

Find Common Subsequence

```
1:  $i \leftarrow n, j \leftarrow m, S \leftarrow ()$ 
2: while  $i > 0$  and  $j > 0$  do
3:   if  $\pi[i, j] = "\searrow"$  then
4:     add  $A[i]$  to beginning of  $S, i \leftarrow i - 1, j \leftarrow j - 1$ 
5:   else if  $\pi[i, j] = "\uparrow"$  then
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 and a string B

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

Edit Distance with Replacing: Reduction to a Variant of LCS

- Need to match letters in A and B , every letter is matched at most once and there should be no crosses.
- However, we can **match two different letters**: Matching a same letter gives score 2, matching two different letters gives score 1.
- Need to maximize the score.
- DP recursion for the case $i > 0$ and $j > 0$:

$$opt[i, j] = \begin{cases} opt[i - 1, j - 1] + 2 & \text{if } A[i] = B[j] \\ \max \begin{cases} opt[i - 1, j] \\ opt[i, j - 1] \\ opt[i - 1, j - 1] + 1 \end{cases} & \text{if } A[i] \neq B[j] \end{cases}$$

- Relation : $\#OPs = \text{length}(A) + \text{length}(B) - \text{max_score}$

Edit Distance (with Replacing): using DP directly

- $opt[i, j], 0 \leq i \leq n, 0 \leq j \leq m$: edit distance between $A[1 .. i]$ and $B[1 .. j]$.

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- 1 Weighted Interval Scheduling
- 2 Subset Sum Problem
- 3 Knapsack Problem
- 4 Longest Common Subsequence**
 - Longest Common Subsequence in Linear Space
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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  $n$  do
4:    $opt[i, 0] \leftarrow 0$ 
5:   for  $j \leftarrow 1$  to  $m$  do
6:     if  $A[i] = B[j]$  then
7:        $opt[i, j] \leftarrow opt[i - 1, j - 1] + 1$ 
8:     else if  $opt[i, j - 1] \geq opt[i - 1, j]$  then
9:        $opt[i, j] \leftarrow opt[i, j - 1]$ 
10:    else
11:       $opt[i, j] \leftarrow opt[i - 1, j]$ 
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Obs. The i -th row of table only depends on $(i - 1)$ -th row.

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Q: How to use this observation to reduce space?

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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  $n$  do
4:    $opt[i \bmod 2, 0] \leftarrow 0$ 
5:   for  $j \leftarrow 1$  to  $m$  do
6:     if  $A[i] = B[j]$  then
7:        $opt[i \bmod 2, j] \leftarrow opt[i - 1 \bmod 2, j - 1] + 1$ 
8:     else if  $opt[i \bmod 2, j - 1] \geq opt[i - 1 \bmod 2, j]$  then
9:        $opt[i \bmod 2, j] \leftarrow opt[i \bmod 2, j - 1]$ 
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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How to Recover LCS Using Linear Space?

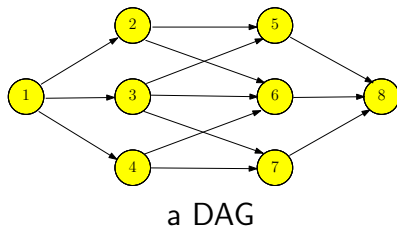
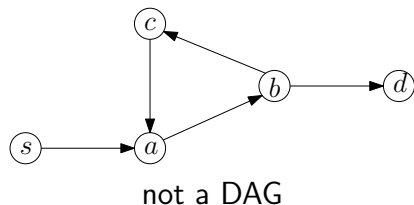
- Only keep the last two rows: only know how to match $A[n]$
- Can recover the LCS using n rounds: time = $O(n^2m)$
- Using **Divide and Conquer** + Dynamic Programming:
 - Space: $O(m + n)$
 - Time: $O(nm)$

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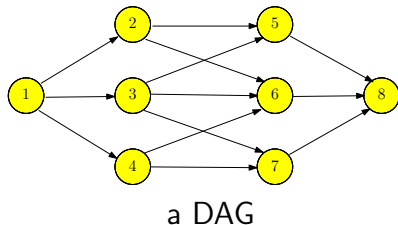
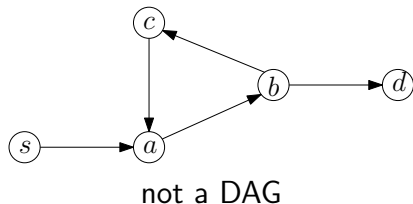
Directed Acyclic Graphs

Def. A directed acyclic graph (DAG) is a directed graph without (directed) cycles.



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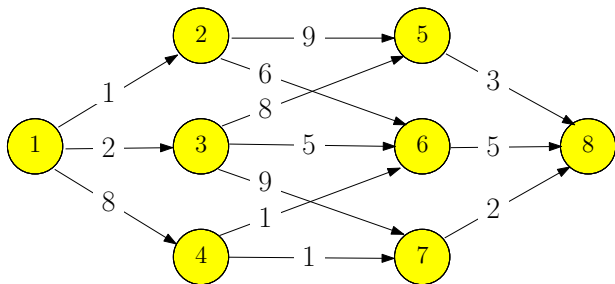
Lemma A directed graph is a DAG if and only if its vertices can be topologically sorted.

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 $i \in V$

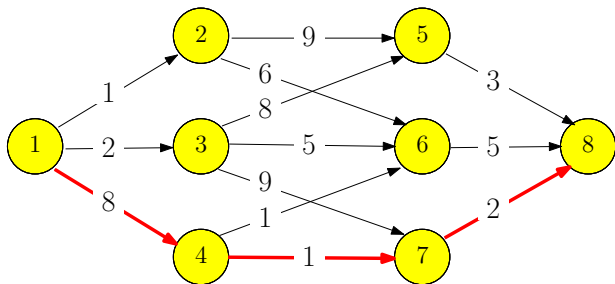


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Shortest Paths in DAG

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

Shortest Paths in DAG

```
1:  $f[1] \leftarrow 0$   
2: for  $i \leftarrow 2$  to  $n$  do  
3:    $f[i] \leftarrow \infty$   
4:   for each incoming edge  $(j, i)$  of  $i$  do  
5:     if  $f[j] + w(j, i) < f[i]$  then  
6:        $f[i] \leftarrow f[j] + w(j, i)$ 
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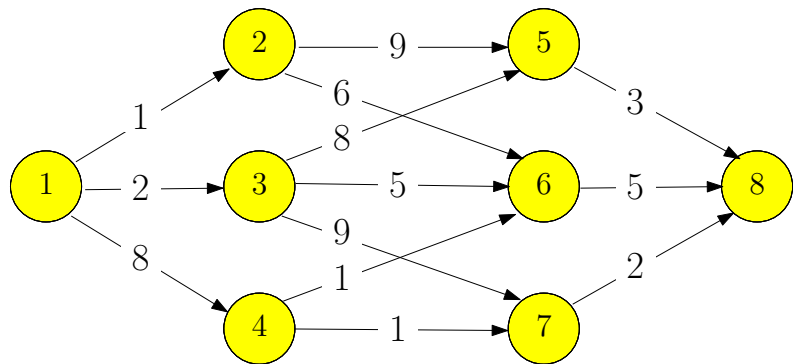
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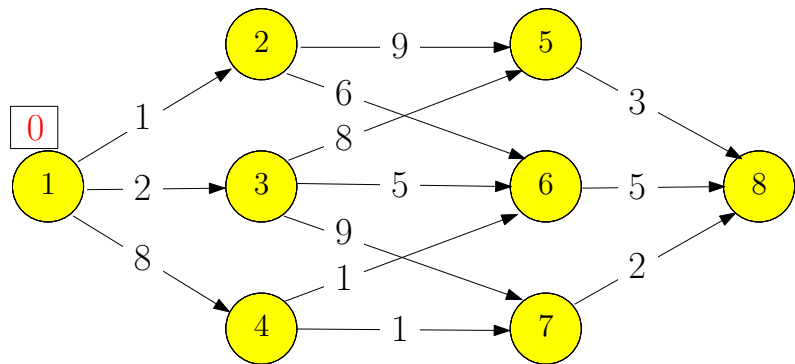
print-path(t)

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

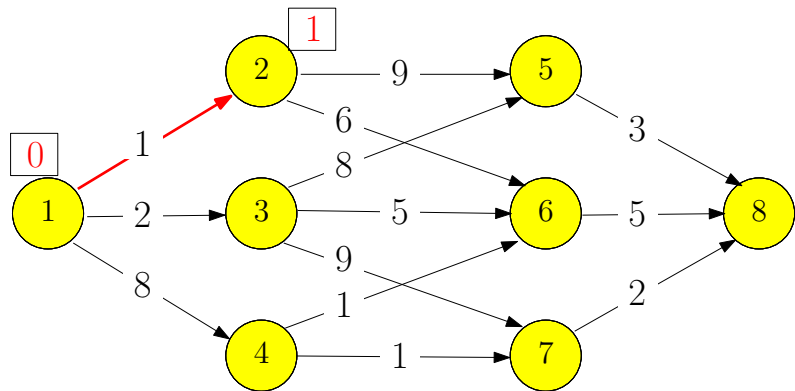
Example



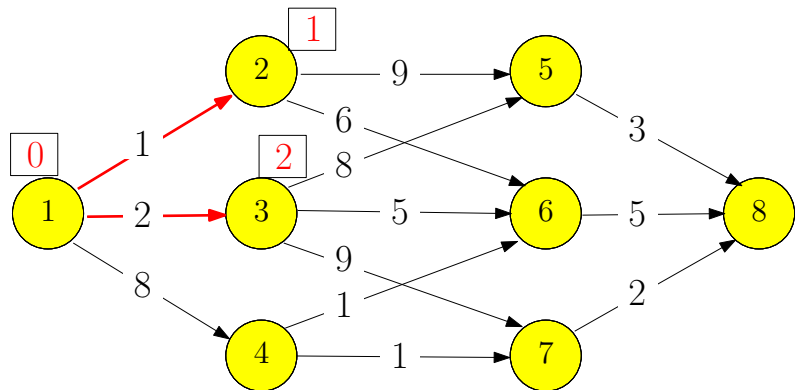
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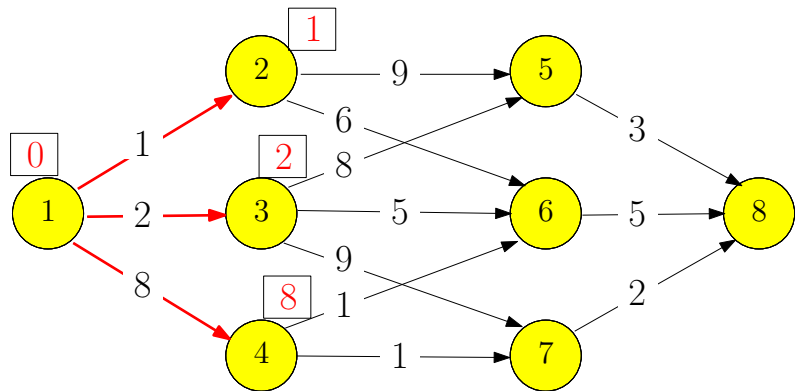
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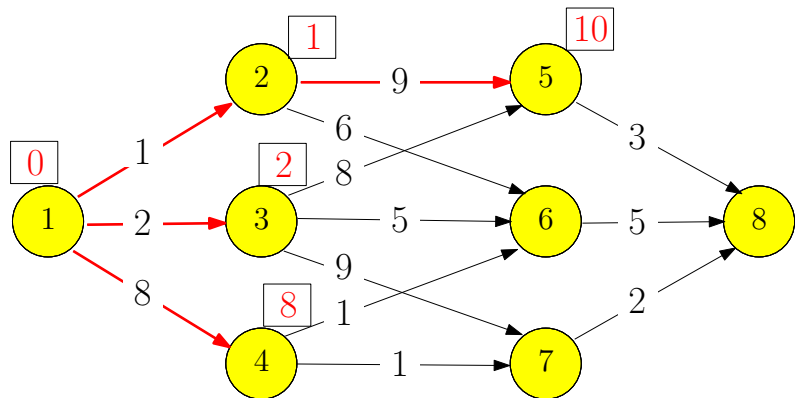
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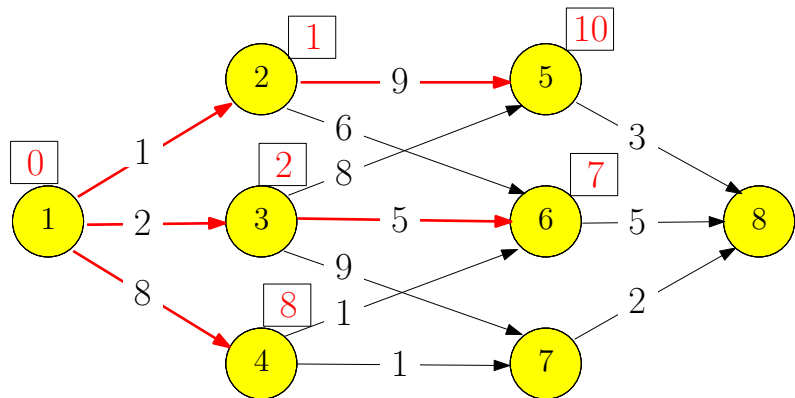
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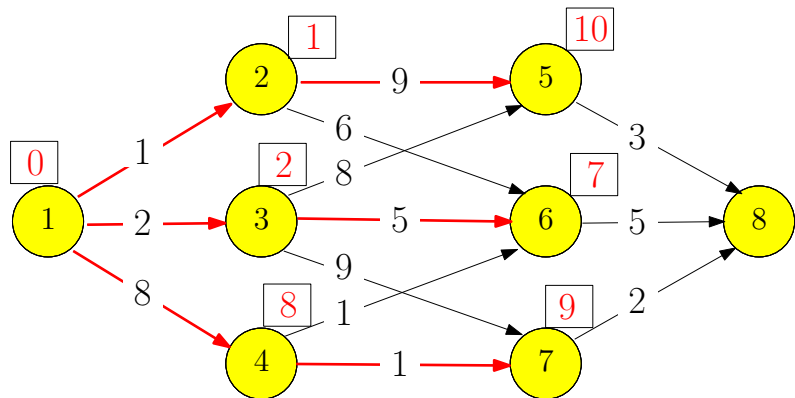
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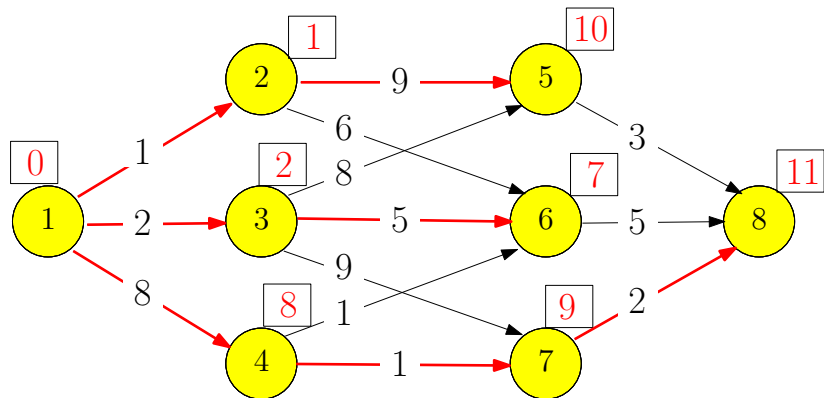
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Assume $V = \{1, 2, 3, \dots, n\}$ is topologically sorted: if $(i, j) \in E$, then $i < j$

Output: the path with the **largest** weight (the **heaviest** path) from 1 to n .

- $f[i]$: weight of the **heaviest** path from 1 to i

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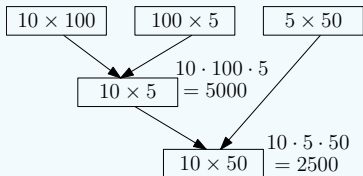
Input: n matrices A_1, A_2, \dots, A_n of sizes $r_1 \times c_1, r_2 \times c_2, \dots, r_n \times c_n$, such that $c_i = r_{i+1}$ for every $i = 1, 2, \dots, n - 1$.

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

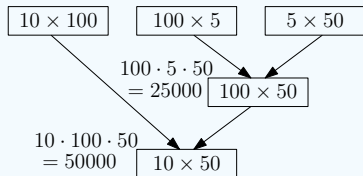
Fact Multiplying two matrices of size $r \times k$ and $k \times c$ takes $r \times k \times c$ multiplications.

Example:

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



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

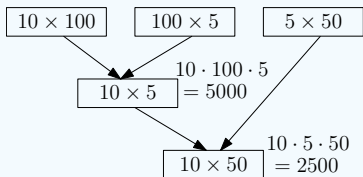


$$\text{cost} = 25000 + 50000 = 75000$$

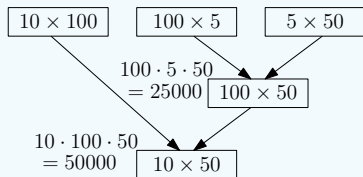
- $(A_1A_2)A_3: 10 \times 100 \times 5 + 10 \times 5 \times 50 = 7500$
- $A_1(A_2A_3): 100 \times 5 \times 50 + 10 \times 100 \times 50 = 75000$

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$$opt[i, j] = \begin{cases} 0 & i = j \\ \min_{k:i \leq k < j} (opt[i, k] + opt[k + 1, j] + r_i c_k c_j) & i < j \end{cases}$$