Computer Algorithms

Segment 6

Shortest Path

SINGLE-SOURCE SHORTEST PATHS

Generalization of BFS to handle weighted graphs

- Direct Graph G = (V, E), edge weight function; $w : E \to R$
- In BFS w(e)=1 for all $e \hat{i} E$

Weight of path
$$p = v_1 \rightarrow v_2 \rightarrow ... \rightarrow v_k$$
 is $w(p) = \sum_{i=1}^{k-1} w(v_i, v_{i+1})$

Shortest Path = Path of minimum weight

$$\frac{\delta(u,v)}{\delta(u,v)} = \begin{cases} \min\{w(p): u^{p} \\ v\}; & \text{if there is a path from u to v,} \end{cases}$$
otherwise.

Shortest-Path Variants

Shortest-Path problems

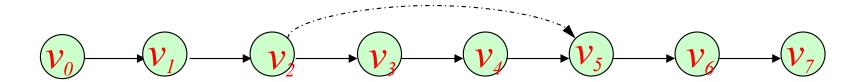
- Single-source shortest-paths problem: Find the shortest path from s
 to each vertex v. (e.g. BFS)
- Single-destination shortest-paths problem: Find a shortest path to a given *destination* vertex t from each vertex v.
- Single-pair shortest-path problem: Find a shortest path from u to v for given vertices u and v.
- All-pairs shortest-paths problem: Find a shortest path from u to v for every pair of vertices u and v.

Optimal Substructure Property

Theorem: Subpaths of shortest paths are also shortest paths

- Let $P_{1k} = \langle v_1, ..., v_k \rangle$ be a shortest path from v_l to v_k
- Let $P_{ij} = \langle v_i, ..., v_j \rangle$ be subpath of P_{1k} from v_i to v_j for any i, j
- Then P_{ij} is a shortest path from v_i to v_j

Proof: By cut and paste



- If some subpath were not a shortest path
- We could substitute a shorter subpath to create a *shorter total path*
- Hence, the original path would not be shortest path

Optimal Substructure Property

Definition:

• $\delta(u,v)$ = weight of the shortest path(s) from u to v

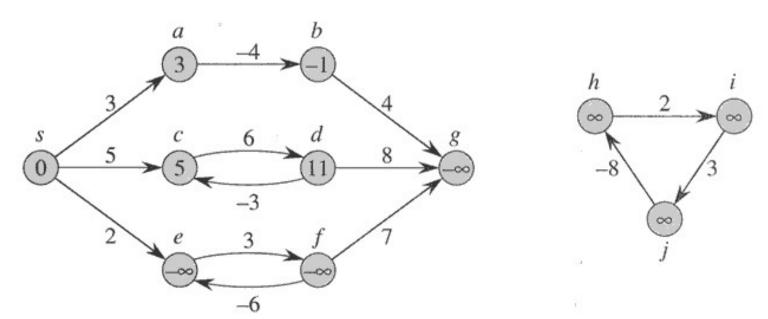
Well Definedness:

- *negative-weight cycle in graph*: Some shortest paths may not be defined
- *argument*:can always get a shorter path by going around the cycle again

cycle

Negative-weight edges

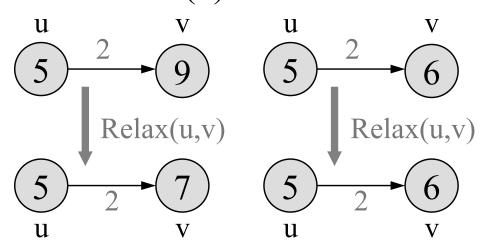
- Negative weight edges can be allowed as long as there are no negative weight cycles
- If there are negative weight cycles, then there cannot be a shortest path from s to any node t (why?)
- If we disallow negative weight cycles, then there always is a shortest path that contains no cycles
- No problem, as long as no negative-weight cycles are reachable from the source
- Otherwise, we can just keep going around it, and get $w(s, v) = -\infty$ for all v on the cycle.



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Relaxation technique

- For each vertex v, we maintain an upper bound d[v] on the weight of shortest path from s to v
- d[v] initialized to infinity
- Relaxing an edge (u,v)
 - Can we improve the shortest path to v by going through u?
 - If d[v] > d[u] + w(u,v), d[v] = d[u] + w(u,v)
 - This can be done in O(1) time



Relaxation

Algorithms keep track of d[v], π [v]. **Initialized** as follows:

```
Initialize(G, s)

for each v \in V[G] do

d[v] := \infty;

\pi[v] := NIL

d[s] := 0
```

These values are changed when an edge (u, v) is relaxed:

```
Relax(u, v, w)

if d[v] > d[u] + w(u, v) then

d[v] := d[u] + w(u, v);

\pi[v] := u
```

Properties of Relaxation

- Triangle inequality for a given vertex $s \mid V$ and for every edge $(u,v) \mid E$, we have $\delta(s,v) \leq \delta(s,u) + w(u,v)$
- Upper-bound property
 We always have $d[v] \ge \delta(s, v)$ for all vertices v îV, and once d[v] achieves the value $\delta(s, v)$, it never changes.
- No-path property If there is no path from s to v, then $d[v] = \delta(s, v) = \infty$.
- Convergence property If $s \sim u \rightarrow v$ is a shortest path in G for some u, v îV, and if $d[u] = \delta(s, u)$ at any time prior to relaxing edge (u, v), then $d[v] = \delta(s, v)$ at all times afterward.
- Path-relaxation property

Bellman-Ford Algorithm

- Can have negative-weight edges. Will "detect" <u>reachable</u> negative-weight cycles.
- Given a weighted, directed graph G=(V,E) with source s and weight function $w: E \rightarrow \mathbb{R}$, the Bellman-Ford algorithm returns a Boolean value indicating whether or not there is a negative-weight cycle that is reachable from the source.

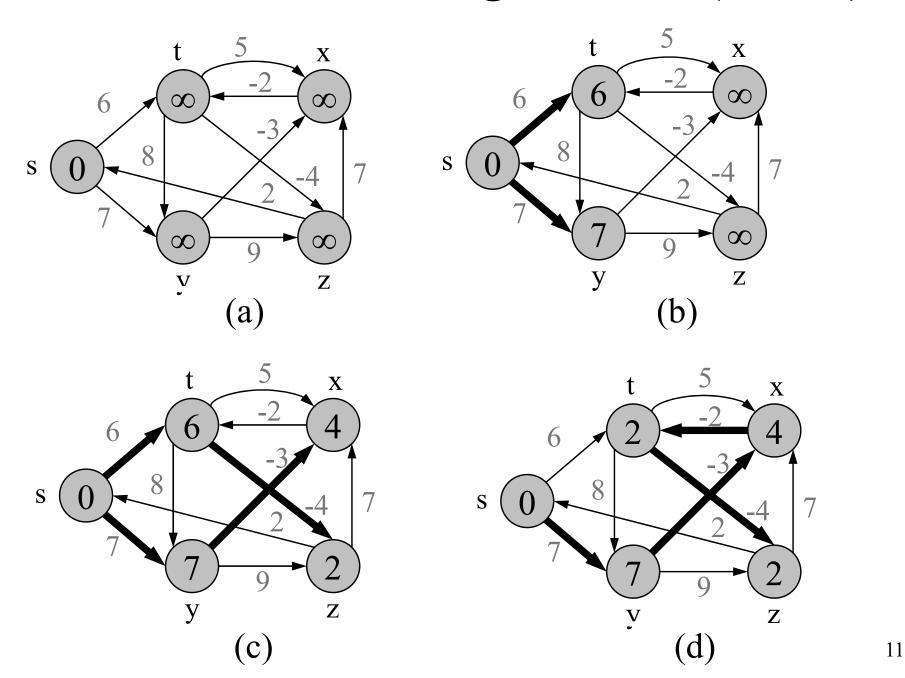
Bellman-Ford(G, w, s)

- 1. Initialize(G, s);
- **2.** for i := 1 to |V/G| 1 do
- 3. for each (u, v) in E[G] do
- 4. Relax(u, v, w)
- 5. for each (u, v) in E[G] do
- 6. if d[v] > d[u] + w(u, v) then
- 7. return false
- **8.** return true

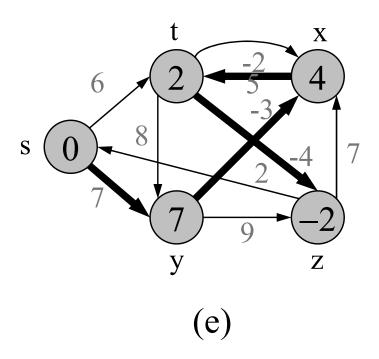
Time Complexity is O(VE).

d and π values are the final values

Bellman-Ford Algorithm (cont.)



Bellman-Ford Algorithm (cont.)



d and π values in (e) are the final values

• Bellman-Ford running time:

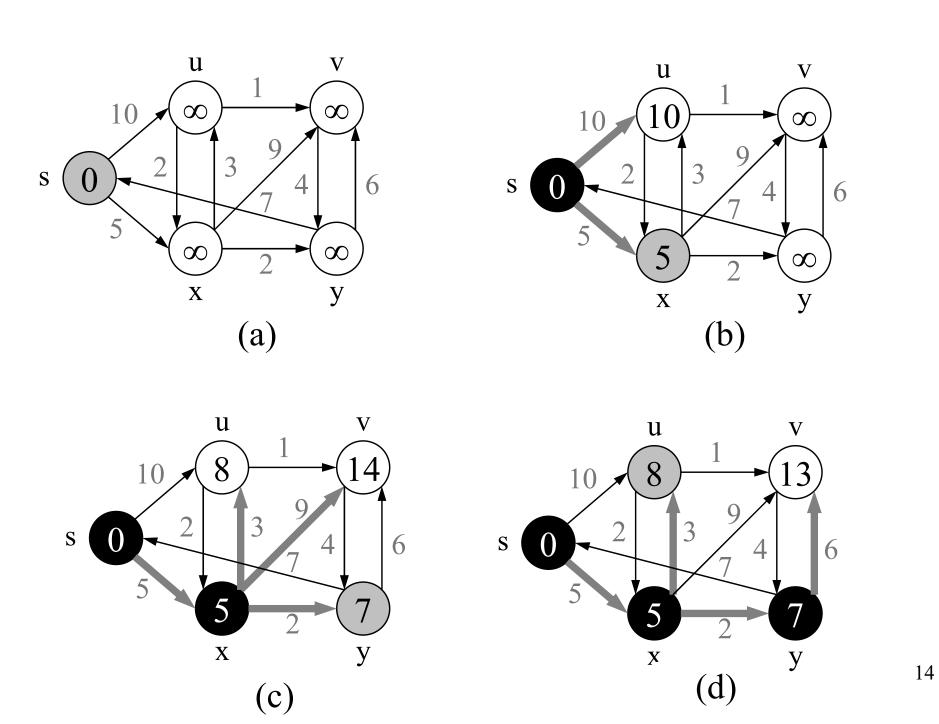
$$-(|V|-1)|E|+|E|=\Theta(VE)$$

Dijkstra's Algorithm For Shortest Paths

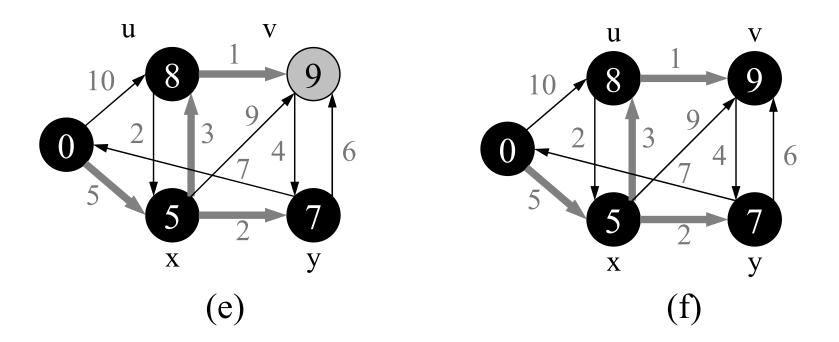
- Non-negative edge weight
- Like BFS: If all edge weights are equal, then use BFS, otherwise use this algorithm
- Use Q = priority queue keyed on d[v] values (note: BFS uses FIFO)

```
Dijkstra(G,w,s)
   Initialize(G, s);
  S := \varnothing;
3. Q := V[G];
   while Q \neq \emptyset do
5.
   u := \text{Extract-Min}(Q);
6. S := S \cup \{u\};
7. for each v \in Adj[u] do
8.
               Relax(u, v, w)
```

Dijkstra's Algorithm For Shortest Paths



Dijkstra's Algorithm For Shortest Paths



d and π values in (f) are the final values

Running Time Analysis cont'd

- O(E) edge relaxations
- Priority Queue operations
 - O(E) decrease key operations
 - O(V) extract-min operations
- Three implementations of priority queues
 - Array: $O(V^2)$ time
 - decrease-key is O(1) and extract-min is O(V)
 - Binary heap: $O(E \log V)$ time assuming $E \ge V$
 - decrease-key and extract-min are O(log V)
 - Fibonacci heap: $O(V \log V + E)$ time
 - decrease-key is O(1) amortized time and extract-min is O(log V)
- Running time of Dijkstra's algorithm is lower than that of Bellman-Ford algorithm

All-Pairs Shortest Paths

- We now want to compute a table giving the length of the shortest path between any two vertices. (We also would like to get the shortest paths themselves.)
- Assume input graph is given by an adjacency matrix.

$$W = (w_{ij})$$
 where

$$w_{ij} = \begin{cases} 0 & \text{if } i = j \\ \text{the weight of directed edg}(i,j), & \text{if } i \neq j \text{ and } (i,j) \in E, \end{cases}$$

$$\text{• Let } d_{ij}^{(m)} = \text{minimum weight of any path from vertex } i \text{ to vertex } j,$$

containing at most m edges.

Dynamic programming algorithms for all-pairs shortest path

• We will study a new technique—dynamic programming algorithms (typically for optimization problems)

• Ideas:

- Characterize the structure of an optimal solution
- Recursively define the value of an optimal solution
- Compute the value of an optimal solution in a bottomup fashion (using matrix to compute)
- Backtracking to construct an optimal solution from computed information.

Floyd-Warshall algorithm for shortest path:

- Use a different dynamic-programming formulation to solve the all-pairs shortest-paths problem on a directed graph G=(V,E).
- The resulting algorithm, known as the Floyd-Warshall algorithm, runs in O (V³) time.
 - negative-weight edges may be present,
 - but we shall assume that there are no negativeweight cycles.

The structure of a shortest path:

- We use a different characterization of the structure of a shortest path than we used in the matrix-multiplication-based all-pairs algorithms.
- The algorithm considers the "intermediate" vertices of a shortest path, where an intermediate vertex of a simple path $p=\langle v_1,v_2,...,v_l\rangle$ is any vertex in p other than v_1 or v_l , that is, any vertex in the set $\{v_2,v_3,...,v_{l-1}\}$

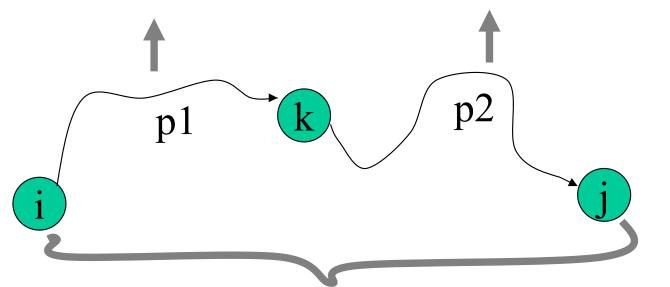
Continue:

- Let the vertices of G be V={1,2,...,n}, and consider a subset {1,2,...,k} of vertices for some k.
- For any pair of vertices $i,j \in V$, consider all paths from i to j whose intermediate vertices are all drawn from $\{1,2,\ldots,k\}$, and let p be a minimum-weight path from among them.
- The Floyd-Warshall algorithm exploits a relationship between path p and shortest paths from i to j with all intermediate vertices in the set {1,2,...,k-1}.

Relationship:

- The relationship depends on whether or not k is an intermediate vertex of path p.
- If k is not an intermediate vertex of path p, then all intermediate vertices of path p are in the set {1,2,...,k-1}. Thus, a shortest path from vertex i to vertex j with all intermediate vertices in the set {1,2,...,k-1} is also a shortest path from i to j with all intermediate vertices in the set {1,2,...,k}.
- If k is an intermediate vertex of path p,then we break p down into i $\xrightarrow{p_1}$ k $\xrightarrow{p_2}$ j as shown Figure 2.p1 is a shortest path from i to k with all intermediate vertices in the set $\{1,2,...,k-1\}$, so as p2.

All intermediate vertices in $\{1,2,...,k-1\}$



P:all intermediate vertices in $\{1,2,...,k\}$

Figure 2. Path p is a shortest path from vertex i to vertex j, and k is the highest-numbered intermediate vertex of p. Path p1, the portion of path p from vertex i to vertex k, has all intermediate vertices in the set {1,2,...,k-1}. The same holds for path p2 from vertex k to vertex j.

A recursive solution to the allpairs shortest paths problem:

• Let $d_{ij}^{(k)}$ be the weight of a shortest path from vertex i to vertex j with all intermediate vertices in the set $\{1,2,\ldots,k\}$. A recursive definition is given by

•
$$d_{ij}^{(k)} = \begin{cases} w_{ij} & \text{if } k=0, \\ \min(d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)}) & \text{if } k \ge 1. \end{cases}$$

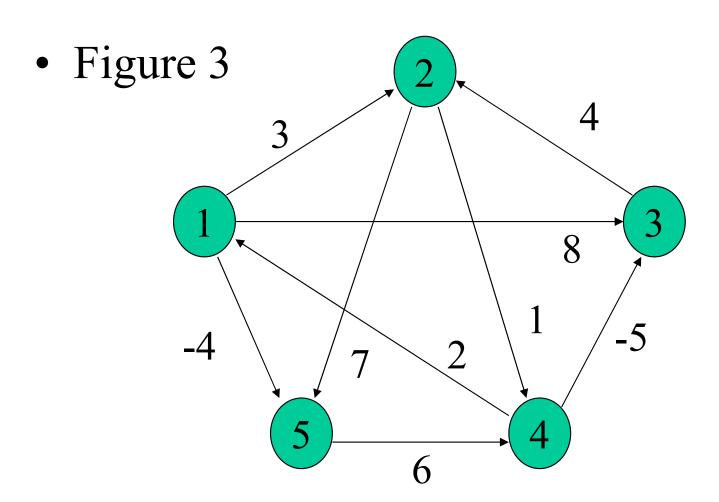
• The matrix $D^{(n)}=(d_{ij}^{(n)})$ gives the final answer- $d_{ij}^{(n)}=\delta(i,j)$ for all $i,j \in V$ -because all intermediate vertices are in the set $\{1,2,\ldots,n\}$.

Computing the shortest-path weights bottom up:

```
    FLOYD-WARSHALL(W)
    n ← rows[W]
    D<sup>(0)</sup> ← W
    for k ← 1 to n
    do for i ← 1 to n
    do for j ← 1 to n
    do for j ← 1 to n
```

• return D⁽ⁿ⁾

Example:



$$D(0) = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix}$$

$$D(0) = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \prod (0) = \begin{pmatrix} NIL & 1 & 1 & NIL & 1 \\ NIL & NIL & NIL & NIL & 2 & 2 \\ NIL & 3 & NIL & NIL & NIL \\ 4 & NIL & 4 & NIL & NIL \\ NIL & NIL & NIL & 5 & NIL \end{pmatrix}$$

$$D(1) = \begin{bmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix}$$

$$D(1) = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi(1) = \begin{pmatrix} NIL & 1 & 1 & NIL & 1 \\ NIL & NIL & NIL & NIL & 2 & 2 \\ NIL & 3 & NIL & NIL & NIL \\ 4 & 1 & 4 & NIL & 1 \\ NIL & NIL & NIL & 5 & NIL \end{pmatrix}$$

$$D(2) = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix}$$

$$D(2) = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & 5 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi(2) = \begin{pmatrix} NIL & 1 & 1 & 2 & 1 \\ NIL & NIL & NIL & 2 & 2 \\ NIL & 3 & NIL & 2 & 2 \\ 4 & 1 & 4 & NIL & 1 \\ NIL & NIL & NIL & 5 & NIL \end{pmatrix}$$

$$D(3) = \begin{bmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{bmatrix}$$

$$D(3) = \begin{pmatrix} 0 & 3 & 8 & 4 & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix} \qquad \Pi(3) = \begin{pmatrix} NIL & 1 & 1 & 2 & 1 \\ NIL & NIL & NIL & 2 & 2 \\ NIL & 3 & NIL & 2 & 2 \\ 4 & 3 & 4 & NIL & 1 \\ NIL & NIL & NIL & 5 & NIL \end{pmatrix}$$

$$D(4) = \begin{pmatrix} 0 & 3 & -1 & 4 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix}$$

$$D(4) = \begin{pmatrix} 0 & 3 & -1 & 4 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix} \qquad \qquad \prod (4) = \begin{pmatrix} NIL & 1 & 4 & 2 & 1 \\ 4 & NIL & 4 & 2 & 1 \\ 4 & 3 & NIL & 2 & 1 \\ 4 & 3 & 4 & NIL & 1 \\ 4 & 3 & 4 & 5 & NIL \end{pmatrix}$$

$$D(5) = \begin{pmatrix} 0 & 1 & 3 & 2 & 4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix}$$

$$D(5) = \begin{pmatrix} 0 & 1 & -3 & 2 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 3 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{pmatrix} \qquad \Pi(5) = \begin{pmatrix} NIL & 3 & 4 & 5 & 1 \\ 4 & NIL & 4 & 2 & 1 \\ 4 & 3 & NIL & 2 & 1 \\ 4 & 3 & 4 & NIL & 1 \\ 4 & 3 & 4 & 5 & NIL \end{pmatrix}$$

Constructing a shortest path:

 $\pi_{ij}^{(k)}$: the predecessor of vertex j on a shortest path from i with all intermediate vertices in the set $\{1, 2, ..., k\}$

$$\pi_{ij}^{(0)} = \begin{cases} NIL & \text{if } i = j \text{ or } w_{ij} = \infty \\ i & \text{if } i \neq j \text{ and } w_{ij} < \infty \end{cases} \dots (25.6)$$

For $k \ge 1$, if we take the path $i \leadsto k \leadsto j$, where $k \ne j$, then the predecessor of j we choose is the same as the predecessor of j we chose on a shortest path from k with all intermediate vertices in the set $\{1, 2, ..., k-1\}$. Otherwise, we choose the same predecessor of j that we chose on a shortest path from i with all intermediate vertices in the set $\{1, 2, ..., k-1\}$. Formally, for $k \ge 1$,

$$\pi_{ij}^{(k)} = \begin{cases} \pi_{ij}^{(k-1)} & \text{if } d_{ij}^{(k-1)} \leq d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \\ \pi_{kj}^{(k-1)} & \text{if } d_{ij}^{(k-1)} > d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \end{cases} \dots 25.7$$

Print a shortest path from vertex i to vertex j

Print-All-Pairs-Shortest-Path(Π , i,j)

- 1. **if** i=j
- 2. then print i
- 3. else if $\pi_{ij} = NIL$
- 4. then print "no path from" i "to" j "exists"
- 5. else Print-All-Pairs-Shortest-Path (Π, i, π_{ij})
- **6.** print j