Lecture 22: Shortest Paths Cont.

- Quick Review of Previous Class
- Concept of Edge Relaxation

```
Relax(u, v)

If u.d + w(u, v) < v.d Then

v.d = u.d + w(u, v)

v.p = u
```

- Bellman-Ford Algorithm: relax all edges V-1 times in arbitrary order $\Theta(VE)$.
- Shortest path in a Directed Acyclic Graph: relax all edges exactly once in topological order $\Theta(V + E)$.
- Algorithms work with negative weights.
- Shortest paths are not applicable for negative cycles.

Outline

- Single Source Shortest Path
 - Dijkstra Algorithm
- All-Pairs Shortest Paths
 - First DP Formulation
 - 2nd DP Formulation
 - Floyd-Warshall

SPs in a graph with cycles and nonnegative weights

Dijkstra's algorithm.

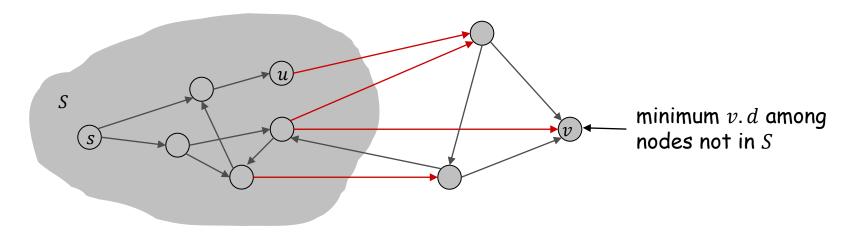
• Maintain a set S of explored nodes.

Initialize $S = \{s\}$, s.d = 0, $v.d = \infty$.

Assume we know, $\forall u \in S, u.d = \delta(s, u)$.

Key lemma: If all edges leaving S were already relaxed, let v be the vertex in V-S with the minimum v.d. Then $v.d=\delta(s,v)$,

- This v can then be added to S, and process repeated.



Dijkstra's Algorithm

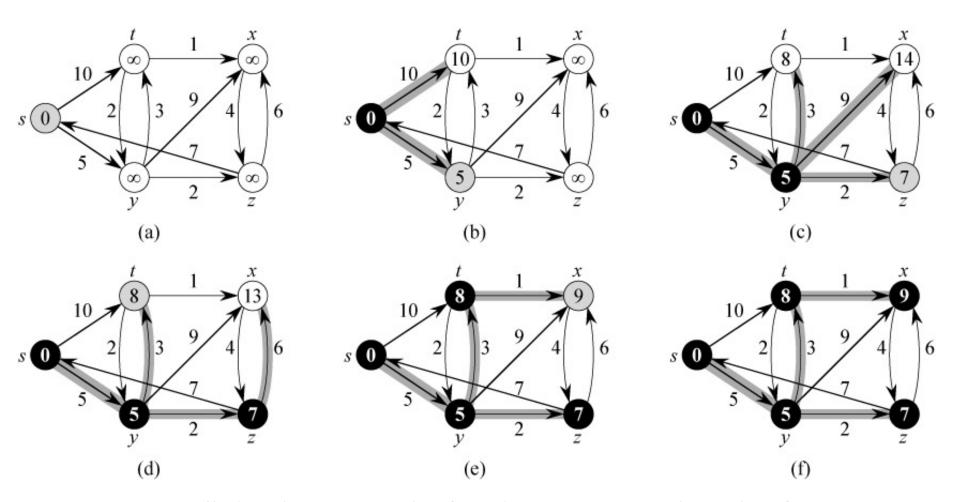
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Dijkstra(G, s):
for each v \in V do
      v.d \leftarrow \infty, v.p \leftarrow nil, v.color \leftarrow white
s,d \leftarrow 0
insert all nodes into a min-heap Q with d as key
while Q \neq \emptyset
      u \leftarrow \texttt{Extract-Min}(Q)
      u.color \leftarrow black
      for each v \in Adj[u] do % relax all edges leaving v
            if v.color = white and u.d + w(u,v) < v.d then
                  v.p \leftarrow u
                  v.d \leftarrow u.d + w(u,v)
                  Decrease-Key (Q, v, v, d)
```

Running time: $O(E \log V)$

Very similar to Prim's algorithm

```
Analysis Assumption: G is connected so V = O(E).
```

Dijkstra's Algorithm: Example



Note: All the shortest paths found by Dijkstra's algorithm form a tree (shortest-path tree).

Dijkstra's Algorithm: Implementation

```
Dijkstra(G, s):
for each v \in V do
      v.d \leftarrow \infty, v.p \leftarrow nil, v.color \leftarrow white
s,d \leftarrow 0
Insert (0, s, s. d)
while 0 \neq \emptyset
      u \leftarrow \texttt{Extract-Min}(Q)
      if u.color = black then continue
      output (u, u, d, u, p)
      u.color \leftarrow black
      for each v \in Adj[u] do % relax all edges leaving v
            if v.color = white and u.d + w(u,v) < v.d then
                  v.p \leftarrow u
                  v.d \leftarrow u.d + w(u,v)
                   Insert (Q, v, v, d)
```

Running time: $O(E \log V)$

Dijkstra's Algorithm: Correctness

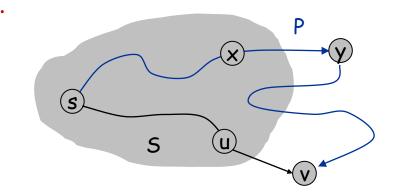
Lemma. Suppose $u.d = \delta(s,u)$ for all $u \in S$, and all edges leaving S have been relaxed. Then $v.d = \delta(s,v)$, where v is the vertex with minimum v.d in V-S.

Pf. (by contradiction) (assume $v.d \neq \delta(s, v)$)

Note that v.d starts $= \infty$. Whenever v.d is updated, it's because a path with distance v.d was found. So always have $v.d \ge \delta(s,v)$.

Thus if $v.d \neq \delta(s,v)$ then $v.d > \delta(s,v)$.

- $_{ exttt{ iny Consider}}$ a shortest path P from s to v.
 - Suppose $x \rightarrow y$ is the first edge on P that takes P out of S.
 - Since $x \in S$, we have $x \cdot d = \delta(s, x)$.



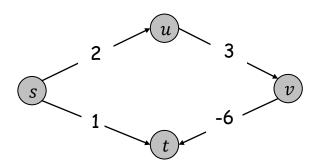
- The edge $x \to y$ has been relaxed, so $y.d \le x.d + w(x,y)$.
- P is a shortest path => its subpath (s, ..., x, y) must also be a shortest path, => $x \cdot d + w(x, y) = \delta(s, y)$.
- $\delta(s, y) \leq \delta(s, v)$, assuming nonnegative weights

$$v.d > \delta(s,v) \ge \delta(s,y) = x.d + w(x,y) \ge y.d,$$

contradicting fact that v.d is the smallest in V-S.

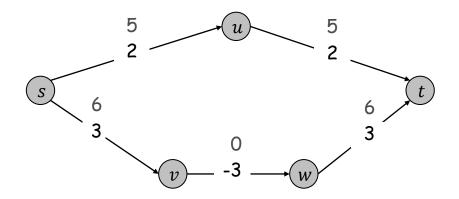
Dijkstra fails with Negative Weights

Example



Dijkstra would calculate $\delta(s,t)=1$, but correct answer is $\delta(s,t)=-1$.

Re-weighting. Might think that this can be "fixed" by adding a constant to every edge weight. This doesn't work.



Add 3 to every weight. Dijkstra would find shortest s-t path is (s,u,v), but shortest s-t path in original graph is (s,v,w,t).

Exercise on Most Reliable Paths

Consider a directed graph corresponding to a communication network. Each edge (u,v) is associated with a reliability value r(u,v), that represents the probability that the channel from from u to v will not fail. Assume that the edge probabilities are independent. Modify Dijkstra's algorithm to find the most reliable path between a node s and every other vertex.

Solution

```
Set d[s] = 1, and d[u] = 0 for all u \neq s

Insert all vertices in a max heap Q on d[\cdot]

While Q is not empty
u \coloneqq \mathsf{Extract\text{-}max}(Q)
For each edge (u,v) \ / \ v is in the adjacency list of u
If d[u] \cdot r(u,v) > d[v] \ / \ relax \ (u,v)
d[v] \coloneqq d[u] \cdot r(u,v)
Increase-key(Q,v,d[v])
Set u to be the predecessor of v
```

A^* for s-t shortest path

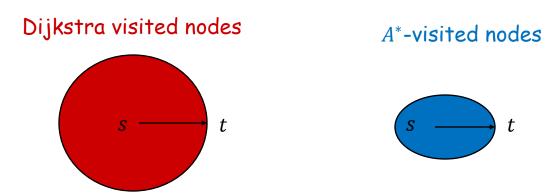
We wish to find the shortest path between s and t.

Assume that the weight of each edge (u, v) corresponds to the length of the road connecting them. Then, $\delta(u, t)$ between any node u and t, is their network distance. Let E(u, t) be the Euclidean distance between u and t. Then, $E(u, t) \leq \delta(u, t)$.

When Dijkstra visits a node u, it inserts in the min heap d[u], i.e., the current network distance from s. It extracts from the min heap the node u with min d[u].

When A^* -search visits a node u, it inserts into the min heap d[u] + E(u,t). It extracts from the heap the node u that minimizes d[u] + E(u,t), i.e., guides search towards the destination. It terminates when we reach t.

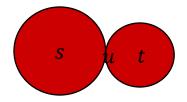
 A^* can be used with any function f provided that $f(u,t) \leq \delta(u,t)$. Faster than Dijkstra in practice, but asymptotically the same.



Other fast algorithms s-t shortest path

Bidirectional: start Dijkstra expansions from both s and t in parallel. When you find a common node u in both expansions, stop. The shortest path has distance: $\delta(s, u) + \delta(t, u)$.

Can also be combined with A^* .



Continuous monitoring of shortest path: the previous algorithms return a one-time path, assuming fixed edge weights. Real navigation systems monitor the traffic conditions and continuously update your path when traffic conditions change (e.g., accidents).

Many later algorithms for s-t paths (based on contraction hierarchies, partial materialization, landmarks etc) are much faster than Dijkstra in practice.

All-Pairs Shortest Paths

Input:

- Directed graph G = (V, E).
- Weight w(e) =length of edge e.

Output:

- $\delta(u,v)$, for all pairs of nodes u,v.
- A data structure from which the shortest path from u to v can be extracted efficiently, for any pair of nodes u,v
 - Note: Storing all shortest paths explicitly for all pairs requires $O(V^3)$ space.

Graph representation

- Assume adjacency matrix
 - w(u, v) can be extracted in O(1) time.
 - w(u,u) = 0, $w(u,v) = \infty$ if there is no edge from u to v.
- If the graph is stored in adjacency lists format, can convert to adjacency matrix in $O(V^2)$ time.

Using previous algorithms

When there are no negative cost edges

- Apply Dijkstra's algorithm to each vertex (as the source).
- Recall that Dijkstra algorithm runs in $O(E \log V)$
- This gives an $O(VE \log V)$ -time algorithm
- If the graph is dense, this is $O(n^3 \log n)$.

When negative-weight edges are present

- The Bellman-Ford algorithm permits negative edges and solves the single-source shortest path problem in O(VE) time
 - Run the B-F algorithm from each vertex.
- $_{\square}$ $O(V^2E)$ time, which is $O(n^4)$ for dense graphs.

Dynamic Programming: Solution 1

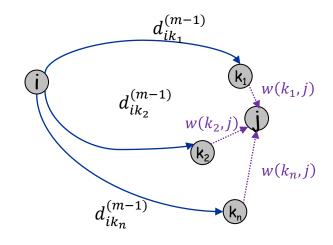
Def: $d_{ij}^{(m)} = \text{length of the shortest path from } i \text{ to } j \text{ that contains at most } m \text{ edges.}$

Use $D^{(m)}$ to denote the matrix $\left[d_{ij}^{(m)}\right]$.

Recurrence:

For some k, let P' be the shortest path from i to k containing at most m-1 edges. $length(P')=d_{ik}^{(m-1)}$

Then P' followed by j is a path from from i to j containing at most m edges and has length $d_{ik}^{(m-1)} + w(k,j)$



$$d_{ij}^{(m)} = \min_{1 \le k \le n} \{d_{ik}^{(m-1)} + w(k,j)\}$$
$$d_{ij}^{(1)} = w(i,j)$$

Solution 1: Algorithm

Def: $d_{ij}^{(m)} = \text{length of the shortest path from } i \text{ to } j \text{ that contains at most } m \text{ edges.}$

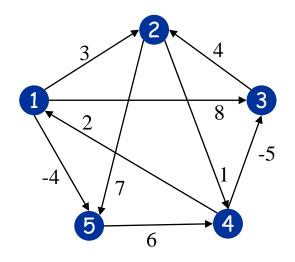
Use $D^{(m)}$ to denote the matrix $\begin{bmatrix} d_{ij}^{(m)} \end{bmatrix}$.

Recurrence: $d_{ij}^{(m)} = \min_{1 \le k \le n} \{d_{ik}^{(m-1)} + w(k,j)\}$ $d_{ij}^{(1)} = w(i,j)$

Goal: $D^{(n-1)}$, since no shortest path can have more than n-1 edges

```
\begin{split} \frac{\text{Slow-All-Pairs-Shortest-Paths}\left(G\right):}{d_{ij}^{(1)} = w(i,j) \text{ for all } 1 \leq i,j \leq n} \\ \text{for } m \leftarrow 2 \text{ to } n-1 \\ & \text{let } D^{(m)} \text{ be a new } n \times n \text{ matrix} \\ \text{for } i \leftarrow 1 \text{ to } n \\ & \text{for } j \leftarrow 1 \text{ to } n \\ & d_{ij}^{(m)} \leftarrow \infty \\ & \text{for } k \leftarrow 1 \text{ to } n \\ & \text{if } d_{ik}^{(m-1)} + w(k,j) < d_{ij}^{(m)} \text{ then } d_{ij}^{(m)} \leftarrow d_{ik}^{(m-1)} + w(k,j) \end{split} return D^{(n-1)}
```

Analysis: $O(n^4)$ time, $O(n^3)$ space, can be improved to $O(n^2)$



Example of Solution 1

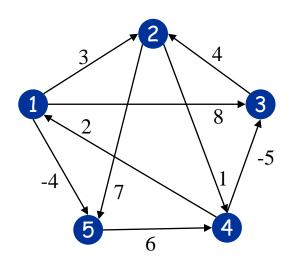
- Algorithm starts with $D^{(1)}$, initial edge lengths
- It then iteratively constructs $D^{(2)}$, $D^{(3)}$, $D^{(4)}$
- $D^{(4)}$ is the final solution, containing all shortest path lengths.

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

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

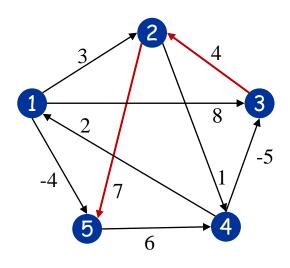
$$D^{(2)} = \begin{pmatrix} 0 & 3 & 6 & 2 & -4 \\ 3 & 0 & -4 & 1 & 7 \\ \infty & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & \infty & 1 & 6 & 0 \end{pmatrix}$$

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



$$d^{(1)}(3,5) = \infty$$

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

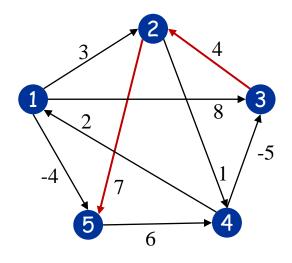


$$d^{(1)}(3,5) = \infty$$

$$d^{(2)}(3,5) = 11$$

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

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

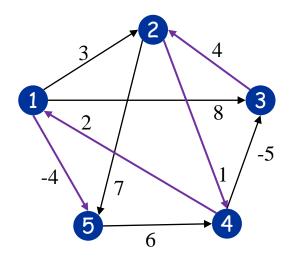


$$d^{(1)}(3,5) = \infty$$
 $d^{(3)}(3,5) = 11$
 $d^{(2)}(3,5) = 11$

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

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

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



$$d^{(1)}(3,5) = \infty$$
 $d^{(3)}(3,5) = 11$

$$d^{(3)}(3,5) = 11$$

$$d^{(2)}(3,5) = 11$$
 $d^{(4)}(3,5) = 3$

$$d^{(4)}(3,5) = 3$$

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

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

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

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

Dynamic Programming: Solution 2

Observation:

- To compute $d_{ij}^{(m)}$, instead of looking at the last stop before j, we look at the middle point.
- This cuts down the problem size by half.

New recurrence:

$$d_{ij}^{(2s)} = \min_{1 \le k \le n} \{d_{ik}^{(s)} + d_{kj}^{(s)}\}$$

Algorithm:

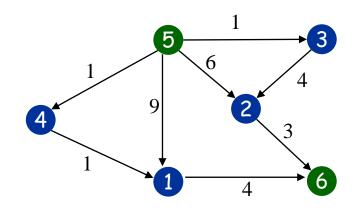
- $^{\Box}$ Calculate $D^{(1)}, D^{(2)}, D^{(4)}, D^{(8)}, ...$
- ^L Calculating each matrix takes $O(n^3)$ time: total time = $O(n^3 \log n)$.

Q: This might overshoot $D^{(n-1)}$. Is algorithm still correct?

A: It's OK. $D^{(n')}$, n' > n-1, contains length of shortest paths with at most n' edges; it will not miss any shortest path with up to n-1 edges.

^ Actually, $D^{(n')} = D^{(n-1)}$ for any n' > n-1, since no shortest path has more than n-1 edges.

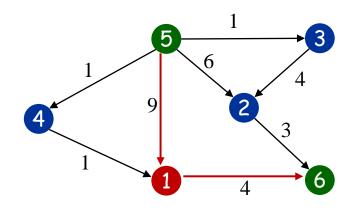
Def: $d_{ij}^{(k)} = \text{length of the shortest path from } i \text{ to } j \text{ that such that all intermediate vertices on the path (if any) are in the set <math>\{1,2,\ldots,k\}$.



 $d_{5.6}^{(0)} = \infty$ No Path

Initially: $d_{ij}^{(0)} = w(i,j)$

Def: $d_{ij}^{(k)} = \text{length of the shortest path from } i \text{ to } j \text{ that such that all intermediate vertices on the path (if any) are in the set <math>\{1,2,\ldots,k\}$.

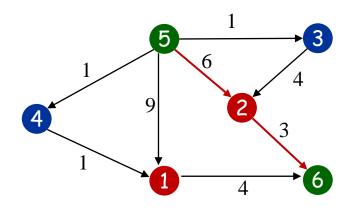


$$d_{5,6}^{(0)} = \infty$$
 No Path

$$d_{5,6}^{(1)} = 13 \quad (5 \ 1 \ 6)$$

Initially: $d_{ij}^{(0)} = w(i,j)$

Def: $d_{ij}^{(k)} = \text{length of the shortest path from } i \text{ to } j \text{ that such that all intermediate vertices on the path (if any) are in the set <math>\{1,2,\ldots,k\}$.



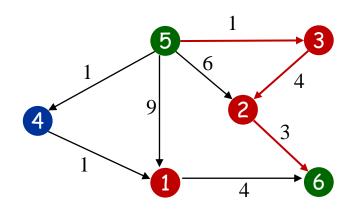
$$d_{5.6}^{(0)} = \infty$$
 No Path

$$d_{5.6}^{(1)} = 13 \quad (5 \ 1 \ 6)$$

$$d_{5.6}^{(2)} = 9$$
 (5 2 6)

Initially: $d_{ij}^{(0)} = w(i,j)$

Def: $d_{ij}^{(k)} = \text{length of the shortest path from } i \text{ to } j \text{ that such that all intermediate vertices on the path (if any) are in the set <math>\{1,2,\ldots,k\}$.



$$d_{5,6}^{(0)} = \infty$$
 No Path

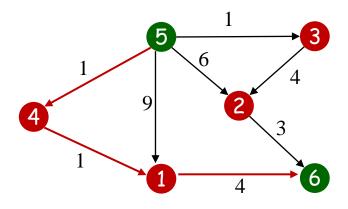
$$d_{5,6}^{(1)} = 13 \quad (5 \ 1 \ 6)$$

$$d_{5,6}^{(2)} = 9$$
 (5 2 6)

$$d_{5,6}^{(3)} = 8$$
 (5 3 2 6)

Initially: $d_{ij}^{(0)} = w(i,j)$

Def: $d_{ij}^{(k)} = \text{length of the shortest path from } i \text{ to } j \text{ that such that all intermediate vertices on the path (if any) are in the set <math>\{1,2,\ldots,k\}$.



$$d_{5,6}^{(0)} = \infty$$
 No Path

$$d_{5,6}^{(1)} = 13 \quad (5 \ 1 \ 6)$$

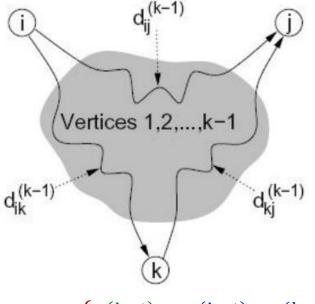
$$d_{5,6}^{(2)} = 9$$
 (5 2 6)

$$d_{5.6}^{(3)} = 8$$
 (5 3 2 6)

$$d_{5,6}^{(4)} = 6$$
 (5 4 1 6)

Initially: $d_{ij}^{(0)} = w(i,j)$

Recurrence



$$d_{ij}^{(k)} = min \left\{ d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \right\}$$

When computing $d_{ij}^{(k)}$, there are two cases:

- Case 1: k is not a vertex on the shortest path from i to j => then the path uses only vertices in $\{1,2,\ldots,k-1\}$. $d_{ij}^{(k-1)}$
- Case 2: k is an intermediate node on the shortest path from i to j, => path can be split into shortest subpath from i to k and a subpath from k to j. Both subpaths use only vertices in $\{1,2,\ldots,k-1\}$ $d_{ik}^{(k-1)}+d_{kj}^{(k-1)}$

Floyd-Warshall Algorithm

```
\begin{split} \frac{\textbf{Floyd-Warshall}\left(G\right):}{d_{ij}^{(0)} = w(i,j) \text{ for all } 1 \leq i,j \leq n \\ \textbf{for } k \leftarrow 1 \text{ to } n \\ & \textbf{let } D^{(k)} \text{ be a new } n \times n \text{ matrix} \\ \textbf{for } i \leftarrow 1 \text{ to } n \\ & \textbf{for } j \leftarrow 1 \text{ to } n \\ & \textbf{if } d_{ik}^{(k-1)} + d_{kj}^{(k-1)} < d_{ij}^{(k-1)} \text{ then } \\ & d_{ij}^{(k)} \leftarrow d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \\ & \textbf{else} \\ & d_{ij}^{(k)} \leftarrow d_{ij}^{(k-1)} \end{split}
```

Analysis:

- $_{\scriptscriptstyle \square}$ $O(n^3)$ time
- $_{\scriptscriptstyle \square}$ $O(n^3)$ space, but can be improved to $O(n^2)$

Surprising discovery: If we just drop all the superscripts, i.e., the algorithm just uses one $n \times n$ array D, the algorithm still works! (why?)

Floyd-Warshall Algorithm: Final Version

```
\begin{aligned} & \underline{\textbf{Floyd-Warshall}\,(\textit{G}):} \\ & d_{ij} = w(i,j) \text{ and } intermed[i,j] \leftarrow 0 \text{ for all } 1 \leq i,j \leq n \\ & \text{for } k \leftarrow 1 \text{ to } n \\ & \text{for } i \leftarrow 1 \text{ to } n \\ & \text{ for } j \leftarrow 1 \text{ to } n \\ & & \text{ if } d_{ik} + d_{kj} < d_{ij} \text{ then } \\ & & d_{ij} \leftarrow d_{ik} + d_{kj} \\ & & intermed[i,j] \leftarrow k \end{aligned} return D
```

Analysis:

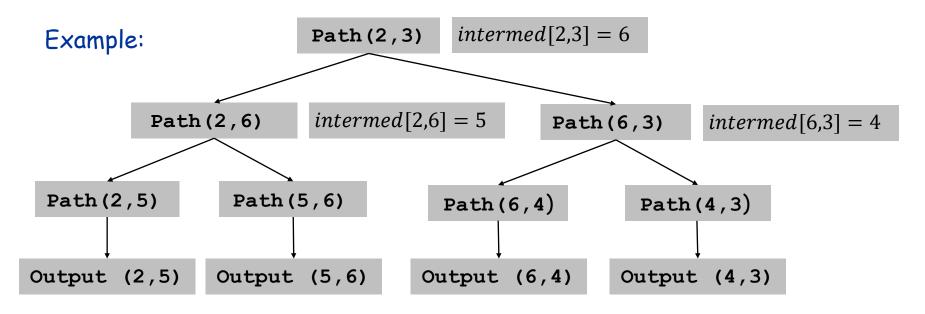
- $O(n^3)$ time
- $_{\square}$ $O(n^2)$ space

The intermed[i,j] array records one intermediate node on the shortest path from i to j.

It is nil if the shortest path does not pass any intermediate nodes.

Extracting Shortest Paths

```
Path(i,j):
if intermed[i,j] = nil then
   output (i,j)
else
   Path(i,intermed[i,j])
   Path(intermed[i,j],j)
```



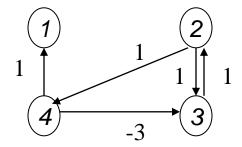
Running time: O(length of the shortest path)

Exercise on Detection of Negative Cycles

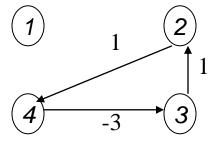
Given a directed weighted graph G=(V,E), use Floyd-Warshall in order to find if a graph has negative cycles

Assume that w(i, i) = 0, for each vertex i

graph G



Negative cycle



Solution for Negative Cycles

- Let's consider the smallest negative cycle \mathcal{C} (i.e., the one involving the smallest number of vertices).
- Let k be the highest-numbered vertex in C, and let i be any other vertex in C.
- $\label{eq:continuous_problem} \text{Then, } d_{i,i}^{(k)} = \min\left\{d_{i,i}^{(k-1)}, d_{i,k}^{(k-1)} + d_{k,i}^{(k-1)}\right\} < 0$
- Therefore, as soon as we see $d_{i,i}^{(k)} < 0$ for any i, we conclude that there is a negative cycle and abort the algorithm.

Exercise on Transitive Closure

Given a directed unweighted graph G = (V, E), we want to generate $G^* = (V, E^*)$, where $E^* = \{(i, j): \text{ there is a path from } i \text{ to } j \text{ in } G\}$

Input: an adjacency matrix A of G:

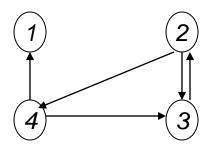
- a(i,j) = 1 if there is an edge from vertex i to j in G
- a(i,j) = 0 if there is no edge from vertex i to j in G

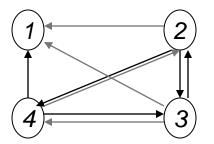
Output: an adjacency matrix A^* of G^* :

- $a^*(i,j) = 1$ if there is a path from vertex i to j in G
- $a^*(i,j) = 0$, otherwise

graph G

transitive closure G^*





Solution 1 on Transitive Closure

We first derive the weight matrix as follows

$$w(i,j) = 1$$
, if $a(i,j) = 1$

$$w(i,j) = \infty$$
, if $a(i,j) = 0$

Apply Floyd-Warshall and obtain shortest distance matrix $D^{(n)}$

 $d_{i,j}^{(n)}$ is the length of the shortest path from vertex i to j in G, in terms of the number of edges.

If
$$d_{i,j}^{(n)} < \infty$$
, set $a^*(i,j) = 1$

If
$$d_{i,j}^{(n)} = \infty$$
, set $a^*(i,j) = 0$

Solution 2 on Transitive Closure

Based on Boolean Operators

Define boolean matrix $T^{(0)} = A$

$$T_{i,j}^{(0)} = a(i,j)$$

Optimal substructure

$$T_{i,j}^{(k)} = T_{i,j}^{(k-1)} \vee \left(T_{i,k}^{(k-1)} \wedge T_{k,j}^{(k-1)} \right)$$

$$A^* = T^{(n)}$$

Asymptotic complexity same as that of Floyd-Warshall $\Theta(n^3)$.

- However, more efficient in practice because boolean operators are faster than arithmetic operators
- Needs less space for the boolean matrix (instead of the distance matrix)