

# 6.4: Single-Source Shortest Paths

Frank Stajano

Thomas Sauerwald

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#### **Outline**

#### Bellman-Ford

Dijkstra's Algorithm

All-Pairs Shortest Path

APSP via Matrix Multiplication

Johnson's Algorithm



# The Bellman-Ford Algorithm

```
BELLMAN-FORD (G, w, s)
0: assert(s in G.vertices())
1: for v in G.vertices()
2: v.predecessor = None
3: v.d = Infinity
4: s.d = 0
5:
6: repeat |V|-1 times
7: for e in G.edges()
8: Relax edge e=(u,v): Check if u.d + w(u,v) < v.d
         if e.start.d + e.weight.d < e.end.d:
9:
10:
            e.end.d = e.start.d + e.weight
11:
            e.end.predecessor = e.start
12:
13: for e in G.edges()
14: if e.start.d + e.weight.d < e.end.d:</pre>
15:
         return FALSE
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### The Bellman-Ford Algorithm (modified)

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- Requires that all edges have non-negative weights
- Use a special order for relaxing edges



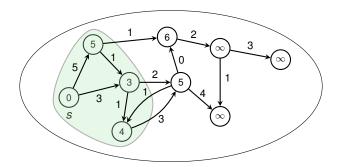
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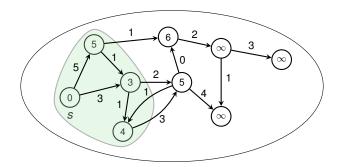


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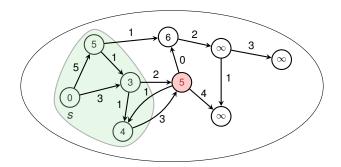


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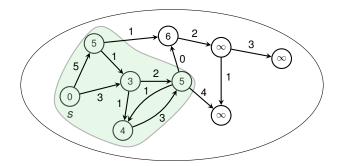


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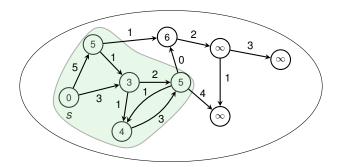


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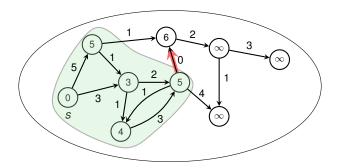


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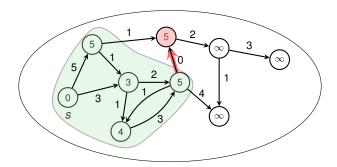


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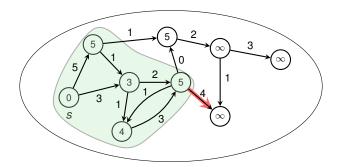


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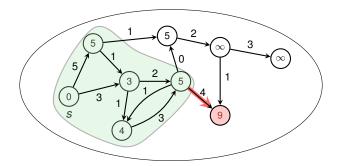


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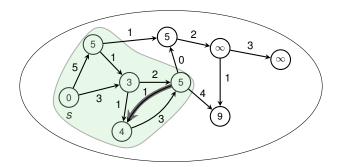


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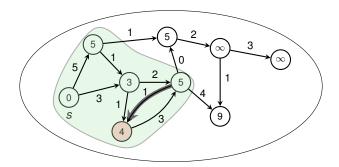


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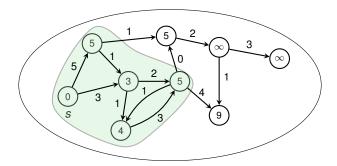


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DIJKSTRA(G,w,s)

0: INITIALIZE(G,s)

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4: u = \text{Extract-Min}(Q)

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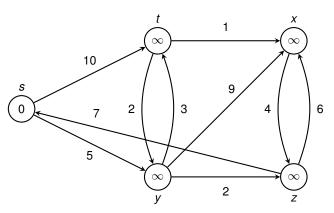
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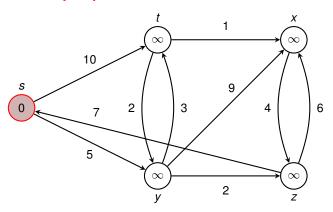
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$$(s,0),(t,\infty),(x,\infty),(y,\infty),(z,\infty)$$



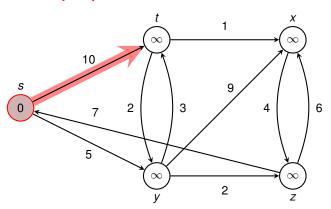


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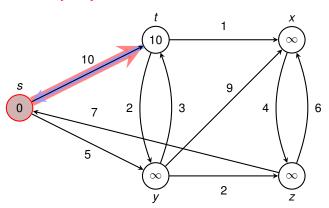


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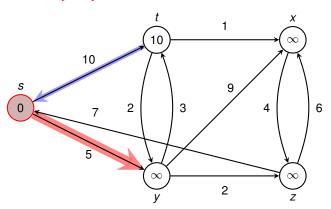


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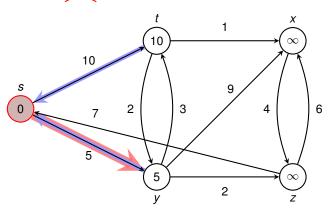


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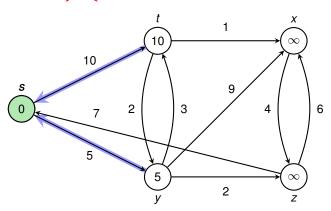


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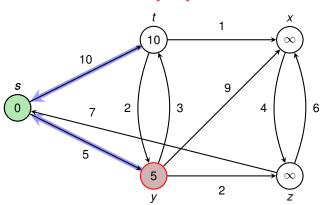


$$(t, 10), (x, \infty), (y, 5), (z, \infty)$$



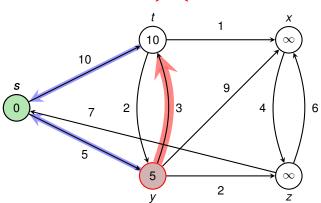


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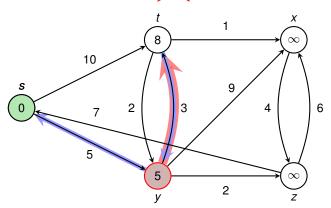


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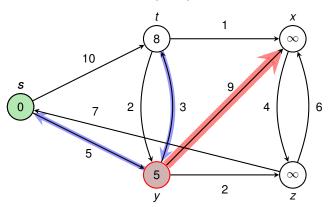


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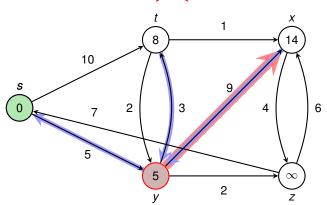


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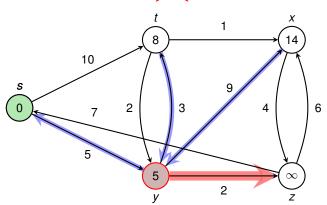


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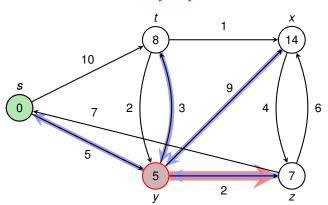




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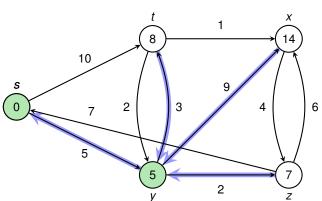






#### Priority Queue Q:

(t,8),(x,14),(x,7)









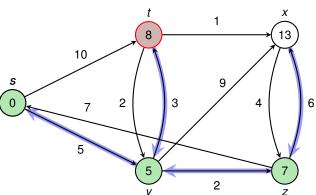














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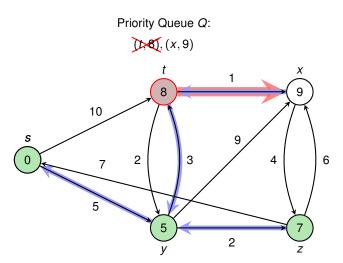


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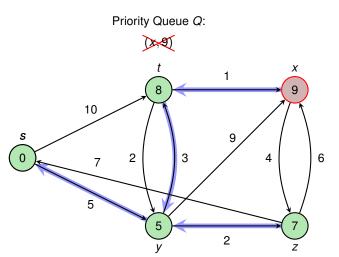




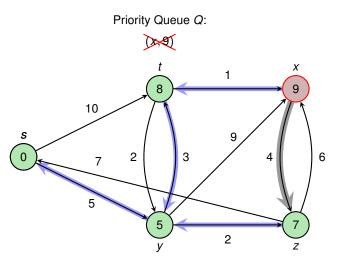


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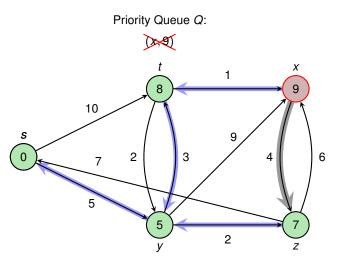
















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- Initialization (I. 0-2):  $\mathcal{O}(V)$
- ExtractMin (I. 4):  $\mathcal{O}(V \cdot \log V)$
- DecreaseKey (I. 7): O(E · 1)
- $\Rightarrow$  Overall:  $\mathcal{O}(V \log V + E)$

Theorem 24.6

For any directed graph G=(V,E) with non-negative edge weights  $w:E\to\mathbb{R}^+$  and source s, Dijkstra terminates with  $u.d=u.\delta$  for all  $u\in V$ .

Proof: Invariant: If v is extracted,  $v.d = v.\delta$ 



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## Proof: Invariant: If v is extracted, $v.d = v.\delta$

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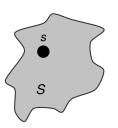
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## Proof: Invariant: If v is extracted, $v.d = v.\delta$

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• Let *u* be the first vertex with this property



#### Theorem 24.6

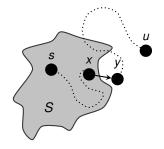
For any directed graph G=(V,E) with non-negative edge weights  $w:E\to\mathbb{R}^+$  and source s, Dijkstra terminates with  $u.d=u.\delta$  for all  $u\in V$ .

## Proof: Invariant: If v is extracted, $v.d = v.\delta$

• Suppose there is  $u \in V$ , when extracted,

$$u.d > u.\delta$$

- Let *u* be the first vertex with this property
- Take a shortest path from s to u and let (x, y) be the first edge from S to  $V \setminus S$





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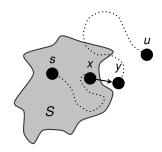
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u.d





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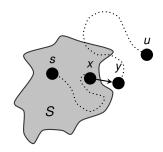
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$$u.d \leq y.d$$



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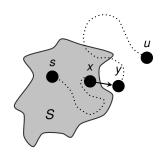
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$$u.d \le y.d$$
 $u$  is extracted before  $y$ 





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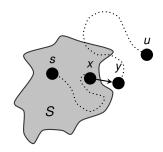
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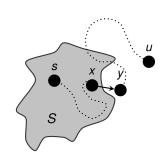
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$$u.d \leq y.d = y.\delta$$

since  $x.d = x.\delta$  when x is extracted, and then (x, y) is relaxed  $\Rightarrow$  Convergence Property



#### Theorem 24.6

For any directed graph G=(V,E) with non-negative edge weights  $w:E\to\mathbb{R}^+$  and source s, Dijkstra terminates with  $u.d=u.\delta$  for all  $u\in V$ .

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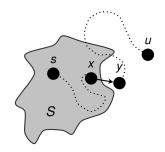
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$$u.\delta < u.d \le y.d = y.\delta$$



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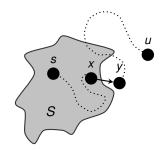
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$$u.\delta < u.d < v.d = v.\delta$$

This contradicts that y is on a shortest path from s to y.



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$$u.\delta < u.d < v.d = v.\delta$$





This step requires non-negative weights!



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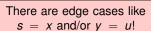
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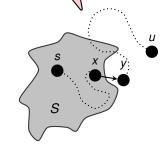
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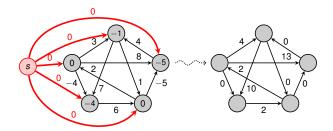


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This contradicts that y is on a shortest path from s to y.







#### 6.5: All-Pairs Shortest Paths

Frank Stajano

**Thomas Sauerwald** 





#### **Outline**

Bellman-Ford

Dijkstra's Algorithm

All-Pairs Shortest Path

APSP via Matrix Multiplication

Johnson's Algorithm



### Formalizing the Problem

#### All-Pairs Shortest Path Problem

• Given: directed graph G = (V, E),  $V = \{1, 2, ..., n\}$ , with edge weights represented by a matrix W:

$$w_{i,j} = egin{cases} ext{weight of edge } (i,j) & ext{for an edge } (i,j) \in E, \ \infty & ext{if there is no edge from } i ext{ to } j, \ 0 & ext{if } i = j. \end{cases}$$



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• Goal: Obtain a matrix of shortest path weights L, that is

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Goal: Obtain a matrix of shortest path weights L, that is

$$\ell_{i,j} = egin{cases} \text{weight of a shortest path from } i \text{ to } j, & \text{if } j \text{ is reachable from } i \\ \infty & \text{otherwise.} \end{cases}$$

Here we will only compute the weight of the shortest path without keeping track of the edges of the path!



#### **Outline**

Bellman-Ford

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Basic Idea -

 Any shortest path from i to j of length k ≥ 2 is the concatenation of a shortest path of length k − 1 and an edge





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- Let  $\ell_{i,j}^{(m)}$  be min. weight of any path from i to j with at most m edges





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- Any shortest path from i to j of length k ≥ 2 is the concatenation of a shortest path of length k − 1 and an edge
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$$\ell_{i,j}^{(m)} = \min \Bigl( \ell_{i,j}^{(m-1)}, \min_{1 < k < n} \ell_{i,k}^{(m-1)} + w_{k,j} \Bigr)$$





- Any shortest path from i to j of length k > 2 is the concatenation of a shortest path of length k-1 and an edge
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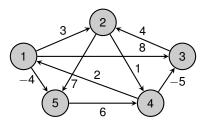




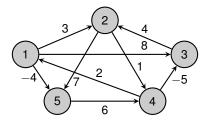
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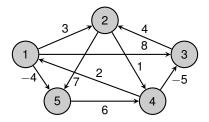
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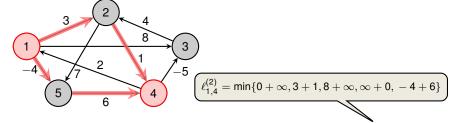


$$L^{(1)} = W = \begin{pmatrix} 0 & 3 & 8 & \infty & -4 \\ \infty & 0 & \infty & 1 & 7 \\ \infty & 4 & 0 & \infty & \infty \\ 2 & \infty & -5 & 0 & \infty \\ \infty & \infty & \infty & 6 & 0 \end{pmatrix}$$



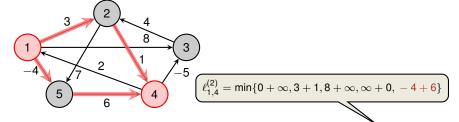
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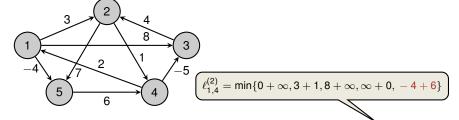
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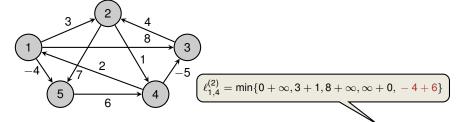


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$$L^{(3)} = \left(\begin{array}{ccccc} 0 & 3 & -3 & 2 & -4 \\ 3 & 0 & -4 & 1 & -1 \\ 7 & 4 & 0 & 5 & 11 \\ 2 & -1 & -5 & 0 & -2 \\ 8 & 5 & 1 & 6 & 0 \end{array}\right)$$



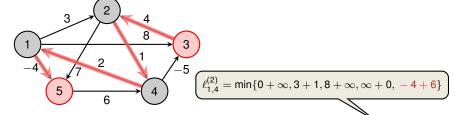


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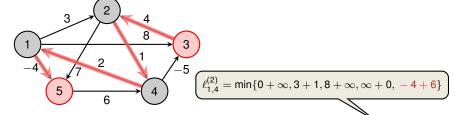
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 $\ell_{3.5}^{(4)} = \min\{7 - 4, 4 + 7, 0 + \infty, 5 + \infty, 11 + 0\}$ 





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$$\ell_{i,j}^{(m)} = \min_{1 \le k \le n} \left( \ell_{i,k}^{(m-1)} + \mathbf{W}_{k,j} \right)$$

•  $L^{(n-1)} = L^{(n)} = L^{(n+1)} = \dots = L$ , since every shortest path uses at most n-1 = |V|-1 edges (assuming absence of negative-weight cycles)



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- Computing  $L^{(m)}$ :



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The correspondence is as follows:

$$\begin{array}{ccc} \min & \Leftrightarrow & \sum \\ + & \Leftrightarrow & \times \end{array}$$



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$$L^{(m)} \text{ can be computed in } \mathcal{O}(n^3)$$

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• For, say, n = 738, we subsequently compute

$$L^{(1)}, L^{(2)}, L^{(3)}, L^{(4)}, \dots, L^{(737)} = L$$



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Since we don't need the intermediate matrices, a more efficient way is

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We need  $L^{(4)} = L^{(2)} \cdot L^{(2)} = L^{(3)} \cdot L^{(1)}!$  (see Ex. 25.1-4)

Takes  $\mathcal{O}(\log n \cdot n^3)$ .



### **Outline**

Bellman-Ford

Dijkstra's Algorithm

All-Pairs Shortest Path

APSP via Matrix Multiplication







Overview -

allow negative-weight edges and negative-weight cycles



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- ullet one pass of Bellman-Ford and |V| passes of Dijkstra



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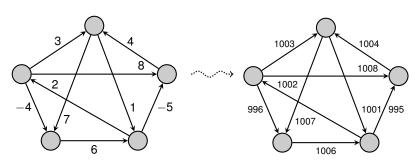
Adding a constant to every edge doesn't work!



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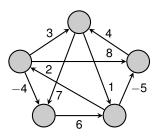
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Johnson's Algorithm —

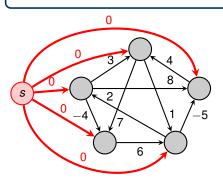
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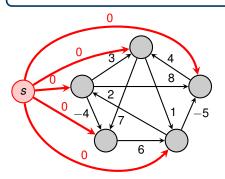
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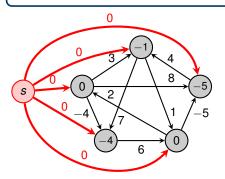


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- 2. Run Bellman-Ford on this augmented graph with source  $\boldsymbol{s}$



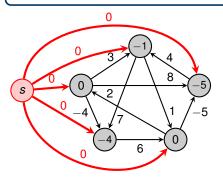


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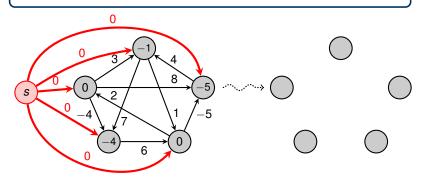


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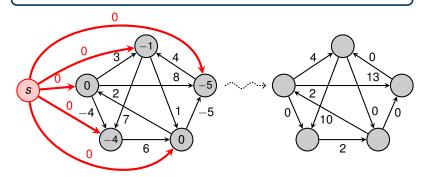


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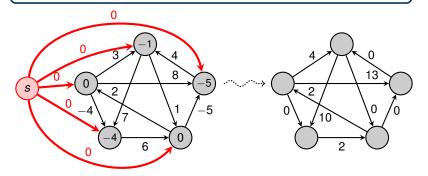


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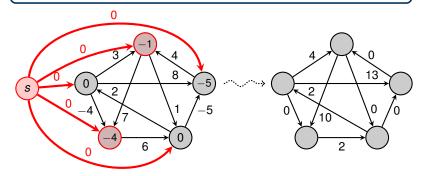




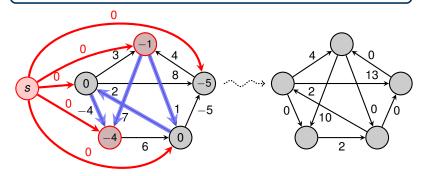
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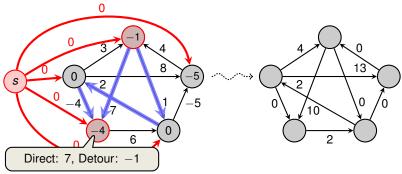
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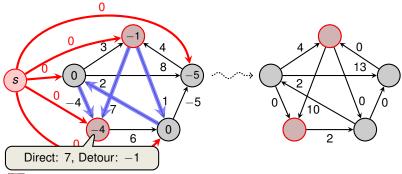


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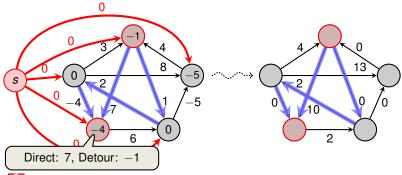


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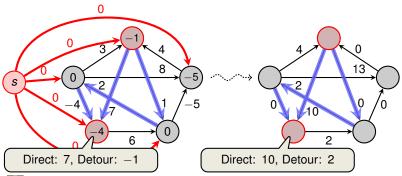


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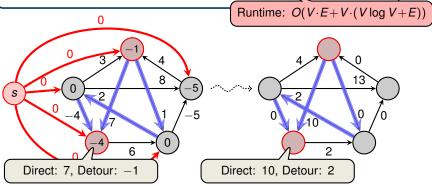


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## **Correctness of Johnson's Algorithm**

#### Theorem

For any graph G = (V, E, w) without negative-weight cycles:

- 1. After reweighting, all edges are non-negative
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Proof of 1.



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$$u.\delta + w(u,v) \ge v.\delta \qquad \text{(triangle inequality)}$$
 
$$\Rightarrow \qquad \widetilde{w}(u,v) + u.\delta + w(u,v) \ge w(u,v) + u.\delta - v.\delta + v.\delta$$



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$$\begin{array}{ll} u.\delta + w(u,v) \geq v.\delta & \text{(triangle inequality)} \\ \Rightarrow & \widetilde{w}(u,v) + u.\delta + w(u,v) \geq w(u,v) + u.\delta - v.\delta + v.\delta \\ \Rightarrow & \widetilde{w}(u,v) \geq 0 \end{array}$$



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### Proof of 2.

Let  $p = (v_0, v_1, \dots, v_k)$  be any path

• In the original graph, the weight is  $\sum_{i=1}^{k} w(v_{i-1}, v_i) = w(p)$ .

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# **Comparison of all Shortest-Path Algorithms**

Algorithm	SSSP		APSP		negative
Aigoritiiii	sparse	dense	sparse	dense	weights
Bellman-Ford	V <sup>2</sup>	<i>V</i> <sup>3</sup>	<i>V</i> <sup>3</sup>	$V^4$	✓
Dijkstra	V log V	$V^2$	$V^2 \log V$	$V^3$	Х
Matrix Mult.	_	_	$V^3 \log V$	$V^3 \log V$	(√)
Johnson	_	_	$V^2 \log V$	$V^3$	✓



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Johnson	_	_	$V^2 \log V$	$V^3$	/ 🗸

can handle negative weight edges, but not negative-weight cycles

