

CH08-320201

# Algorithms and Data Structures

ADS

## Lecture 23

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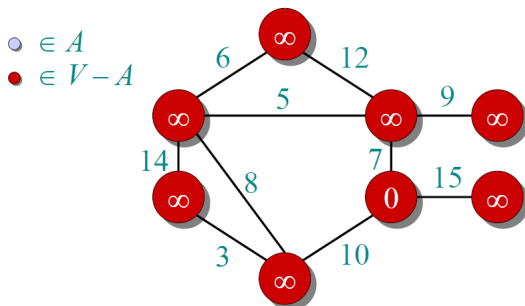
Spring 2019

# Prim's Algorithm Pseudocode

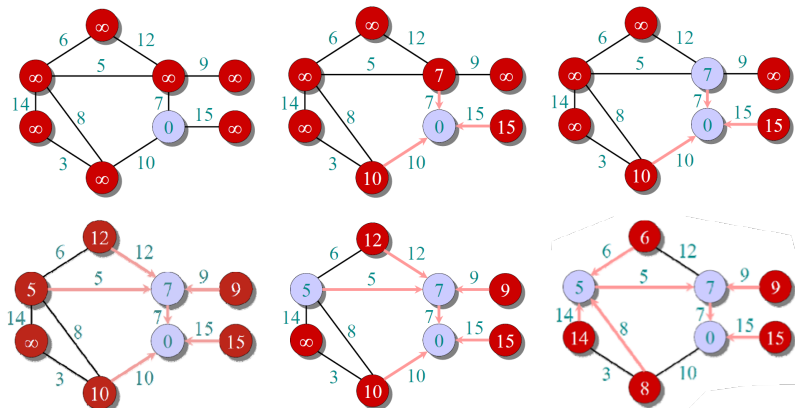
```
 $Q \leftarrow V$   
 $key[v] \leftarrow \infty$  for all  $v \in V$   
 $key[s] \leftarrow 0$  for some arbitrary  $s \in V$   
while  $Q \neq \emptyset$   
  do  $u \leftarrow \text{EXTRACT-MIN}(Q)$   
    for each  $v \in \text{Adj}[u]$   
      do if  $v \in Q$  and  $w(u, v) < key[v]$   
        then  $key[v] \leftarrow w(u, v)$   
           $\pi[v] \leftarrow u$ 
```

- ▶ The output is provided by storing predecessors  $\pi[v]$  of each node  $v$ .
- ▶ The set  $\{(v, \pi[v]) \mid v \in V\}$  forms the MST.

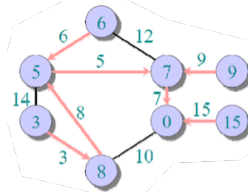
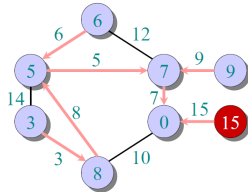
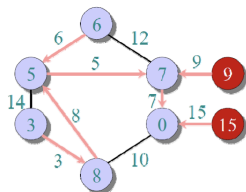
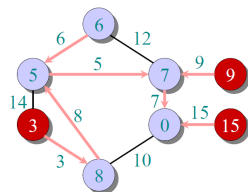
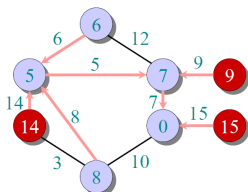
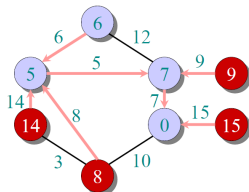
## Example (1)



## Example (2)



## Example (3)



```

 $\Theta(V)$  total {
     $Q \leftarrow V$ 
     $key[v] \leftarrow \infty$  for all  $v \in V$ 
     $key[s] \leftarrow 0$  for some arbitrary  $s \in V$ 
    while  $Q \neq \emptyset$ 
    do  $u \leftarrow \text{EXTRACT-MIN}(Q)$ 
    for each  $v \in Adj[u]$ 
    do if  $v \in Q$  and  $w(u, v) < key[v]$ 
    then  $key[v] \leftarrow w(u, v)$ 
     $\pi[v] \leftarrow u$ 
}

```

 $\Theta(E)$  implicit DECREASE-KEY's.

## Complexity Analysis (2)

$$\text{Time} = \Theta(V) \cdot T_{\text{EXTRACT-MIN}} + \Theta(E) \cdot T_{\text{DECREASE-KEY}}$$

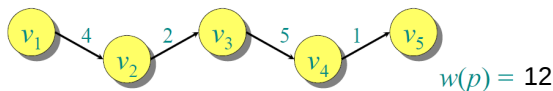
$Q$	$T_{\text{EXTRACT-MIN}}$	$T_{\text{DECREASE-KEY}}$	Total
min-heap	$O(\lg V)$	$O(\lg V)$	$O(E \lg V)$
array	$O(V)$	$O(1)$	$O(V^2)$

## Definition: Path

- ▶ Consider a directed graph  $G = (V, E)$ , where each edge  $e \in E$  is assigned a non-negative weight  $w : E \rightarrow \mathbb{R}^+$ .
- ▶ A path is a sequence of vertices in the graph, where two consecutive vertices are connected by a respective edge.
- ▶ The weight of a path  $p = (v_1, \dots, v_k)$  is defined by

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

- ▶ Example:





## Definition: Shortest Path

- ▶ A shortest path from a vertex  $u$  to a vertex  $v$  in a graph  $G$  is a path of minimum weight.
- ▶ The weight of a shortest path from  $u$  to  $v$  is defined as  $\delta(u, v) = \min\{w(p) : p \text{ is a path from } u \text{ to } v\}$ .
- ▶ Note that  $\delta(u, v) = \infty$ , if no path from  $u$  to  $v$  exists.
- ▶ Why of interest?  
One example is finding a shortest route in a road network.

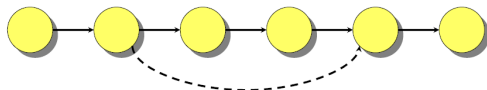
## Optimal Substructure

### Theorem:

A subpath of a shortest path is a shortest path.

### Proof:

- ▶ Let  $p = (v_1, \dots, v_k)$  be a shortest path and  $q = (v_i, \dots, v_j)$  a subpath of  $p$ .
- ▶ Assume that  $q$  is not a shortest path.
- ▶ Then, there exists a shorter path from  $v_i$  to  $v_j$  than  $q$ .
- ▶ But then, there is also a shorter path from  $v_1$  to  $v_k$  than  $p$ .  
Contradiction.

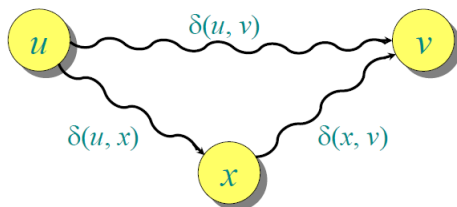


# Triangle Inequality

Theorem:

For all  $u, v, x \in V$ , we have that  $\delta(u, v) \leq \delta(u, x) + \delta(x, v)$ .

Proof:



## (Single-Source) Shortest Paths

### Problem:

Given a source vertex  $s \in V$ , find for all  $v \in V$  the shortest-path weights  $\delta(s, v)$ .

**Idea:** Greedy approach.

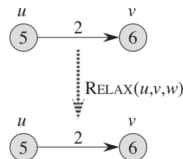
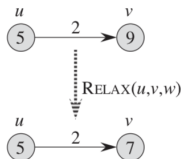
1. Maintain a set  $S$  of vertices whose shortest-path distances from  $s$  are known.
2. At each step, add to  $S$  the vertex  $v \in V \setminus S$  whose distance estimate from  $s$  is minimal.
3. Update the distance estimates of vertices adjacent to  $v$ .

# Dijkstra's Algorithm

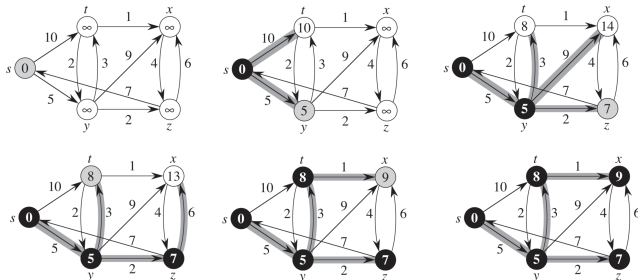
```

d[s] := 0
for each v ∈ V \ {s}
    d[v] := infinity
S := ∅
Q := V // min-priority queue maintaining V \ S.
while Q != ∅
    u := Extract-Min(Q)
    S := S ∪ {u}
    for each v ∈ Adj[u]
        if d[v] > d[u] + w(u,v) // *****
            then d[v] := d[u] + w(u,v) // Relaxation
                pi[v] := u // *****

```



# Example Dijkstra's Algorithm



```

while Q !=  $\emptyset$ 
  u := Extract-Min(Q)
  S := S  $\cup$  {u}
  for each v  $\in$  Adj[u]
    if d[v] > d[u] + w(u,v)
      then d[v] := d[u] + w(u,v)
         pi[v] := u
  
```

S = {s, y, z, t, x}

## Correctness of Dijkstra's Algorithm

Correctness can be shown in 3 steps:

- (i)  $d[v] \geq \delta(s, v)$  at all steps (for all  $v$ )
- (ii)  $d[v] = \delta(s, v)$  after relaxation from  $u$ ,
- (iii) if  $(u, v)$  on shortest path (for all  $v$ ) algorithm terminates with  $d[v] = \delta(s, v)$

## Correctness (i)

Lemma:

- ▶ Initializing  $d[s] = 0$  and  $d[v] = \infty$  for all  $v \in V \setminus \{s\}$  establishes  $d[v] \geq \delta(s, v)$  for all  $v \in V$ .
- ▶ This invariant is maintained over any sequence of relaxation steps.

Proof:

Suppose the Lemma is not true, then let  $v$  be the first vertex for which  $d[v] < \delta(s, v)$  and let  $u$  be the vertex that caused  $d[v]$  to change by  $d[v] = d[u] + w(u, v)$ . Then,

$$\begin{array}{ll}
 d[v] < \delta(s, v) & \text{supposition} \\
 \leq \delta(s, u) + \delta(u, v) & \text{triangle inequality} \\
 \leq \delta(s, u) + w(u, v) & \text{sh. path} \leq \text{specific path} \\
 \leq d[u] + w(u, v) & v \text{ is first violation}
 \end{array}$$

Contradiction.



## Correctness (ii)

### Lemma:

- ▶ Let  $u$  be  $v$ 's predecessor on a shortest path from  $s$  to  $v$ .
- ▶ Then, if  $d[u] = \delta(s, u)$ , we have  $d[v] = \delta(s, v)$  after the relaxation of edge  $(u, v)$ .

### Proof:

- ▶ Observe that  $\delta(s, v) = \delta(s, u) + w(u, v)$ .
- ▶ Suppose that  $d[v] > \delta(s, v)$  before relaxation (else: done).
- ▶ Then,  $d[v] > \delta(s, v) = \delta(s, u) + w(u, v) = d[u] + w(u, v)$  (if clause in the algorithm).
- ▶ Thus, the algorithm sets  $d[v] = d[u] + w(u, v) = \delta(s, v)$ .

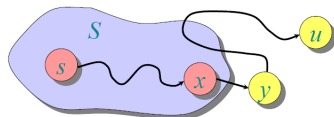
## Correctness (iii)

### Theorem:

Dijkstra's algorithm terminates with  $d[v] = \delta(s, v)$  for all  $v \in V$ .

### Proof:

- ▶ It suffices to show that  $d[v] = \delta(s, v)$  for every  $v \in V$  when  $v$  is added to  $S$ .
- ▶ Suppose  $u$  is the first vertex added to  $S$  with  $d[u] > \delta(s, u)$ .
- ▶ Let  $y$  be the first vertex in  $V \setminus S$  along the shortest path from  $s$  to  $u$ , and let  $x$  be its predecessor.
- ▶ Then,  $d[x] = \delta(s, x)$  and  $d[y] = \delta(s, y) \leq \delta(s, u) < d[u]$ .
- ▶ But we chose  $u$  such that  $d[u] \leq d[y]$ . Contradiction.



# Complexity Analysis

```

    while  $Q \neq \emptyset$ 
      do  $u \leftarrow \text{EXTRACT-MIN}(Q)$ 
          $S \leftarrow S \cup \{u\}$ 
         for each  $v \in \text{Adj}[u]$ 
           do if  $d[v] > d[u] + w(u, v)$ 
              then  $d[v] \leftarrow d[u] + w(u, v)$ 

```

$|V|$  times {  $\text{degree}(u)$  times {

- ▶ Similar to Prim's minimum spanning tree algorithm, we get the computation time

$$\Theta(V \cdot T_{\text{EXTRACT-MIN}} + E \cdot T_{\text{DECREASE-KEY}})$$

- ▶ Hence, depending on what data structure we use, we get the same computation times as for Prim's algorithm.

# Unweighted Graphs

- ▶ Suppose that we have an unweighted graph, i.e., the weights  $w(u, v) = 1$  for all  $(u, v) \in E$ .
- ▶ Can we improve the performance of Dijkstra's algorithm?
- ▶ **Observation:** The vertices in our data structure  $Q$  are processed following the FIFO principle.
- ▶ Hence, we can replace the min-priority queue with a queue.
- ▶ This leads to a breadth-first search.

## BFS Algorithm

```
d[s] := 0
for each v  $\in$  V \ {s}
    d[v] := infinity
Enqueue (Q, s)
while Q  $\neq$   $\emptyset$ 
    u := Dequeue(Q)
    for each v  $\in$  Adj[u]
        if d[v] = infinity
            then d[v] := d[u] + 1
                pi[v] := u
                Enqueue(Q, v)
```

## Analysis: BFS Algorithm

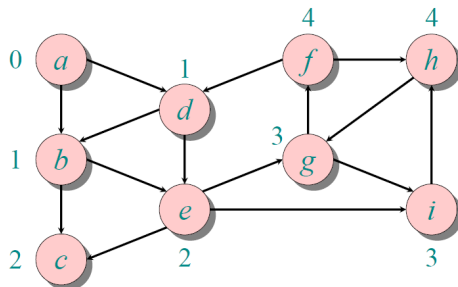
### Correctness:

- ▶ The FIFO queue  $Q$  mimics the min-priority queue in Dijkstra's algorithm.
- ▶ Invariant:  
If  $v$  follows  $u$  in  $Q$ , then  $d[v] = d[u]$  or  $d[v] = d[u] + 1$ .
- ▶ Hence, we always dequeue the vertex with smallest  $d$ .

### Time complexity:

$$O(|V|T_{Dequeue} + |E|T_{Enqueue}) = O(|V| + |E|)$$

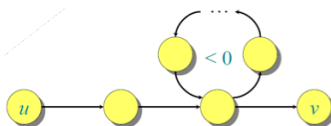
## Example: BFS Algorithm



*Q*: *a b d c e g i f h*

## Negative Weights

- ▶ We had postulated that all weights are nonnegative.
- ▶ How can we extend the algorithm to also handle negative entries?
- ▶ The problems are caused by negative weight cycles.



- ▶ **Goal:** Find shortest-path lengths from a source vertex  $s \in V$  to all vertices  $v \in V$  or determine the existence of a negative-weight cycle.



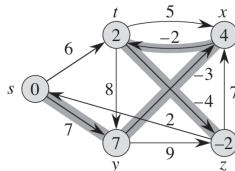
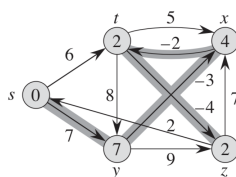
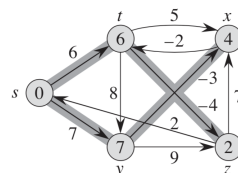
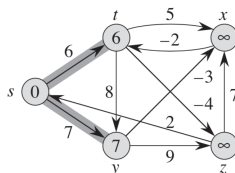
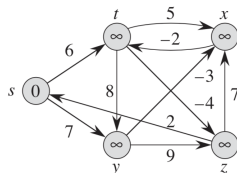
# Bellmann-Ford Algorithm

```
d[s] := 0
for each v  $\in$  V \ {s}
    d[v] := infinity
for i:=1 to |V|-1
    for each (u,v)  $\in$  E
        if d[v] > d[u] + w(u,v)
            then d[v] := d[u] + w(u,v)
                pi[v] := u

for each (u,v)  $\in$  E
    if d[v] > d[u] + w(u,v)
        report existence of negative-weight cycle
```

Time complexity:  $O(|V| \cdot |E|)$

# Example: Bellman-Ford Algorithm



```

for i:=1 to |V|-1
  for each (u,v) ∈ E
    if d[v] > d[u] + w(u,v)
      then d[v] := d[u] + w(u,v)
          pi[v] :=u
  
```

# Bellman-Ford Algorithm: Correctness (1)

## Theorem:

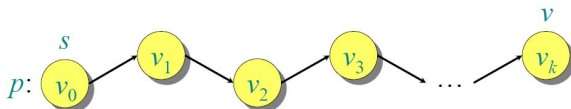
If  $G = (V, E)$  contains no negative-weight cycles, then the Bellman-Ford algorithm terminates with  $d[v] = \delta(s, v)$  for all  $v \in V$ .

## Proof:

Let  $v \in V$  be any vertex.

Consider a shortest path  $p = (v_0, \dots, v_k)$  from  $s$  to  $v$ .

Then,  $\delta(s, v_i) = \delta(s, v_{i-1}) + w(v_{i-1}, v_i)$  for  $i = 1, \dots, k$ .



## Bellmann-Ford Algorithm: Correctness (2)

Initially,  $d[v_0] = 0 = \delta(s, v_0)$ .

According to our Lemma from Dijkstra's algorithm we have  $d[v] \geq \delta(s, v)$ , i.e.,  $d[v_0]$  is not changed.

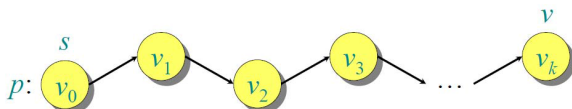
After the 1<sup>st</sup> pass, we have  $d[v_1] = \delta(s, v_1)$ .

After the 2<sup>nd</sup> pass, we have  $d[v_2] = \delta(s, v_2)$ .

...

After the  $k^{\text{th}}$  pass, we have  $d[v_k] = \delta(s, v_k)$ .

Since  $G$  has no negative-weight cycles,  $p$  is a simple path, i.e., it has  $\leq |V| - 1$  edges.



## Detecting Negative-Weight Cycles

### Corollary:

If a value  $d[v]$  fails to converge after  $|V| - 1$  passes, there exists a negative-weight cycle in  $G$  reachable from  $s$ .

## Excuse: Linear Programming

### Linear programming problem:

Let  $A$  be matrix of size  $m \times n$ ,  $b$  a vector of size  $m$ , and  $c$  a vector of size  $n$ .

Find a vector  $x$  of size  $n$  that maximizes  $c^T x$  subject to  $Ax \leq b$ , or determine that no such solution exists.

$$\begin{matrix} n \\ m \end{matrix} \begin{matrix} A \\ \cdot \end{matrix} \begin{matrix} x \\ \leq \end{matrix} \begin{matrix} b \end{matrix} \quad \text{maximizing} \quad \begin{matrix} c^T \\ \cdot \end{matrix} \begin{matrix} x \end{matrix}$$

## Example: Difference Constraints

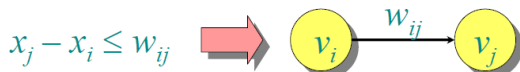
Linear programming example, where each row of  $A$  contains exactly one 1 and one  $-1$ , other entries are 0.

$$\left. \begin{array}{l} x_1 - x_2 \leq 3 \\ x_2 - x_3 \leq -2 \\ x_1 - x_3 \leq 2 \end{array} \right\} x_j - x_i \leq w_{ij}$$

**Goal:** Find 3-vector  $x$  that satisfies these inequations.

**Solution:**  $x_1 = 3$ ,  $x_2 = 0$ ,  $x_3 = 2$ .

Build constraint graph (matrix  $A$  of size  $|E| \times |V|$ ):



## Case 1: Unsatisfiable Constraints

### Theorem:

If the constraint graph contains a negative-weight cycle, then the constraints are unsatisfiable.

### Proof:

Suppose we have a negative-weight cycle:

$$v_1 \rightarrow v_2 \rightarrow \cdots \rightarrow v_k \rightarrow v_1.$$

Then,

$$\begin{aligned}x_2 - x_1 &\leq w_{12} \\x_3 - x_2 &\leq w_{23} \\&\vdots \\x_k - x_{k-1} &\leq w_{k-1, k} \\x_1 - x_k &\leq w_{k1}\end{aligned}$$

Summing the inequations delivers:  $LHS = 0$ ,  $RHS < 0$ .

Hence, no  $x$  exists that satisfies the inequations.



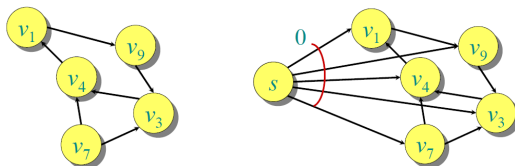
## Case 2: Satisfiable Constraints (1)

### Theorem:

If no negative-weight cycle exists in the constraint graph, then the constraints are satisfiable.

### Proof:

Add a vertex  $s$  with a 0-weight edge to all vertices. Note that this does not introduce a negative-weight cycle.



## Case 2: Satisfiable Constraints (2)

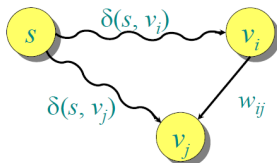
Show that the assignments  $x_i = \delta(s, v_i)$  for  $i = 1, \dots, n$  solve the constraints.

Consider any constraint  $x_j - x_i \leq w_{ij}$ .

Then, consider the shortest path from  $s$  to  $v_j$  and  $v_i$ .

The triangle inequality delivers  $\delta(s, v_j) \leq \delta(s, v_i) + w_{ij}$ .

Since  $x_i = \delta(s, v_i)$  and  $x_j = \delta(s, v_j)$ , constraint  $x_j - x_i \leq w_{ij}$  is satisfied.



# Bellmann-Ford for Linear Programming

## Corollary:

The Bellman-Ford algorithm can solve a system of  $m$  difference constraints on  $n$  variables in  $O(mn)$  time.

## Remark:

Single-source shortest paths is a simple linear programming problem.