

CSE 431/531: Algorithm Analysis and Design (Spring 2019)

# Dynamic Programming

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*Department of Computer Science and Engineering  
University at Buffalo*

# Paradigms for Designing Algorithms

## Greedy algorithm

- Make a greedy choice
- Prove that the greedy choice is safe
- Reduce the problem to a sub-problem and solve it iteratively
- Usually for optimization problems

## Divide-and-conquer

- Break a problem into many **independent** sub-problems
- Solve each sub-problem separately
- Combine solutions for sub-problems to form a solution for the original one
- Usually used to design more efficient algorithms

# Paradigms for Designing Algorithms

## Dynamic Programming

- Break up a problem into many **overlapping** sub-problems
- Build solutions for larger and larger sub-problems
- Use a **table** to store solutions for sub-problems for reuse

# Recall: Computing the $n$ -th Fibonacci Number

- $F_0 = 0, F_1 = 1$
- $F_n = F_{n-1} + F_{n-2}, \forall n \geq 2$
- Fibonacci sequence: 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89,  $\dots$

## Fib( $n$ )

- 1  $F[0] \leftarrow 0$
- 2  $F[1] \leftarrow 1$
- 3 for  $i \leftarrow 2$  to  $n$  do
- 4      $F[i] \leftarrow F[i - 1] + F[i - 2]$
- 5 return  $F[n]$

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  - 5 return  $F[n]$
- Store each  $F[i]$  for future use.

# Outline

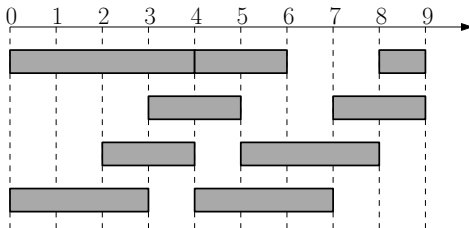
- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem
- 4 Longest Common Subsequence
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication
- 7 Summary

## Recall: Interval Scheduling

**Input:**  $n$  jobs, job  $i$  with start time  $s_i$  and finish time  $f_i$

$i$  and  $j$  are compatible if  $[s_i, f_i)$  and  $[s_j, f_j)$  are disjoint

**Output:** a maximum-size subset of mutually compatible jobs

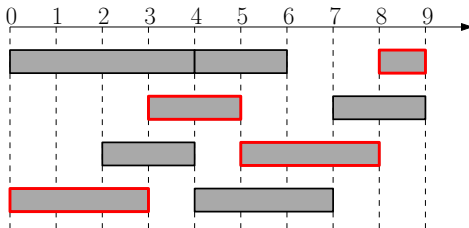


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## Weighted Interval Scheduling

**Input:**  $n$  jobs, job  $i$  with start time  $s_i$  and finish time  $f_i$

each job has a weight (or value)  $v_i > 0$

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**Output:** a maximum-weight subset of mutually compatible jobs

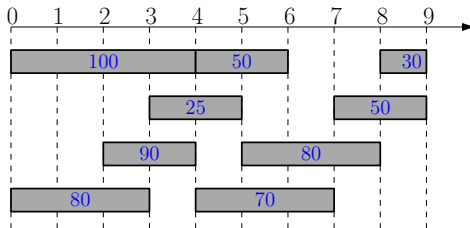
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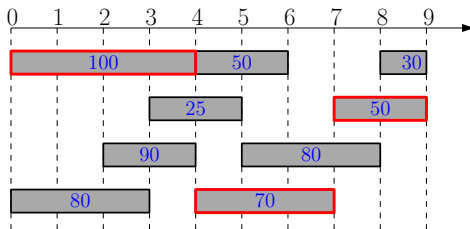
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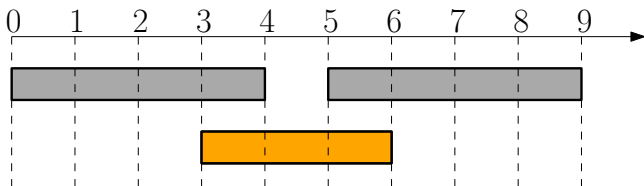
No, when weights are equal, this is the shortest job

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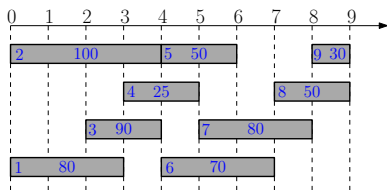
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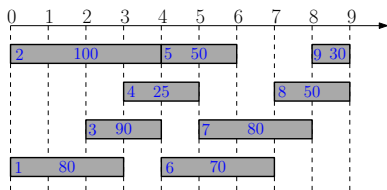
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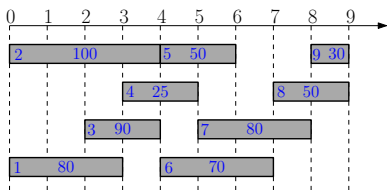
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- $opt[i]$ : optimal value for instance only containing jobs  $\{1, 2, \dots, i\}$

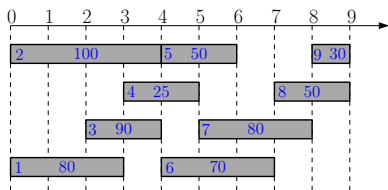
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$i$	$opt[i]$
0	
1	
2	
3	
4	
5	
6	
7	
8	
9	

# Designing a Dynamic Programming Algorithm

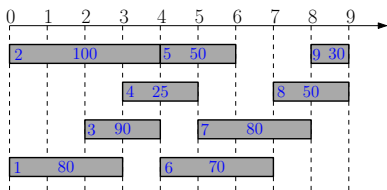


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2	
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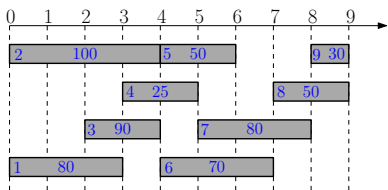
# Designing a Dynamic Programming Algorithm



- Sort jobs according to non-decreasing order of finish times
- $opt[i]$ : optimal value for instance only containing jobs  $\{1, 2, \dots, i\}$

$i$	$opt[i]$
0	0
1	80
2	
3	
4	
5	
6	
7	
8	
9	

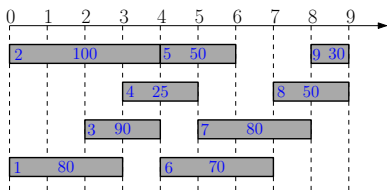
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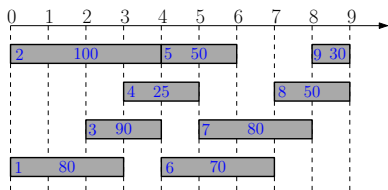
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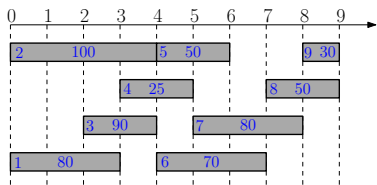
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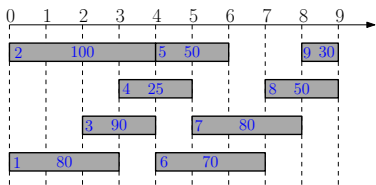
$i$	$opt[i]$
0	0
1	80
2	100
3	100
4	105
5	150
6	170
7	185
8	220
9	220

# Designing a Dynamic Programming Algorithm



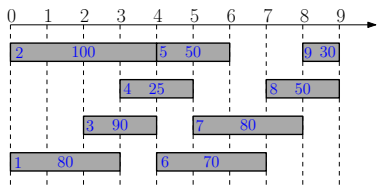
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# Designing a Dynamic Programming Algorithm



- Focus on instance  $\{1, 2, 3, \dots, i\}$ ,
- $opt[i]$ : optimal value for the instance
- assume we have computed  $opt[0], opt[1], \dots, opt[i - 1]$

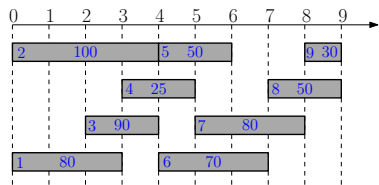
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**Q:** The value of optimal solution that **does not contain**  $i$ ?

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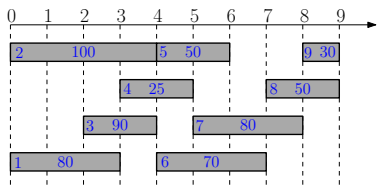
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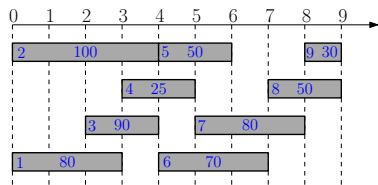
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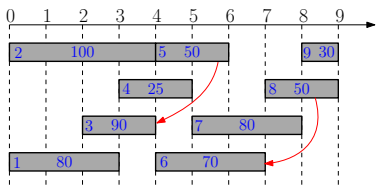
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**A:**  $v_i + opt[p_i]$ ,  $p_i =$  the largest  $j$  such that  $f_j \leq s_i$

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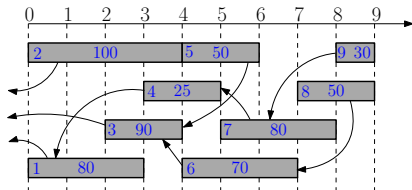
Recursion for  $opt[i]$ :

$$opt[i] = \max \{opt[i - 1], v_i + opt[p_i]\}$$

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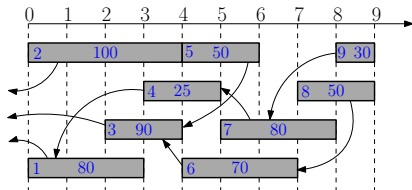


- $opt[0] = 0$
- $opt[1] = \max\{opt[0], 80 + opt[0]\} = 80$
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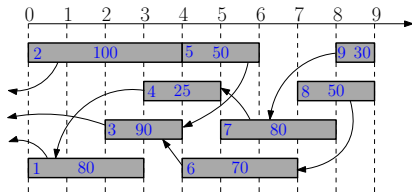


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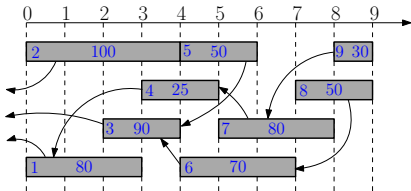
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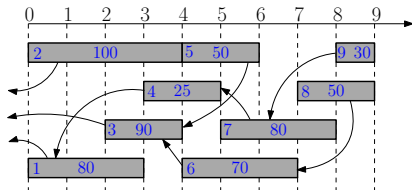


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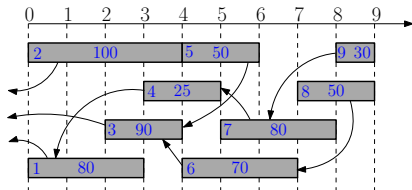


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- $opt[5] =$

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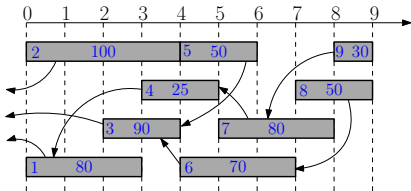


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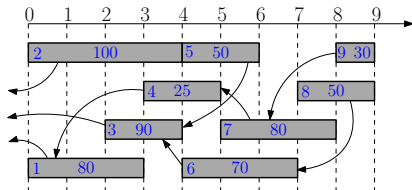


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- $opt[4] = \max\{opt[3], 25 + opt[1]\}$
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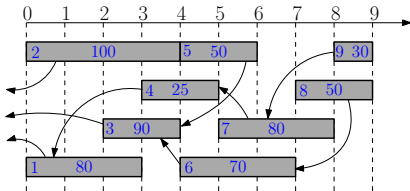


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- $opt[5] =$

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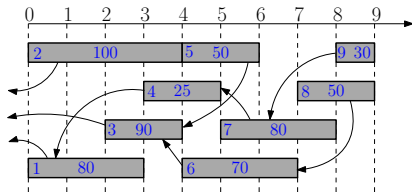


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- $opt[3] = \max\{opt[2], 90 + opt[0]\} = 100$
- $opt[4] = \max\{opt[3], 25 + opt[1]\} = 105$
- $opt[5] = \max\{opt[4], 50 + opt[3]\}$

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Recursion for  $opt[i]$ :

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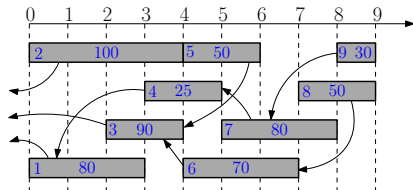


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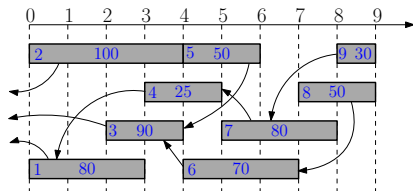
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# Designing a Dynamic Programming Algorithm

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- $opt[0] = 0$ ,  $opt[1] = 80$ ,  $opt[2] = 100$
- $opt[3] = 100$ ,  $opt[4] = 105$ ,  $opt[5] = 150$
- $opt[6] = \max\{opt[5], 70 + opt[3]\} = 170$
- $opt[7] = \max\{opt[6], 80 + opt[4]\} = 185$
- $opt[8] = \max\{opt[7], 50 + opt[6]\} = 220$
- $opt[9] = \max\{opt[8], 30 + opt[7]\} = 220$

# Recursive Algorithm to Compute $opt[n]$

- 1 sort jobs by non-decreasing order of finishing times
- 2 compute  $p_1, p_2, \dots, p_n$
- 3 return  $compute-opt(n)$

## $compute-opt(i)$

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- Running time can be exponential in  $n$
- Reason: we are computed each  $opt[i]$  many times
- Solution: store the value of  $opt[i]$ , so it's computed only once

# Memoized Recursive Algorithm

- 1 sort jobs by non-decreasing order of finishing times
- 2 compute  $p_1, p_2, \dots, p_n$
- 3  $opt[0] \leftarrow 0$  and  $opt[i] \leftarrow \perp$  for every  $i = 1, 2, 3, \dots, n$
- 4 return compute-opt( $n$ )

## compute-opt( $i$ )

- 1 if  $opt[i] = \perp$  then
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- Running time sorting:  $O(n \lg n)$

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- Running time for computing  $opt[n]$ :  $O(n)$

# Dynamic Programming

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# How Can We Recover the Optimum Schedule?

- 1 sort jobs by non-decreasing order of finishing times
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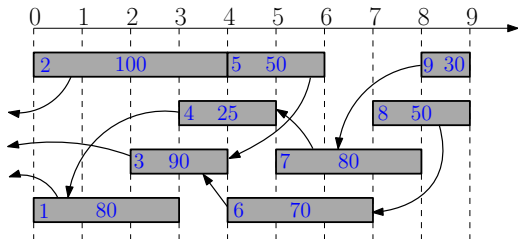
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- 1  $i \leftarrow n, S \leftarrow \emptyset$
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- 5     else
- 6          $S \leftarrow S \cup \{i\}$
- 7          $i \leftarrow p_i$
- 8 return  $S$

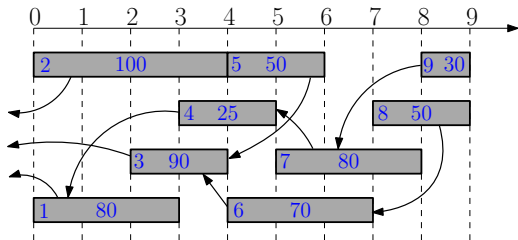
# Recovering Optimum Schedule: Example

$i$	$opt[i]$	$b[i]$
0	0	$\perp$
1	80	
2	100	
3	100	
4	105	
5	150	
6	170	
7	185	
8	220	
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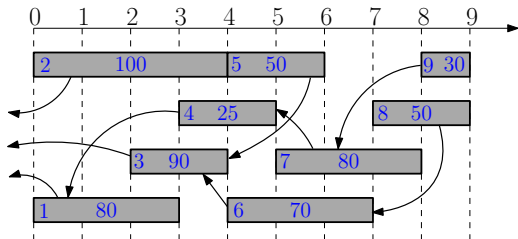
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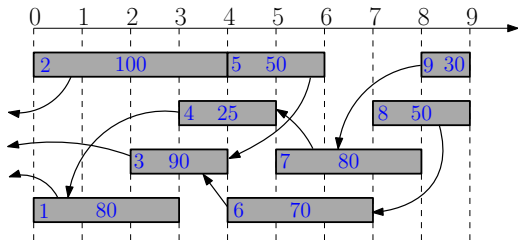
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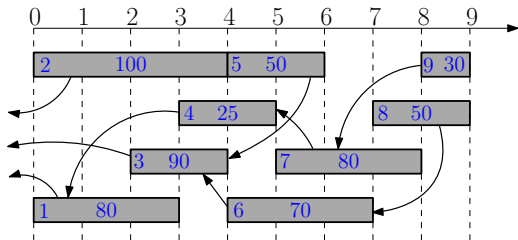
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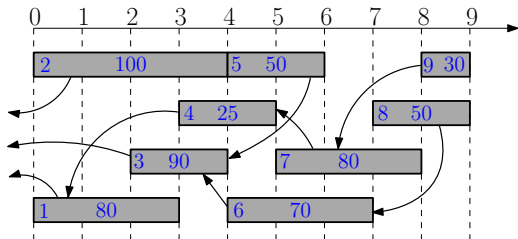
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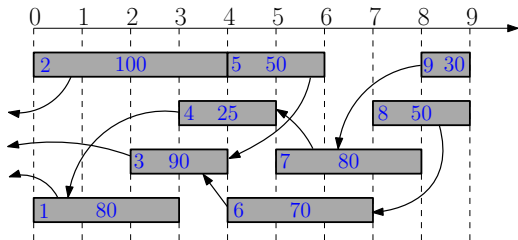
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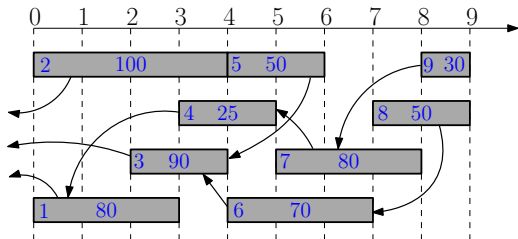
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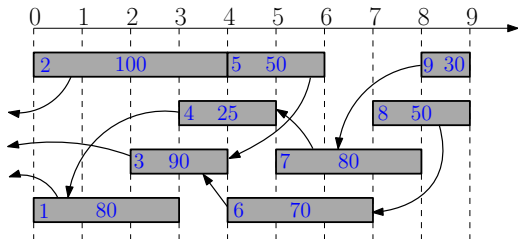
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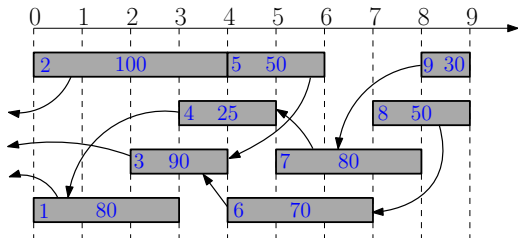
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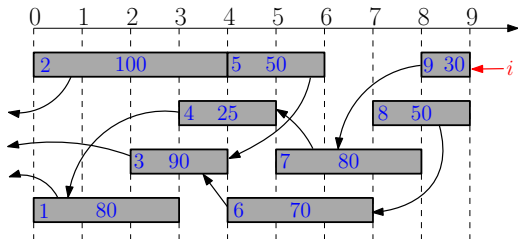
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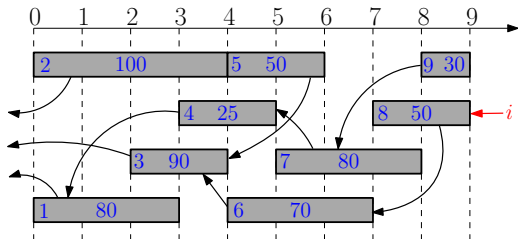
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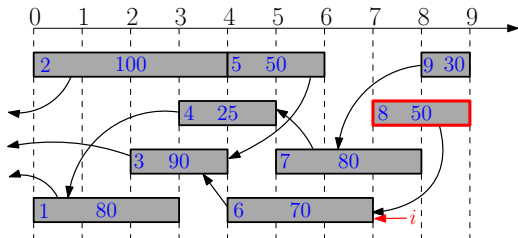
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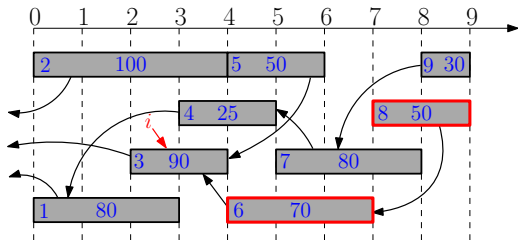
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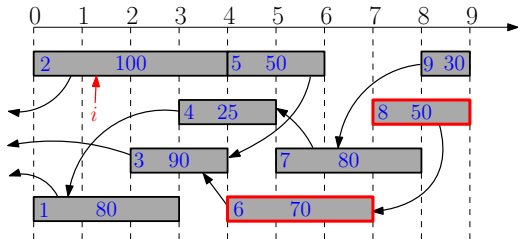
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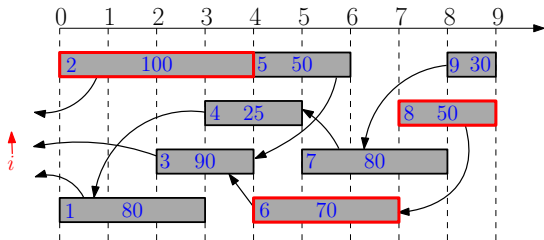
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# Dynamic Programming

- Break up a problem into many **overlapping** sub-problems
- Build solutions for larger and larger sub-problems
- Use a **table** to store solutions for sub-problems for reuse

# Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem**
- 3 Knapsack Problem
- 4 Longest Common Subsequence
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication
- 7 Summary



## Subset Sum Problem

**Input:** an integer bound  $W > 0$

a set of  $n$  items, each with an integer weight  $w_i > 0$

**Output:** a subset  $S$  of items that

$$\text{maximizes } \sum_{i \in S} w_i \quad \text{s.t. } \sum_{i \in S} w_i \leq W.$$

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### Example:

- $W = 35, n = 5, w = (14, 9, 17, 10, 13)$

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- Motivation: you have budget  $W$ , and want to buy a subset of items, so as to spend as much money as possible.

### Example:

- $W = 35, n = 5, w = (14, 9, 17, 10, 13)$
- Optimum:  $S = \{1, 2, 4\}$  and  $14 + 9 + 10 = 33$

# Greedy Algorithms for Subset Sum

## Candidate Algorithm:

- Sort according to non-increasing order of weights
- Select items in the order as long as the total weight remains below  $W$

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**A:** No.  $W = 100, n = 3, w = (1, 50, 50)$

# Design a Dynamic Programming Algorithm

- Consider the instance:  $i, W', (w_1, w_2, \dots, w_i)$ ;
- $opt[i, W']$ : the optimum value of the instance

**Q:** The value of the optimum solution that **does not contain**  $i$ ?

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**A:**  $opt[i - 1, W']$

**Q:** The value of the optimum solution that **contains**  $i$ ?

**A:**  $opt[i - 1, W' - w_i] + w_i$

- Consider the instance:  $i, W', (w_1, w_2, \dots, w_i)$ ;
- $opt[i, W']$ : the optimum value of the instance

$$opt[i, W'] = \begin{cases} & i = 0 \\ & i > 0, w_i > W' \\ & i > 0, w_i \leq W' \end{cases}$$

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- Consider the instance:  $i, W', (w_1, w_2, \dots, w_i)$ ;
- $opt[i, W']$ : the optimum value of the instance

$$opt[i, W'] = \begin{cases} 0 & i = 0 \\ opt[i - 1, W'] & i > 0, w_i > W' \\ \max \left\{ \begin{array}{l} opt[i - 1, W'] \\ opt[i - 1, W' - w_i] + w_i \end{array} \right\} & i > 0, w_i \leq W' \end{cases}$$

# Dynamic Programming

- 1 for  $W' \leftarrow 0$  to  $W$
- 2      $opt[0, W'] \leftarrow 0$
- 3 for  $i \leftarrow 1$  to  $n$
- 4     for  $W' \leftarrow 0$  to  $W$
- 5          $opt[i, W'] \leftarrow opt[i - 1, W']$
- 6         if  $w_i \geq W'$  and  $opt[i - 1, W' - w_i] + w_i \geq opt[i, W']$   
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- 1 for  $W' \leftarrow 0$  to  $W$
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- 8  $opt[i, W'] \leftarrow opt[i - 1, W' - w_i] + w_i$
- 9  $b[i, W'] \leftarrow \mathbf{Y}$
- 10 return  $opt[n, W]$

# Recover the Optimum Set

- 1  $i \leftarrow n, W' \leftarrow W, S \leftarrow \emptyset$
- 2 while  $i > 0$
- 3     if  $b[i, W'] = Y$  then
- 4          $W' \leftarrow W' - w_i$
- 5          $S \leftarrow S \cup \{i\}$
- 6      $i \leftarrow i - 1$
- 7 return  $S$

# Running Time of Algorithm

- 1 for  $W' \leftarrow 0$  to  $W$
- 2      $opt[0, W'] \leftarrow 0$
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# Running Time of Algorithm

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1 for  $W' \leftarrow 0$  to  $W$ 
2    $opt[0, W'] \leftarrow 0$ 
3 for  $i \leftarrow 1$  to  $n$ 
4   for  $W' \leftarrow 0$  to  $W$ 
5      $opt[i, W'] \leftarrow opt[i - 1, W']$ 
6     if  $w_i \leq W'$  and  $opt[i - 1, W' - w_i] + w_i \geq opt[i, W']$ 
7       then
8          $opt[i, W'] \leftarrow opt[i - 1, W' - w_i] + w_i$ 
9 return  $opt[n, W]$ 
```

- Running time is  $O(nW)$

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- Running time is  $O(nW)$
- Running time is **pseudo-polynomial** because it depends on value of the input integers.

# Avoiding Unnecessary Computation and Memory Using Memoized Algorithm and Hash Map

compute-opt( $i, W'$ )

- 1 if  $opt[i, W'] \neq \perp$  return  $opt[i, W']$
- 2 if  $i = 0$  then  $r \leftarrow 0$
- 3 else
- 4      $r \leftarrow \text{compute-opt}(i - 1, W')$
- 5     if  $w_i \leq W'$  then
- 6          $r' \leftarrow \text{compute-opt}(i - 1, W' - w_i) + w_i$
- 7         if  $r' > r$  then  $r \leftarrow r'$
- 8      $opt[i, W'] \leftarrow r$
- 9 return  $r$

- Use hash map for  $opt$



# Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem**
- 4 Longest Common Subsequence
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication
- 7 Summary

## Knapsack Problem

**Input:** an integer bound  $W > 0$

a set of  $n$  items, each with an integer weight  $w_i > 0$

a value  $v_i > 0$  for each item  $i$

**Output:** a subset  $S$  of items that

$$\text{maximizes } \sum_{i \in S} v_i \quad \text{s.t.} \quad \sum_{i \in S} w_i \leq W.$$

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- Motivation: you have budget  $W$ , and want to buy a subset of items of maximum total value

# DP for Knapsack Problem

- $opt[i, W']$ : the optimum value when budget is  $W'$  and items are  $\{1, 2, 3, \dots, i\}$ .
- If  $i = 0$ ,  $opt[i, W'] = 0$  for every  $W' = 0, 1, 2, \dots, W$ .

$$opt[i, W'] = \begin{cases} & i = 0 \\ & i > 0, w_i > W' \\ & i > 0, w_i \leq W' \end{cases}$$

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$$opt[i, W'] = \begin{cases} 0 & i = 0 \\ opt[i - 1, W'] & i > 0, w_i > W' \\ \max \left\{ \begin{array}{l} opt[i - 1, W'] \\ opt[i - 1, W' - w_i] + v_i \end{array} \right\} & i > 0, w_i \leq W' \end{cases}$$

## Exercise: Items with 3 Parameters

**Input:** integer bounds  $W > 0$ ,  $Z > 0$ ,  
a set of  $n$  items, each with an integer weight  $w_i > 0$   
a size  $z_i > 0$  for each item  $i$   
a value  $v_i > 0$  for each item  $i$

**Output:** a subset  $S$  of items that

$$\begin{aligned} & \text{maximizes } \sum_{i \in S} v_i \quad \text{s.t.} \\ & \sum_{i \in S} w_i \leq W \quad \text{and} \quad \sum_{i \in S} z_i \leq Z \end{aligned}$$



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# Subsequence

- $A = bacdca$
- $C = adca$

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**Def.** Given two sequences  $A[1 .. n]$  and  $C[1 .. t]$  of letters,  $C$  is called a **subsequence** of  $A$  if there exists integers  $1 \leq i_1 < i_2 < i_3 < \dots < i_t \leq n$  such that  $A[i_j] = C[j]$  for every  $j = 1, 2, 3, \dots, t$ .

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- Exercise: how to check if sequence  $C$  is a subsequence of  $A$ ?

## Longest Common Subsequence

**Input:**  $A[1 .. n]$  and  $B[1 .. m]$

**Output:** the longest common subsequence of  $A$  and  $B$

### Example:

- $A = \text{'bacdca'}$
- $B = \text{'adbcdca'}$

## Longest Common Subsequence

**Input:**  $A[1 .. n]$  and  $B[1 .. m]$

**Output:** the longest common subsequence of  $A$  and  $B$

### Example:

- $A = 'bacdca'$
- $B = 'adbcdca'$
- $LCS(A, B) = 'adca'$

## Longest Common Subsequence

**Input:**  $A[1 .. n]$  and  $B[1 .. m]$

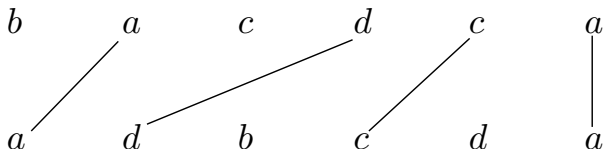
**Output:** the longest common subsequence of  $A$  and  $B$

### Example:

- $A = \text{'bacdca'}$
  - $B = \text{'adbcdca'}$
  - $\text{LCS}(A, B) = \text{'adca'}$
- 
- Applications: edit distance (diff), similarity of DNAs



# Matching View of LCS



- Goal of LCS: find a maximum-size non-crossing matching between letters in  $A$  and letters in  $B$ .

# Reduce to Subproblems

- $A = \text{'bacdca'}$
- $B = \text{'adbcdca'}$

# Reduce to Subproblems

- $A = \text{'bacdca'}$
- $B = \text{'adbcdca'}$

# Reduce to Subproblems

- $A = \text{'bacdc'}$
- $B = \text{'adbcd'}$

# Reduce to Subproblems

- $A = \text{'bacdc'}$
- $B = \text{'adbcd'}$
- either the last letter of  $A$  is not matched:
- or the last letter of  $B$  is not matched:

# Reduce to Subproblems

- $A = \text{'bacdc'}$
- $B = \text{'adbcd'}$
- either the last letter of  $A$  is not matched:
  - need to compute  $\text{LCS}(\text{'bacdc'}, \text{'adbcd'})$
- or the last letter of  $B$  is not matched:

# Reduce to Subproblems

- $A = \text{'bacdc'}$
- $B = \text{'adbcd'}$
- either the last letter of  $A$  is not matched:
  - need to compute  $\text{LCS}(\text{'bacdc'}, \text{'adbcd'})$
- or the last letter of  $B$  is not matched:
  - need to compute  $\text{LCS}(\text{'bacd'}, \text{'adbcd'})$

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$ : length of longest common sub-sequence of  $A[1 .. i]$  and  $B[1 .. j]$ .



# Dynamic Programming for LCS

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$ : length of longest common sub-sequence of  $A[1 .. i]$  and  $B[1 .. j]$ .
- if  $i = 0$  or  $j = 0$ , then  $opt[i, j] = 0$ .

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$ : length of longest common sub-sequence of  $A[1 .. i]$  and  $B[1 .. j]$ .
- if  $i = 0$  or  $j = 0$ , then  $opt[i, j] = 0$ .
- if  $i > 0, j > 0$ , then

$$opt[i, j] = \begin{cases} & \text{if } A[i] = B[j] \\ & \text{if } A[i] \neq B[j] \end{cases}$$

# Dynamic Programming for LCS

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$ : length of longest common sub-sequence of  $A[1 .. i]$  and  $B[1 .. j]$ .
- if  $i = 0$  or  $j = 0$ , then  $opt[i, j] = 0$ .
- if  $i > 0, j > 0$ , then

$$opt[i, j] = \begin{cases} opt[i - 1, j - 1] + 1 & \text{if } A[i] = B[j] \\ & \text{if } A[i] \neq B[j] \end{cases}$$

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$ : length of longest common sub-sequence of  $A[1 .. i]$  and  $B[1 .. j]$ .
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- if  $i > 0, j > 0$ , then

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# Dynamic Programming for LCS

```
1 for  $j \leftarrow 0$  to  $m$  do
2    $opt[0, j] \leftarrow 0$ 
3 for  $i \leftarrow 1$  to  $n$ 
4    $opt[i, 0] \leftarrow 0$ 
5   for  $j \leftarrow 1$  to  $m$ 
6     if  $A[i] = B[j]$  then
7        $opt[i, j] \leftarrow opt[i - 1, j - 1] + 1$ 
8     elseif  $opt[i, j - 1] \geq opt[i - 1, j]$  then
9        $opt[i, j] \leftarrow opt[i, j - 1]$ 
10    else
11       $opt[i, j] \leftarrow opt[i - 1, j]$ 
```

# Dynamic Programming for LCS

- 1 for  $j \leftarrow 0$  to  $m$  do
- 2      $opt[0, j] \leftarrow 0$
- 3 for  $i \leftarrow 1$  to  $n$
- 4      $opt[i, 0] \leftarrow 0$
- 5     for  $j \leftarrow 1$  to  $m$
- 6         if  $A[i] = B[j]$  then
- 7              $opt[i, j] \leftarrow opt[i - 1, j - 1] + 1, \pi[i, j] \leftarrow \text{"↖"}$
- 8         elseif  $opt[i, j - 1] \geq opt[i - 1, j]$  then
- 9              $opt[i, j] \leftarrow opt[i, j - 1], \pi[i, j] \leftarrow \text{"←"}$
- 10         else
- 11              $opt[i, j] \leftarrow opt[i - 1, j], \pi[i, j] \leftarrow \text{"↑"}$

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥						
2	0 ⊥						
3	0 ⊥						
4	0 ⊥						
5	0 ⊥						
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	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←					
2	0 ⊥						
3	0 ⊥						
4	0 ⊥						
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←				
2	0 ⊥						
3	0 ⊥						
4	0 ⊥						
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖			
2	0 ⊥						
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	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←		
2	0 ⊥						
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	
2	0 ⊥						
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
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1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
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1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑					
4	0 ⊥						
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6	0 ⊥						

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<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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3	0 ⊥	1 ↑	1 ←				
4	0 ⊥						
5	0 ⊥						
6	0 ⊥						

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<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
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	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖		
4	0 ⊥						
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6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	
4	0 ⊥						
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥						
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥						
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑					
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖				
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←			
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←		
5	0 ⊥						
6	0 ⊥						



# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥						
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑					
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑				
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←			
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖		
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	
6	0 ⊥						



# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥						

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖					

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑				

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←			

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑		

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	

# Example

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖



# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
4	0 ⊥	1 ↑	2 ↖	2 ←	2 ←	3 ↖	3 ←
5	0 ⊥	1 ↑	2 ↑	2 ←	3 ↖	3 ←	3 ←
6	0 ⊥	1 ↖	2 ↑	2 ←	3 ↑	3 ←	4 ↖

# Example: Find Common Subsequence

	1	2	3	4	5	6
<i>A</i>	b	a	c	d	c	a
<i>B</i>	a	d	b	c	d	a

	0	1	2	3	4	5	6
0	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥	0 ⊥
1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
2	0 ⊥	1 ↖	1 ←	1 ←	1 ←	1 ←	2 ↖
3	0 ⊥	1 ↑	1 ←	1 ←	2 ↖	2 ←	2 ←
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1	0 ⊥	0 ←	0 ←	1 ↖	1 ←	1 ←	1 ←
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# Find Common Subsequence

- 1  $i \leftarrow n, j \leftarrow m, S \leftarrow ""$
- 2 while  $i > 0$  and  $j > 0$
- 3   if  $\pi[i, j] = "\searrow"$  then
- 4      $S \leftarrow A[i] \bowtie S, i \leftarrow i - 1, j \leftarrow j - 1$
- 5   else if  $\pi[i, j] = "\uparrow"$
- 6      $i \leftarrow i - 1$
- 7   else
- 8      $j \leftarrow j - 1$
- 9 return  $S$

# Variants of Problem

## Edit Distance with Insertions and Deletions

**Input:** a string  $A$

each time we can delete a letter from  $A$  or insert a letter to  $A$

**Output:** minimum number of operations (insertions or deletions) we need to change  $A$  to  $B$ ?

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**Obs.**  $\#OPs = \text{length}(A) + \text{length}(B) - 2 \cdot \text{length}(\text{LCS}(A, B))$

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## Edit Distance with Insertions, Deletions and Replacing

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### Example:

- $A = \text{ocurrance}$ ,  $B = \text{occurrence}$ .
- 2 operations: insert 'c', change 'a' to 'e'
  
- Not related to LCS any more

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- Input: acbcedeacab

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Example:

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- Output: **acedeca**

# Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem
- 4 Longest Common Subsequence**
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication
- 7 Summary

# Computing the Length of LCS

```
1 for  $j \leftarrow 0$  to  $m$  do
2    $opt[0, j] \leftarrow 0$ 
3 for  $i \leftarrow 1$  to  $n$ 
4    $opt[i, 0] \leftarrow 0$ 
5   for  $j \leftarrow 1$  to  $m$ 
6     if  $A[i] = B[j]$ 
7        $opt[i, j] \leftarrow opt[i - 1, j - 1] + 1$ 
8     elseif  $opt[i, j - 1] \geq opt[i - 1, j]$ 
9        $opt[i, j] \leftarrow opt[i, j - 1]$ 
10    else
11       $opt[i, j] \leftarrow opt[i - 1, j]$ 
```

**Obs.** The  $i$ -th row of table only depends on  $(i - 1)$ -th row.

# Reducing Space to $O(n + m)$

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# Reducing Space to $O(n + m)$

**Obs.** The  $i$ -th row of table only depends on  $(i - 1)$ -th row.

**Q:** How to use this observation to reduce space?

**A:** We only keep two rows: the  $(i - 1)$ -th row and the  $i$ -th row.

# Linear Space Algorithm to Compute Length of LCS

- 1 for  $j \leftarrow 0$  to  $m$  do
- 2      $opt[0, j] \leftarrow 0$
- 3 for  $i \leftarrow 1$  to  $n$
- 4      $opt[i \bmod 2, 0] \leftarrow 0$
- 5     for  $j \leftarrow 1$  to  $m$
- 6         if  $A[i] = B[j]$
- 7              $opt[i \bmod 2, j] \leftarrow opt[i - 1 \bmod 2, j - 1] + 1$
- 8         elseif  $opt[i \bmod 2, j - 1] \geq opt[i - 1 \bmod 2, j]$
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- 10         else
- 11              $opt[i \bmod 2, j] \leftarrow opt[i - 1 \bmod 2, j]$
- 12 return  $opt[n \bmod 2, m]$



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# Recall: Single Source Shortest Path Problem

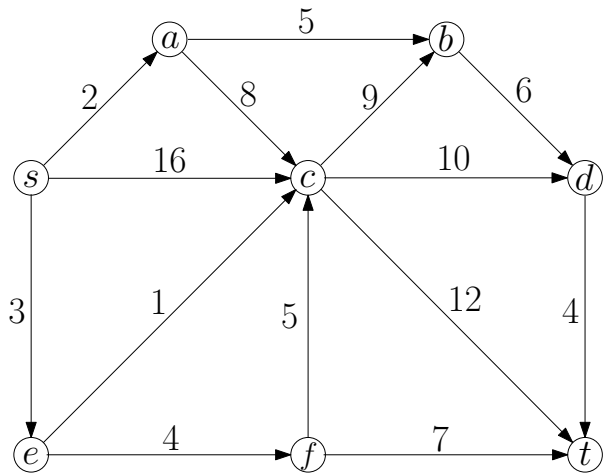
## Single Source Shortest Paths

**Input:** directed graph  $G = (V, E)$ ,  $s \in V$

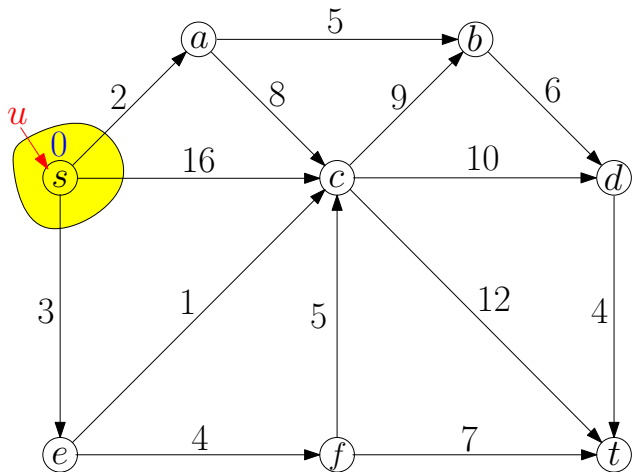
$$w : E \rightarrow \mathbb{R}_{\geq 0}$$

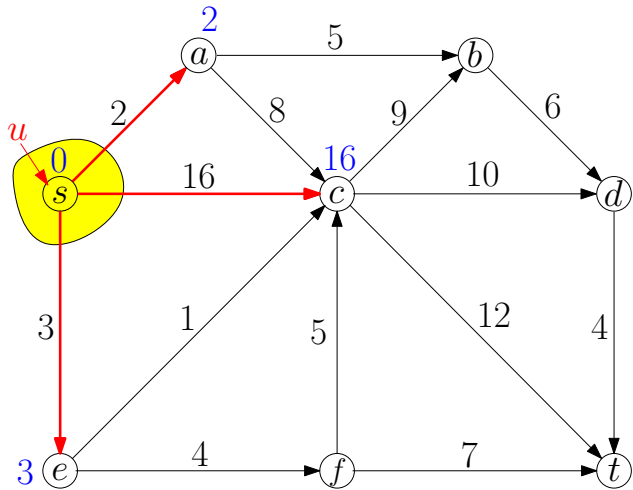
**Output:** shortest paths from  $s$  to all other vertices  $v \in V$

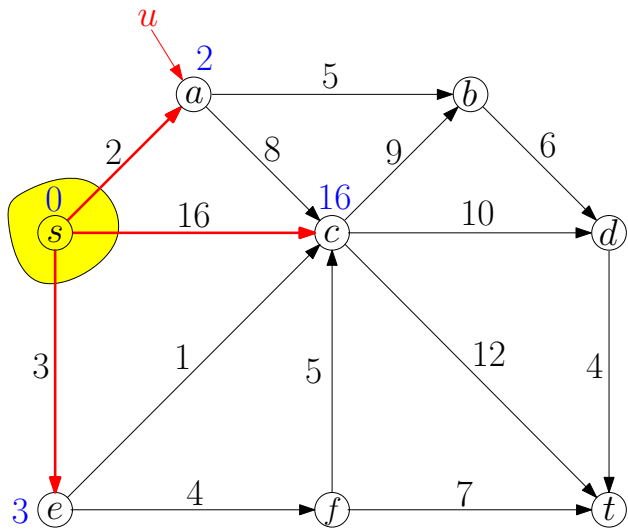
- Algorithm for the problem: Dijkstra's algorithm

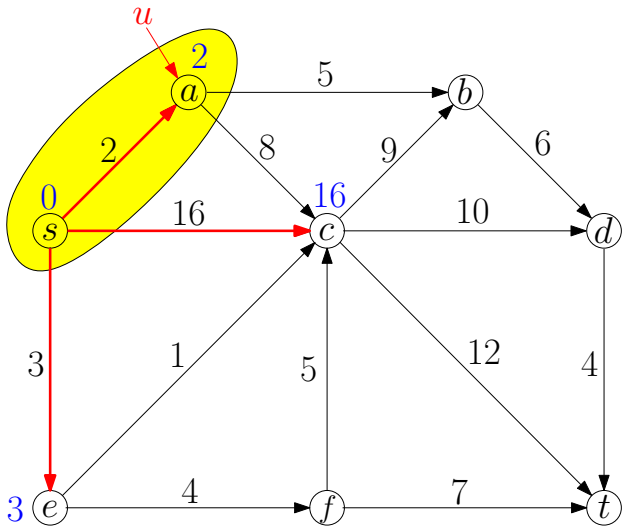


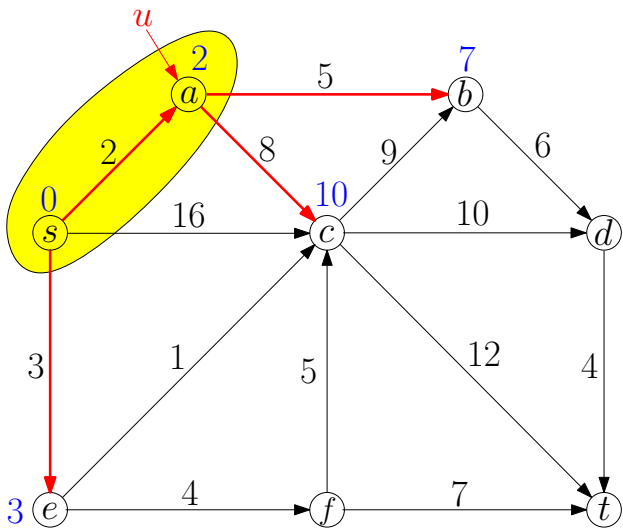


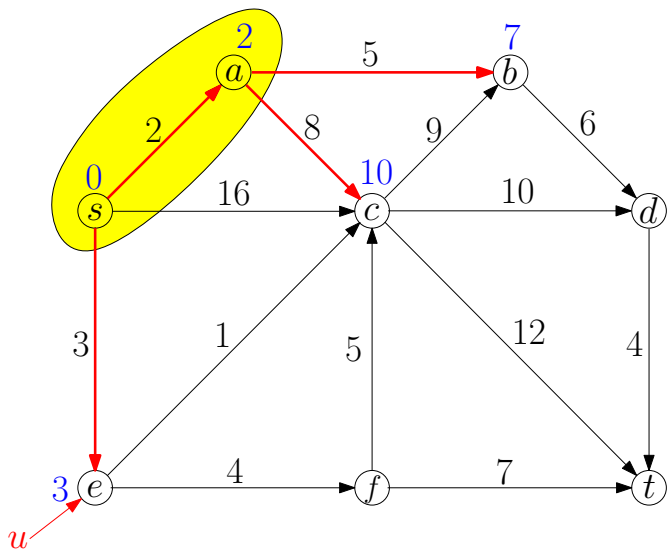


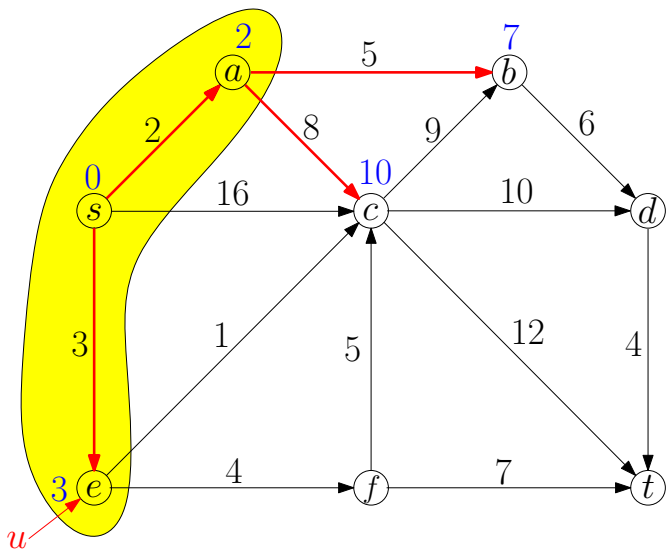


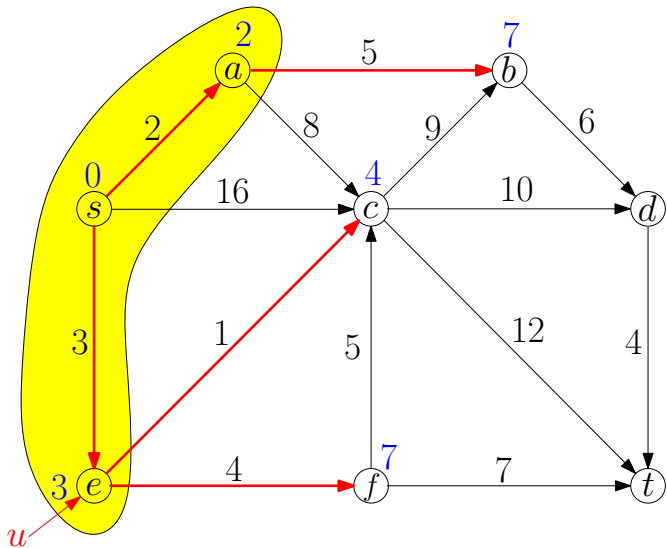




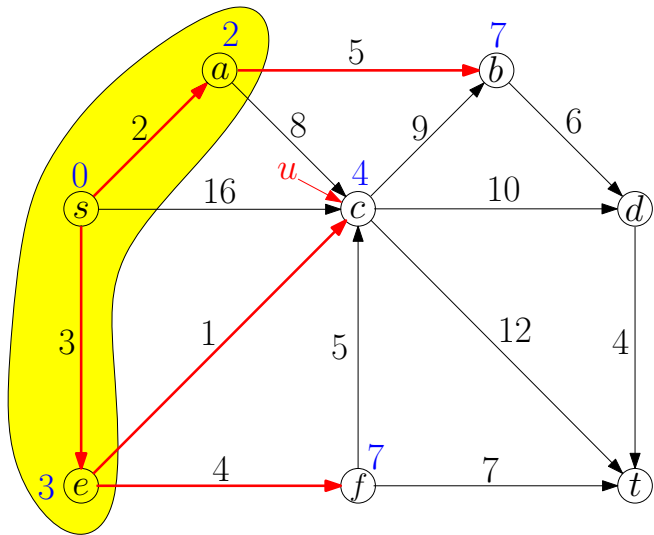


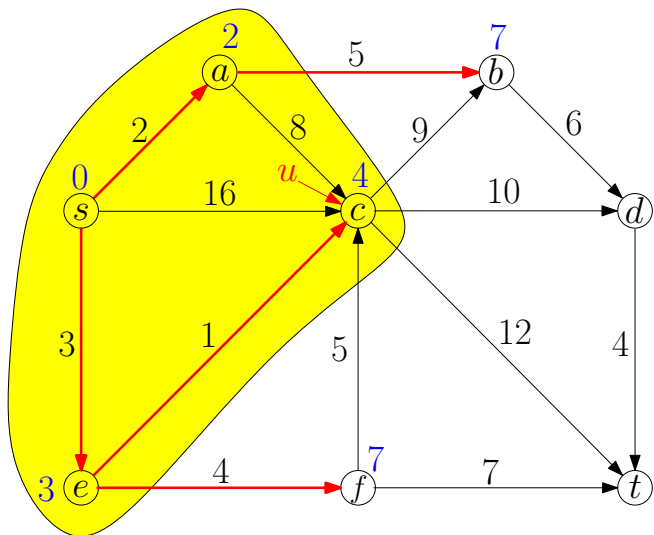


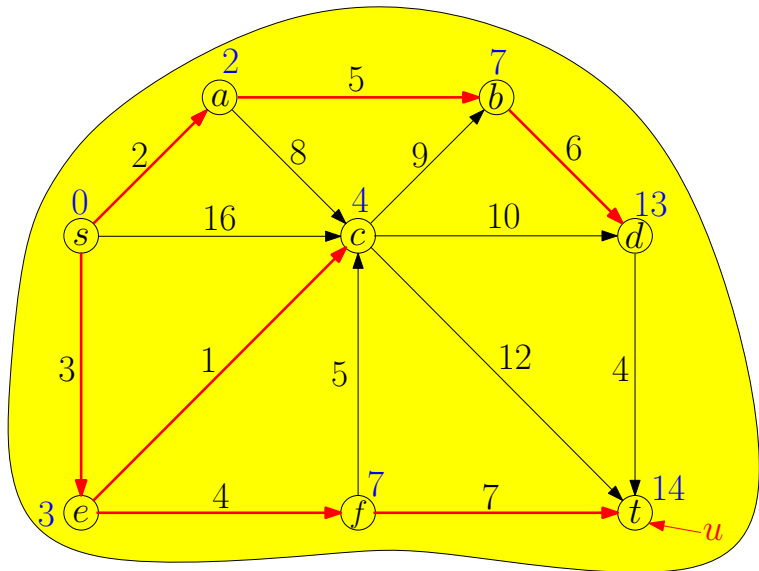












# Dijkstra's Algorithm Using Priority Queue

## Dijkstra( $G, w, s$ )

- 1  $S \leftarrow \emptyset, d(s) \leftarrow 0$  and  $d(v) \leftarrow \infty$  for every  $v \in V \setminus \{s\}$
- 2  $Q \leftarrow$  empty queue, for each  $v \in V$ :  $Q.insert(v, d(v))$
- 3 while  $S \neq V$ , do
- 4      $u \leftarrow Q.extract\_min()$
- 5      $S \leftarrow S \cup \{u\}$
- 6     for each  $v \in V \setminus S$  such that  $(u, v) \in E$
- 7         if  $d(u) + w(u, v) < d(v)$  then
- 8              $d(v) \leftarrow d(u) + w(u, v)$ ,  $Q.decrease\_key(v, d(v))$
- 9              $\pi(v) \leftarrow u$
- 10 return  $(\pi, d)$

- Running time =  $O(m + n \lg n)$ .

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**Input:** directed graph  $G = (V, E)$ ,  $s \in V$

assume all vertices are reachable from  $s$

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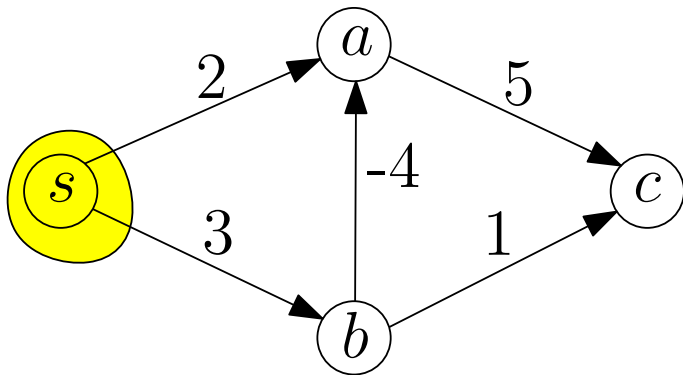
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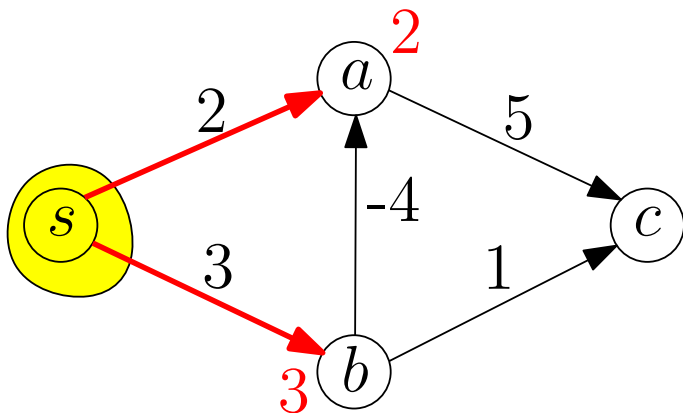
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- In transition graphs, negative weights make sense
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- **Dijkstra's algorithm does not work any more!**

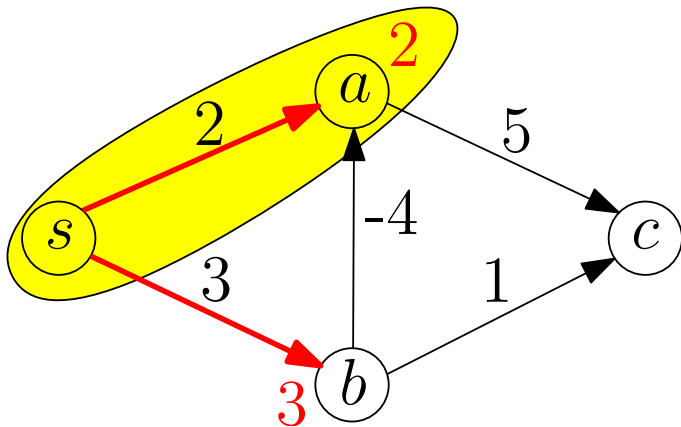
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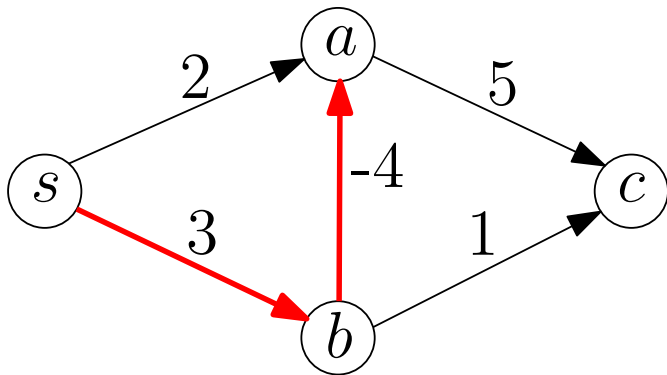
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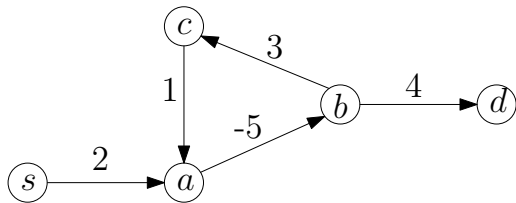


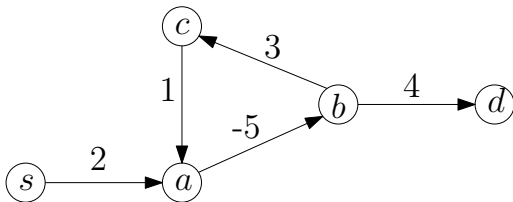
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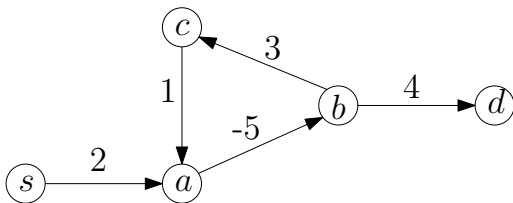






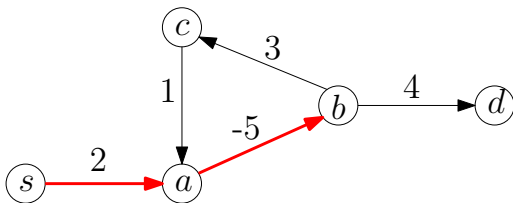
**Q:** What is the length of the shortest path from  $s$  to  $d$ ?





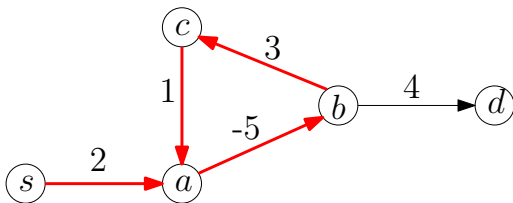
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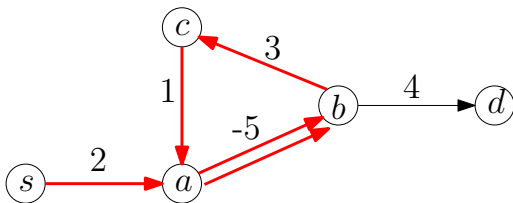
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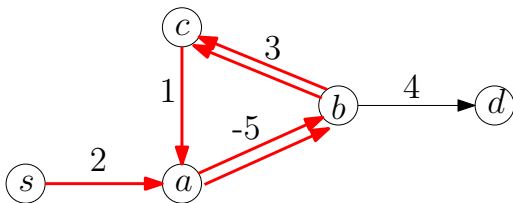
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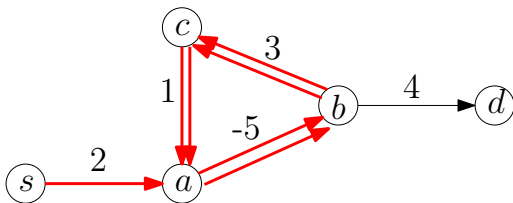
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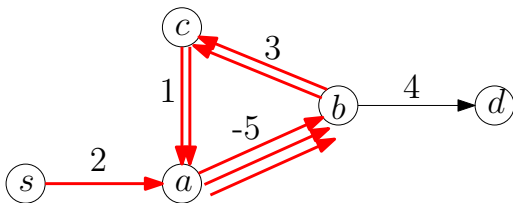
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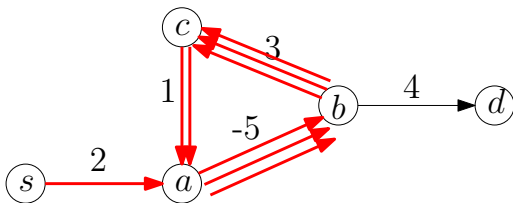
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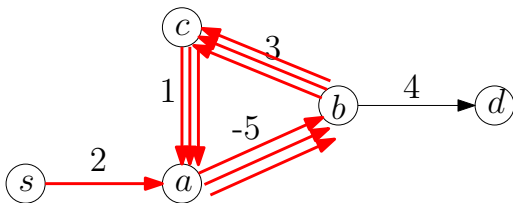
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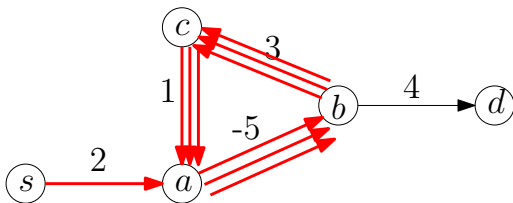
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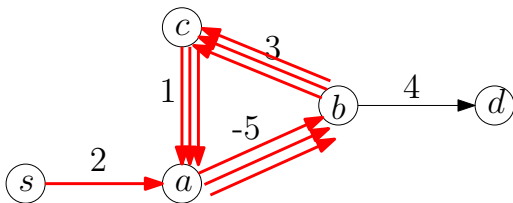
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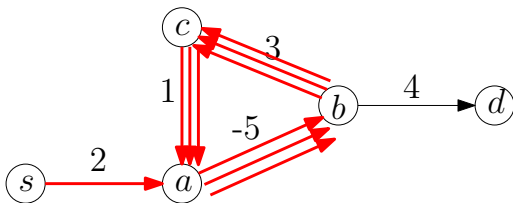


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Dealing with Negative Cycles



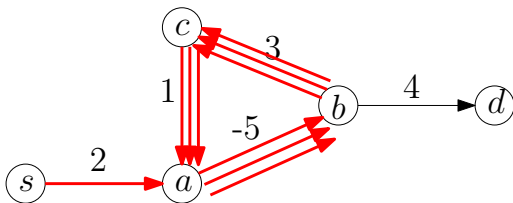
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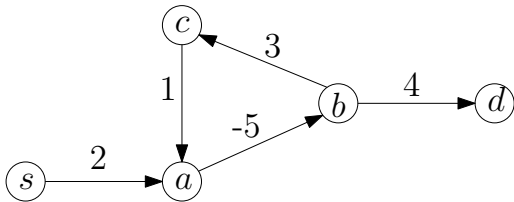
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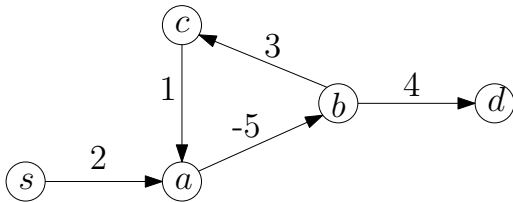
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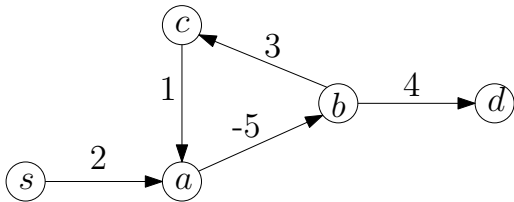
### Dealing with Negative Cycles

- assume the input graph does not contain negative cycles, or
- allow algorithm to report “negative cycle exists”





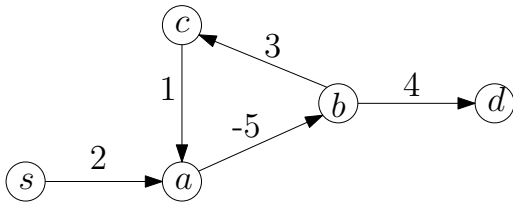
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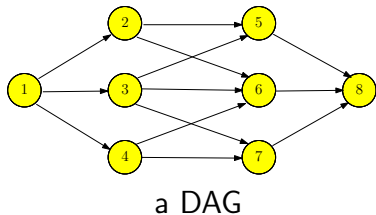
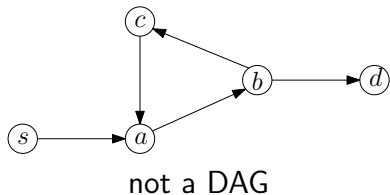
- Unfortunately, computing the shortest simple path between two vertices is an **NP-hard** problem.

# Outline

- 1 Weighted Interval Scheduling
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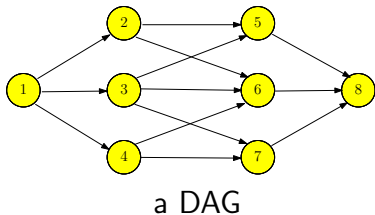
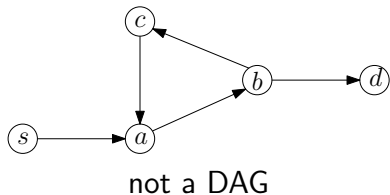
# Directed Acyclic Graphs

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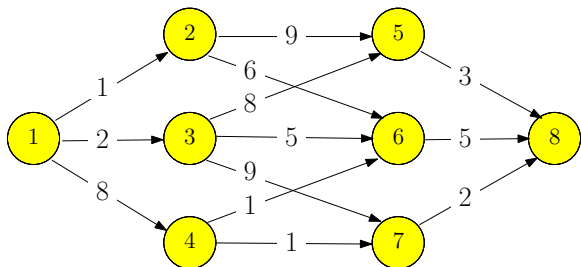
**Lemma** A directed graph is a DAG if and only if its vertices can be topologically sorted.

## Shortest Paths in DAG

**Input:** directed acyclic graph  $G = (V, E)$  and  $w : E \rightarrow \mathbb{R}$ .

Assume  $V = \{1, 2, 3, \dots, n\}$  is topologically sorted: if  $(i, j) \in E$ , then  $i < j$

**Output:** the shortest path from 1 to  $i$ , for every  $i \in V$

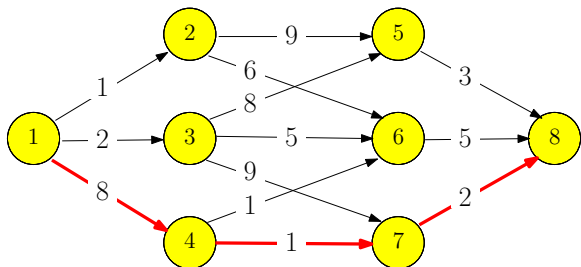


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- $f[i]$ : length of the shortest path from 1 to  $i$

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- Use an adjacency list for incoming edges of each vertex  $i$

## Shortest Paths in DAG

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- 3      $f[i] \leftarrow \infty$
- 4     for each incoming edge  $(j, i) \in E$  of  $i$
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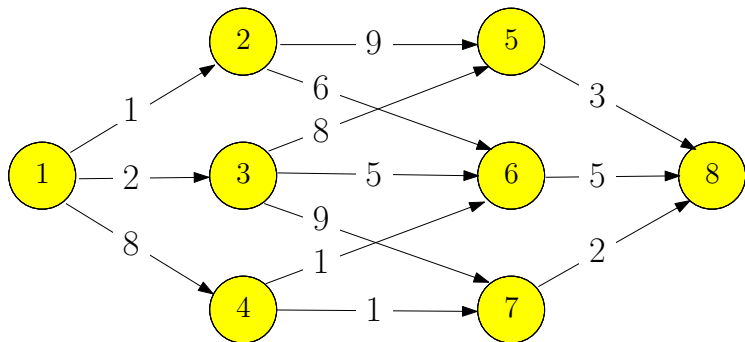
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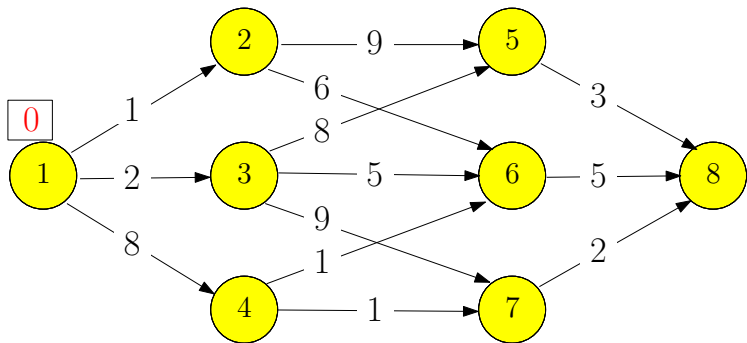
## print-path( $t$ )

- 1 if  $t = 1$  then
- 2     print(1)
- 3     return
- 4     print-path( $\pi(t)$ )
- 5     print(", ",  $t$ )

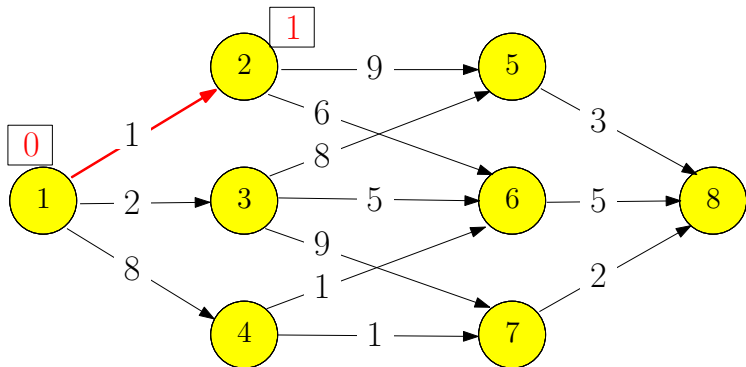
# Example



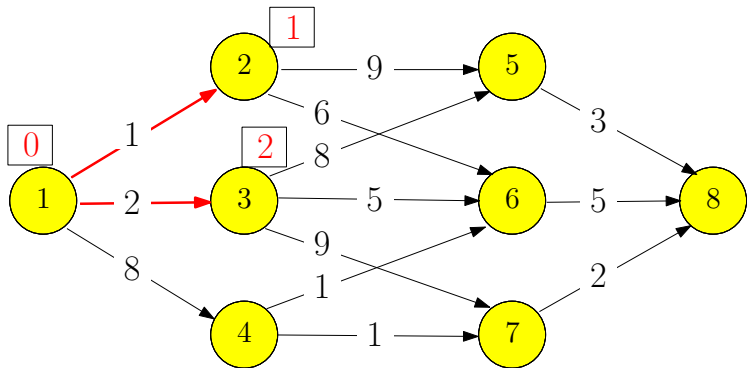
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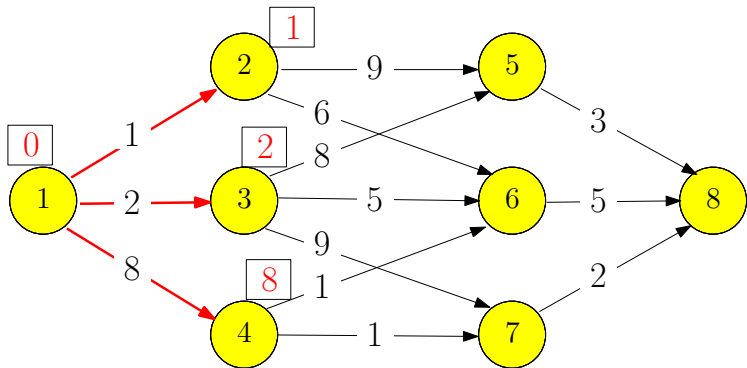


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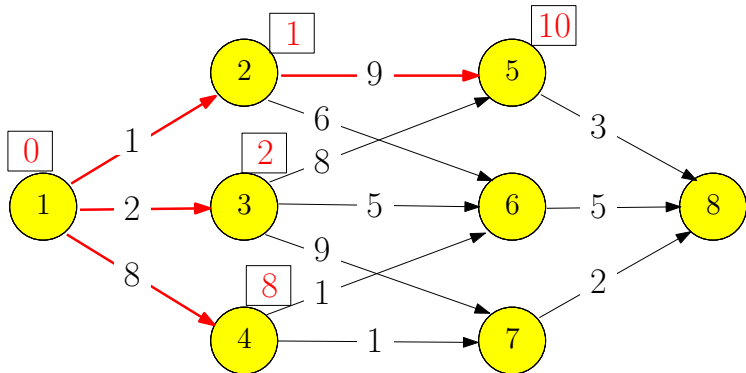




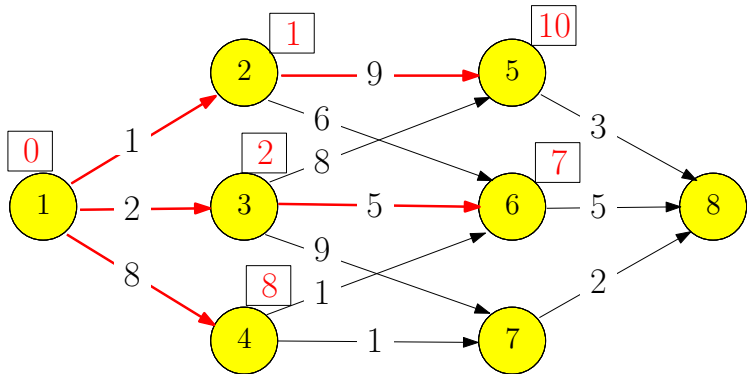
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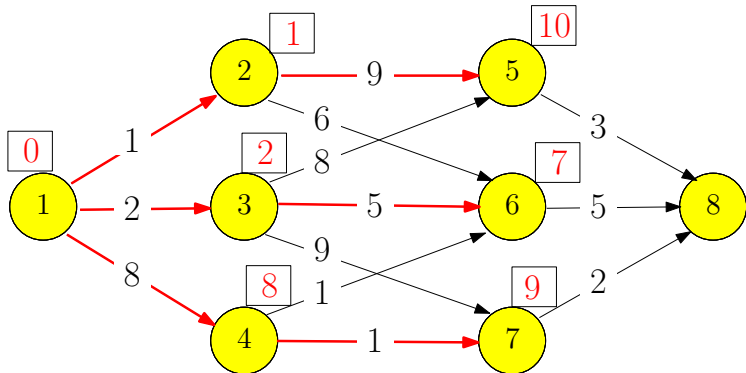
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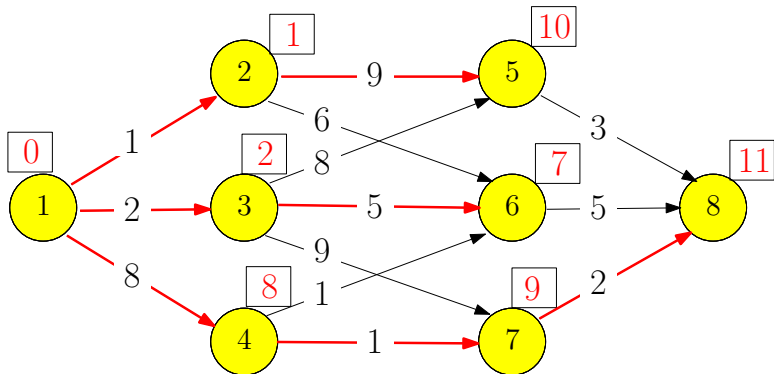
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## Single Source Shortest Paths, Weights May be Negative

**Input:** directed graph  $G = (V, E)$ ,  $s \in V$

assume all vertices are reachable from  $s$

$w : E \rightarrow \mathbb{R}$

**Output:** shortest paths from  $s$  to all other vertices  $v \in V$

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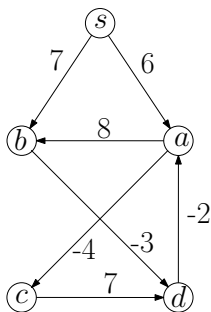
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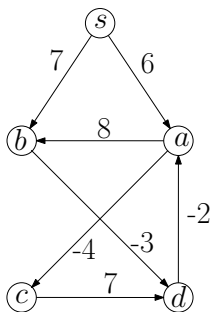
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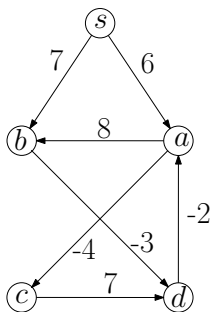
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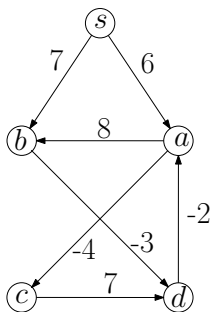
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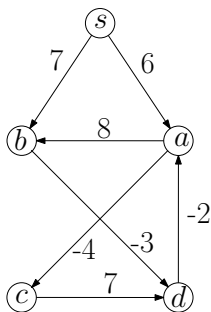
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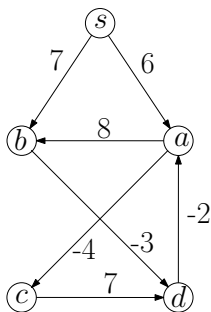
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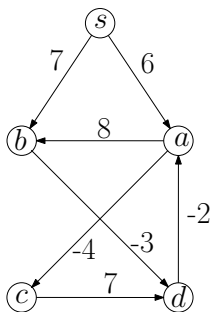
$$f^\ell[v] = \left\{ \begin{array}{l} \end{array} \right.$$

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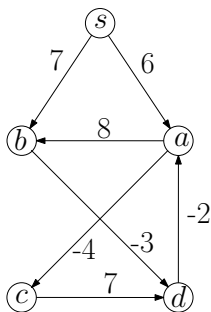
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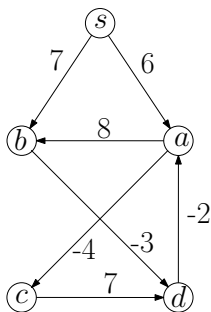
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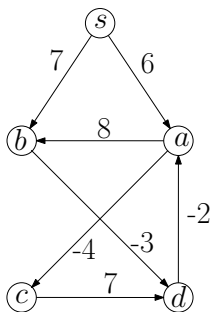
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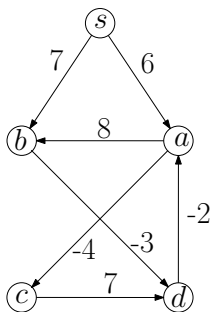
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$$f^{\ell-1}[v]$$

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$$f^\ell[v] = \begin{cases} 0 & \ell = 0, v = s \\ \infty & \ell = 0, v \neq s \\ \min \left\{ \begin{array}{l} f^{\ell-1}[v] \\ \min_{u:(u,v) \in E} (f^{\ell-1}[u] + w(u, v)) \end{array} \right. & \ell > 0 \end{cases}$$

## dynamic-programming( $G, w, s$ )

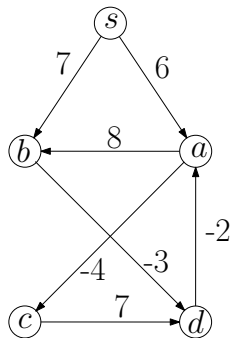
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**Obs.** Assuming there are no negative cycles, then a shortest path contains at most  $n - 1$  edges

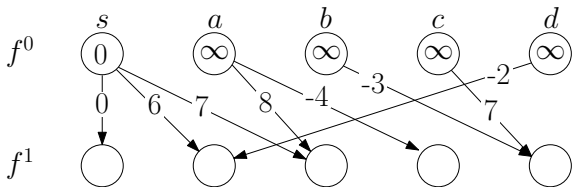
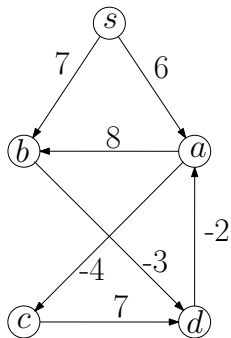
# Dynamic Programming: Example



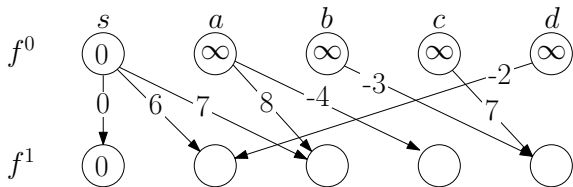
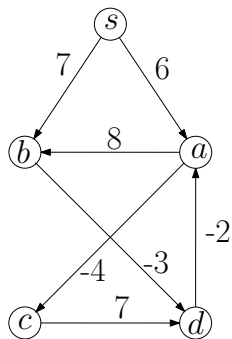
$$f^0 \quad \begin{matrix} s \\ \textcircled{0} \end{matrix} \quad \begin{matrix} a \\ \textcircled{\infty} \end{matrix} \quad \begin{matrix} b \\ \textcircled{\infty} \end{matrix} \quad \begin{matrix} c \\ \textcircled{\infty} \end{matrix} \quad \begin{matrix} d \\ \textcircled{\infty} \end{matrix}$$



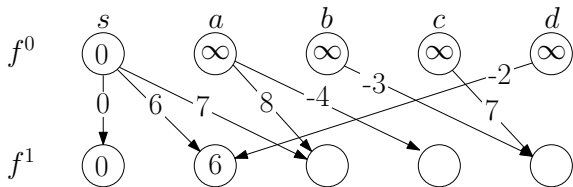
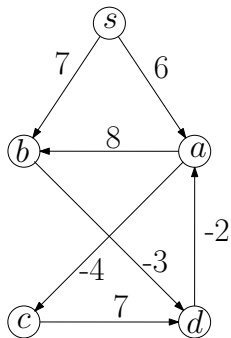
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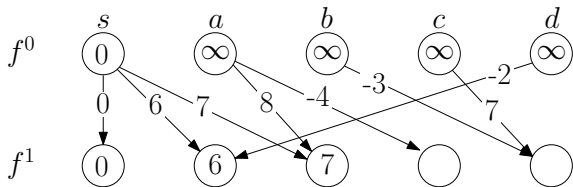
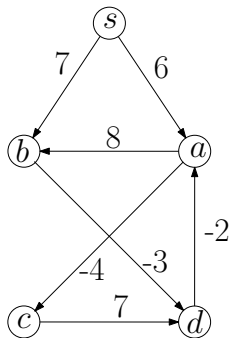
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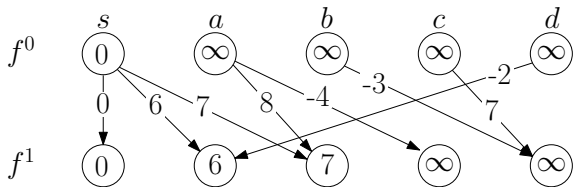
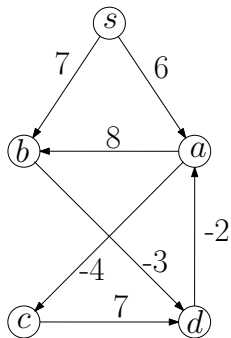
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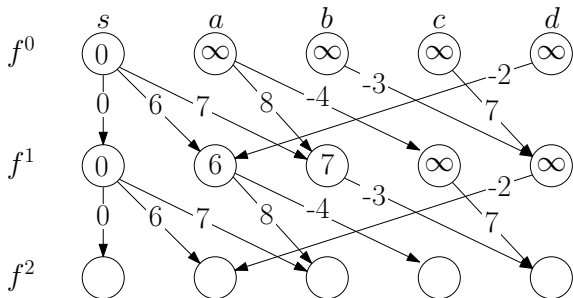
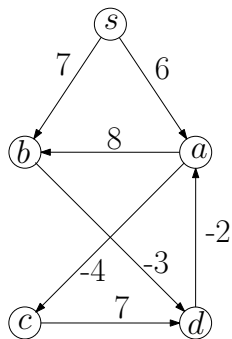
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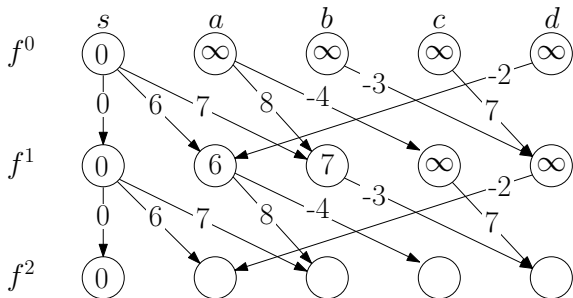
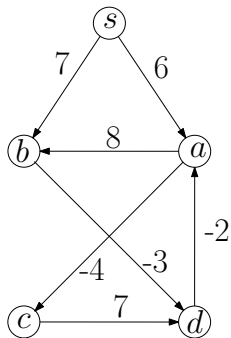
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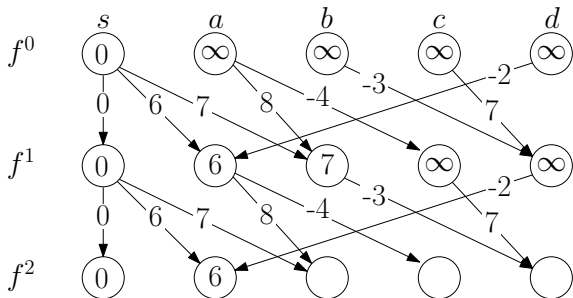
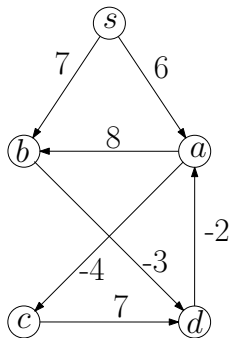
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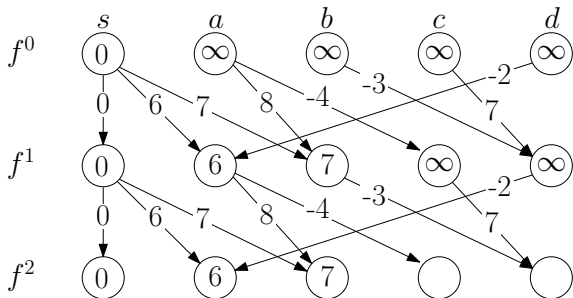
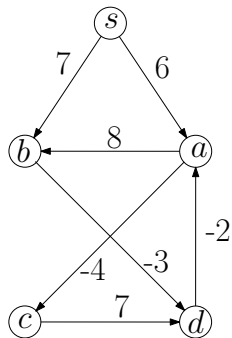


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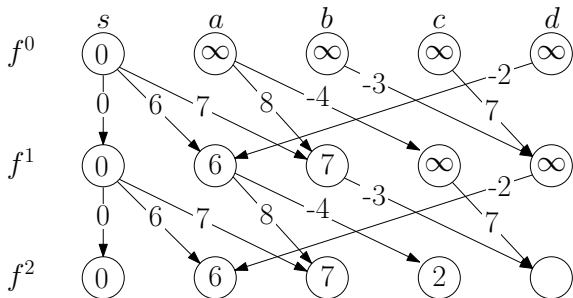
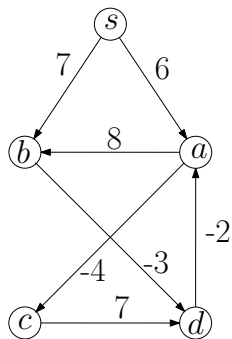




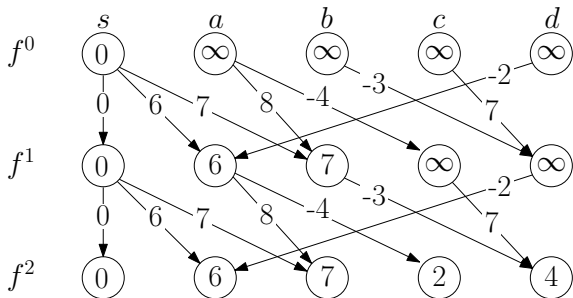
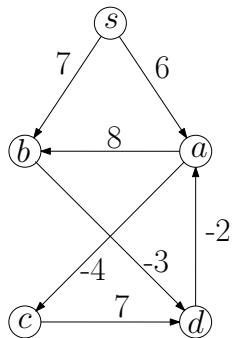
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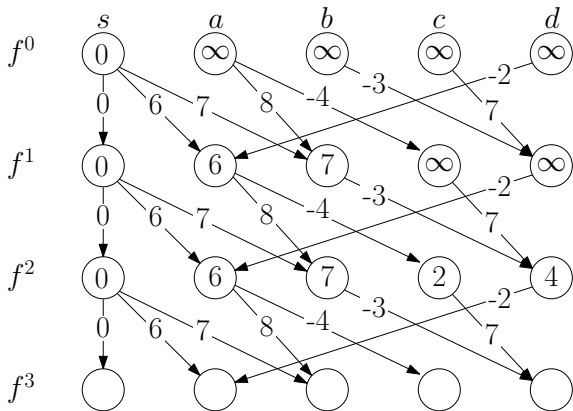
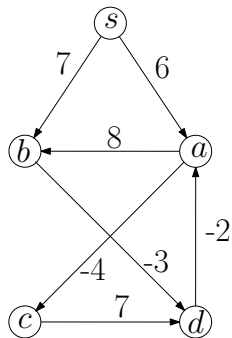
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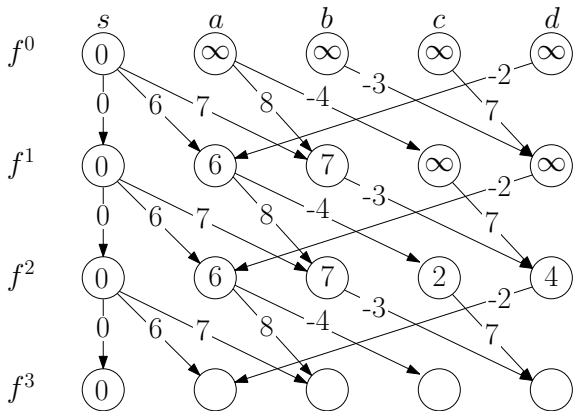
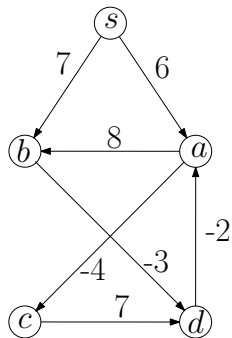
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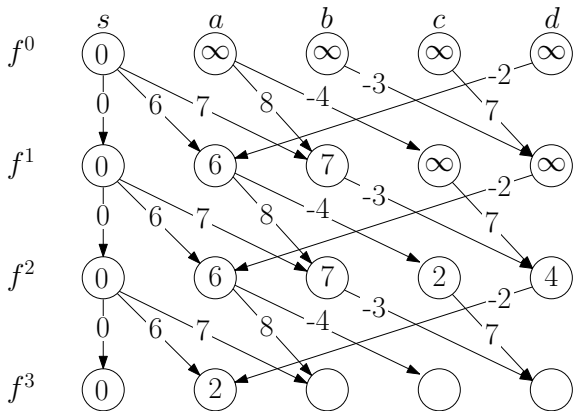
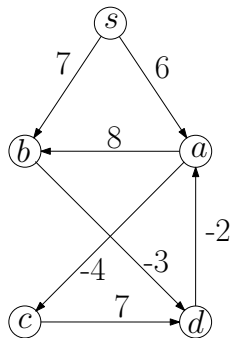
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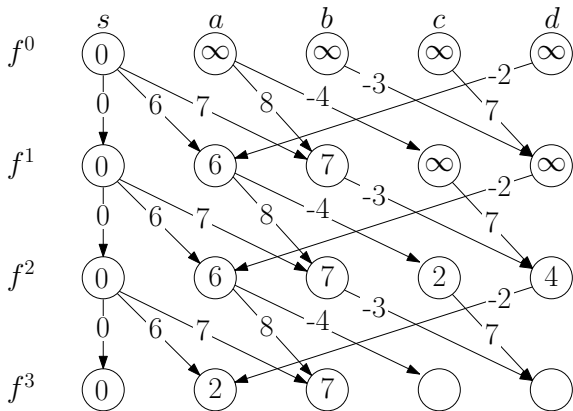
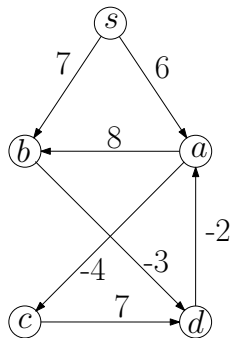
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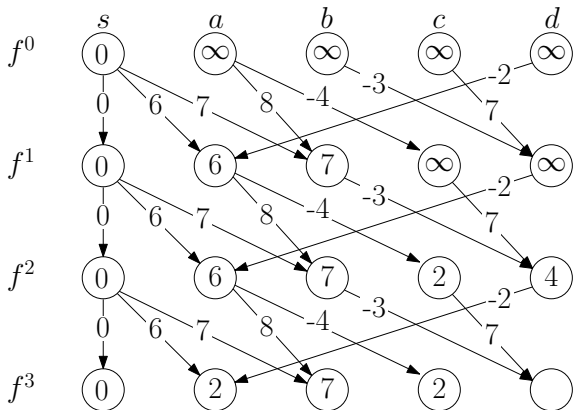
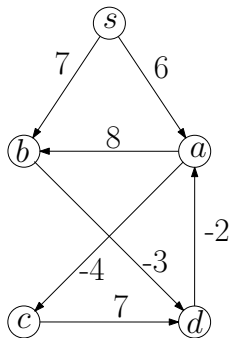
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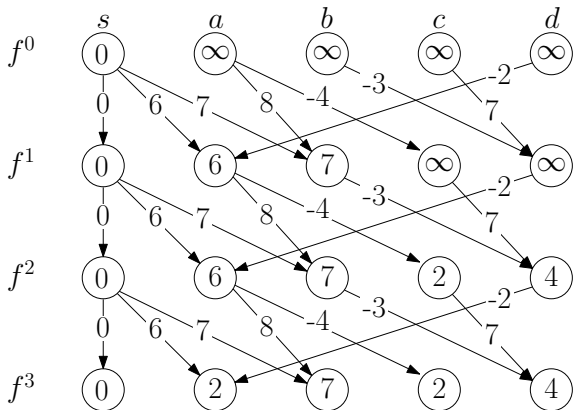
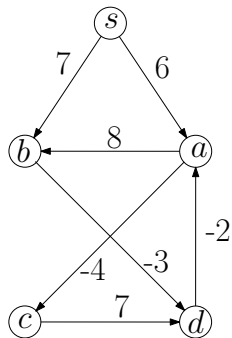


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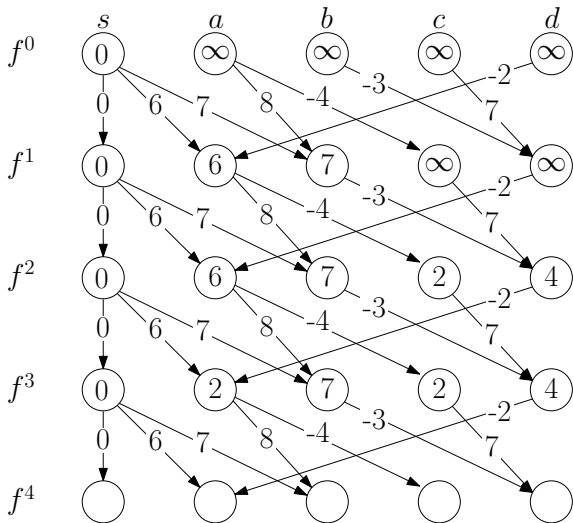
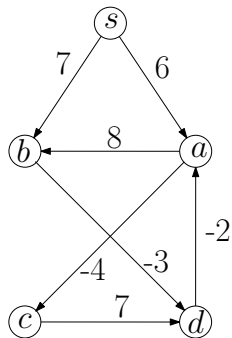




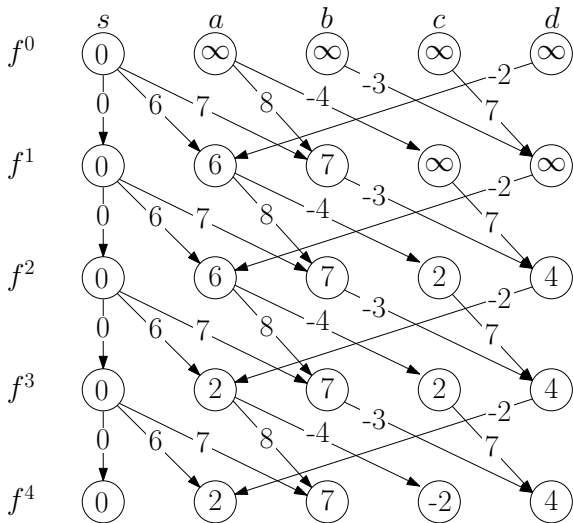
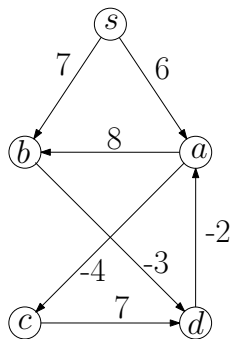
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**Obs.** Assuming there are no negative cycles, then a shortest path contains at most  $n - 1$  edges

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**Q:** What if there are negative cycles?

# Dynamic Programming With Negative Cycle Detection

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- 8         if  $f^{n-1}[u] + w(u, v) < f^{n-1}[v]$
- 9             report “negative cycle exists” and exit
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# Dynamic Programming with Better Space Usage

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- **Assuming there are no negative cycles, after iteration  $n - 1$ ,  $f[v] =$  length of shortest path from  $s$  to  $v$**

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- $\pi[v]$ : the parent of  $v$  in the shortest path tree
- Running time =  $O(nm)$

# Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem
- 4 Longest Common Subsequence
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication**
- 7 Summary

# Matrix Chain Multiplication

## Matrix Chain Multiplication

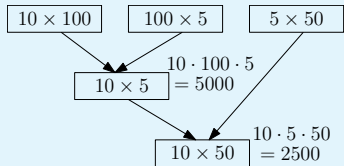
**Input:**  $n$  matrices  $A_1, A_2, \dots, A_n$  of sizes  $r_1 \times c_1, r_2 \times c_2, \dots, r_n \times c_n$ , such that  $c_i = r_{i+1}$  for every  $i = 1, 2, \dots, n - 1$ .

**Output:** the order of computing  $A_1 A_2 \dots A_n$  with the minimum number of multiplications

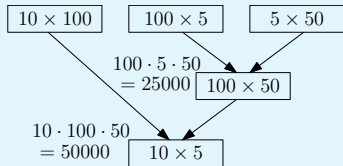
**Fact** Multiplying two matrices of size  $r \times k$  and  $k \times c$  takes  $r \times k \times c$  multiplications.

## Example:

- $A_1 : 10 \times 100$ ,  $A_2 : 100 \times 5$ ,  $A_3 : 5 \times 50$



$$\text{cost} = 5000 + 2500 = 7500$$

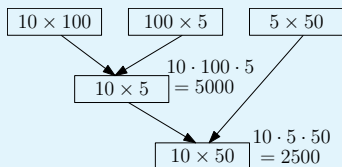


$$\text{cost} = 25000 + 50000 = 75000$$

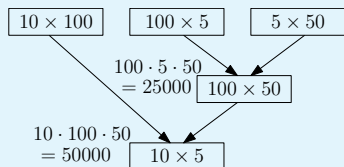
- $(A_1 A_2) A_3 : 10 \times 100 \times 5 + 10 \times 5 \times 50 = 7500$
- $A_1 (A_2 A_3) : 100 \times 5 \times 50 + 10 \times 100 \times 50 = 75000$

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- $(A_1 A_2) A_3: 10 \times 100 \times 5 + 10 \times 5 \times 50 = 7500$
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- Assume the last step is  $(A_1A_2 \cdots A_i)(A_{i+1}A_{i+2} \cdots A_n)$

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- Cost of last step:  $r_1 \times c_i \times c_n$
- Optimality for sub-instances: we need to compute  $A_1A_2 \cdots A_i$  and  $A_{i+1}A_{i+2} \cdots A_n$  optimally

# Matrix Chain Multiplication: Design DP

- Assume the last step is  $(A_1A_2 \cdots A_i)(A_{i+1}A_{i+2} \cdots A_n)$
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$$opt[i, j] = \begin{cases} 0 & i = j \\ \min_{k:i \leq k < j} (opt[i, k] + opt[k + 1, j] + r_i c_k c_j) & i < j \end{cases}$$

## matrix-chain-multiplication( $n, r[1..n], c[1..n]$ )

- 1 let  $opt[i, i] \leftarrow 0$  for every  $i = 1, 2, \dots, n$
- 2 for  $\ell \leftarrow 2$  to  $n$
- 3     for  $i \leftarrow 1$  to  $n - \ell + 1$
- 4          $j \leftarrow i + \ell - 1$
- 5          $opt[i, j] \leftarrow \infty$
- 6         for  $k \leftarrow i$  to  $j - 1$
- 7             if  $opt[i, k] + opt[k + 1, j] + r_i c_k c_j < opt[i, j]$
- 8                  $opt[i, j] \leftarrow opt[i, k] + opt[k + 1, j] + r_i c_k c_j$
- 9 return  $opt[1, n]$

# Outline

- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem
- 4 Longest Common Subsequence
  - Longest Common Subsequence in Linear Space
- 5 Shortest Paths in Graphs with Negative Weights
  - Shortest Paths in Directed Acyclic Graphs
  - Bellman-Ford Algorithm
- 6 Matrix Chain Multiplication
- 7 Summary



## Dynamic Programming

- Break up a problem into many **overlapping** sub-problems
- Build solutions for larger and larger sub-problems
- Use a **table** to store solutions for sub-problems for reuse

# Definition of Cells for Problems We Learnt

- Weighted interval scheduling:  $opt[i]$  = value of instance defined by jobs  $\{1, 2, \dots, i\}$
- Subset sum, knapsack:  $opt[i, W']$  = value of instance with items  $\{1, 2, \dots, i\}$  and budget  $W'$
- Longest common subsequence:  $opt[i, j]$  = value of instance defined by  $A[1..i]$  and  $B[1..j]$
- Matrix chain multiplication:  $opt[i, j]$  = value of instances defined by matrices  $i$  to  $j$

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- Matrix chain multiplication:  $opt[i, j]$  = value of instances defined by matrices  $i$  to  $j$
- Shortest paths in DAG:  $f[v]$  = length of shortest path from  $s$  to  $v$
- Bellman-Ford:  $f^\ell[v]$  = length of shortest path from  $s$  to  $v$  that uses at most  $\ell$  edges