

CSE 548: Analysis of Algorithms

Prerequisites Review 7
(More Graph Algorithms: Basic and Beyond)

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Breadth-First Search (BFS)

Input: Unweighted directed or undirected graph $G = (V, E)$ with vertex set V and edge set E , and a source vertex $s \in G.V$. For each $v \in V$, the adjacency list of v is $G.Adj[v]$.

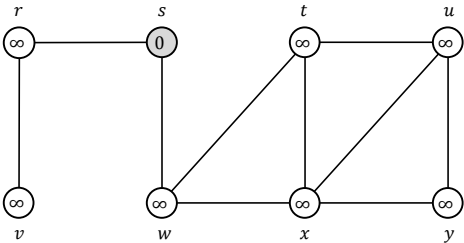
Output: For all $v \in G[V]$, $v.d$ is set to the shortest distance (in terms of the number of edges) from s to v . Also, $v.\pi$ pointers form a breadth-first tree rooted at s that contains all vertices reachable from s .

```
BFS ( G, s )
1.  for each vertex  $u \in G.V \setminus \{s\}$  do
2.     $u.color \leftarrow \text{WHITE}$ ,  $u.d \leftarrow \infty$ ,  $u.\pi \leftarrow \text{NIL}$ 
3.   $s.color \leftarrow \text{GRAY}$ ,  $s.d \leftarrow 0$ ,  $s.\pi \leftarrow \text{NIL}$ 
4.  Queue  $Q \leftarrow \emptyset$ 
5.  ENQUEUE ( Q, s )
6.  while  $Q \neq \emptyset$  do
7.     $u \leftarrow \text{DEQUEUE} ( Q )$ 
8.    for each  $v \in G.Adj[u]$  do
9.      if  $v.color = \text{WHITE}$  then
10.        $v.color \leftarrow \text{GRAY}$ ,  $v.d \leftarrow u.d + 1$ ,  $v.\pi \leftarrow u$ 
11.       ENQUEUE ( Q, v )
12.    $u.color \leftarrow \text{BLACK}$ 
```

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Breadth-First Search (BFS)

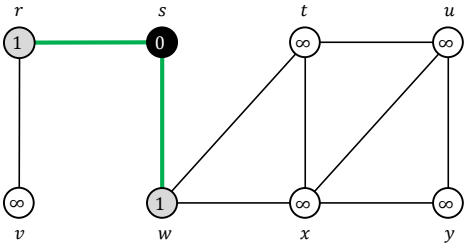
ENQUEUE (Q, s)



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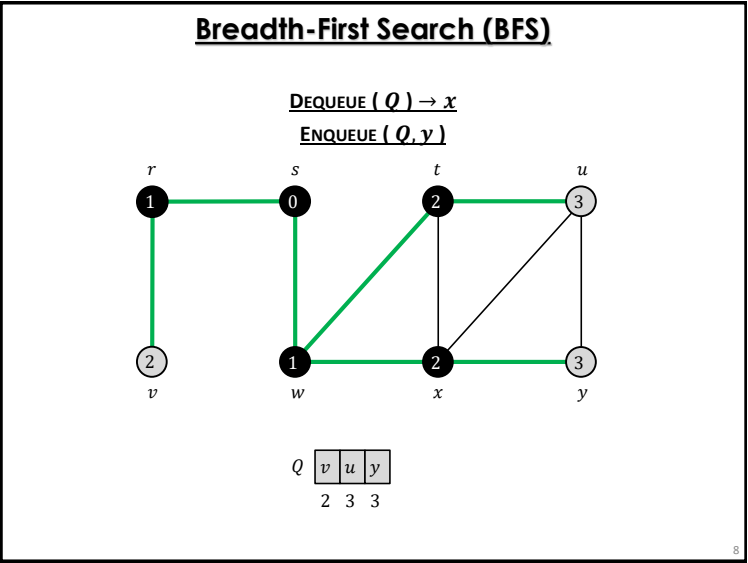
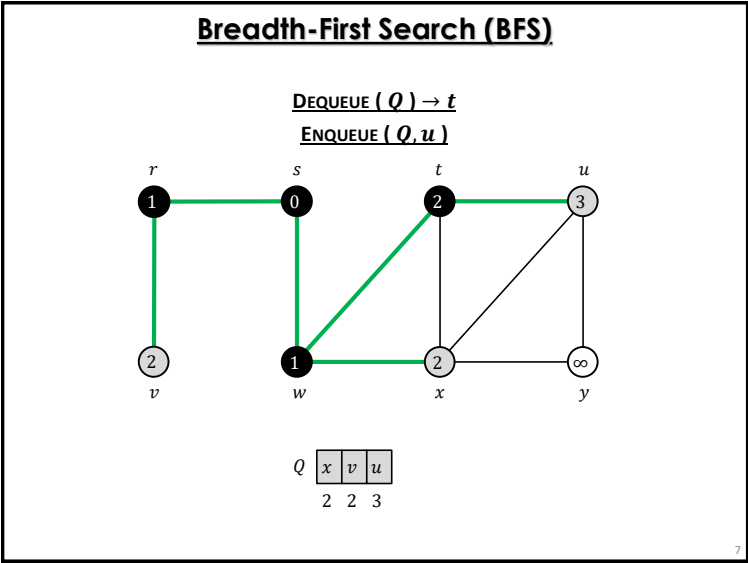
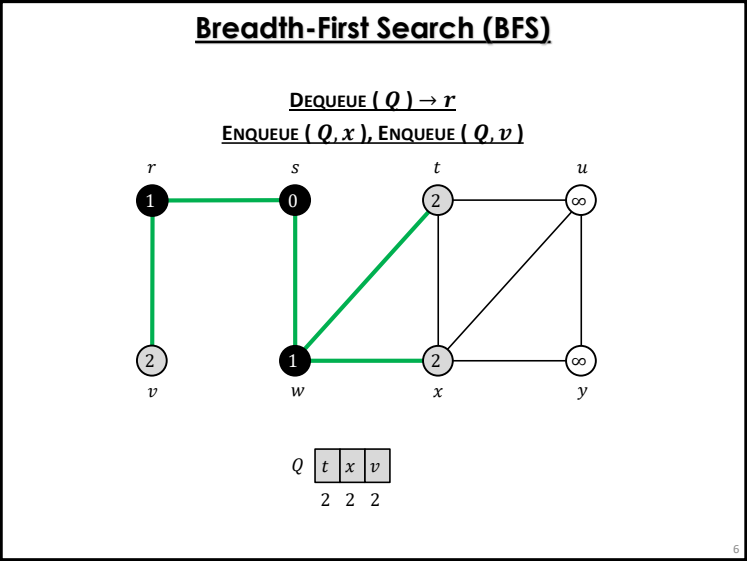
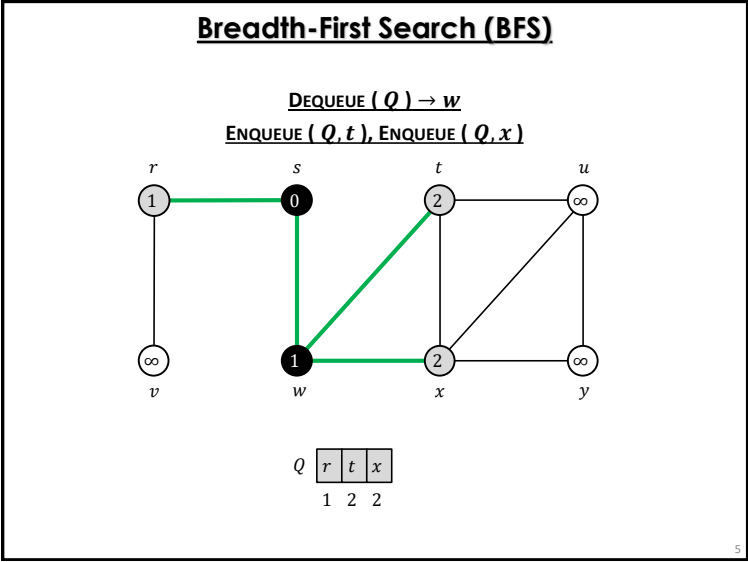
Breadth-First Search (BFS)

DEQUEUE (Q) \rightarrow s
ENQUEUE (Q, w), ENQUEUE (Q, r)



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(Prerequisites Review 7): More Graph Algorithms: Basic and Beyond



Breadth-First Search (BFS)

DEQUEUE (Q) → v

Q

u

y

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Breadth-First Search (BFS)

DEQUEUE (Q) → u

Q

y

3

10

Breadth-First Search (BFS)

DEQUEUE (Q) → y

Q

∅

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Breadth-First Search (BFS)

```
BFS ( G, s )
1.  for each vertex u ∈ G.V \ {s} do
2.      u.color ← WHITE, u.d ← ∞, u.π ← NIL
3.  s.color ← GRAY, s.d ← 0, s.π ← NIL
4.  Queue Q ← ∅
5.  ENQUEUE( Q, s )
6.  while Q ≠ ∅ do
7.      u ← DEQUEUE( Q )
8.      for each v ∈ G.Adj[u] do
9.          if v.color = WHITE then
10.             v.color ← GRAY, v.d ← u.d + 1, v.π ← u
11.             ENQUEUE( Q, v )
12.             u.color ← BLACK
```

Let $n = |G.V|$ and $m = |G.E|$

Time spent
– initializing = $\Theta(n)$
– enqueueing / dequeuing = $\Theta(n)$
– scanning the adjacency lists = $\Theta(\sum_{v \in G.V} |G.Adj[v]|)$ = $\Theta(m)$

 \therefore Total cost = $\Theta(m + n)$

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Depth-First Search (DFS)

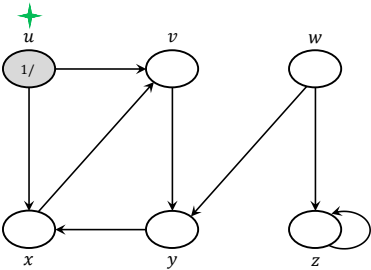
Input: Unweighted directed or undirected graph $G = (V, E)$ with vertex set V and edge set E . For each $v \in V$, the adjacency list of v is $G.Adj[v]$.

Output: For each $v \in G[V]$, $v.d$ is set to the time when v was first discovered and $v.f$ is set to the time when v 's adjacency list has been examined completely. Also, $v.\pi$ pointers form a breadth-first tree rooted at s that contains all vertices reachable from s .

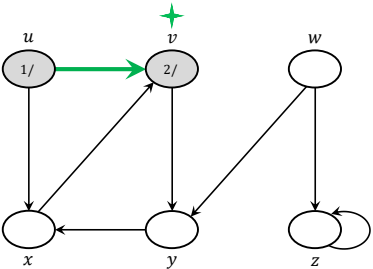
```
DFS ( G )
1.  for each vertex  $u \in G.V$  do
2.     $u.color \leftarrow WHITE, u.\pi \leftarrow NIL$ 
3.   $time \leftarrow 0$ 
4.  for each  $u \in G.V$  do
5.    if  $u.color = WHITE$  then
6.      DFS-Visit(  $G, u$  )
```

```
DFS-Visit ( G, u )
1.   $time \leftarrow time + 1$ 
2.   $u.d \leftarrow time$ 
3.   $u.color \leftarrow GRAY$ 
4.  for each  $v \in G.Adj[u]$  do
5.    if  $v.color = WHITE$  then
6.       $v.\pi \leftarrow u$ 
7.      DFS-Visit(  $G, v$  )
8.   $u.color \leftarrow BLACK$ 
9.   $time \leftarrow time + 1$ 
10.  $u.f \leftarrow time$ 
```

Depth-First Search (DFS)

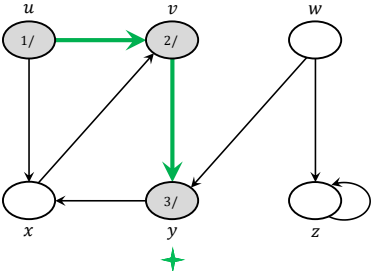


Depth-First Search (DFS)

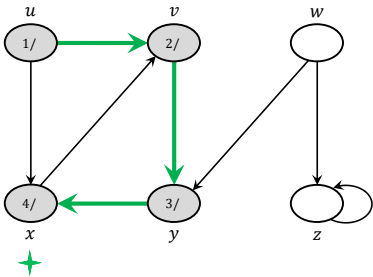


Tree Edge (T): These are edges in the depth-first forest G_π . Edge (u, v) is a tree edge if v was first discovered by exploring that edge. In the example above, we will make all tree edges green and thick.

Depth-First Search (DFS)

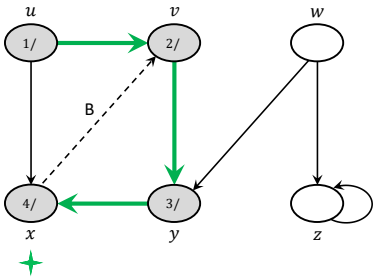


Depth-First Search (DFS)



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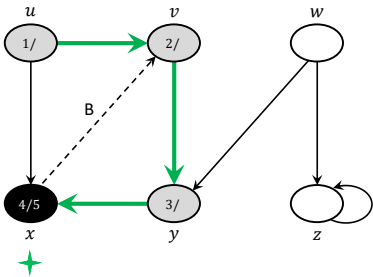
Depth-First Search (DFS)



Back Edge (B): A back edge goes from a vertex to its ancestor in a depth-first tree. Self-loops are also considered back edges.

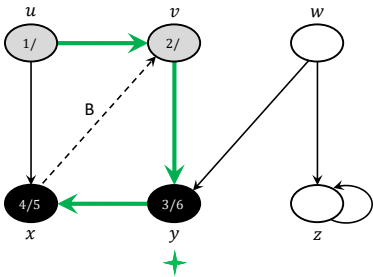
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Depth-First Search (DFS)



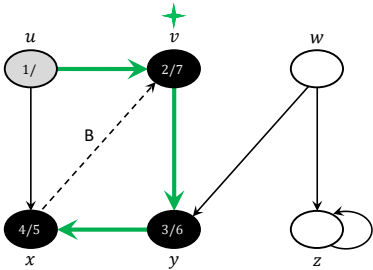
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Depth-First Search (DFS)



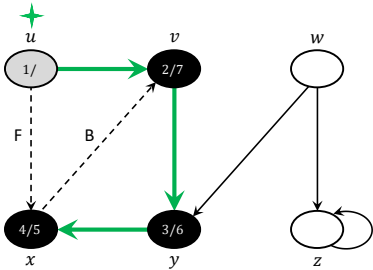
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Depth-First Search (DFS)



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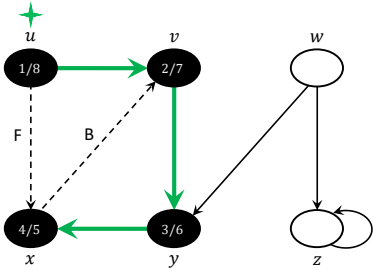
Depth-First Search (DFS)



Forward Edge (F): A forward edge is a nontree edge that connects a vertex to a descendant in a depth-first tree.

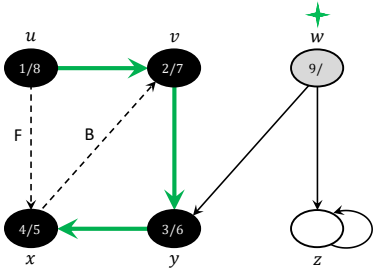
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Depth-First Search (DFS)



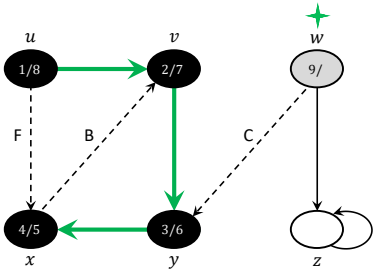
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Depth-First Search (DFS)



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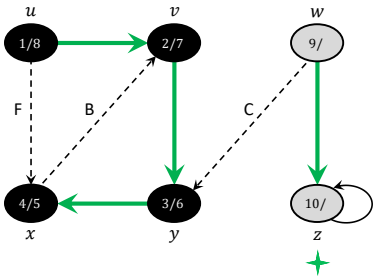
Depth-First Search (DFS)



Cross Edge (C): If a non-tree edge is neither a back edge nor a forward edge then it's a cross edge. Cross edges can go between vertices in the same depth-first tree or in different depth-first trees.

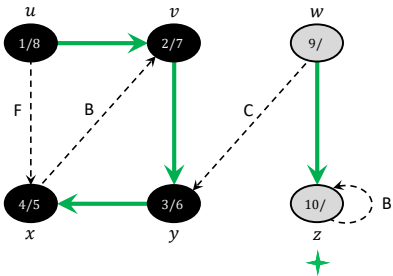
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Depth-First Search (DFS)



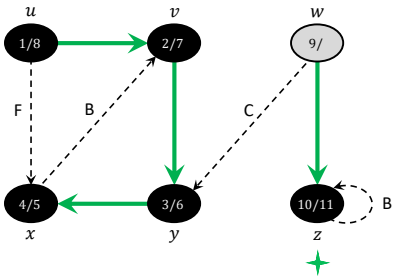
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Depth-First Search (DFS)



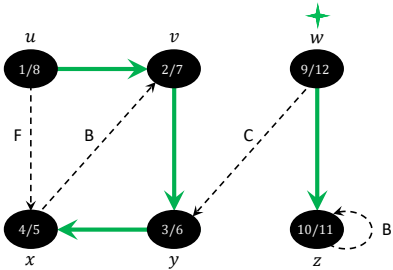
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Depth-First Search (DFS)



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Depth-First Search (DFS)



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Depth-First Search (DFS)

```
DFS ( G )
1.  for each vertex u ∈ G.V do
2.    u.color ← WHITE, u.π ← NIL
3.  time ← 0
4.  for each u ∈ G.V do
5.    if u.color = WHITE then
6.      DFS-VISIT( G, u )
```

```
DFS-VISIT ( G, u )
1.  time ← time + 1
2.  u.d ← time
3.  u.color ← GRAY
4.  for each v ∈ G.Adj[u] do
5.    if v.color = WHITE then
6.      v.π ← u
7.      DFS-VISIT( G, v )
8.  u.color ← BLACK
9.  time ← time + 1
10. u.f ← time
```

Let $n = |G.V|$ and $m = |G.E|$

Time spent

- in *DFS* (exclusive of calls to *DFS-VISIT*) = $\Theta(n)$
- in *DFS-VISIT* scanning the adjacency lists = $\Theta(\sum_{v \in G.V} |G.Adj[v]|)$ = $\Theta(m)$

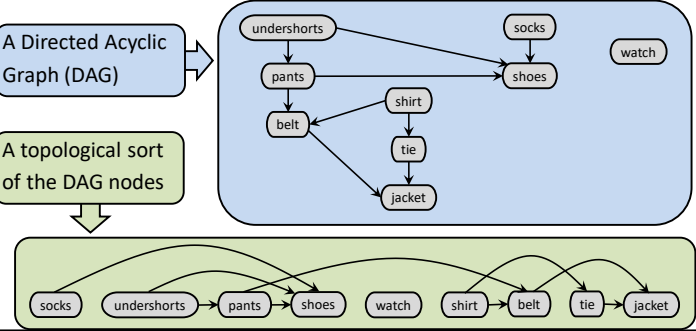
∴ Total cost = $\Theta(m + n)$

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Topological Sort

A **topological sort** of a DAG (i.e., directed acyclic graph) $G = (V, E)$ is a linear ordering of all its vertices such that if G contains an edge (u, v) , then u appears before v in the ordering.

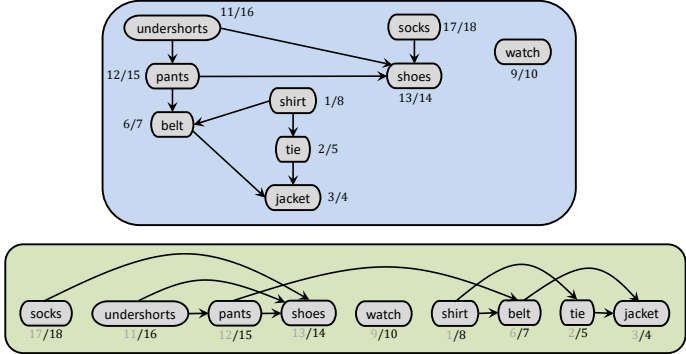
We can view a topological sort of a graph as an ordering of its vertices along a horizontal line so that all directed edges go from left to right.



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Topological Sort

```
TOPOLOGICAL-SORT ( G )
1.  call DFS ( G ) to compute the finish times v.f for each vertex v ∈ G.V
2.  as each vertex is finished, insert it into the front of a linked list
3.  return the linked list of vertices
```



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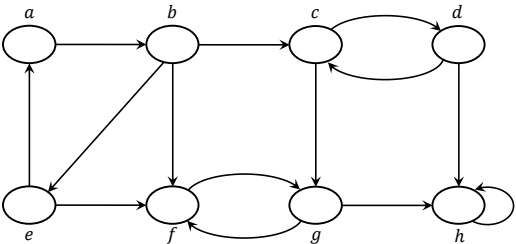
Strongly Connected Components

A **strongly connected component** of a directed graph $G = (V, E)$ is a maximal set of vertices $C \subseteq V$ such that for every pair of vertices u and v in C , we have both $u \rightsquigarrow v$ and $v \rightsquigarrow u$; that is, vertices u and v are reachable from each other.

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Strongly Connected Components

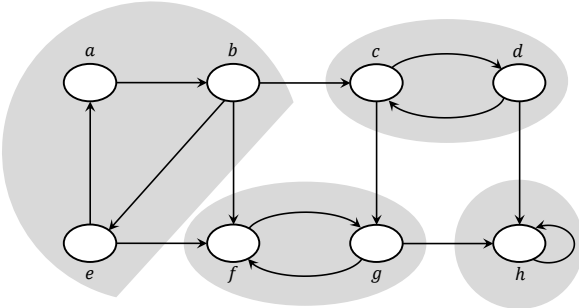
A **strongly connected component** of a directed graph $G = (V, E)$ is a maximal set of vertices $C \subseteq V$ such that for every pair of vertices u and v in C , we have both $u \rightsquigarrow v$ and $v \rightsquigarrow u$; that is, vertices u and v are reachable from each other.



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Strongly Connected Components

A **strongly connected component** of a directed graph $G = (V, E)$ is a maximal set of vertices $C \subseteq V$ such that for every pair of vertices u and v in C , we have both $u \rightsquigarrow v$ and $v \rightsquigarrow u$; that is, vertices u and v are reachable from each other.



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Strongly Connected Components

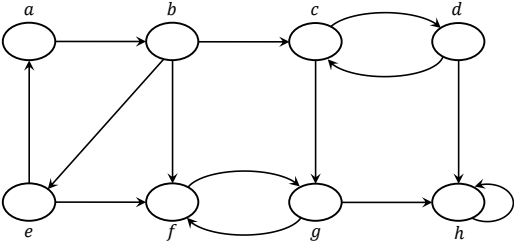
- STRONGLY-CONNECTED-COMPONENTS (G)**
1. call $DFS (G)$ to compute the finish times $v.f$ for each vertex $v \in G.V$
 2. compute G^T
 3. call $DFS (G^T)$, but in the main loop of DFS , consider the vertices in order of decreasing $v.f$ (as computed in line 1)
 4. output the vertices of each tree in the depth-first forest formed in line 3 as a separate strongly connected component

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Strongly Connected Components

STRONGLY-CONNECTED-COMPONENTS (G)

1. call $DFS (G)$ to compute the finish times $v.f$ for each vertex $v \in G.V$
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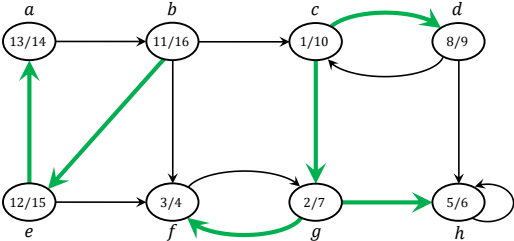


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Strongly Connected Components

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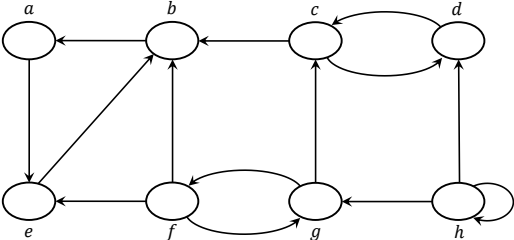


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Strongly Connected Components

STRONGLY-CONNECTED-COMPONENTS (G)

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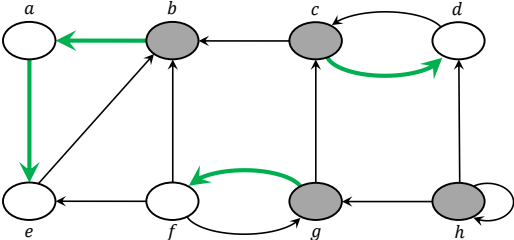


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Strongly Connected Components

STRONGLY-CONNECTED-COMPONENTS (G)

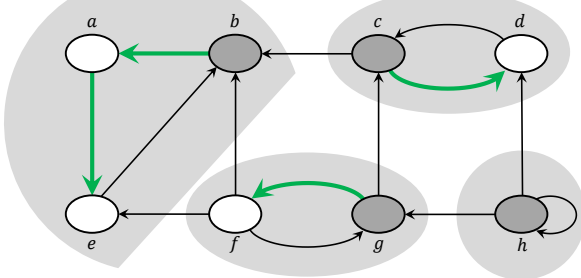
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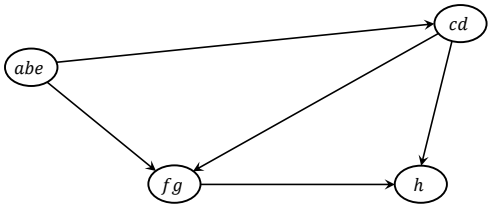
Strongly Connected Components

```
STRONGLY-CONNECTED-COMPONENTS ( G )
1.  call DFS ( G ) to compute the finish times v.f for each vertex v ∈ G.V
2.  compute GT
3.  call DFS ( GT ), but in the main loop of DFS, consider the vertices in order
    of decreasing v.f (as computed in line 1)
4.  output the vertices of each tree in the depth-first forest formed in line 3 as
    a separate strongly connected component
```



Strongly Connected Components

```
STRONGLY-CONNECTED-COMPONENTS ( G )
1.  call DFS ( G ) to compute the finish times v.f for each vertex v ∈ G.V
2.  compute GT
3.  call DFS ( GT ), but in the main loop of DFS, consider the vertices in order
    of decreasing v.f (as computed in line 1)
4.  output the vertices of each tree in the depth-first forest formed in line 3 as
    a separate strongly connected component
```



The Single-Source Shortest Paths (SSSP) Problem

We are given a weighted, directed graph $G = (V, E)$ with vertex set V and edge set E , and a weight function w such that for each edge $(u, v) \in E$, $w(u, v)$ represents its weight.

We are also given a source vertex $s \in V$.

Our goal is to find a shortest path (i.e., a path of the smallest total edge weight) from s to each vertex $v \in V$.

SSSP: Relaxation

```
INITIALIZE-SINGLE-SOURCE ( G = (V, E), s )
1.  for each vertex v ∈ G.V do
2.    v.d ← ∞
3.    v.π ← NIL
4.    s.d ← 0
```

```
RELAX ( u, v, w )
1.  if u.d + w(u, v) < v.d then
2.    v.d ← u.d + w(u, v)
3.    v.π ← u
```

SSSP: Properties of Shortest Paths and Relaxation

The **weight** $w(p)$ of path $p = \langle v_0, v_1, \dots, v_k \rangle$ is the sum of the weights of its constituent edges:

$$w(p) = \sum_{i=1}^k w(v_{i-1}, v_i)$$

We define the **shortest-path weight** $\delta(u, v)$ from u to v by

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

A **shortest path** from vertex u to vertex v is then defined as any path p with weight $w(p) = \delta(u, v)$.

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SSSP: Properties of Shortest Paths and Relaxation

Triangle inequality (Lemma 24.10 of CLRS)

For any edge $(u, v) \in E$, we have $\delta(s, v) \leq \delta(s, u) + w(u, v)$.

Upper-bound inequality (Lemma 24.11 of CLRS)

We always have $v.d \geq \delta(s, v)$ for all vertices $v \in V$, and once $v.d$ achieves the value $\delta(u, v)$, it never changes.

No-path property (Corollary 24.12 of CLRS)

If there is no path from s to v , then we always have $v.d = \delta(s, v) = \infty$.

Convergence property (Lemma 24.14 of CLRS)

If $s \rightsquigarrow u \rightarrow v$ is a shortest path in G for some $u, v \in V$, and if $u.d = \delta(s, u)$ at any time prior to relaxing edge (u, v) , then $v.d = \delta(s, v)$ at all times afterward.

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SSSP: Properties of Shortest Paths and Relaxation

Path-relaxation property (Lemma 24.15 of CLRS)

If $p = \langle v_0, v_1, \dots, v_k \rangle$ is a shortest path from $s = v_0$ to v_k , and we relax the edges of p in the order $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$, then $v_k.d = \delta(s, v_k)$. This property holds regardless of any other relaxation steps that occur, even if they are intermixed with relaxations on the edges of p .

Predecessor-subgraph property (Lemma 24.17 of CLRS)

Once $v.d = \delta(s, v)$ for all $v \in V$, the predecessor subgraph is a shortest-paths tree rooted at s .

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Dijkstra's SSSP Algorithm with a Min-Heap
(SSSP: Single-Source Shortest Paths)

Since we already discussed Dijkstra's SSSP algorithm when we talked about greedy algorithms, we will skip over it in this lecture.

Dijkstra's SSSP Algorithm with a Min-Heap
(SSSP: Single-Source Shortest Paths)

Input: Weighted graph $G = (V, E)$ with vertex set V and edge set E , a non-negative weight function w , and a source vertex $s \in G[V]$.

Output: For all $v \in G[V]$, $v.d$ is set to the shortest distance from s to v .

```
Dijkstra-SSSP( $G = (V, E), w, s$ )
1.  for each vertex  $v \in G[V]$  do
2.     $v.d \leftarrow \infty$ 
3.     $v.\pi \leftarrow \text{NIL}$ 
4.     $s.d \leftarrow 0$ 
5.  Min-Heap  $Q \leftarrow \emptyset$ 
6.  for each vertex  $v \in G[V]$  do
7.    INSERT( $Q, v$ )
8.  while  $Q \neq \emptyset$  do
9.     $u \leftarrow \text{EXTRACT-MIN}(Q)$ 
10.   for each  $(u, v) \in G.E$  do
11.     if  $u.d + w(u, v) < v.d$  then
12.        $v.d \leftarrow u.d + w(u, v)$ 
13.        $v.\pi \leftarrow u$ 
14.     DECREASE-KEY( $Q, v, u.d + w(u, v)$ )
```

Let $n = |G[V]|$ and $m = |G[E]|$

Worst-case running time:

Using a binary min-heap
= $O((m + n) \log n)$

Using a Fibonacci heap
= $O(m + n \log n)$

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(SSSP: Single-Source Shortest Paths)

Input: Weighted graph $G = (V, E)$ with vertex set V and edge set E , a non-negative weight function w , and a source vertex $s \in G[V]$.

Output: For all $v \in G[V]$, $v.d$ is set to the shortest distance from s to v .

```
Dijkstra-SSSP (  $G = (V, E), w, s$  )
1.  for each vertex  $v \in G.V$  do
2.       $v.d \leftarrow \infty$ 
3.       $v.\pi \leftarrow NIL$ 
4.   $s.d \leftarrow 0$ 
5.  Min-Heap  $Q \leftarrow \emptyset$ 
6.  for each vertex  $v \in G.V$  do
7.      INSERT(  $Q, v$  )
8.  while  $Q \neq \emptyset$  do
9.       $u \leftarrow \text{EXTRACT-MIN}( Q )$ 
10.     for each  $(u, v) \in G.E$  do
11.         if  $u.d + w(u, v) < v.d$  then
12.              $v.d \leftarrow u.d + w(u, v)$ 
13.              $v.\pi \leftarrow u$ 
14.             DECREASE-KEY(  $Q, v, u.d + w(u, v)$  )
```

Let $n = |G[V]|$ and $m = |G[E]|$

Worst-case running time:
Using a binary min-heap
= $O((m + n) \log n)$
Using a Fibonacci heap
= $O(m + n \log n)$



The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

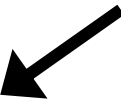
Input: Weighted graph $G = (V, E)$ with vertex set V and edge set E , a weight function w , and a source vertex $s \in G[V]$. Negative-weight edges are allowed (unlike Dijkstra's SSSP algorithm).

Output: Returns FALSE if a negative-weight cycle is reachable from s , otherwise returns TRUE and for all $v \in G[V]$, sets $v.d$ to the shortest distance from s to v .

```
INITIALIZE-SINGLE-SOURCE (  $G = (V, E), s$  )
1.  for each vertex  $v \in G.V$  do
2.       $v.d \leftarrow \infty$ 
3.       $v.\pi \leftarrow NIL$ 
4.   $s.d \leftarrow 0$ 
```

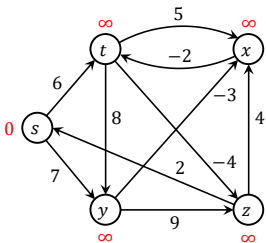
```
RELAX (  $u, v, w$  )
1.  if  $u.d + w(u, v) < v.d$  then
2.       $v.d \leftarrow u.d + w(u, v)$ 
3.       $v.\pi \leftarrow u$ 
```

```
BELLMAN-FORD (  $G = (V, E), w, s$  )
1.  INITIALIZE-SINGLE-SOURCE(  $G, s$  )
2.  for  $i \leftarrow 1$  to  $|G.V| - 1$  do
3.      for each  $(u, v) \in G.E$  do
4.          RELAX(  $u, v, w$  )
5.  for each  $(u, v) \in G.E$  do
6.      if  $u.d + w(u, v) < v.d$  then
7.          return FALSE
8.  return TRUE
```



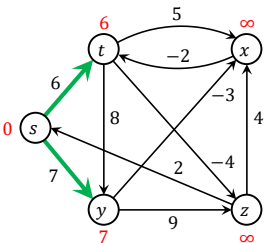
The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

Initial State (with initial tentative distances)



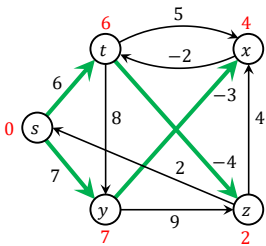
The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

Iteration 1



The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

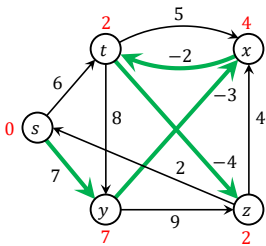
Iteration 2



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The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

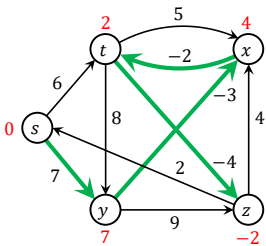
Iteration 3



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The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

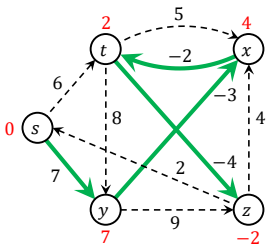
Iteration 4



55

The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

Done!



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The Bellman-Ford (SSSP) Algorithm
(SSSP: Single-Source Shortest Paths)

```
INITIALIZE-SINGLE-SOURCE ( G = (V, E), s )
1. for each vertex v ∈ G.V do
2.   v.d ← ∞
3.   v.π ← NIL
4.   s.d ← 0
```

```
RELAX ( u, v, w )
1. if u.d + w(u, v) < v.d then
2.   v.d ← u.d + w(u, v)
3.   v.π ← u
```

```
BELLMAN-FORD ( G = (V, E), w, s )
1. INITIALIZE-SINGLE-SOURCE( G, s )
2. for i ← 1 to |G.V| - 1 do
3.   for each (u, v) ∈ G.E do
4.     RELAX( u, v, w )
5. for each (u, v) ∈ G.E do
6.   if u.d + w(u, v) < v.d then
7.     return FALSE
8. return TRUE
```

Let $n = |V|$ and $m = |E|$
Time taken by: Line 1: $\Theta(n)$
Lines 2 – 4: $\Theta(mn)$
Lines 5 – 7: $\Theta(m)$
Total time: $\Theta(mn)$



Correctness of the Bellman-Ford Algorithm

LEMMA 24.2 (CLRS): Let $G = (V, E)$ be a weighted, directed graph with source s and weight function $w: E \rightarrow \mathbb{R}$, and suppose G contains no negative-weight cycles reachable from s . Then, after the $|V| - 1$ iterations of the for loop of lines 2–4 of **BELLMAN-FORD**, we have $v.d = \delta(s, v)$ for all vertices v that are reachable from s .

PROOF: The proof is based on the **path-relaxation property**. Consider any $v \in G.V$ reachable from s , and let $p = \langle v_0, v_1, \dots, v_k \rangle$, where $v_0 = s$ and $v_k = v$, be any shortest path from s to v . Because shortest paths are simple, p has at most $|V| - 1$ edges, and so $k \leq |V| - 1$. Each of the $|V| - 1$ iterations of the for loop of lines 2–4 relaxes all $|E|$ edges. Among the edges relaxed in the i^{th} iteration, for $i = 1, 2, \dots, k$, is (v_{i-1}, v_i) . By the path-relaxation property, therefore, $v.d = v_k.d = \delta(s, v_k) = \delta(s, v)$.



Correctness of the Bellman-Ford Algorithm

COROLLARY 24.3 (CLRS): Let $G = (V, E)$ be a weighted, directed graph with source s and weight function $w: E \rightarrow \mathbb{R}$, and suppose G contains no negative-weight cycles reachable from s . Then, for each $v \in V$, there is a path from s to v if and only if **BELLMAN-FORD** terminates with $v.d < \infty$ when it is run on G .



Correctness of the Bellman-Ford Algorithm

THEOREM 24.4 (CLRS): Let **BELLMAN-FORD** be run on a weighted, directed graph $G = (V, E)$ with source s and weight function $w: E \rightarrow \mathbb{R}$. If G contains no negative-weight cycles reachable from s , then the algorithm returns TRUE, we have $v.d = \delta(s, v)$ for all $v \in V$, and the predecessor subgraph G_π is a shortest-paths tree rooted at s . If G does contain a negative-weight cycle reachable from s , then the algorithm returns FALSE.

Correctness of the Bellman-Ford Algorithm

PROOF OF THEOREM 24.4: Two cases:
G contains no negative-weight cycles reachable from s:
If $v \in G.V$ is reachable from s then according to Lemma 24.2 we have $v.d = \delta(s, v)$ at termination. Otherwise, $v.d = \delta(s, v) = \infty$ follows from the *no-path property*.
The *predecessor-subgraph property*, along with $v.d = \delta(s, v)$, implies that G_π is a shortest-paths tree.
Now, since at termination, for all edges $(u, v) \in G.E$, we have, $v.d = \delta(s, v)$ and $u.d = \delta(s, u)$, then by *triangle inequality*:
$$v.d = \delta(s, v) \leq \delta(s, u) + w(u, v) = u.d + w(u, v).$$

So, none of the tests in line 6 causes **BELLMAN-FORD** to return FALSE. Therefore, it returns TRUE.

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Correctness of the Bellman-Ford Algorithm

PROOF OF THEOREM 24.4 (CONTINUED):
G contains a negative-weight cycle reachable from s:
Let $c = \langle v_0, v_1, \dots, v_k \rangle$ be the cycle, where $v_0 = v_k$. Then
$$\sum_{i=1}^k w(v_{i-1}, v_i) < 0.$$

Assume for the sake of contradiction that **BELLMAN-FORD** returns TRUE. Then $v_i.d \leq v_{i-1}.d + w(v_{i-1}, v_i)$ for $i = 1, 2, \dots, k$. Thus,
$$\sum_{i=1}^k v_i.d \leq \sum_{i=1}^k (v_{i-1}.d + w(v_{i-1}, v_i)) = \sum_{i=1}^k v_{i-1}.d + \sum_{i=1}^k w(v_{i-1}, v_i)$$

But $\sum_{i=1}^k v_i.d = \sum_{i=1}^k v_{i-1}.d$, and by Corollary 24.3, each $v_i.d$ is finite. Thus, $\sum_{i=1}^k w(v_{i-1}, v_i) \geq 0$, which contradicts our initial assumption that $c = \langle v_0, v_1, \dots, v_k \rangle$ is a negative-weight cycle.

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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

Input: Weighted DAG $G = (V, E)$ with vertex set V and edge set E , a weight function w , and a source vertex $s \in G[V]$. Negative-weight edges are allowed (unlike Dijkstra's SSSP algorithm).
Output: For all $v \in G[V]$, sets $v.d$ to the shortest distance from s to v .

INITIALIZE-SINGLE-SOURCE ($G = (V, E), s$)

- for each vertex $v \in G.V$ do
- $v.d \leftarrow \infty$
- $v.\pi \leftarrow NIL$
- $s.d \leftarrow 0$

RELAX (u, v, w)

- if $u.d + w(u, v) < v.d$ then
- $v.d \leftarrow u.d + w(u, v)$
- $v.\pi \leftarrow u$

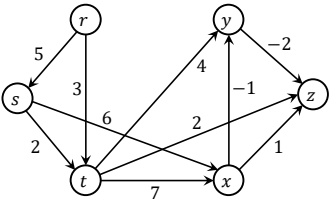
DAG-SHORTEST-PATHS ($G = (V, E), w, s$)

- topologically sort the vertices of G
- INITIALIZE-SINGLE-SOURCE** (G, s)
- for each $v \in V.G$ taken in topologically sorted order do
- for each $(u, v) \in G.E$ do
- RELAX** (u, v, w)

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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

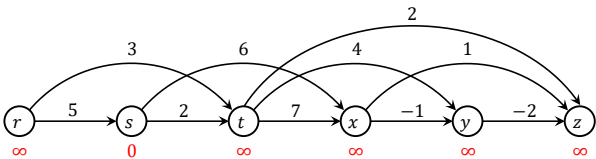
Given DAG



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

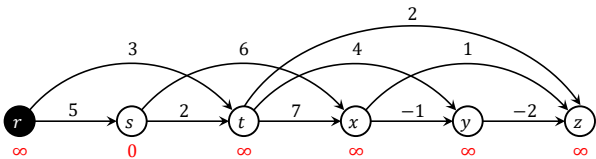
After Topological Sorting (with initial tentative distances)



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

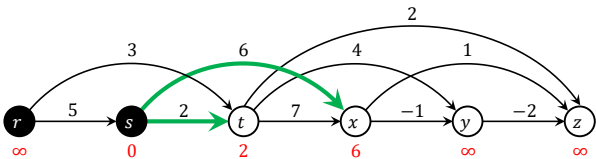
After Iteration 1



66

SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

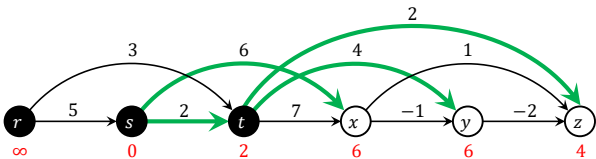
After Iteration 2



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

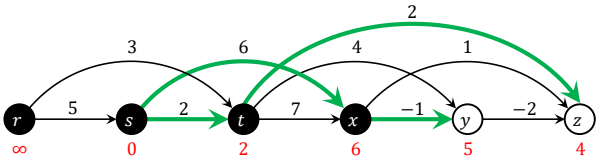
After Iteration 3



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

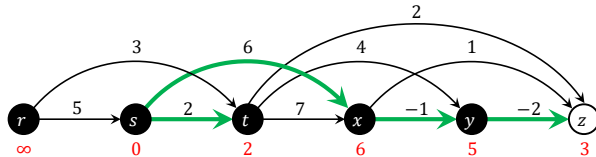
After Iteration 4



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

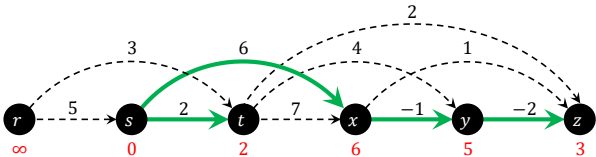
After Iteration 5



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

Done!



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SSSP in Directed Acyclic Graphs (DAGs)
(SSSP: Single-Source Shortest Paths)

```
INITIALIZE-SINGLE-SOURCE ( G = (V, E), s )
1. for each vertex v in G.V do
2.   v.d ← ∞
3.   v.π ← NIL
4.   s.d ← 0
```

```
RELAX ( u, v, w )
1. if u.d + w(u, v) < v.d then
2.   v.d ← u.d + w(u, v)
3.   v.π ← u
```

```
DAG-SHORTEST-PATHS ( G = (V, E), w, s )
1. topologically sort the vertices of G
2. INITIALIZE-SINGLE-SOURCE( G, s )
3. for each v in V.G taken in topologically sorted order do
4.   for each (u, v) in G.E do
5.     RELAX( u, v, w )
```

Let $n = |V|$ and
 $m = |E|$

Time taken by: Line 1: $\Theta(n + m)$
Line 2: $\Theta(n)$
Lines 3 – 5: $\Theta(m)$

Total time: $\Theta(n + m)$

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Correctness of DAG-SHORTEST-PATHS

THEOREM 24.5 (CLRS): If a weighted, directed graph $G = (V, E)$ has a source vertex s and no cycles, then at the termination of the **DAG-SHORTEST-PATHS** procedure, $v.d = \delta(s, v)$ for all vertices $v \in G.V$, and the predecessor subgraph G_π is a shortest-paths tree.

PROOF: Consider any $v \in G.V$.

If v is not reachable from s then $v.d = \delta(s, v) = \infty$ follows from the **no-path property**.

If v is reachable from s , and let $p = \langle v_0, v_1, \dots, v_k \rangle$, where $v_0 = s$ and $v_k = v$, be any shortest path from s to v . Since we process the vertices in topological order, we relax the edges on p in the order $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$. The **path-relaxation property** implies that $v_i.d = \delta(s, v_i)$ at termination for $i = 1, 2, \dots, k$.

By the **predecessor-subgraph property**, G_π is a shortest-paths tree.

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Correctness of DAG-SHORTEST-PATHS

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If v is reachable from s , and let $p = \langle v_0, v_1, \dots, v_k \rangle$, where $v_0 = s$ and $v_k = v$, be any shortest path from s to v . Since we process the vertices in topological order, we relax the edges on p in the order $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$. The **path-relaxation property** implies that $v_i.d = \delta(s, v_i)$ at termination for $i = 1, 2, \dots, k$.

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74



Correctness of DAG-SHORTEST-PATHS

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If v is not reachable from s then $v.d = \delta(s, v) = \infty$ follows from the **no-path property**.

If v is reachable from s , and let $p = \langle v_0, v_1, \dots, v_k \rangle$, where $v_0 = s$ and $v_k = v$, be any shortest path from s to v . Since we process the vertices in topological order, we relax the edges on p in the order $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$. The **path-relaxation property** implies that $v_i.d = \delta(s, v_i)$ at termination for $i = 1, 2, \dots, k$.

By the **predecessor-subgraph property**, G_π is a shortest-paths tree.

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The All-Pairs Shortest Paths (APSP) Problem

We are given a weighted, directed graph $G = (V, E)$ with vertex set V and edge set E , and a weight function w such that for each edge $(u, v) \in E$, $w(u, v)$ represents its weight.

Our goal is to find, for every pair of vertices $u, v \in G.V$, a shortest path (i.e., a path of the smallest total edge weight) from u to v .

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The All-Pairs Shortest Paths (APSP) Problem

One can solve the APSP problem by running an SSSP algorithm $n = |G.V|$ times, once for each vertex as the source.

If all edge weights are nonnegative, one can use **Dijkstra's SSSP algorithm**. Using a binary min-heap as the priority queue, one can solve the problem in $O(n(m + n) \log n)$ time, where $m = |G.E|$. Using a Fibonacci heap as the priority queue yields a running time of $O(n^2 \log n + mn)$.

If G has negative-weight edges, then one can use the slower **Bellman-Ford SSSP algorithm** resulting in a running time of $O(mn^2)$ which is $O(n^4)$ for dense graphs.

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The All-Pairs Shortest Paths (APSP) Problem

We assume that the edge-weights are given as an $n \times n$ adjacency matrix $W = (w_{ij})$, where

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

We allow negative-weight edges, but we assume for the time being that G contains no negative-weight cycles.

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APSP: Extending SPs by One Edge at a Time

Let $l_{ij}^{(m)}$ be the minimum weight of any path from vertex i to vertex j that contains at most m edges. Then

$$l_{ij}^{(m)} = \begin{cases} 0, & \text{if } m = 0 \text{ and } i = j, \\ \infty & \text{if } m = 0 \text{ and } i \neq j, \\ \min_{1 \leq k \leq n} \{l_{ik}^{(m-1)} + w_{kj}\}, & \text{otherwise (i.e., } m > 0). \end{cases}$$

If G has no negative-weight cycles, then for every pair of vertices i and j for which $\delta(i, j) < \infty$, there is a shortest path from i to j that is simple and thus contains at most $n - 1$ edges. A path from vertex i to vertex j with more than $n - 1$ edges cannot have lower weight than a shortest path from i to j . Hence,

$$\delta(i, j) = l_{ij}^{(n-1)} = l_{ij}^{(n)} = l_{ij}^{(n+1)} = \dots.$$

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APSP: Extending SPs by One Edge at a Time

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$$l_{ij}^{(m)} = \begin{cases} 0, & \text{if } m = 0 \text{ and } i = j, \\ \infty & \text{if } m = 0 \text{ and } i \neq j, \\ \min_{1 \leq k \leq n} \{l_{ik}^{(m-1)} + w_{kj}\}, & \text{otherwise (i.e., } m > 0). \end{cases}$$

If G has no negative-weight cycles, then for every pair of vertices i and j for which $\delta(i, j) < \infty$, there is a shortest path from i to j that is simple and thus contains at most $n - 1$ edges. A path from vertex i to vertex j with more than $n - 1$ edges cannot have lower weight than a shortest path from i to j . Hence,

$$\delta(i, j) = l_{ij}^{(n-1)} = l_{ij}^{(n)} = l_{ij}^{(n+1)} = \dots.$$

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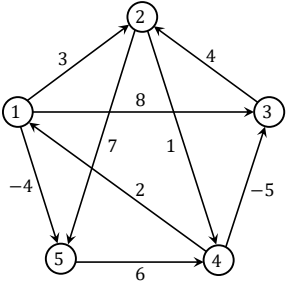
APSP: Extending SPs by One Edge at a Time

```
EXTEND-SHORTEST-PATHS ( L, W )
1.  n ← L.rows
2.  let L' = (l'_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      l'_{ij} ← ∞
6.      for k ← 1 to n do
7.        l'_{ij} ← min(l'_{ij}, l'_{ik} + w_{kj})
8.  return L'
```

```
SLOW-ALL-PAIRS-SHORTEST-PATHS ( W )
1.  n ← W.rows
2.  L^{(1)} ← W
3.  for m ← 2 to n - 1 do
4.    let L^{(m)} be a new n × n matrix
5.    L^{(m)} ← EXTEND-SHORTEST-PATHS( L^{(m-1)}, W )
6.  return L^{(n-1)}
```

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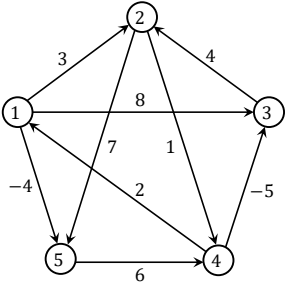
APSP: Extending SPs by One Edge at a Time



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

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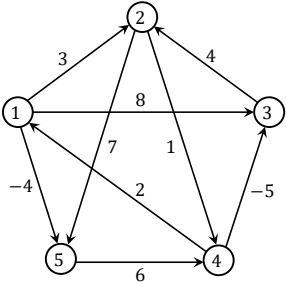
APSP: Extending SPs by One Edge at a Time



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

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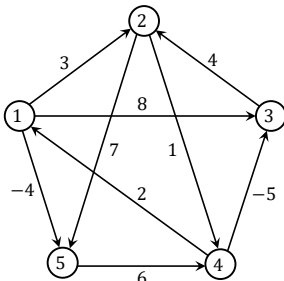
APSP: Extending SPs by One Edge at a Time



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

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APSP: Extending SPs by One Edge at a Time



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

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

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APSP: Extending SPs by One Edge at a Time

Note the similarity between *EXTEND-SHORTEST-PATHS* and *SQUARE-MATRIX-MULTIPLY*:

```
EXTEND-SHORTEST-PATHS ( L, W )
1.  n ← L.rows
2.  let L' = (l'_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      l'_{ij} ← ∞
6.      for k ← 1 to n do
7.        l'_{ij} ← min(l'_{ij}, l'_{ik} + w_{kj})
8.  return L'
```

```
SQUARE-MATRIX-MULTIPLY ( A, B )
1.  n ← A.rows
2.  let C = (c_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      c_{ij} ← 0
6.      for k ← 1 to n do
7.        c_{ij} ← c_{ij} + a_{ik} · b_{kj}
8.  return C
```

Both have the same $\Theta(n^3)$ running time.

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APSP: Extending SPs by One Edge at a Time

```
EXTEND-SHORTEST-PATHS ( L, W )
1.  n ← L.rows
2.  let L' = (l'_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      l'_{ij} ← ∞
6.      for k ← 1 to n do
7.        l'_{ij} ← min(l'_{ij}, l'_{ik} + w_{kj})
8.  return L'
```

Running time
= $\Theta(n^3)$

```
SLOW-ALL-PAIRS-SHORTEST-PATHS ( W )
1.  n ← W.rows
2.  L^{(1)} ← W
3.  for m ← 2 to n - 1 do
4.    let L^{(m)} be a new n × n matrix
5.    L^{(m)} ← EXTEND-SHORTEST-PATHS( L^{(m-1)}, W )
6.  return L^{(n-1)}
```

Running time
= $n \times \Theta(n^3)$
= $\Theta(n^4)$

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APSP: Extending SPs by Repeated Squaring

```
EXTEND-SHORTEST-PATHS ( L, W )
1.  n ← L.rows
2.  let L' = (l'_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      l'_{ij} ← ∞
6.      for k ← 1 to n do
7.        l'_{ij} ← min(l'_{ij}, l'_{ik} + w_{kj})
8.  return L'
```

```
FASTER-ALL-PAIRS-SHORTEST-PATHS ( W )
1.  n ← W.rows
2.  L^{(1)} ← W
3.  m ← 1
4.  while m < n - 1 do
5.    let L^{(2m)} be a new n × n matrix
6.    L^{(2m)} ← EXTEND-SHORTEST-PATHS( L^{(m)}, L^{(m)} )
7.    m ← 2m
8.  return L^{(m)}
```

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APSP: Extending SPs by Repeated Squaring

```
EXTEND-SHORTEST-PATHS ( L, W )
1.  n ← L.rows
2.  let L' = (l'_{ij}) be a new n × n matrix
3.  for i ← 1 to n do
4.    for j ← 1 to n do
5.      l'_{ij} ← ∞
6.      for k ← 1 to n do
7.        l'_{ij} ← min(l'_{ij}, l'_{ik} + w_{kj})
8.  return L'
```

Running time
= $\Theta(n^3)$

```
FASTER-ALL-PAIRS-SHORTEST-PATHS ( W )
1.  n ← W.rows
2.  L^{(1)} ← W
3.  m ← 1
4.  while m < n - 1 do
5.    let L^{(2m)} be a new n × n matrix
6.    L^{(2m)} ← EXTEND-SHORTEST-PATHS( L^{(m)}, L^{(m)} )
7.    m ← 2m
8.  return L^{(m)}
```

Running time
= $\lceil \log_2(n - 1) \rceil$
 $\times \Theta(n^3)$
= $\Theta(n^3 \log n)$

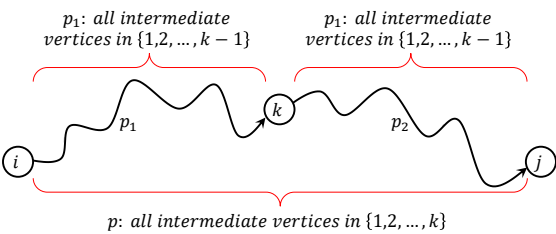


APSP: Floyd-Warshall's Algorithm

Let $d_{ij}^{(k)}$ be the minimum weight of any path from vertex i to vertex j for which all intermediate vertices are in $\{1, 2, \dots, k\}$. Then

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

Then $D^{(n)} = (d_{ij}^{(n)})$ gives: $d_{ij}^{(n)} = \delta(i, j)$ for all $i, j \in G.V$.



APSP: Floyd-Warshall's Algorithm

```
FLOYD-WARSHALL ( W )
1.  n ← W.rows
2.  D^{(0)} ← W
3.  for k ← 1 to n do
4.    let D^{(k)} = (d_{ij}^{(k)}) be a new n × n matrix
5.    for i ← 1 to n do
6.      for j ← 1 to n do
7.        d_{ij}^{(k)} ← min(d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)})
8.  return D^{(n)}
```

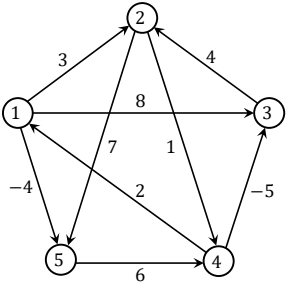


APSP: Floyd-Warshall with Predecessor Matrix

```
FLOYD-WARSHALL ( W )
1.  n ← W.rows
2.  D^{(0)} ← W
3.  let Π^{(0)} = (π_{ij}^{(0)}) be a new n × n matrix
4.  for i ← 1 to n do
5.    for j ← 1 to n do
6.      if i = j or w_{ij} = ∞ then π_{ij}^{(0)} ← NIL
7.      else π_{ij}^{(0)} ← i
8.  for k ← 1 to n do
9.    let D^{(k)} = (d_{ij}^{(k)}) and Π^{(k)} = (π_{ij}^{(k)}) be new n × n matrices
10.   for i ← 1 to n do
11.     for j ← 1 to n do
12.       if d_{ij}^{(k-1)} ≤ d_{ik}^{(k-1)} + d_{kj}^{(k-1)} then π_{ij}^{(k)} ← π_{ij}^{(k-1)}
13.       else π_{ij}^{(k)} ← π_{kj}^{(k-1)}
14.       d_{ij}^{(k)} ← min(d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)})
15.  return D^{(n)} and Π^{(n)}
```

APSP: Floyd-Warshall with Predecessor Matrix

```
PRINT-ALL-PAIRS-SHORTEST-PATH ( Π, i, j )
1.  if i = j then
2.    print i
3.  elseif πij = NIL then
4.    print "no path from" i "to" j "exists"
5.  else PRINT-ALL-PAIRS-SHORTEST-PATH ( Π, i, πij )
6.    print j
```



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

APSP: Floyd-Warshall with Predecessor Matrix

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

APSP: Floyd-Warshall with Predecessor Matrix

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

APSP: Floyd-Warshall with Predecessor Matrix

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

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

APSP: Floyd-Warshall with Predecessor Matrix

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

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

APSP: Floyd-Warshall with Predecessor Matrix

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

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

APSP: Floyd-Warshall's Algorithm

```
FLOYD-WARSHALL ( W )
1.  n ← W.rows
2.  D(0) ← W
3.  for k ← 1 to n do
4.    let D(k) = (dij(k)) be a new n × n matrix
5.    for i ← 1 to n do
6.      for j ← 1 to n do
7.        dij(k) ← min ( dij(k-1), dik(k-1) + dkj(k-1) )
8.  return D(n)
```

Running Time = $\Theta(n^3)$
Space Complexity = $\Theta(n^3)$

APSP: Floyd-Warshall's Algorithm

But $D^{(k)}$ depends only on $D^{(k-1)}$.

```
FLOYD-WARSHALL-QUADRATIC-SPACE ( W )
1.  n ← W.rows
2.  let  $D^{(0)} = (d_{ij}^{(0)})$  and  $D^{(1)} = (d_{ij}^{(1)})$  be new  $n \times n$  matrices
3.   $D^{(0)} \leftarrow W$ 
4.  for k ← 1 to n do
5.    for i ← 1 to n do
6.      for j ← 1 to n do
7.         $d_{ij}^{(1)} \leftarrow \min(d_{ij}^{(0)}, d_{ik}^{(0)} + d_{kj}^{(0)})$ 
8.   $D^{(0)} \leftarrow D^{(1)}$ 
9.  return  $D^{(0)}$ 
```

Running Time = $\Theta(n^3)$
Space Complexity = $\Theta(n^2)$



APSP: Floyd-Warshall's Algorithm

Can be solved in-place!

```
FLOYD-WARSHALL-IN-PLACE ( W )
1.  n ← W.rows
2.  for k ← 1 to n do
3.    for i ← 1 to n do
4.      for j ← 1 to n do
5.         $w_{ij} \leftarrow \min(w_{ij}, w_{ik} + w_{kj})$ 
6.  return W
```

Running Time = $\Theta(n^3)$
Space Complexity = $\Theta(n^2)$

