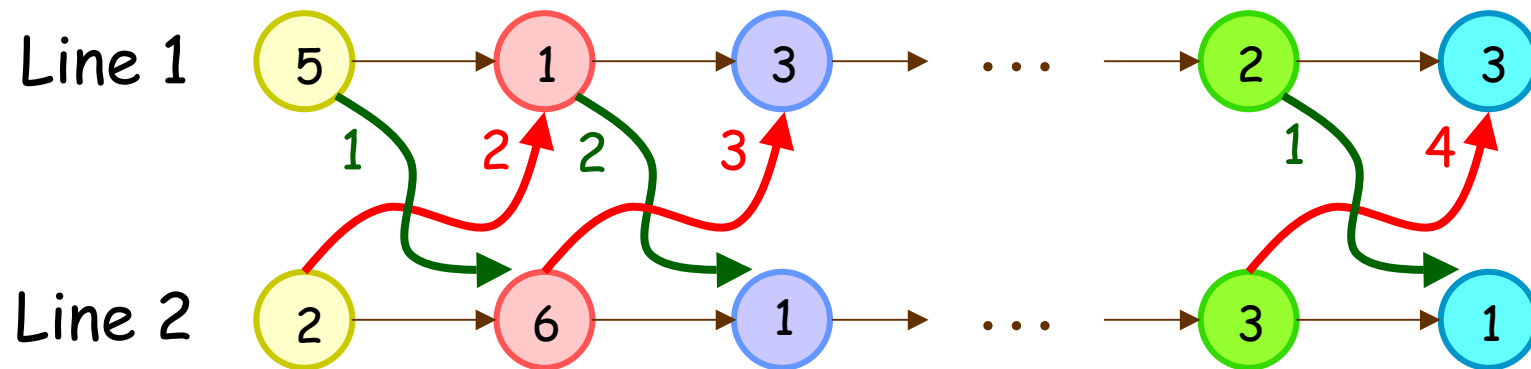
# Assembly Line Scheduling

- With some transportation cost, after a step in a line, we can process the model in the other line during the next step



# Assembly Line Scheduling

- When there is an urgent request, we may finish faster if we can make use of both lines + transportation in between



E.g., Process Step 0 at Line 2, then process Step 1 at Line 1,  
→ better than process both steps in Line 1



# Assembly Line Scheduling

Question: How to compute the **fastest** assembly time?

Let  $p_{1,k}$  = Step  $k$ 's processing time in Line 1

$p_{2,k}$  = Step  $k$ 's processing time in Line 2

$t_{1,k}$  = transportation cost from Step  $k$  in Line 1 (to Step  $k+1$  in Line 2)

$t_{2,k}$  = transportation cost from Step  $k$  in Line 2 (to Step  $k+1$  in Line 1)

# Assembly Line Scheduling

Let  $f_{1,j}$  = fastest time to finish Steps 0 to  $j$ ,  
ending at Line 1

$f_{2,j}$  = fastest time to finish Steps 0 to  $j$ ,  
ending at Line 2

So, we have:

$$f_{1,0} = p_{1,0} \quad , \quad f_{2,0} = p_{2,0}$$

$$\text{fastest time} = \min \{ f_{1,n}, f_{2,n} \}$$

# Assembly Line Scheduling

Lemma: For any  $j > 0$ ,

$$f_{1,j} = \min \{ f_{1,j-1} + p_{1,j}, f_{2,j-1} + t_{2,j-1} + p_{1,j} \}$$

$$f_{2,j} = \min \{ f_{2,j-1} + p_{2,j}, f_{1,j-1} + t_{1,j-1} + p_{2,j} \}$$

Proof: By contradiction!

Here, optimal solution to a problem (e.g.,  $f_{1,j}$ ) is based on optimal solution to subproblems (e.g.,  $f_{1,j-1}$  and  $f_{2,j-1}$ )

→ optimal substructure property

# Assembly Line Scheduling

Define a function  $\text{Compute\_F}(i,j)$  as follows:

$\text{Compute\_F}(i, j)$  /\* Finding  $f_{i,j}$  \*/

1. if ( $j == 0$ ) return  $p_{i,0}$ ;

2.  $g = \text{Compute\_F}(i, j-1) + p_{i,j}$  ;

3.  $h = \text{Compute\_F}(3-i, j-1) + t_{3-i, j-1} + p_{i,j}$  ;

4. return  $\min \{ g, h \}$  ;

Calling  $\text{Compute\_F}(1,n)$  and  $\text{Compute\_F}(2,n)$   
gives the fastest assembly time

# Assembly Line Scheduling

Question: What is the running time of `Compute_F(i,n)`?

Let  $T(n)$  denote its running time

So,  $T(n) = 2T(n-1) + \Theta(1)$

→ By Recursion-Tree Method,

$$T(n) = \Theta(2^n)$$

# Assembly Line Scheduling

To improve the running time, observe that:

To  $\text{Compute\_F}(1,j)$  and  $\text{Compute\_F}(2,j)$ ,  
both requires the **SAME** subproblems:  
 $\text{Compute\_F}(1,j-1)$  and  $\text{Compute\_F}(2,j-1)$

So, in our recursive algorithm, there are  
many repeating subproblems which create  
redundant computations!

Question: Can we avoid it?

# Bottom-Up Approach (Method I)

- In the assembly problem, we notice that
  - (i) all  $f_{i,j}$  are eventually computed at least once, and
  - (ii)  $f_{i,j}$  depends only on  $f_{i,k}$  with  $k < j$
- By (i), let us create a 2D table  $F$  to store all  $f_{i,j}$  values once they are computed
- By (ii), let us compute  $f_{i,j}$  from  $j = 0$  to  $n$

# Bottom-Up Approach (Method I)

`BottomUp_F()` /\* Finding fastest time \*/

1.  $F[1,0] = p_{i,0}$  ,  $F[2,0] = p_{2,0}$ ;

2. for ( $j = 1, 2, \dots, n$ ) {

    Compute  $F[1,j]$  and  $F[2,j]$ ;

    // Based on  $F[1,j-1]$  and  $F[2,j-1]$

}

3. return  $\min \{ F[1,n] , F[2,n] \}$  ;

Running Time =  $\Theta(n)$



# Memoization (Method II)

- Similar to **Bottom-Up Approach**, we create a table **F** to store all  $f_{i,j}$  once computed
- However, we modify the recursive algorithm a bit, so that we still solve compute the fastest time in a **Top-Down**
- Assume: entries of **F** are initialized empty

Memoization comes from the word "memo"

# Original Recursive Algorithm

`Compute_F(i, j) /* Finding  $f_{i,j}$  */`

1. `if (j == 0) return  $p_{i,0}$ ;`

2. `g = Compute_F(i, j-1) +  $p_{i,j}$ ;`

3. `h = Compute_F(3-i, j-1) +  $t_{3-i, j-1}$  +  $p_{i,j}$ ;`

4. `return min { g, h } ;`

# Memoized Version

`Memo_Compute_F(i, j) /* Finding  $f_{i,j}$  */`

1. `if (j == 0) return  $p_{i,0}$ ;`

2. `if (F[i,j-1] is empty)`

`F[i,j-1] = Memo_Compute_F(i,j-1);`

3. `if (F[3-i,j-1] is empty)`

`F[3-i,j-1] = Memo_Compute_F(3-i,j-1);`

4. `g = F[i,j-1] +  $p_{i,j}$ ;`

5. `h = F[3-i,j-1] +  $t_{3-i,j-1}$  +  $p_{i,j}$ ;`

6. `return min { g, h } ;`

# Memoized Version (Running Time)

To find Memo\_Compute\_F(1, n):

1. Memo\_Compute\_F(i, j) is only called when F[i, j] is empty (it becomes nonempty afterwards)  
→  $\Theta(n)$  calls
2. Each Memo\_Compute\_F(i, j) call only needs  $\Theta(1)$  time apart from recursive calls

Running Time =  $\Theta(n)$

# Dynamic Programming

The previous strategy that applies “tables” is called **dynamic programming (DP)**

[ Here, **programming** means:

a good way to plan things / to optimize the steps ]

- A problem that can be solved efficiently by DP often has the following properties:
  1. **Optimal Substructure** (allows recursion)
  2. **Overlapping Subproblems** (allows speed up)

# Assembly Line Scheduling

**Challenge:** We now know how to compute the **fastest** assembly time. How to get the exact sequence of steps to achieve this time?

**Answer:** When we compute  $f_{i,j}$ , we remember whether its value is based on  $f_{1,j-1}$  or  $f_{2,j-1}$   
→ easy to modify code to get the sequence

# Sharing Gold Coins

Five lucky pirates has discovered a treasure chest with 1000 gold coins ...



# Sharing Gold Coins

There are rankings among the pirates:



... and they decide to share the gold coins in the following way:



# Sharing Gold Coins

First, Rank-1 pirate proposes how to share the coins...

- If at least half of them agree, go with the proposal
- Else, Rank-1 pirate is out of the game



Hehe, I am going to make the first proposal ... but there is a danger that I cannot share any coins

# Sharing Gold Coins

If Rank-1 pirate is out, then Rank-2 pirate proposes how to share the coins...

- If at least half of the remaining agree, go with the proposal
- Else, Rank-2 pirate is out of the game



Hehe, I get a chance to propose if Rank-1 pirate is out of the game

# Sharing Gold Coins

In general, if Rank-1, Rank-2, ..., Rank- $k$  pirates are out, then Rank- $(k+1)$  pirate proposes how to share the coins...

- If at least half of the remaining agree, go with the proposal
- Else, Rank- $(k+1)$  pirate is out of the game

**Question:** If all the pirates are smart, who will get the most coin? Why?