



Lecture 16 - Dynamic Programming, All Pairs Shortest Path Problem and Floyd-Warshall Algorithm

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Course Outline (After Midterm)

- Part 3: Data Structures
 - Graphs, Graph Search (DFS, BFS) and Applications (Finding SSCs w/ DFS)
- Part 4: Dynamic Programming
 - Shortest-Path: Dijkstra, **Bellman-Ford, Floyd-Warshall Algorithms** ➡
 - More General DP: Longest Common Subsequence, Knapsack Problem
- Part 5: Greedy Algorithms and Others
 - Scheduling Problem, Optimal Codes
 - Minimum Spanning Trees
 - Max Flow, Min Cut and Ford-Fulkerson Algorithms
 - Stable Matching, Gale-Shapley Algorithm

Recap: Bellman-Ford Algorithm

1. Initialize $d[s] = 0$, others ∞ .

2. Repeat $|V| - 1$ times:

Relax **every edge** $(u, v) \in E$: $d[v] \leftarrow \min(d[v], d[u] + w(u, v))$

3. Extra pass:

If any edge (u, v) can still be relaxed, i.e., $d[v] > d[u] + w(u, v)$

→ **negative cycle detected** .

Bellman-Ford as Dynamic Programming

Recall:

$d_k(v) = d_k[v]$ = shortest distance from s to v using at most k edges.

Recurrence:

$$d_k[v] = \min \left\{ d_{k-1}[v], \min_{(u,v) \in E} (d_{k-1}[u] + w(u, v)) \right\}$$

- Build solutions iteratively: from paths with $\leq k - 1$ edges \rightarrow paths with $\leq k$ edges.
- **Runtime:** $O(mn)$; for n iterations, we loop through all the edges.
- **Space:** can reuse arrays (only keep last iteration).
 - To compute d_k , we only need d_{k-1} (not all of d_{k-1}, \dots, d_0).

What's Really Happening?

- Shortest path with $\leq k$ edges can be built from a shortest path with $\leq k - 1$ edges.
- **DP Principle:** Store and reuse intermediate results instead of recomputing.
- Similar to divide-and-conquer, but with **memoization / tabulation** to avoid repeated work.

Dynamic Programming Recipe

When to use DP:

- **Optimal Substructure** → problem can be broken into smaller independent subproblems.
- **Overlapping Subproblems** → subproblems repeat, so store solutions in a table.

Optimal Substructure (Bellman-Ford Example)

The optimal solution to the problem is composed of optimal solutions to smaller *independent* subproblems.

- For shortest paths:

$$d(s, t) = \min_{k \in V} \{d(s, k) + d(k, t)\}$$

- Any shortest $s \rightarrow t$ path is composed of:
 - A shortest $s \rightarrow k$ path, and
 - A shortest $k \rightarrow t$ path.

✓ Optimal solution is built from optimal solutions to subproblems.

Overlapping Subproblems (Bellman-Ford Example)

The optimal solutions of subproblems can be reused multiple times to compute the optimal solutions of larger problems.

- $d(s, k)$ can be used to compute $d(s, t)$ for **any** t where the shortest $s - t$ path contains k .
- If (u, v) and (u, v') are both in E , relaxing (u, v) and (u, v') both need $d_{k-1}[u]$.
- Instead of recomputing many times, **store the computed value** and reuse.

DP Implementations

Two common styles:

1. Bottom-Up (Tabulation)

- Start with smallest subproblems.
- Iteratively fill table → build up to full problem.
- Example: Bellman-Ford.

2. Top-Down (Memoization)

- Write recursion for the problem.
- Store results of subproblems in a table and reuse stored results when needed.

💡 Both approaches are equivalent in power.

Today's Main Topic

So far, we solved the **Single-Source Shortest Paths (SSSP)** problem.

- Input: one source s , find shortest paths to all $v \in V$.

But what if we want the **shortest path between every pair of vertices?**

This leads us to the **All-Pairs Shortest Paths (APSP)**  problem.

- We'll learn the **Floyd–Warshall** algorithm, a dynamic programming approach to solving APSP.

APSP: All-Pairs Shortest Paths

- **Input:** Graph $G = (V, E)$ with edge weights $w(u, v)$.
- **Goal:** Find shortest path distances $d(u, v)$ for **all pairs** $u, v \in V$.

Examples of applications:

- Routing in communication networks
- Social network analysis
- Circuit design

First Attempt 🤔

- Run **Dijkstra** from each node $u \in V$.
 - Runtime: $O(n \cdot (m + n \log n)) = O(mn + n^2 \log n)$
- Or run **Bellman–Ford** from each node.
 - Runtime: $O(n \cdot mn) = O(mn^2)$

Instead of running SSSP n times, **can we leverage Dynamic Programming to solve APSP directly?**

DP Perspective

Recall: DP works when we have

- **Optimal Substructure**
- **Overlapping Subproblems**

For shortest paths:

- If k is an intermediate vertex on a shortest path $u \rightarrow v$:

$$d(u, v) = d(u, k) + d(k, v)$$

Key Idea: Intermediate Nodes

- Label vertices as $1, 2, \dots, n$.
- Define $d^{(k)}(u, v)$ = shortest path distance from u to v using **only** nodes from $\{1, \dots, k\}$ as possible **intermediates** nodes

- Recurrence:

$$d^{(k)}(u, v) = \min \left(d^{(k-1)}(u, v), d^{(k-1)}(u, k) + d^{(k-1)}(k, v) \right)$$

- If P is a shortest path from u to v using nodes $\{1, \dots, k\}$ internally, there are two cases:
 - **1** P does not pass through k : $d^{(k-1)}(u, v)$
 - **2** P passes through k : $d^{(k-1)}(u, k) + d^{(k-1)}(k, v)$

Key Idea: Intermediate Nodes

So:

- $d^{(0)}(u, v)$: shortest path using no intermediate nodes (i.e., just direct edges).
- $d^{(1)}(u, v)$: shortest path possibly passing through vertex 1.
- $d^{(2)}(u, v)$: shortest path possibly passing through vertices $\{1, 2\}$.
- $d^{(3)}(u, v)$: shortest path possibly passing through vertices $\{1, 2, 3\}$.

...and so on, until

- $d^{(n)}(u, v)$: shortest path possibly passing through vertices $\{1, 2, 3, \dots, n\}$.
 - This gives the shortest path over all vertices.

Solving APSP: Floyd–Warshall Algorithm

Initialization

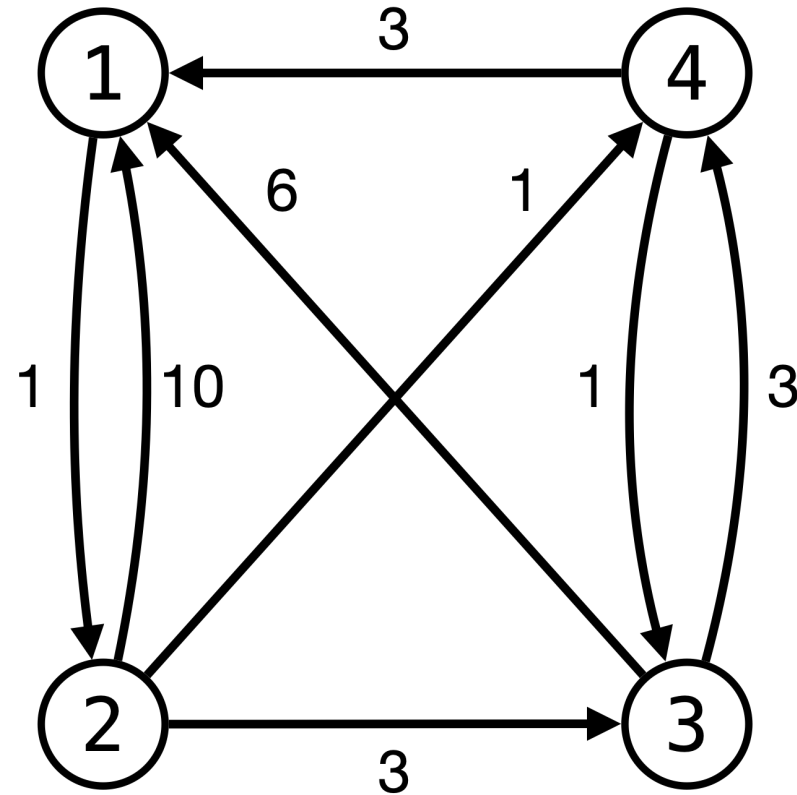
- $d^{(0)}(u, v) = w(u, v)$ if $(u, v) \in E$, else ∞ .
- $d^{(0)}(u, u) = 0$.

Update Rule (for $k = 1 \rightarrow n$):

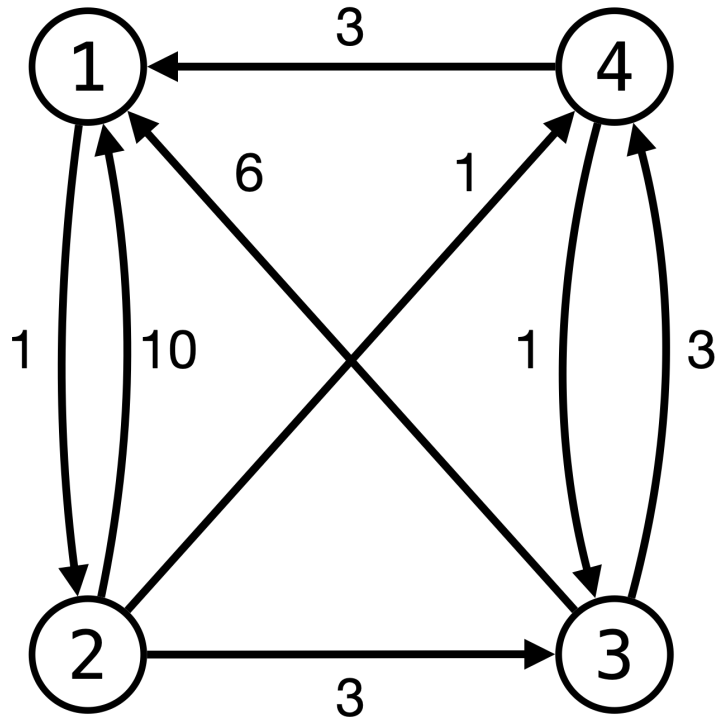
$$d^{(k)}(u, v) = \min \left(d^{(k-1)}(u, v), d^{(k-1)}(u, k) + d^{(k-1)}(k, v) \right)$$

Final Output: $d^{(n)}(u, v)$ = shortest distance from u to v .

Example Walkthrough

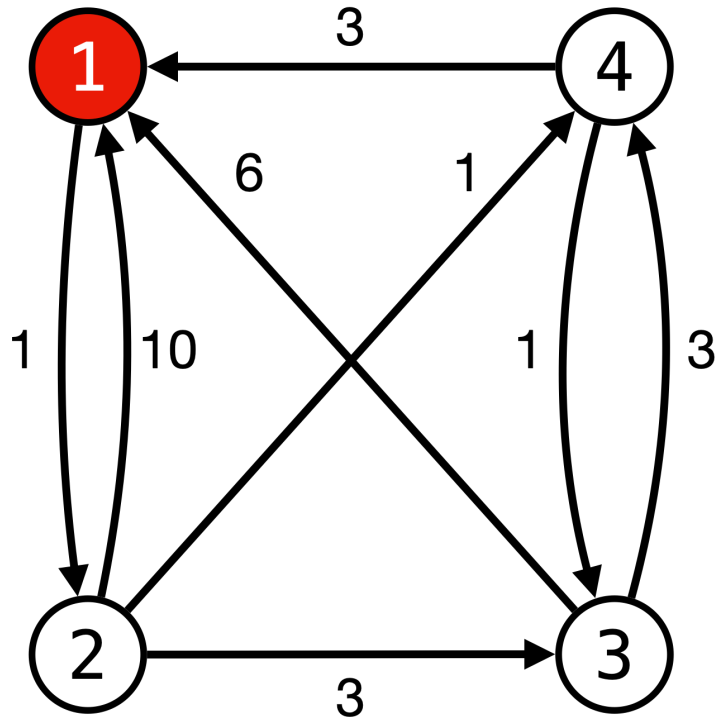


Example Walkthrough: $d^{(0)}$



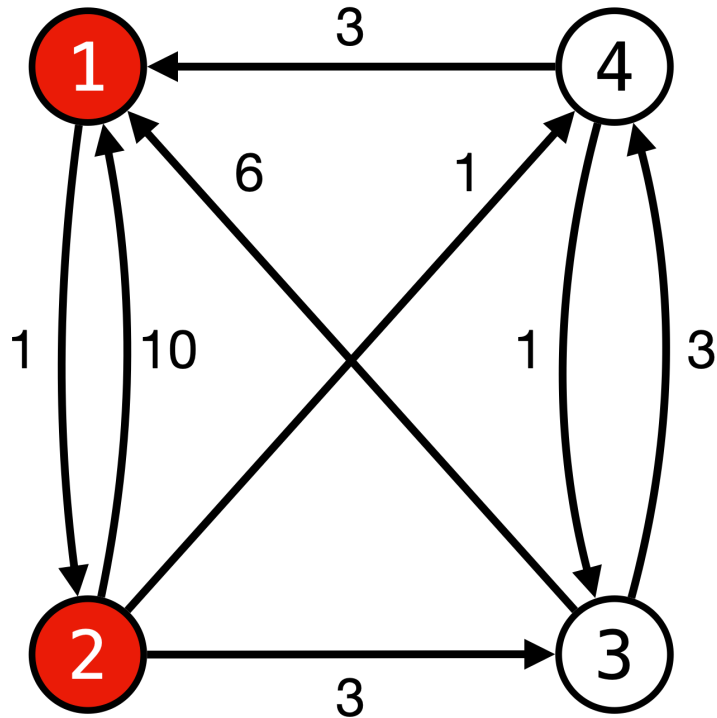
$d^{(0)}$	1	2	3	4
1	0	1	∞	∞
2	10	0	3	1
3	6	∞	0	3
4	3	∞	1	0

Example Walkthrough: $d^{(1)}$



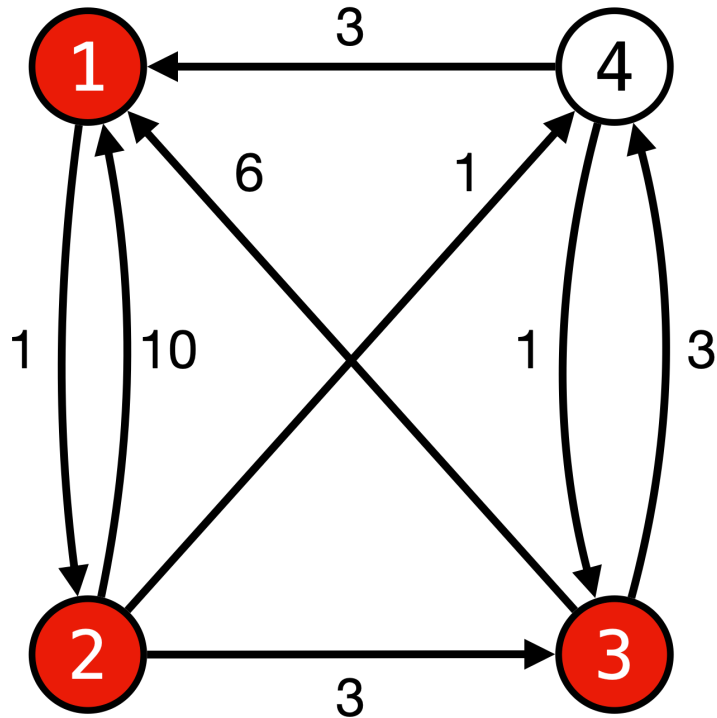
$d^{(1)}$	1	2	3	4
1	0	1	∞	∞
2	10	0	3	1
3	6	7	0	3
4	3	4	1	0

Example Walkthrough: $d^{(2)}$



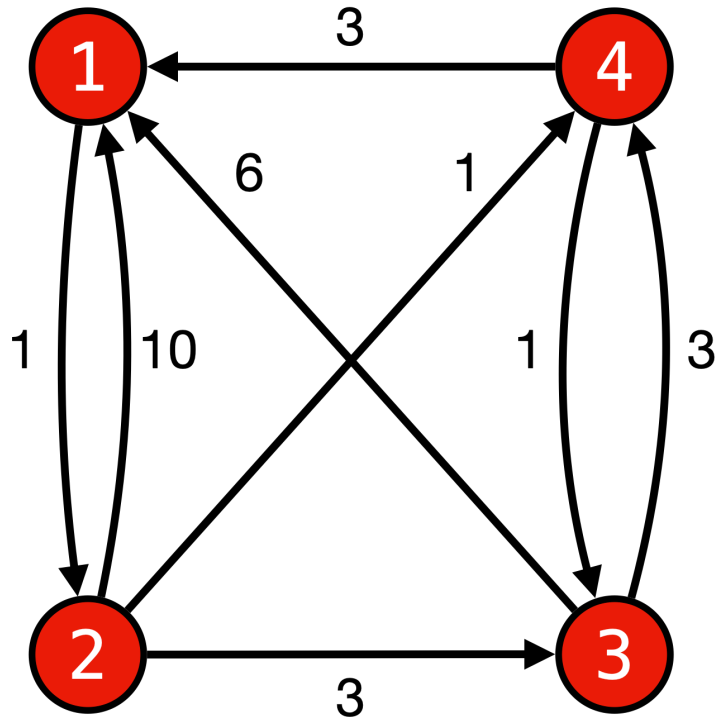
$d^{(2)}$	1	2	3	4
1	0	1	4	2
2	10	0	3	1
3	6	7	0	3
4	3	4	1	0

Example Walkthrough: $d^{(3)}$



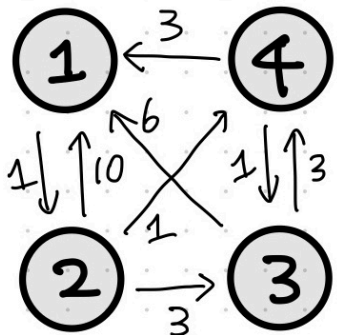
$d^{(3)}$	1	2	3	4
1	0	1	4	2
2	9	0	3	1
3	6	7	0	3
4	3	4	1	0

Example Walkthrough: $d^{(4)}$



$d^{(4)}$	1	2	3	4
1	0	1	3	2
2	4	0	2	1
3	6	7	0	3
4	3	4	1	0

Example Walkthrough: Summary



$$d^{(0)}$$

	1	2	3	4
1	0	1	∞	∞
2	10	0	3	1
3	6	∞	0	3
4	3	∞	1	0

$$d^{(1)}$$

	1	2	3	4
1	0	1	∞	∞
2	10	0	3	1
3	6	7	0	3
4	3	4	1	0

$$d^{(2)}$$

	1	2	3	4
1	0	1	4	2
2	10	0	3	1
3	6	7	0	3
4	3	4	1	0

$$d^{(3)}$$

	1	2	3	4
1	0	1	4	2
2	9	0	3	1
3	6	7	0	3
4	3	4	1	0

$$d^{(4)}$$

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

$$d^{(0)}(u,v) / d^{(0)}(u,1) + d^{(0)}(1,v)$$

3 \rightarrow 2 vs 3 \rightarrow 1 + 1 \rightarrow 2
4 \rightarrow 2 vs 4 \rightarrow 1 + 1 \rightarrow 2

$$d^{(1)}(u,v) / d^{(1)}(u,2) + d^{(1)}(2,v)$$

1 \rightarrow 3 vs 1 \rightarrow 2 + 2 \rightarrow 3
1 \rightarrow 4 vs 1 \rightarrow 2 + 2 \rightarrow 4

$$d^{(2)}(u,v) / d^{(2)}(u,3) + d^{(2)}(3,v)$$

2 \rightarrow 1 vs 2 \rightarrow 3 + 3 \rightarrow 1

$$d^{(3)}(u,v) / d^{(3)}(u,4) + d^{(3)}(4,v)$$

1 \rightarrow 3 vs 1 \rightarrow 4 + 4 \rightarrow 3
2 \rightarrow 1 vs 2 \rightarrow 4 + 4 \rightarrow 1
2 \rightarrow 3 vs 2 \rightarrow 4 + 4 \rightarrow 3

Correctness of Floyd–Warshall (Induction Proof)

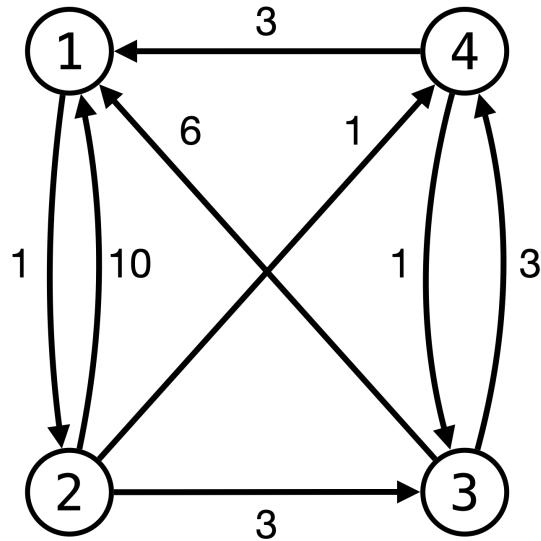
Inductive Claim: For every $k = 0, 1, \dots, n$ and all u, v , the table entry $d^{(k)}(u, v)$ equals the shortest path distance from u to v whose **intermediate vertices** (if any) are drawn only from $\{1, \dots, k\}$.

Thus, after n iterations:

$$d^{(n)}(u, v) = d(u, v)$$

Base Case ($k = 0$):

- Allowed intermediates: none
- Paths are either the $u = v$ path (cost 0) or **single edge** (u, v) (cost $w(u, v)$), else ∞ .
- This is exactly $d^{(0)}$ by initialization. ✓



$d^{(0)}$	1	2	3	4
1	0	1	∞	∞
2	10	0	3	1
3	6	∞	0	3
4	3	∞	1	0

Inductive Step ($k - 1 \rightarrow k$):

Inductive Hypothesis: $d^{(k-1)}(u, v)$ equals the shortest path distance from u to v whose **intermediate vertices** are drawn only from $\{1, \dots, k - 1\}$.

Consider any shortest $u \rightarrow v$ path P whose intermediates lie in $\{1, \dots, k\}$.

Case 1. P does not pass through k

Then P 's intermediates lie in $\{1, \dots, k - 1\}$, so by inductive hypothesis,
 $d^{(k)}(u, v) = d^{(k-1)}(u, v) = \text{cost}(P)$.

Case 2. P passes through k :

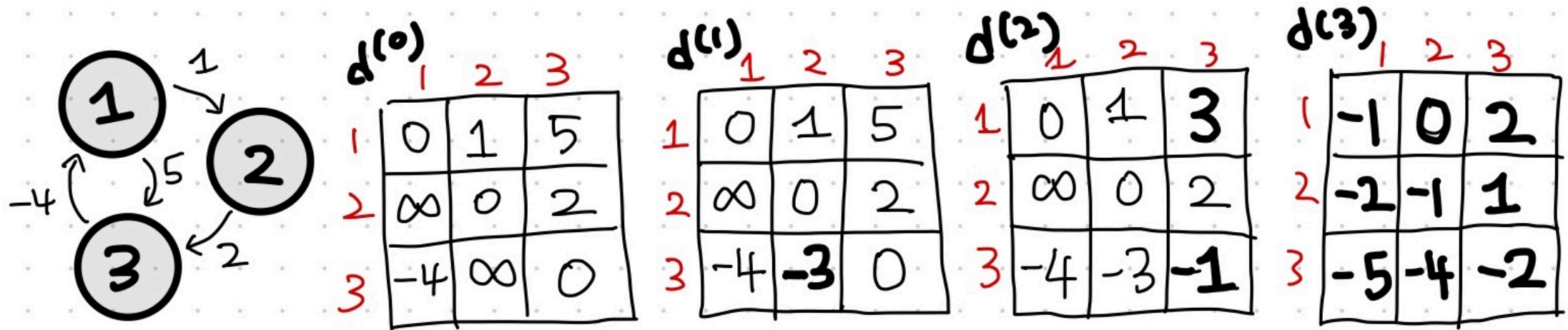
Let $P = (u \rightarrow k) \circ (k \rightarrow v)$. Each subpath's intermediates are in $\{1, \dots, k - 1\}$, so by inductive hypothesis, $d^{(k-1)}(u, k)$ and $d^{(k-1)}(k, v)$ equal their true costs, hence

$$d^{(k)}(u, v) = d^{(k-1)}(u, k) + d^{(k-1)}(k, v) = \text{cost}(P).$$

Handling Negative Cycles

- Floyd–Warshall can also **detect negative cycles**.
- Check the diagonal:
 - If $d^{(n)}(u, u) < 0$ for some u , then there is a negative cycle reachable from u .
- Why?
 - If there is a simple path P from u to u of negative weight (i.e., a negative cycle containing u), then $d^{(n)}(u, u)$ will be at most its weight, and hence, will be negative.

Example: Negative Cycle Detection



- There is a negative cycle reachable from all vertices!

Runtime and Space Complexity

- **Runtime:** Filling an n^2 table across n iterations, i.e., $O(n^3)$
 - **Space:** $O(n^2)$ (store distance matrix).
 - Note: can optimize to use only 2 layers (current + previous k).
- 👉 Simple to implement, practical for dense graphs.

APSP: Dijkstra vs. Floyd–Warshall

Algorithm	Runtime	Works with Negative Weights?	When to Use
Floyd-Warshall	$O(n^3)$	✓ Yes	Good for dense graphs , simple to implement
Dijkstra $\times n$	$O(nm + n^2 \log n)$	✗ No	Best for sparse graphs , more efficient

- **Sparse graphs** ($m = O(n)$): Dijkstra n times $\approx O(n^2 \log n) \rightarrow$ **much faster**
- **Dense graphs** ($m = \Theta(n^2)$): Both $\approx O(n^3) \rightarrow$ Floyd–Warshall may be simpler and practical

Summary

- **APSP Problem:** compute shortest paths between every pair of vertices.
- **Naïve approach:** run SSSP n times.
- **Floyd–Warshall Algorithm:**
 - Elegant **DP** formulation
 - Works with negative edge weights
 - Detects negative cycles
 - Runtime: $O(n^3)$

Announcement

- The bonus assignment details will be uploaded to LMS today.
- The next quizzes will be on November 18 (Tuesday) and December 4 (Thursday).

Appendix: Why is it called Dynamic Programming?

Historical Context

- The term was coined by **Richard Bellman** in the 1950s.
- At the time, he was working at the RAND Corporation on mathematical optimization problems for the U.S. Air Force.
- The U.S. Secretary of Defense (Charles Wilson) had a strong dislike of the words **"research"** and **"mathematics."**
 - If Bellman called his work "mathematical research," it would not get funded. 💵😞
 - So he needed a safer, more appealing name.

Why “Programming”?

- “Programming” here means a **plan** or **schedule of actions** (like in “linear programming” or “planning a program of events”), not computer programming.
- DP is about constructing an optimal plan by combining solutions of smaller subproblems.

Why “Dynamic”?

- “Dynamic” emphasized that the method involved **multistage decision-making** and **updating over time**.
- Bellman also noted that “dynamic” has a positive, action-oriented connotation — it’s hard to use it negatively.
- This made it **politically safe** and even attractive to sponsors.

So... It's called **Dynamic Programming** because:

- **Programming** = planning/optimization, not coding.
- **Dynamic** = problems solved stage by stage, with decisions unfolding over time.
- Bellman chose the term partly for **political reasons** so his work could be supported, while secretly he was doing deep mathematics 🤪.

Credits & Resources

Lecture materials adapted from:

- Stanford CS161 slides and lecture notes
 - <https://stanford-cs161.github.io/winter2025/>
- *Algorithms Illuminated* by Tim Roughgarden
 - <https://algorithmsilluminated.com/>
- Example: <https://favtutor.com/blogs/floyd-warshall-algorithm>