

the right majors, minors & concentrations  
education?  
for students' academic and career success  
ing for many students - *Many students change their  
during college!*

# Dynamic Programming (DP)

the prediction of student success in MMC could  
individual students  
and their right MMC  
achieve their academic goals

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1/7

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# ✓ When D&C Not Efficient?

# Problems Solving via Divide-and-Conquer (D&C)

- Binary Search
- Merge Sort
- Quick Sort
- Matrix Multiplication
  
- N-th Fibonacci Term Computing

# Computing N-th Fibonacci Term via D&C

- (0,) 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, ...
- **Algorithm 1.6** N-th Fibonacci Term (Recursive)
  - Divide-and-Conquer
  - Top-down
  - Exponential time  $O(2^N)$
- $\text{Fib}(n) = \text{Fib}(n - 1) + \text{Fib}(n - 2)$  for  $n \geq 2$ ;
- $\text{Fib}(0) = 0$
- $\text{Fib}(1) = 1$
- Example: **Fib(5)?**
- **5**

# Computing N-th Fibonacci Term via D&C

- In problems where smaller instances are related,
  - A D&C algorithm often ends up repeatedly solving common instances.
  - The result is very inefficient!
- **Overlapping subproblems**

# When D&C Not Efficient

- D&C algorithms should be avoided in the following two cases:
  - An instance of size  $n$  is **divided into two or more instances each almost of size  $n$ .**
  - An instance of size  $n$  is **divided into almost  $n$  instances of size  $n/c$ ,** where  $c$  is a constant.

Then, WHAT?

**DP!**

# ► QUIZ?

- D&C algorithms should be avoided in the following two cases?
  - An instance of size  $n$  is divided into two or more instances each **almost of size  $n$** .
  - An instance of size  $n$  is divided into **almost  $n$  instances** of size  $n/c$ , where  $c$  is a constant.

# ✓ Dynamic Programming (DP)

- An approach/paradigm to designing algorithms!

# Dynamic Programming (DP)

- Similar to the D&C approach
  - An instance of a problem is divided into smaller instances.
- **But, in DP:**
  - **Solve** the **small instances first**,
  - **Store** the results, and
  - **Look** them **up** when we need them **instead of recomputing** them. (**memoization!**)

# Dynamic Programming

- A **bottom-up approach** since the solution is constructed from the bottom up **in an array or sequence of arrays**.
- **Memoization!**
- **DP = Recursion + Memoization = Tabulation**

# Two Steps in Dynamic Programming (DP)

- **First: Establish a recursive property** that gives the solution to an instance of the problem.
- **Second: Solve** an instance of the problem **in a bottom-up fashion** by solving and storing smaller instances first.

# ✓ Dynamic Programming (DP)- based Algorithms

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# Dynamic Programming (DP)-based Algorithms

1. N-th Fibonacci Term via DP
2. Binomial Coefficient via DP
3. Floyd & Warshall's Algorithm - APSP via DP
4. Bellman & Ford's Algorithm – SSSP via DP
5. Chained Matrix Multiplication via DP
6. Traveling Salesperson Problem via DP
7. The 0-1 Knapsack Problem via DP

# 1. N-th Fibonacci Term

- (0,) 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, ...

# N-th Fibonacci Term via D&C

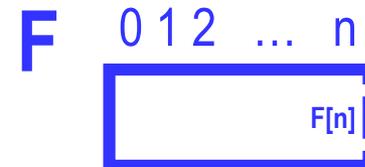
- (0,) 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, ...
- **Algorithm 1.6** N-th Fibonacci Term (Recursive)
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  - **Top-down**
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- $\text{Fib}(n) = \text{Fib}(n - 1) + \text{Fib}(n - 2)$  for  $n \geq 2$ ;
- $\text{Fib}(0) = 0$
- $\text{Fib}(1) = 1$
- Example: **Fib(5)?**
- **5**

# N-th Fibonacci Term via DP

- A more efficient algorithm using DP!

# N-th Fibonacci Term via DP

- (0,) 1, 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, ...
- **Algorithm 1.7** N-th Fibonacci Term (Iterative)
  - **DP**
  - **Bottom-up**
  - **Linear-time  $O(n)$  algorithm!**
- **Recursive Property**
  - **The Array F**
    - $F[i] = F[i - 1] + F[i - 2]$  for  $n \geq 2$ ;
    - $F[0] = 0$
    - $F[1] = 1$
- **Example: Fib(5)?**
  - $F[5]?$
  - 5



# ▶ QUIZ?

- N-th Fibonacci Term via DP?
  - Algorithm 1.7 nth Fibonacci Term (Iterative)
    - DP
    - Bottom-up
    - Linear-time algorithm!

# N-th Fibonacci Term via DP Visualization

- *N-th Fibonacci Term via DP Visualization*



## 2. The Binomial Coefficient

- **n choose k** for  $0 \leq k \leq n$

$$C(n, k) = n! / k! (n-k)!$$

- Example:  $C(4, 2)$ ?

- 6

- We cannot compute the binomial coefficient directly from this definition **because  $n!$  is very large**, even for moderate values of  $n$ .

# The Binomial Coefficient via D&C

- We should eliminate the need to compute  $n!$  or  $k!$  by using **the recursive property**:

$$\begin{aligned} C(n,k) &= C(n-1,k-1) + C(n-1,k) && \text{if } n > k \text{ and } k > 0 \\ &= 1 && \text{if } k = 0 \text{ or } n = k \end{aligned}$$

- How?
  - Apply **D&C!**
  - Recursive calls!

# The Binomial Coefficient via D&C

- **Algorithm 3.1** Binomial Coefficient using **Divide-and-Conquer**
- Example:  $C(4, 2)$ ?
  - 6
- Very inefficient - **Factorial!**

# The Binomial Coefficient via DP

- A more efficient algorithm using DP!

# The Binomial Coefficient via DP

- Idea?
- Step 1: Establish a recursive property.
- **The Array B**

$$B[i][j] = B[i-1][j-1] + B[i-1][j] \quad \text{for } 0 < j < i$$
$$1 \quad \quad \quad \text{for } j = 0 \text{ or } j = i$$

- Step 2: Solve an instance of the problem in a bottom-up fashion by computing values for  $B[i][j]$  starting from  $B[0][0]$ .

# The Array B

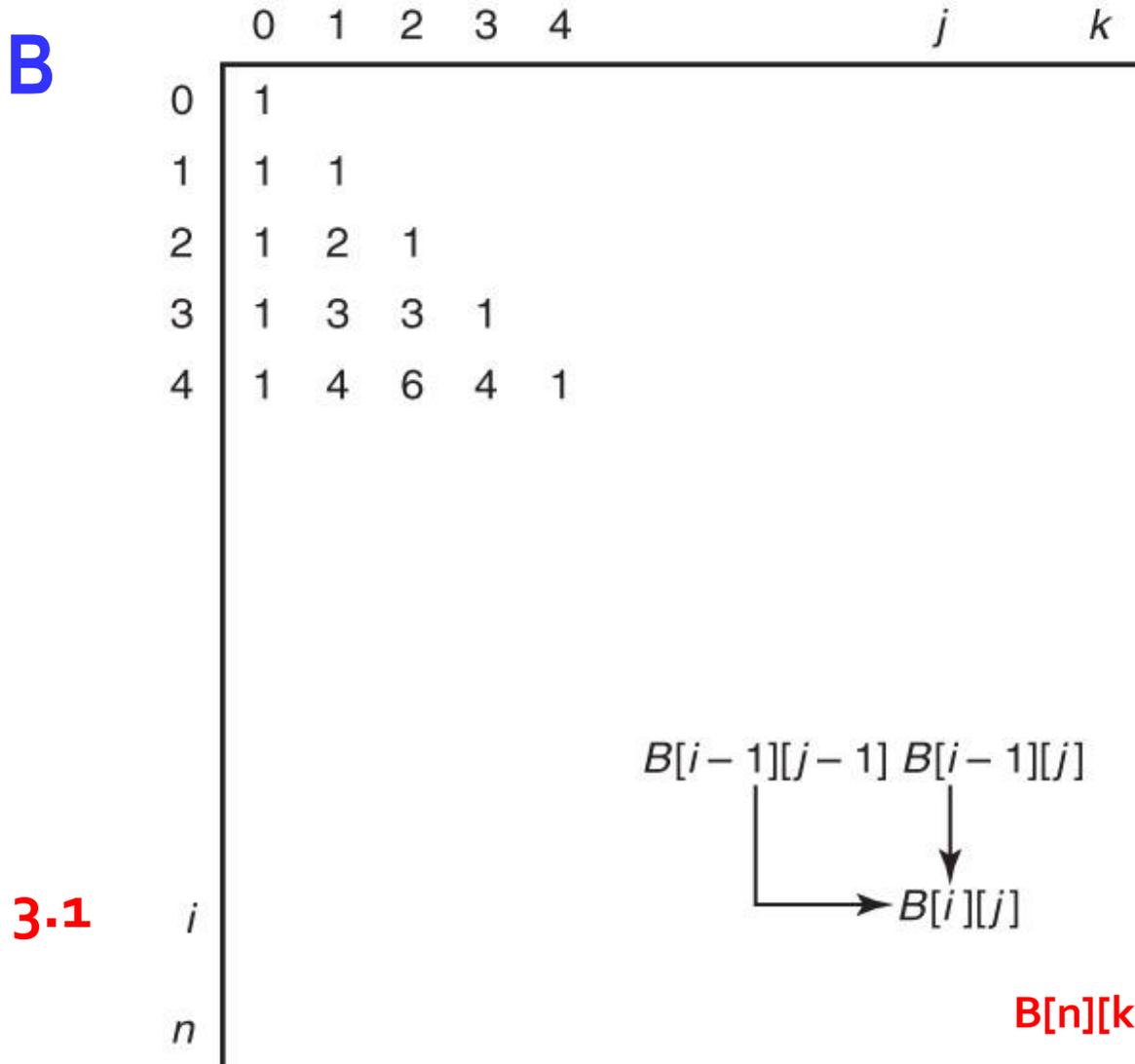


Figure 3.1

# The Binomial Coefficient via DP

- Example:  $C(4, 2)$ ?
  - $B[4][2]$ ?
  - 6
  - Example 3.1

# The Binomial Coefficient via DP

- **Algorithm 3.2 Binomial Coefficient using Dynamic Programming**
- Analysis of Algorithm 3.2
  - $O(nk)$
  - $O(n^2)$

# DP vs D&C

- By using DP instead of D&C, we have developed a much more efficient algorithm!
- In DP, we use the recursive property to **iteratively solve** the instances in sequence, starting with the smallest instance.
  - In this way we solve the smallest instance just once.
- **DP is a good technique to try when D&C leads to an inefficient algorithm!**

# 3. The All-Pairs Shortest Paths Problem

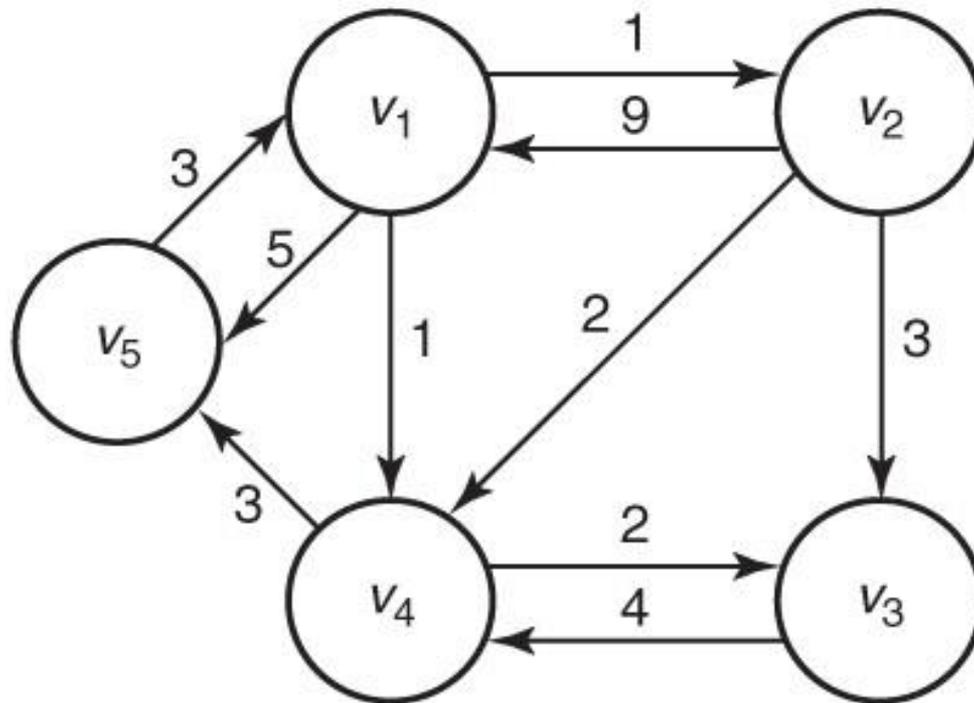
- A problem that has **many applications** is finding the shortest path from each vertex to all the other vertices.
- The Shortest Paths problem is an **optimization problem**.
  - There can be more than one candidate solution to an instance of an optimization problem.
  - Each candidate solution has a value associated with it.
  - A solution to the instance is any candidate solution that has an optimal value.

# The All-Pairs Shortest Paths Problem

- Given a **weighted, directed graph**  $G=(V,E)$  with weight function  $W$  mapping edges to **nonnegative or negative weights**, **but** there is **no negative cycle**
- Find a shortest path from  $u$  to  $v$  for every pair of vertices  $u$  and  $v$  in  $V$ .
  - The **All-Pairs Shortest Paths (APSP) Problem**

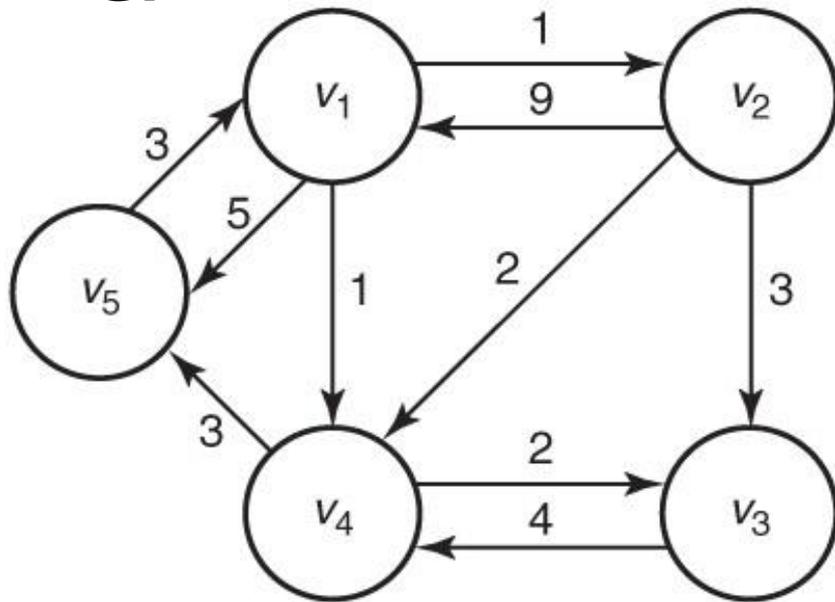
# Example: An Edge-Weighted, Directed Graph

**G:**



# Example: Adjacency Matrix Representation

**G:**



	1	2	3	4	5
1	0	1	$\infty$	1	5
2	9	0	3	2	$\infty$
3	$\infty$	$\infty$	0	4	$\infty$
4	$\infty$	$\infty$	2	0	3
5	3	$\infty$	$\infty$	$\infty$	0

*W*

# From Adjacency Matrix to Path Length Array D

	1	2	3	4	5
1	0	1	$\infty$	1	5
2	9	0	3	2	$\infty$
3	$\infty$	$\infty$	0	4	$\infty$
4	$\infty$	$\infty$	2	0	3
5	3	$\infty$	$\infty$	$\infty$	0

*W*



	1	2	3	4	5
1	0	1	3	1	4
2	8	0	3	2	5
3	10	11	0	4	7
4	6	7	2	0	3
5	3	4	6	4	0

*D*

# From Adjacency Matrix to Path Array

	1	2	3	4	5
1	0	1	$\infty$	1	5
2	9	0	3	2	$\infty$
3	$\infty$	$\infty$	0	4	$\infty$
4	$\infty$	$\infty$	2	0	3
5	3	$\infty$	$\infty$	$\infty$	0

*W*



	1	2	3	4	5
1	0	0	4	0	4
2	5	0	0	0	4
3	5	5	0	0	4
4	5	5	0	0	0
5	0	1	4	1	0

*P*

# The All-Pairs Shortest Paths Problem

- The **brute-force algorithm** is to consider **all possible paths** and take the shortest.
- This is a very inefficient method – **factorial!**

# APSP via DP

- A more efficient algorithm using DP!

# Floyd's Algorithm - APSP via DP

- Using DP, we can create a cubic-time  $O(n^3)$  algorithm!
  - First, we develop an algorithm that determines the lengths of only the shortest paths.
  - After that, we modify it to produce shortest paths as well.
- **Floyd's (&Warshall's) Algorithm**

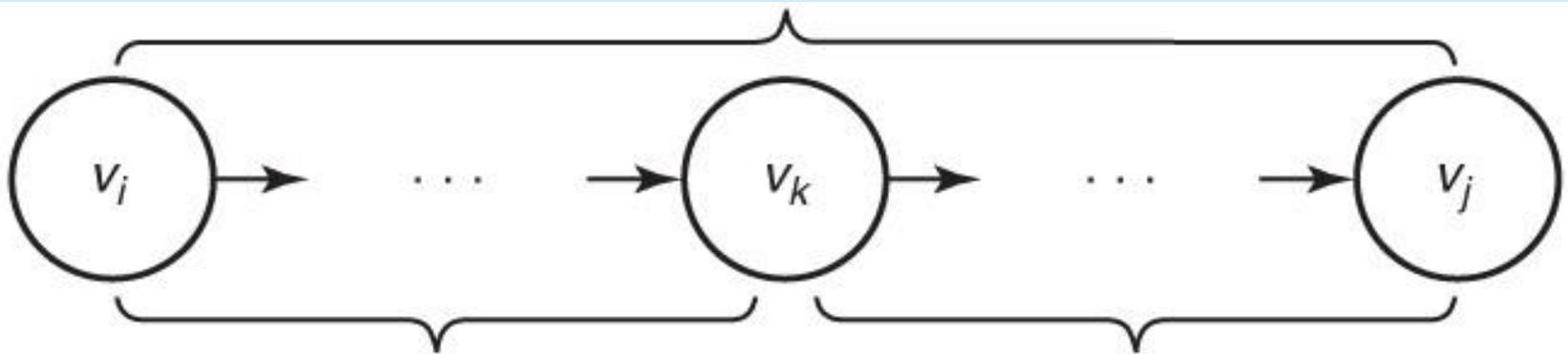
# Floyd & Warshall's Algorithm

- Idea?
  - $V = \{ 1, 2, \dots, |V|=n \}$
  - $D^K [i][j]$  = The weighted length of the shortest path from the vertex  $i$  to the vertex  $j$  & The shortest path contains **no intermediate vertex of index greater than  $K$** .
    - $D^1 [i][j]$
    - $D^2 [i][j]$
    - .
    - .
    - .
    - $D^{|V|=n} [i][j]$

# Floyd & Warshall's Algorithm

- Establish a recursive property.

$$D^K [i][j] = \min (D^{K-1} [i][j], D^{K-1} [i][k] + D^{K-1} [k][j])$$



A shortest path from  $v_i$  to  $v_k$  using only vertices in  $\{v_1, v_2, \dots, v_k\}$

A shortest path from  $v_k$  to  $v_j$  using only vertices in  $\{v_1, v_2, \dots, v_k\}$

# Floyd & Warshall's Algorithm

- Initially,
  - $D^{\text{initial}}[i][j]$  = The weighted length of the shortest path from the vertex  $i$  to the vertex  $j$  & The shortest path contains no intermediate vertex of index greater than  $k$ .
    - $\text{weight}(i,j) =$ 
      - 0 if  $i=j$
      - The weight of the directed edge  $(i,j)$  if  $(i,j)$  in  $E$
      - $\infty$  otherwise

# Floyd & Warshall's Algorithm

**D**initial(o)

	1	2	3	4	5
1	0	1	$\infty$	1	5
2	9	0	3	2	$\infty$
3	$\infty$	$\infty$	0	4	$\infty$
4	$\infty$	$\infty$	2	0	3
5	3	$\infty$	$\infty$	$\infty$	0

*W*

# Floyd & Warshall's Algorithm

- $D^{\text{initial}} [i][j]$
- $D^1 [i][j]$
- $D^2 [i][j]$
- .
- .
- .
- $D^{|V|=n} [i][j]$

# Floyd & Warshall's Algorithm

- We can compute  $D^K$  from  $D^{K-1}$ !

$$D^K[i][j] = \min ( D^{K-1}[i][j] , \\ D^{K-1}[i][k] + D^{K-1}[k][j] )$$

$$D^K [i][j] = \min ( D^{K-1} [i][j] , D^{K-1} [i][k] + D^{K-1} [k][j] )$$

# ► QUIZ?

- Compute  $D^K$  from  $D^{K-1}$  ?

$$D^K[i][j] = \min ( D^{K-1}[i][j] , \\ D^{K-1}[i][K] + D^{K-1}[K][j] )$$

# Floyd & Warshall's Algorithm

- Example 3.2
  - $D^{(5)}[5][3]$ ?

# Floyd & Warshall's Algorithm

- Example 3.3
- Compute
  - $D^{(1)}$
  - $D^{(2)}$
  - $D^{(3)}$
  - $D^{(4)}$
  - $D^{(5)}$

# Floyd & Warshall's Algorithm

**D**<sup>(5)</sup>

	1	2	3	4	5
1	0	1	3	1	4
2	8	0	3	2	5
3	10	11	0	4	7
4	6	7	2	0	3
5	3	4	6	4	0

*D*

# Floyd & Warshall's Algorithm- Analysis

- **Algorithm 3.3 Floyd's Algorithm for APSP**
  - Just lengths of the shortest paths for now!
  - The shortest paths length array  $D$
- Analysis of Algorithm 3.3 Floyd's Algorithm for APSP
  - $O(|V|^3)$

# Floyd & Warshall's Algorithm— Shortest Paths

- **Algorithm 3.4 Floyd's Algorithm for APSP**
  - The shortest paths length array  $D$
  - The path array  $P$  to produce shortest paths!
  - $P[i][j]$  = Highest index of an intermediate vertex on the shortest path from  $i$  to  $j$  & 0 if no intermediate vertex
  - $O(|V|^3)$
  - Figure 3.5

# Floyd & Warshall's Algorithm

- $P^{\text{initial}} [i][j]$
- $P^1 [i][j]$
- $P^2 [i][j]$
- .
- .
- .
- $P^{|V|=n} [i][j]$

$$D^K [i][j] = \min (D^{K-1} [i][j] , D^{K-1} [i][k] + D^{K-1} [k][j])$$

# Floyd & Warshall's Algorithm

- The Path Array P:

	1	2	3	4	5
1	0	0	4	0	4
2	5	0	0	0	4
3	5	5	0	0	4
4	5	5	0	0	0
5	0	1	4	1	0

# Floyd & Warshall's Algorithm

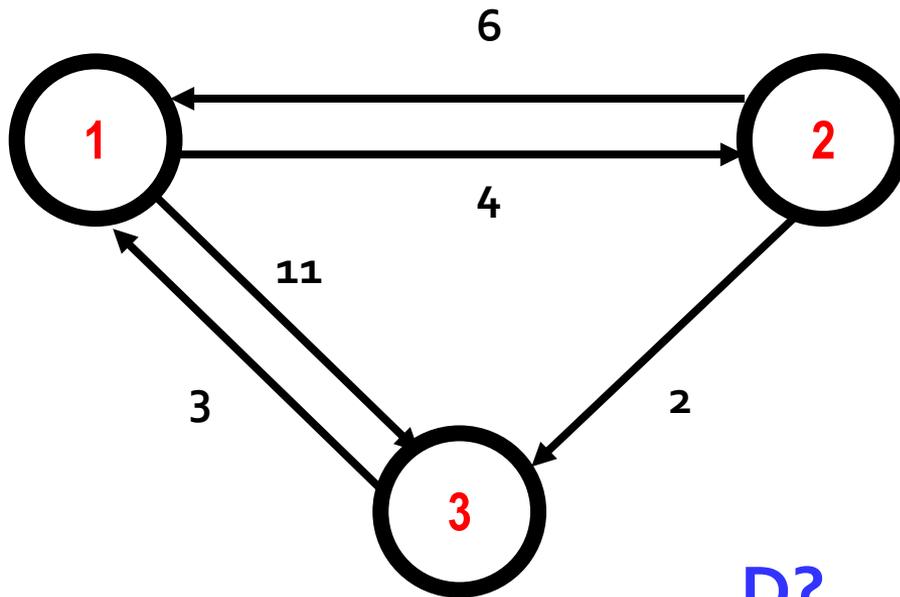
- **Algorithm 3.5 Print Shortest Path**
  - Print the shortest path using the path array
- Analysis of Algorithm 3.5 Print Shortest Path
  - $O(|V|)$

# Floyd & Warshall's Algorithm

- $\text{Path}(v_5, v_3) \Rightarrow v_5 v_1 v_4 v_3$

	1	2	3	4	5
1	0	0	4	0	4
2	5	0	0	0	4
3	5	5	0	0	4
4	5	5	0	0	0
5	0	1	4	1	0

# Example: APSP by Floyd & Warshall's Algorithm



**W**

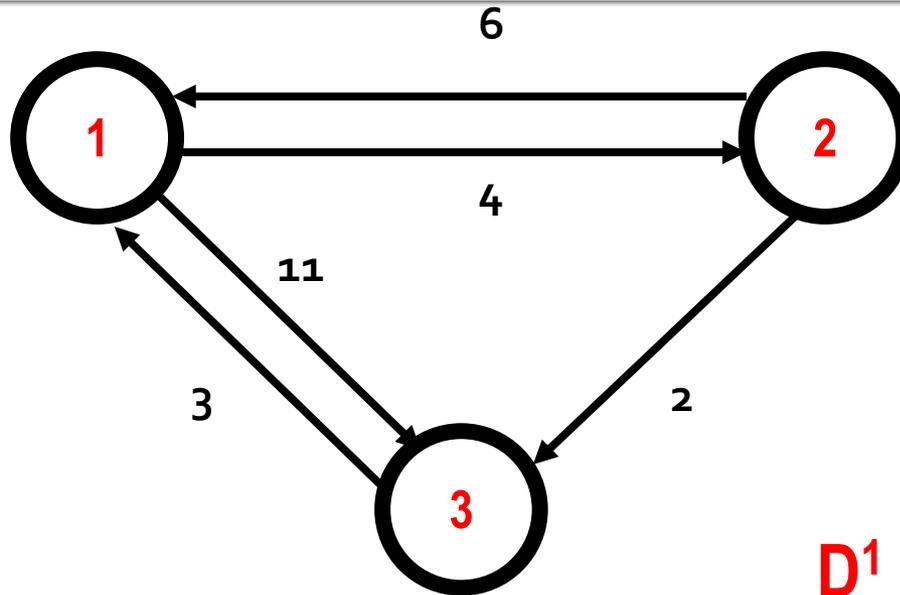
	1	2	3
1	0	4	11
2	6	0	2
3	3	$\infty$	0

D?

P?

Shortest paths?

# Example: APSP by Floyd & Warshall's Algorithm



**D<sup>initial</sup>** 1 2 3

		1	2	3
1	0	4	11	
2	6	0	2	
3	3	$\infty$	0	



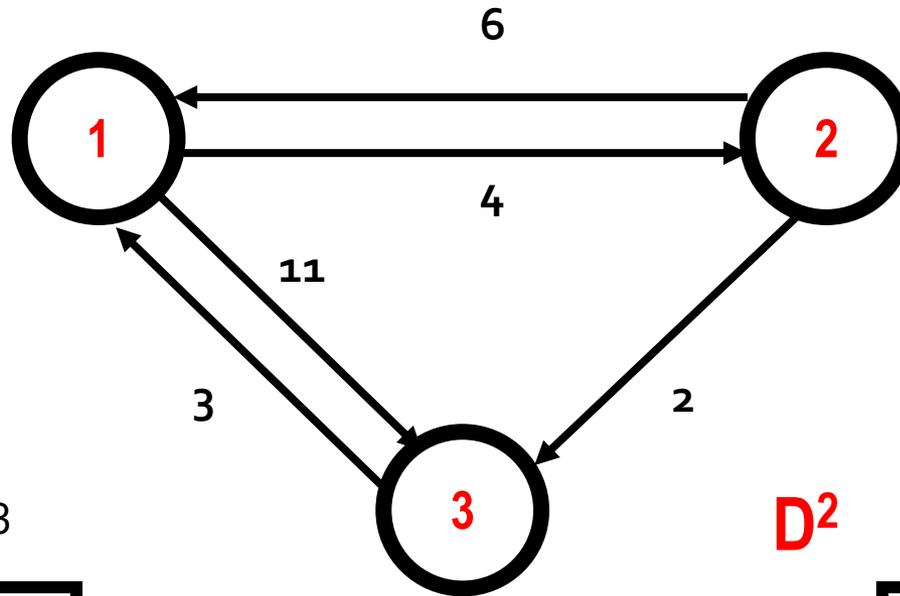
**D<sup>1</sup>**

		1	2	3
1	0	4	11	
2	6	0	2	
3	3	7	0	

**P<sup>1</sup>**

		1	2	3
1	0	0	0	
2	0	0	0	
3	0	1	0	

# Example: APSP by Floyd & Warshall's Algorithm



**D<sup>1</sup>**

	1	2	3
1	0	4	11
2	6	0	2
3	3	7	0



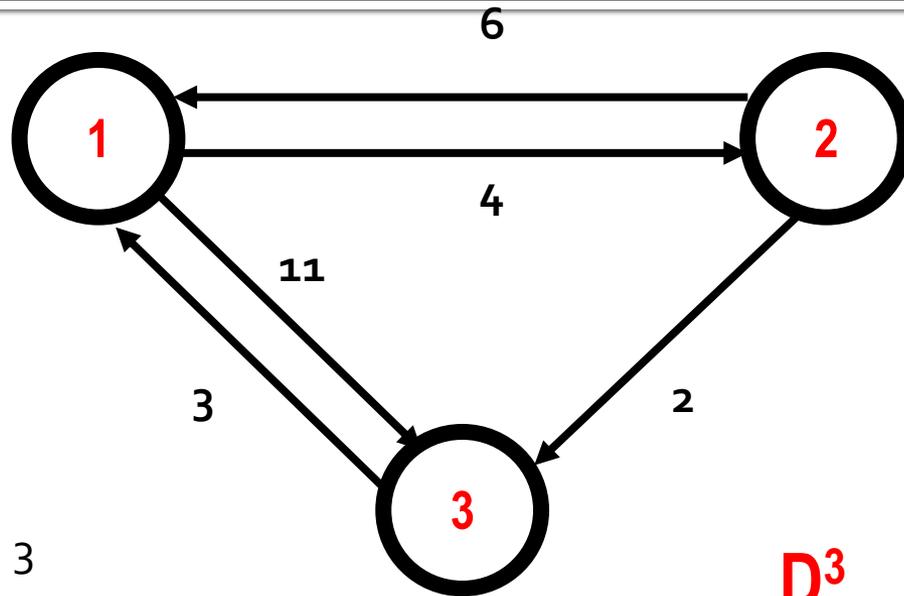
**D<sup>2</sup>**

	1	2	3
1	0	4	6
2	6	0	2
3	3	7	0

**P<sup>2</sup>**

	1	2	3
1	0	0	2
2	0	0	0
3	0	1	0

# Example: APSP by Floyd & Warshall's Algorithm



**D<sup>2</sup>**

	1	2	3
1	0	4	6
2	6	0	2
3	3	7	0



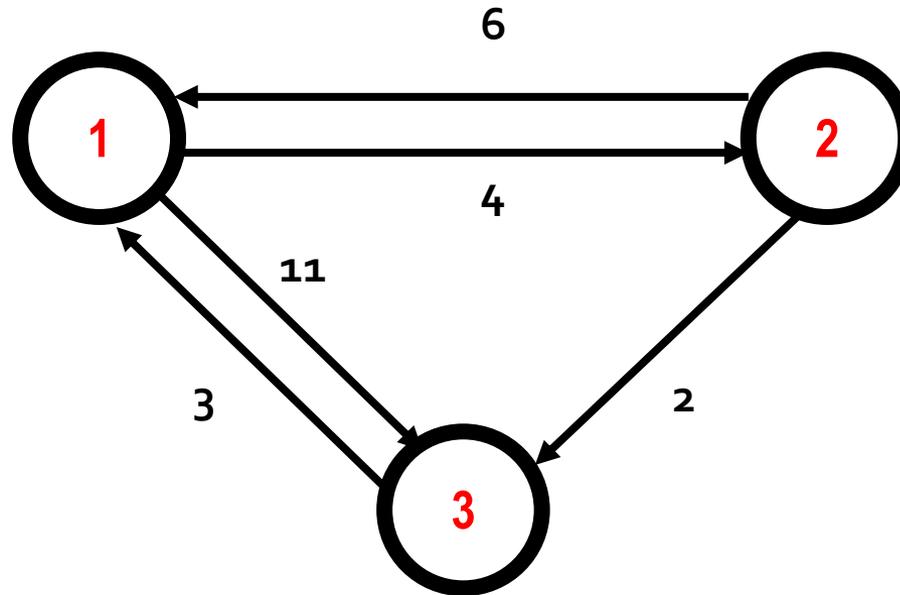
**D<sup>3</sup>**

	1	2	3
1	0	4	6
2	5	0	2
3	3	7	0

**P<sup>3</sup>**

	1	2	3
1	0	0	2
2	3	0	0
3	0	1	0

# Example: APSP by Floyd & Warshall's Algorithm



**D<sup>initial</sup>** 1 2 3

1	0	4	11
2	6	0	2
3	3	$\infty$	0

**D<sup>1</sup>** 1 2 3

1	0	4	11
2	6	0	2
3	3	7	0

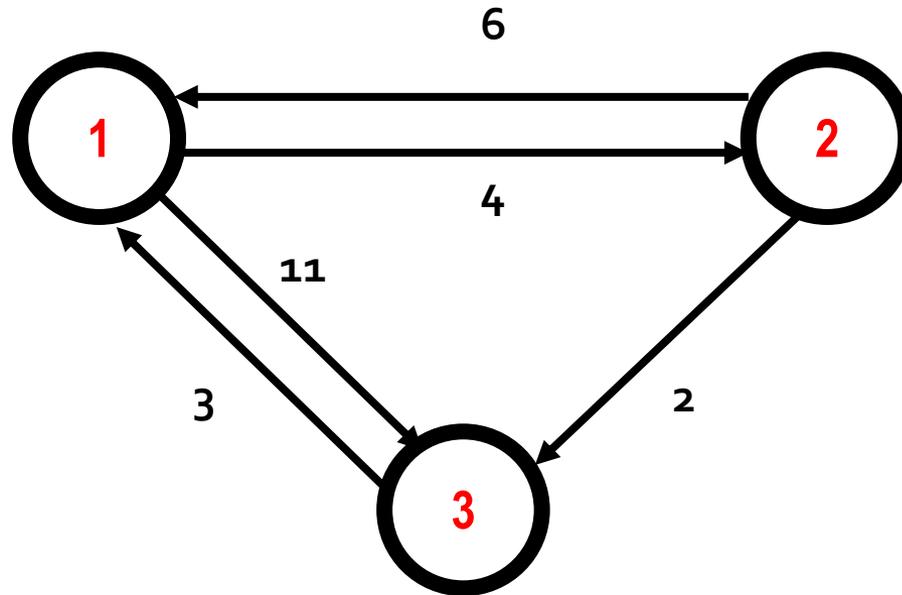
**D<sup>2</sup>** 1 2 3

1	0	4	6
2	6	0	2
3	3	7	0

**D<sup>3</sup>** 1 2 3

1	0	4	6
2	5	0	2
3	3	7	0

# Example: APSP by Floyd & Warshall's Algorithm



**P<sub>initial</sub>**

	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0

**P<sub>1</sub>**

	1	2	3
1	0	0	0
2	0	0	0
3	0	1	0

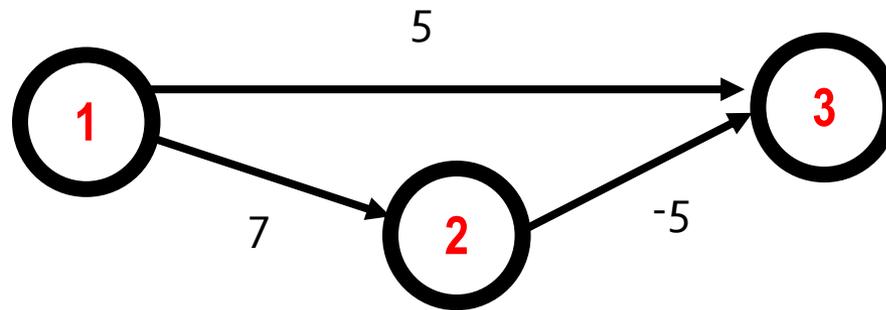
**P<sub>2</sub>**

	1	2	3
1	0	0	2
2	0	0	0
3	0	1	0

**P<sub>3</sub>**

	1	2	3
1	0	0	2
2	3	0	0
3	0	1	0

# ▶ QUIZ? APSP by Floyd & Warshall's Algorithm

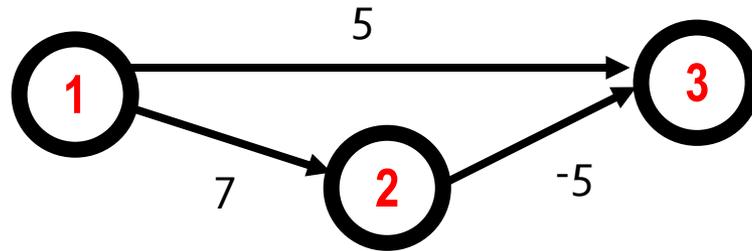


D?

P?

Shortest paths?

# ► QUIZ: APSP by Floyd & Warshall's Algorithm



**P**initial 1 2 3

	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0

**P**1 1 2 3

	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0

**P**2 1 2 3

	1	2	3
1	0	0	2
2	0	0	0
3	0	0	0

**P**3 1 2 3

	1	2	3
1	0	0	2
2	0	0	0
3	0	0	0

**D**initial 1 2 3

	1	2	3
1	0	7	5
2	$\infty$	0	-5
3	$\infty$	$\infty$	0

**D**1 1 2 3

	1	2	3
1	0	7	5
2	$\infty$	0	-5
3	$\infty$	$\infty$	0

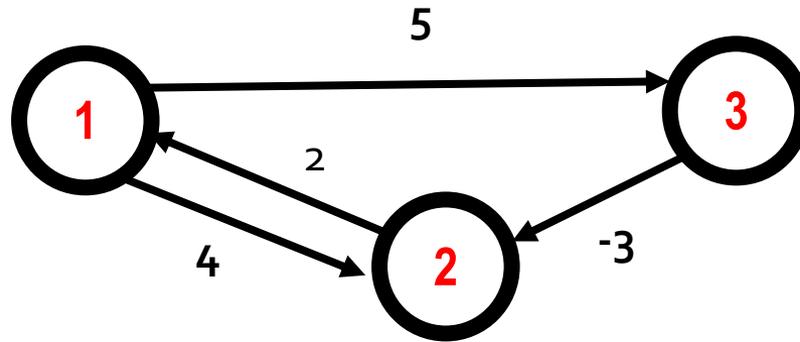
**D**2 1 2 3

	1	2	3
1	0	7	2
2	$\infty$	0	-5
3	$\infty$	$\infty$	0

**D**3 1 2 3

	1	2	3
1	0	7	2
2	$\infty$	0	-5
3	$\infty$	$\infty$	0

# ► QUIZ? APSP by Floyd & Warshall's Algorithm

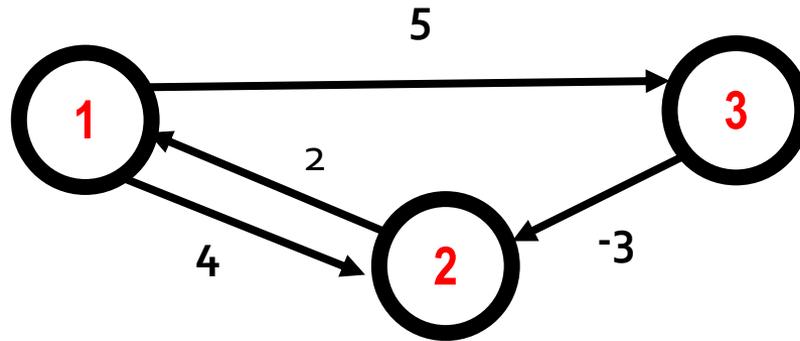


D?

P?

Shortest paths?

# ► QUIZ: APSP by Floyd & Warshall's Algorithm



**D**initial

1 2 3

	1	2	3
1	0	4	5
2	2	0	$\infty$
3	$\infty$	-3	0

**D**<sup>3</sup>

1 2 3

	1	2	3
1	0	2	5
2	2	0	7
3	-1	-3	0

**P**initial

1 2 3

	1	2	3
1	0	0	0
2	0	0	0
3	0	0	0

**P**<sup>3</sup>

1 2 3

	1	2	3
1	0	3	0
2	0	0	1
3	2	0	0

# Floyd & Warshall's APSP Algorithm via DP Visualization

- Floyd & Warshall's APSP Algorithm via DP Visualization



# ✓ DP for Optimization Problems

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# DP and Optimization Problems

- **Floyd & Warshall's Algorithm - APSP via DP**
- **Bellman & Ford's Algorithm – SSSP via DP**
- **Chained Matrix Multiplication via DP**
- **Traveling Salesperson Problem via DP**
- **The 0-1 Knapsack Problem via DP**

# DP and Optimization Problems

- Although it may seem that **any** optimization problem can be solved using dynamic programming, it is **not** true.

# Principle of Optimality

- The **principle of optimality**:
  - An **optimal solution** to an instance of a problem always contains **optimal solutions** to **all subinstances**.

or

- **Optimal Substructure Property**

# Principle of Optimality for DP

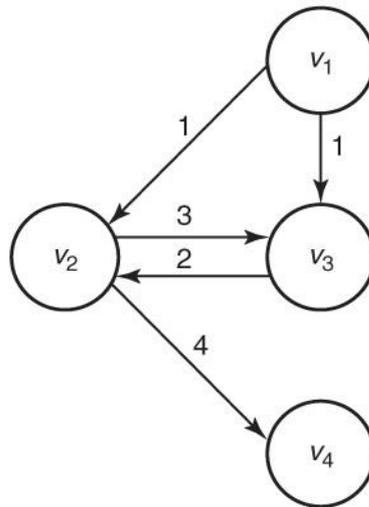
- The principle of optimality must apply in the optimization problem **to use DP!**
- The **shortest paths problem** apply!
  - If  $v_k$  is a node on an optimal path from  $v_i$  to  $v_j$  then **the sub-paths  $v_i$  to  $v_k$  and  $v_k$  to  $v_j$  are also optimal paths.**

# Principle of Optimality

- The principle of optimality does not apply in every problem!

# ► QUIZ? Longest Path Problem

- Example 3.4 The **longest paths problem**
  - The longest path  **$V_1 \rightarrow V_4$** ?



- The principle of optimality does not apply! **No DP!**
- Actually, **NP-complete problem!**

# ▶ QUIZ?

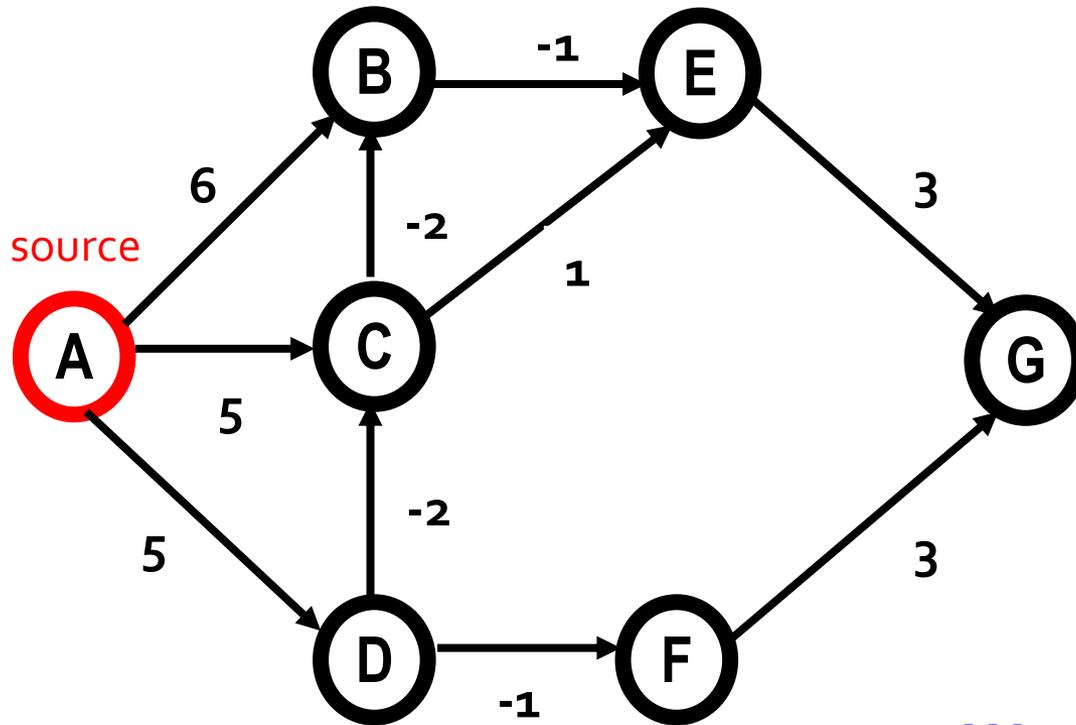
- DP for The longest paths problem?

# 4. The Single-Source Shortest-Paths Problem

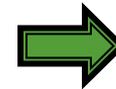
with Negative Edges but No Negative Cycles

- Problem:
  - Given a weighted, directed graph  $G=(V,E)$  with weight function  $W$  mapping edges to real valued weights that **may contain negative edges but there is no negative cycle**,
  - Find a shortest path from a given source vertex  $s$  to every vertex  $v$  in  $V$ .
  - The **single-source/all-destination shortest-paths problem!**

# Example: SSSP by Bellman & Ford's Algorithm



W



Distance?  
Path?  
Shortest paths?

# The Single Source Shortest Paths Problem

- The **brute-force algorithm** is to consider **all possible paths** and take the shortest.
- This is a very inefficient method – **factorial!**

# SSSP via DP

- A more efficient algorithm using DP!

# The Single-Source Shortest-Paths with Negative Edges but No Negative Cycles **Algorithm**

- **Bellman & Ford's algorithm**
- **DP** (Dynamic Programming)!

# Bellman & Ford's Algorithm

- Observation:
  - If there is no cycle of negative weight in a edge-weighted directed graph  $G = (V, E)$  then
  - There exists a shortest path between any two vertices that has **at most  $|V|-1$  edges!**

# Bellman & Ford's Algorithm

- Idea?
  - **Distance<sup>K</sup> [v]** = The weighted length of the shortest path from the **source vertex s** to **v** & **The shortest path contains at most K edges.**
    - Distance<sup>1</sup> [v]
    - Distance<sup>2</sup> [v]
    - Distance<sup>3</sup> [v]
    - .
    - .
    - .
    - **Distance<sup>|V|-1</sup> [v]**

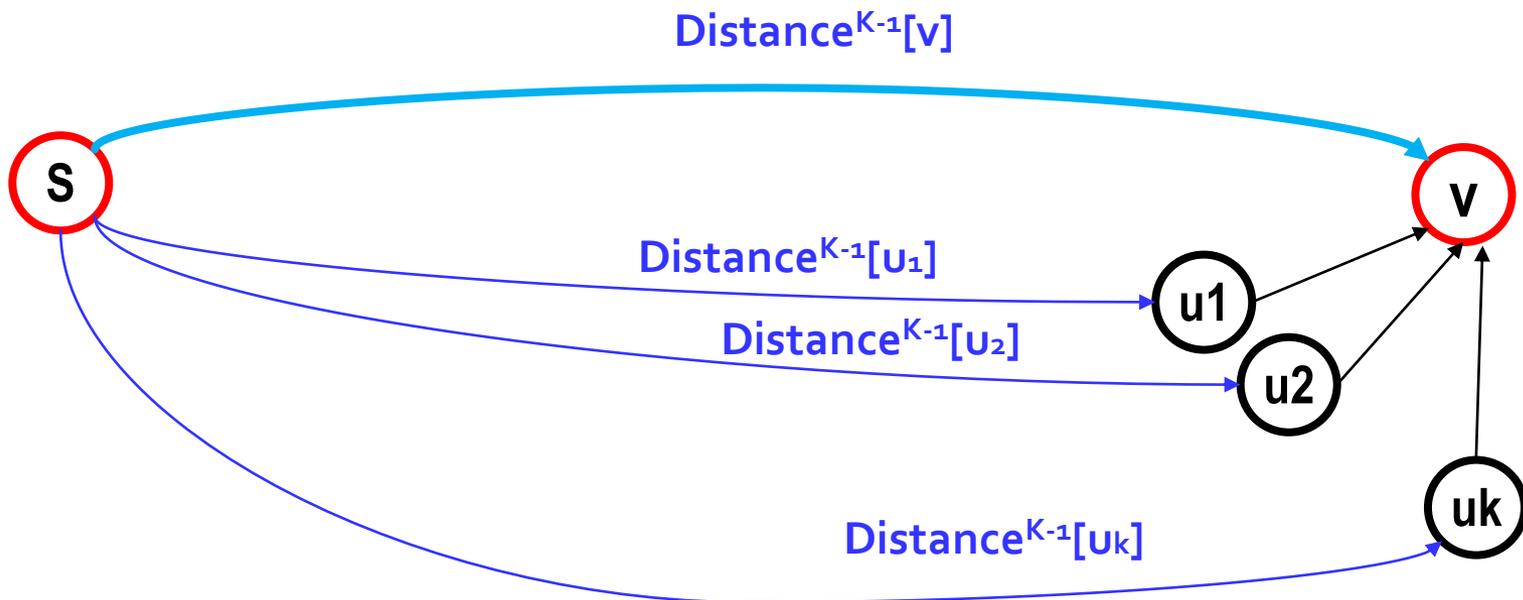
# Bellman & Ford's Algorithm

- For each vertex  $v$ , maintains
  - **Distance<sup>K</sup>[v]** = The weighted length of the shortest path from the source vertex  $s$  to  $v$  & The shortest path contains **at most K edges**.
  - **Path[v]** = The **predecessor of the vertex v** on the shortest path from the source vertex  $s$  to  $v$ .

# Bellman & Ford's Algorithm

- Establish a **recursive property**.

Distance<sup>K</sup>[v] ?



# Bellman & Ford's Algorithm

- **Distance  $^k[v]$  ?**
  - For each vertex  $v$  with an edge  $(u,v)$ ,
    - Compute  $\text{Distance}^{k-1}[u] + \text{weight}(u,v)$ .
    - Select the vertex  $u'$  whose  $\text{Distance}^{k-1}[u] + \text{weight}(u,v)$  is the smallest.
  - If  **$\text{Distance}^{k-1}[v] > \text{Distance}^{k-1}[u'] + \text{weight}(u',v)$**  then
    - **$\text{Distance}^k[v] = \text{Distance}^{k-1}[u'] + \text{weight}(u',v)$**
    - **$\text{Path}^k[v] = u'$**

# Bellman & Ford's Algorithm

- The **recursive property**.

$$\begin{aligned} \text{Distance}^k [v] = & \\ \text{min} & \\ ( & \\ & \text{Distance}^{k-1} [v], \\ & \\ & \text{min (Distance}^{k-1} [u] + \text{weight (u,v)} \\ & \quad \text{for all u with edge (u,v))} \\ & ) \end{aligned}$$

# Bellman & Ford's Algorithm

- We can compute **Distance<sup>K</sup>[v]** from **Distance<sup>K-1</sup>[v]**!

$$\text{Distance}^K[v] = \min(\text{Distance}^{K-1}[v], \min(\text{Distance}^{K-1}[u] + \text{weight}(u,v) \text{ for all } u \text{ with edge } (u,v)) )$$

# Bellman & Ford's Algorithm

- Initially,
  - $\text{Distance}^{\text{initial}}[v]$ 
    - 0 if  $s=v$
    - $\infty$  otherwise
  - $\text{Path}^{\text{initial}}[v] = \text{unknown}$  for all  $v$  in  $V$ .

# Bellman & Ford's Algorithm

- $\text{Distance}^{\text{initial}} [v]$
- $\text{Distance}^1 [v]$
- $\text{Distance}^2 [v]$
- $\text{Distance}^3 [v]$
- .
- .
- .
- $\text{Distance}^{|V|-1} [v]$

# Bellman & Ford's Algorithm

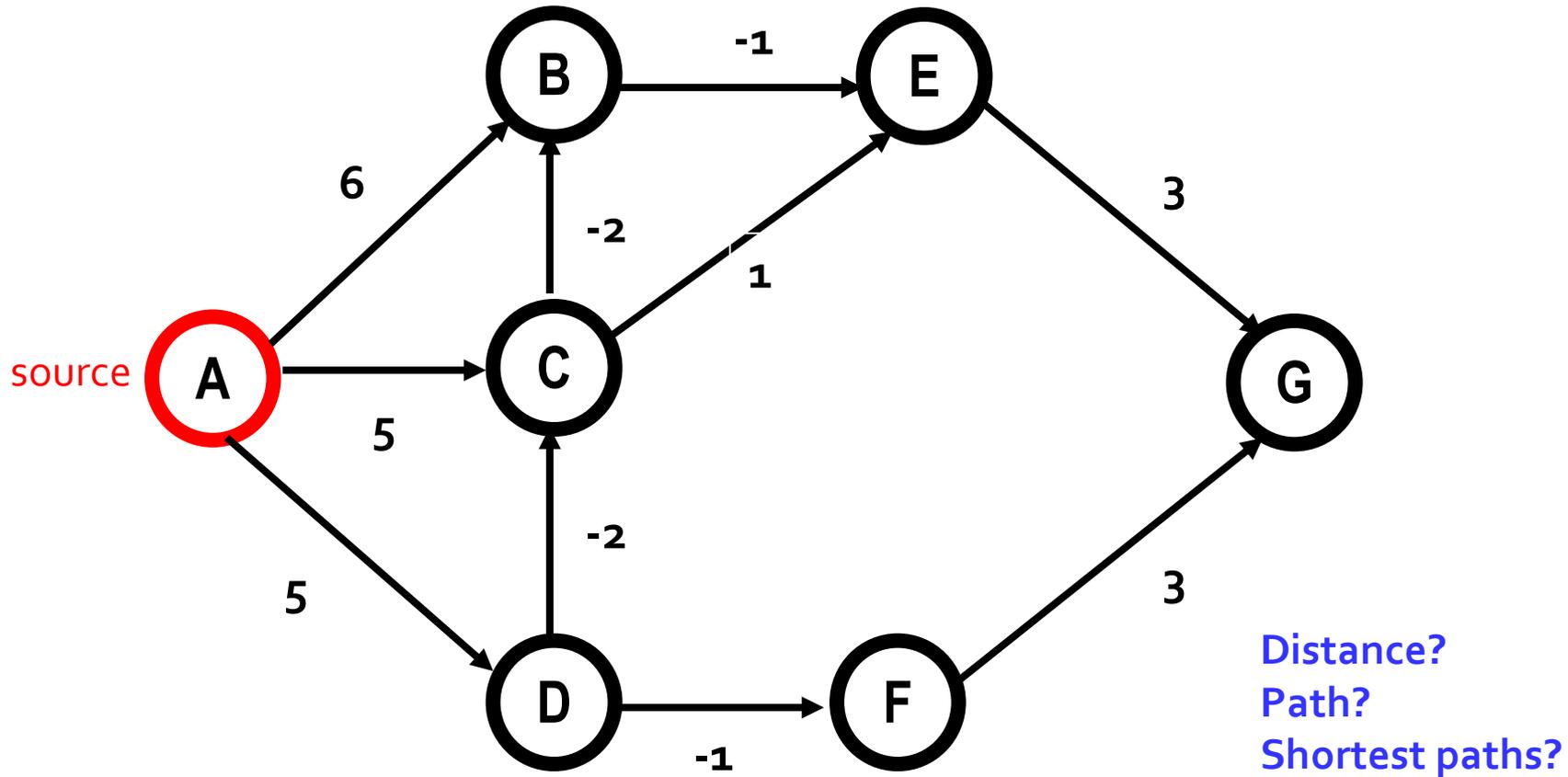
- $\text{Path}^{\text{initial}} [v]$
- $\text{Path}^1 [v]$
- $\text{Path}^2 [v]$
- $\text{Path}^3 [v]$
- .
- .
- .
- $\text{Path}^{|\mathcal{V}|-1} [v]$

# ► QUIZ? Bellman & Ford's Algorithm

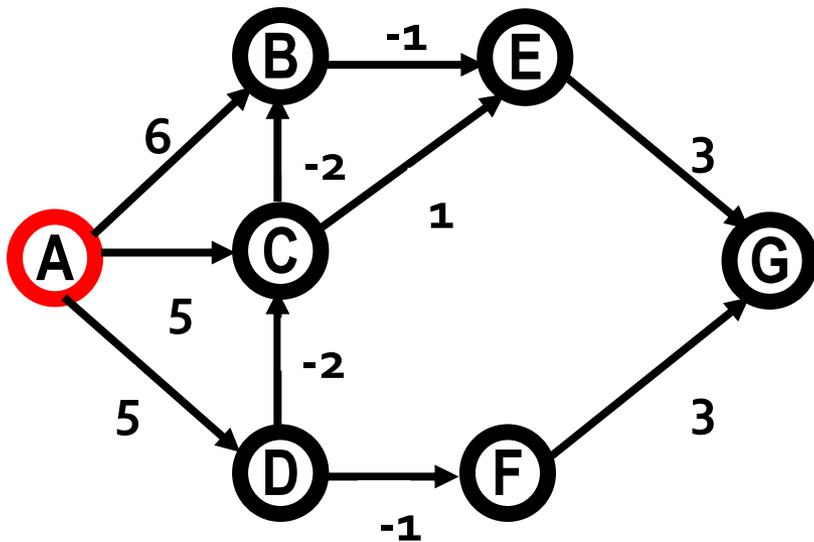
- Compute **Distance<sup>k</sup>** from **Distance<sup>k-1</sup>** ?

$$\text{Distance}^k [v] = \min ( \begin{array}{l} \text{Distance}^{k-1} [v], \\ \min (\text{Distance}^{k-1} [u] + \text{weight} (u,v) \\ \text{for all } u \text{ with edge } (u,v)) \end{array} )$$

# Example: SSSP by Bellman & Ford's Algorithm



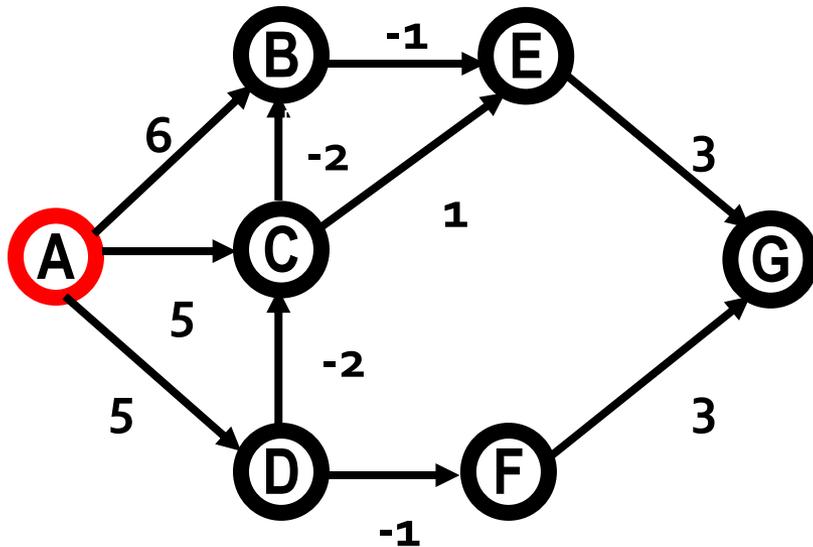
# Example: SSSP by Bellman & Ford's Algorithm



$|V| = 7$

	A	B	C	D	E	F	G
k=0	$D^0$	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
k=1	$D^1$	0	6	5	5	$\infty$	$\infty$
k=2	$D^2$	0	3	3	5	5	4

# Example: SSSP by Bellman & Ford's Algorithm



SPT(Shortest Path Tree)

$|V| = 7$

	A	B	C	D	E	F	G	
k=1	D <sup>1</sup>	0	6	5	5	∞	∞	∞
k=2	D <sup>2</sup>	0	3	3	5	5	4	∞
k=3	D <sup>3</sup>	0	1	3	5	2	4	7
k=4	D <sup>4</sup>	0	1	3	5	0	4	5
k=5	D <sup>5</sup>	0	1	3	5	0	4	3
k=6	D <sup>6</sup>	0	1	3	5	0	4	3
k=6	P <sup>6</sup>	-	C	D	A	B	D	E

# Bellman & Ford's - Algorithm

for all  $v$  in  $V$

    Distance[ $v$ ] = infinity; Path[ $v$ ] = nil;

// Relaxation

for  $i := 1$  to  $|V| - 1$

    for **each**  $(u,v)$  in a specific order in  $E$

        if Distance[ $v$ ] > Distance[ $u$ ] + weight( $u,v$ ) then

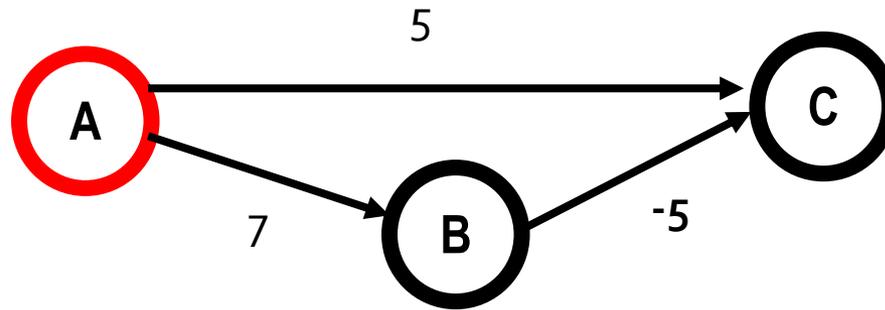
            Distance [ $v$ ] = **Distance [ $u$ ] + weight ( $u,v$ );**

            Path[ $v$ ] =  **$u$** ;

# Bellman & Ford's - Algorithm

- Time complexity
  - $O(|V||E|)$

# ► QUIZ? Bellman & Ford's Algorithm

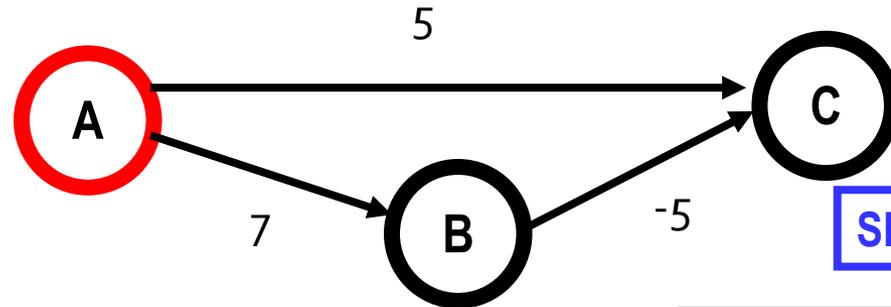


Distance?

Path?

Shortest paths?

# ► QUIZ: Bellman & Ford's Algorithm



SPT(Shortest Path Tree)

$|V| = 3$

Shortest Paths from A:

A-B (7)  
A-B-C (2)

k=0

Distance

0  $\infty$   $\infty$

k=0

Path

- - -

k=1

Distance

0 7 5

k=1

Path

- A A

k=2

Distance

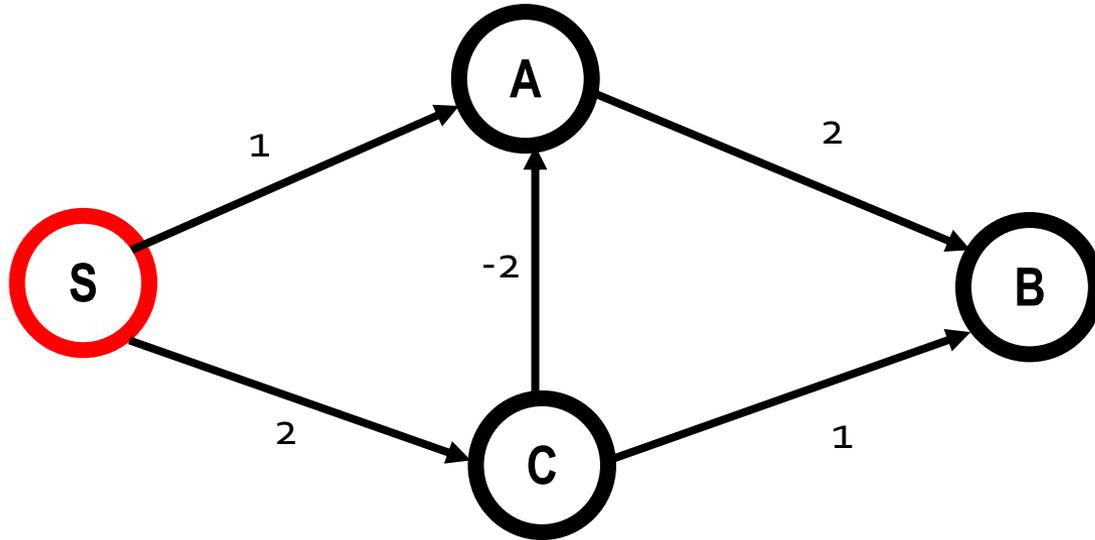
0 7 2

k=2

Path

- A B

# ► QUIZ? Bellman & Ford's Algorithm

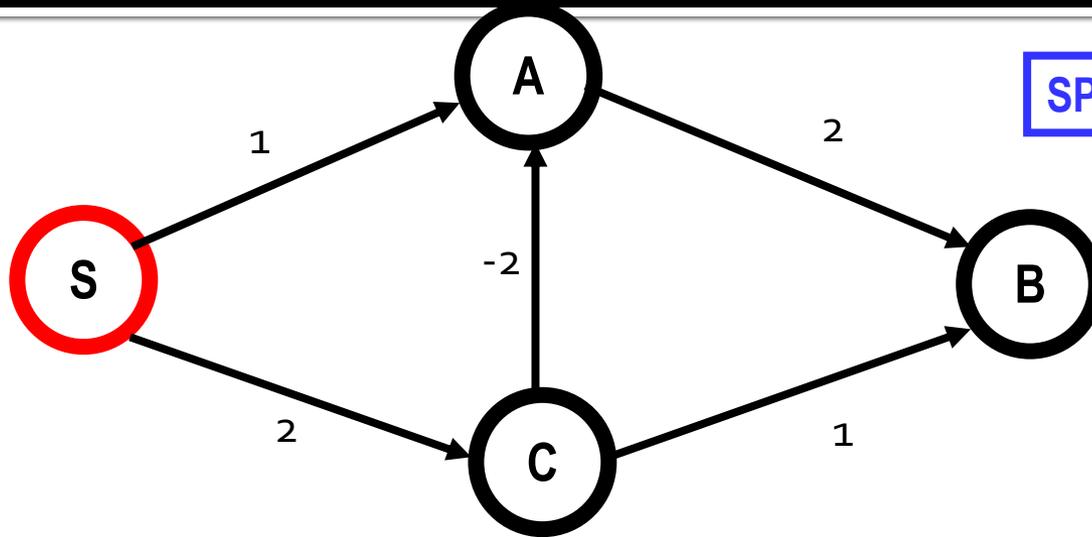


Distance?

Path?

Shortest paths?

# ► QUIZ: Bellman & Ford's Algorithm



SPT(Shortest Path Tree)

Shortest Paths from S:  
 S-C-A (0)  
 S-C-A-B (2)  
 S-C (2)

$|V| = 4$

		S	A	B	C
k=0	Distance	0	$\infty$	$\infty$	$\infty$
k=1	Distance	0	1	$\infty$	2
k=2	Distance	0	0	3	2
k=3	Distance	0	0	2	2

k=0	Path	-	-	-	-
k=1	Path	-	S	-	S
k=2	Path	-	C	A	S
k=3	Path	-	C	A	S

# 5. Chained Matrix Multiplication

- Standard matrix multiplication:

A  $2 \times 3$  matrix times a  $3 \times 4$  matrix is a  $2 \times 4$  matrix:

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} * \begin{bmatrix} 7 & 8 & 9 & 1 \\ 2 & 3 & 4 & 5 \\ 6 & 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} 29 & 35 & 41 & 38 \\ 74 & 89 & 104 & 83 \end{bmatrix}$$

- How many multiplications?
  - 3 multiplications per each entry & 8 entries
  - Total 24

# Chained Matrix Multiplication

- $i*j$  matrix times  $j*k$  matrix needs  $i*j*k$  multiplications!
- Matrix multiplication is an **associative** operation, meaning that **the order in which we multiply does not matter**.

# Chained Matrix Multiplication

- An optimal order for multiplying 4 matrices?

$$\begin{array}{ccccccc} A & * & B & * & C & * & D \\ 20 \times 2 & & 2 \times 30 & & 30 \times 12 & & 12 \times 8 \end{array}$$

- How many different orders?
  - 5

# Chained Matrix Multiplication

$$\begin{array}{ccccccc} \mathbf{A} & * & \mathbf{B} & * & \mathbf{C} & * & \mathbf{D} \\ \mathbf{20 \times 2} & & \mathbf{2 \times 30} & & \mathbf{30 \times 12} & & \mathbf{12 \times 8} \end{array}$$

- $A(B(CD))$  requires 3680 multiplications.  $30 * 12 * 8 + 2 * 30 * 8 + 20 * 2 * 8 = 3,680$
- $(AB)(CD)$  requires 8880 multiplications.  $20 * 2 * 30 + 30 * 12 * 8 + 20 * 30 * 8 = 8,880$
- $A((BC)D)$  requires 1232 multiplications.  $2 * 30 * 12 + 2 * 12 * 8 + 20 * 2 * 8 = 1,232$
- $((AB)C)D$  requires 10320 multiplications.  $20 * 2 * 30 + 20 * 30 * 12 + 20 * 12 * 8 = 10,320$
- $(A(BC))D$  requires 3120 multiplications.  $2 * 30 * 12 + 20 * 2 * 12 + 20 * 12 * 8 = 3,120$

# Chained Matrix Multiplication

- The goal is to develop an optimal order for multiplying  $n$  matrices  $A_1, A_2, \dots, A_n$ :

$A_1 \times A_2 \times \dots \times A_n$

# Chained Matrix Multiplication

- The **brute-force algorithm** is to consider **all possible orders** and take the minimum.
- This is a very inefficient method – **exponential!**
- **Idea?**

# Chained Matrix Multiplication via DP

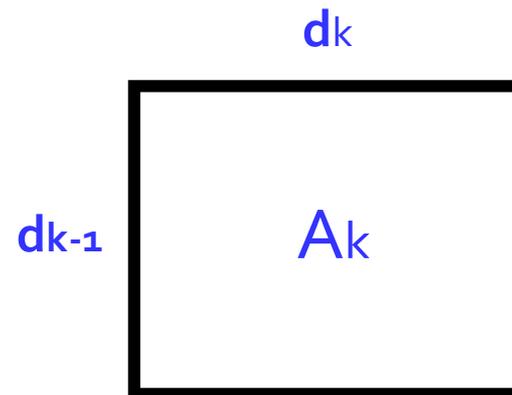
- A more efficient algorithm using DP!

# Chained Matrix Multiplication via DP

- The principle of optimality applies.
- Dynamic programming can be applied!

# Chained Matrix Multiplication via DP

- $M[i,j]$  = minimum number of multiplications needed to multiply  $A_i$  through  $A_j$ 
  - $A_1: d_0 \times d_1$
  - $A_2: d_1 \times d_2$
  - $A_k: d_{k-1} \times d_k$
  - $A_n: d_{n-1} \times d_n$

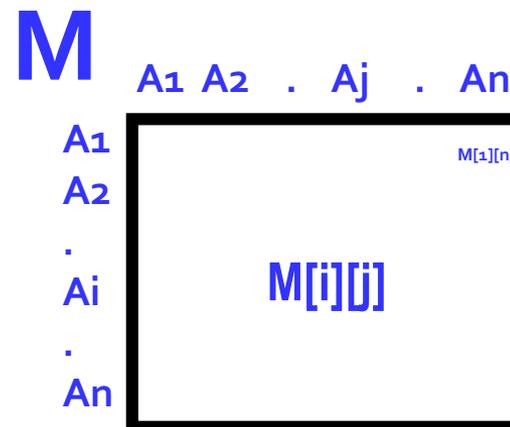


# Chained Matrix Multiplication via DP

- Idea?
- A recursive property when multiplying  $n$  matrices?
  - For  $1 \leq i \leq j \leq n$        $(A_i \dots A_k) (A_{k+1} \dots A_j)$
  - $M[i][j] = \text{MIN}_{1 \leq k \leq j-1}$   
 $(M[i][k] + M[k+1][j] + d_{i-1} d_k d_j)$  if  $i < j$
  - $M[i][i] = 0$

# Chained Matrix Multiplication via DP

- $M[i,j]$  = minimum number of multiplications needed to multiply  $A_i$  through  $A_j$ 
  - $A_1: d_0 \times d_1$
  - $A_2: d_1 \times d_2$
  - $A_k: d_{k-1} \times d_k$
  - $A_n: d_{n-1} \times d_n$

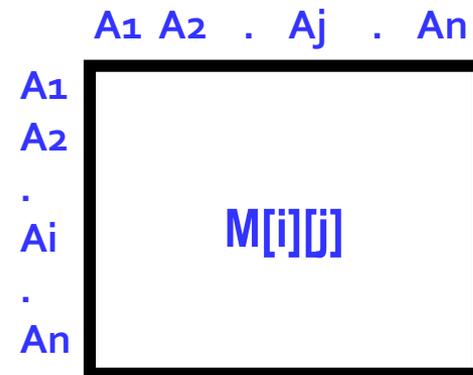


# Chained Matrix Multiplication via DP

- **Algorithm 3.6** Minimum Multiplications & Order
  - Find  $M[1][n]$  for  $A_1 \times A_2 \times \dots \times A_n$ .
  - $O(n^3)$
  - Space  $O(n^2)$
- **Algorithm 3.7** Print Optimal Order
  - $O(n)$

# ► QUIZ? Chained Matrix Multiplication via DP

- A recursive property when multiplying  $n$  matrices?
- For  $1 \leq i \leq j \leq n$



- $M[i][j] = \text{MIN}_{1 \leq k \leq j-1} (M[i][k] + M[k+1][j] + d_{i-1} d_k d_j)$  if  $i < j$
- $M[i][i] = 0$

# 6. Traveling Salesperson Problem (TSP)

- Suppose a salesperson is planning a sales trip.
- Each city is connected to some of the other cities by a road.
- To minimize travel time, we want to determine a **shortest route (tour)** that starts at the salesperson's home city, **visits each of the cities once**, and ends up at the home city.

# Traveling Salesperson Problem

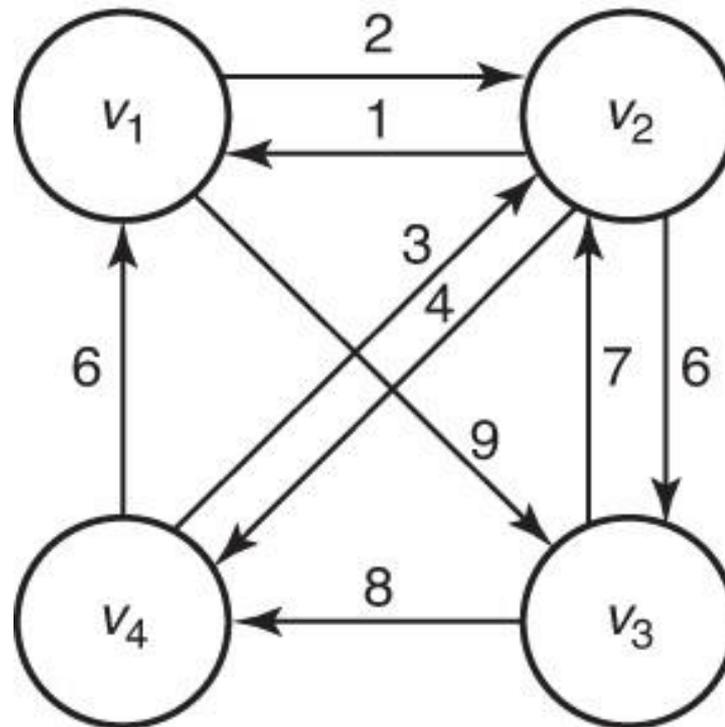
- An instance of this problem can be represented by a weighted directed graph.
- A **tour (Hamiltonian circuit)** is a path from a vertex to itself that passes through each of the other vertices only once.
- An **optimal tour** in a weighted, directed graph is such a path of minimum length.

# Traveling Salesperson Problem

- The **TSP** is to find an optimal tour (Hamiltonian circuit) in a weighted directed graph when at least one tour exists.

# Traveling Salesperson Problem

What is the optimal tour from  $v_1$ ?



# Traveling Salesperson Problem

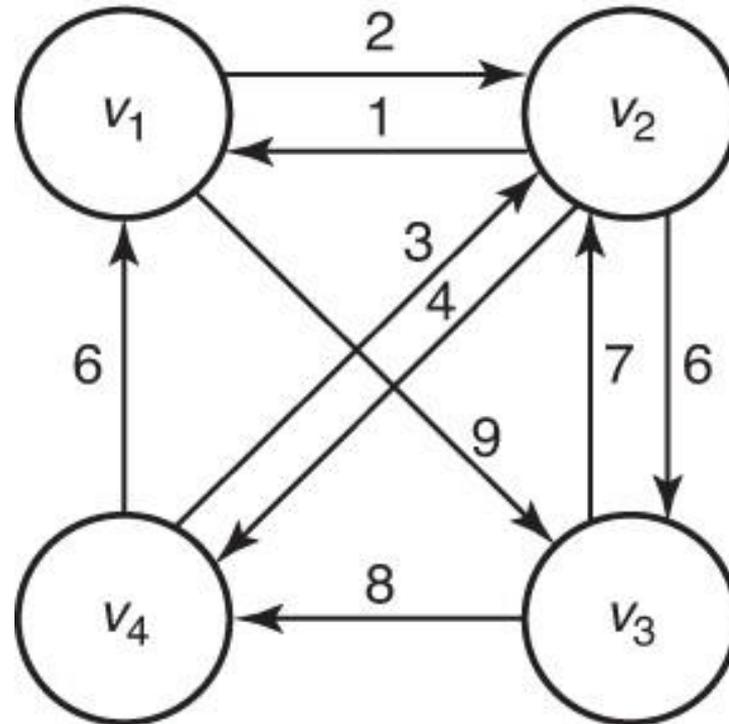


Figure 3.16: **The optimal tour is  $[v_1, v_3, v_4, v_2, v_1]$**

# Traveling Salesperson Problem

- The **brute-force algorithm** is to consider **all possible paths** and take the optimal tour.
- This is a very inefficient method – **factorial!**
- **Idea?**

# Traveling Salesperson Problem via DP

- A more efficient algorithm using DP!

# Traveling Salesperson Problem via DP

- The principle of optimality applies.
- Dynamic programming can be applied!

# Traveling Salesperson Problem via DP

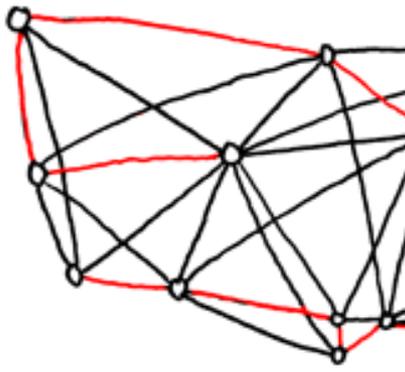
- **Algorithm 3.11 DP Algorithm for the TSP**
  - $O(n^2 2^n)$
  - **BUT, no polynomial time!**
- Example 3.12

# Traveling Salesperson Problem via DP

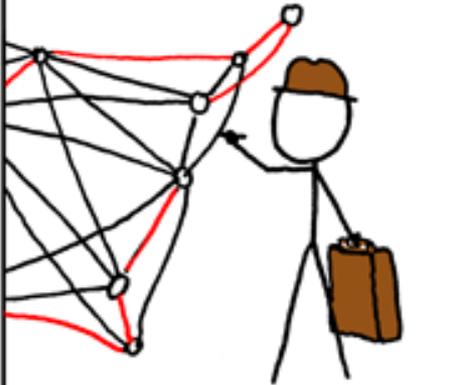
- **No one has ever found** an algorithm for the Traveling Salesperson problem whose worst-case time complexity is **better than exponential!**
- Yet, no one has ever proved that the algorithm is not possible!
- The Traveling Salesperson Problem is **hard.**
- **NP-complete!**

# Traveling Salesperson Problem

BRUTE-FORCE  
SOLUTION:  
 $O(n!)$



DYNAMIC  
PROGRAMMING  
ALGORITHMS:  
 $O(n^2 2^n)$



SELLING ON EBAY:  
 $O(1)$

STILL WORKING  
ON YOUR ROUTE?

SHUT THE  
HELL UP.



## ▶ QUIZ? TSP via DP

- What is the worst-case time complexity of the DP\_based algorithm for TSP?

# 7. The 0-1 Knapsack Problem

- Given a knapsack (rucksack) with maximum weight  $W$  and a set  $S$  of  $n$  items, each with weight  $w$  and profit (value)  $p$ , i.e.,
  - $S = \{(\text{item}_1, w_1, p_1), (\text{item}_2, w_2, p_2), \dots, (\text{item}_n, w_n, p_n)\}$
- Determine the count of each item to include in the knapsack so that
  - The total weight is less than or equal to  $W$  and
  - The total profit (value) is as large as possible.
- For each item, only 1 copy is available & not allowed to break!

# The 0-1 Knapsack Problem via DP

- We can apply **DP** to the 0-1 Knapsack problem!
  - $O(2^n)$  where  $n$  = the number of items
- The 0-1 Knapsack Problem is **hard**.
- **NP-complete!**

# ✓ Dynamic Programming (DP)-based Algorithms Summary

1. N-th Fibonacci Term via DP
2. Binomial Coefficient via DP
3. Floyd & Warshall's Algorithm - APSP via DP
4. Bellman & Ford's Algorithm – SSSP via DP
5. Chained Matrix Multiplication via DP
6. Traveling Salesperson Problem via DP
7. The 0-1 Knapsack Problem via DP

# Homework Assignment

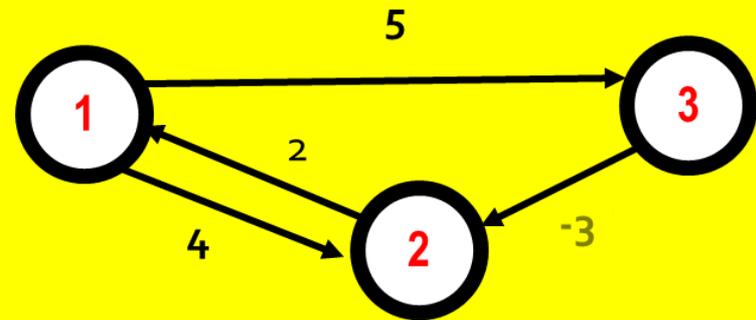
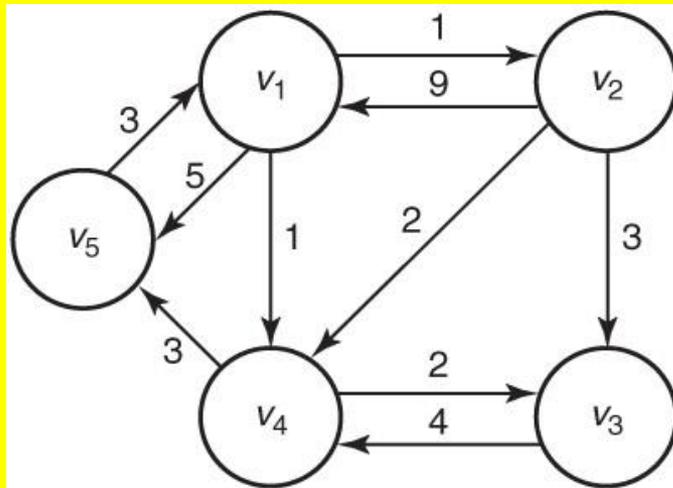
# ▶ Homework Assignment?

- Chapter 3: Exercise #5, #6 and #10

# ▶ Homework Assignment?

- *Dynamic Programming: Chapter 3: Exercise #8 (Dynamic Programming-based Floyd-Warshall Algorithm for the All-Pairs Shortest Path Problem)*

# Test Cases



# ✓ Textbook Readings

- Chapter 3:
  - 3.1
  - 3.2
  - 3.3
  - 3.4
  - 3.6

the right majors, minors & concentrations  
education?

for students' academic and career success  
ing for many students - *Many students change their  
uring college!*

e prediction of student success in MMC could  
dual students  
d their right MMC  
hieve their academic goals

**END**

Y. PARK • DEPT. OF IS&IS, BRUNEL UNIVERSITY

1/7

Prof. Young Park

