

# Lecture 16: Single-Source Shortest Paths

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601.433/633 Introduction to Algorithms

Slides by Michael Dinitz

# Introduction

Setup:

- ▶ Directed graph  $\mathbf{G} = (\mathbf{V}, \mathbf{E})$
- ▶ Length  $\ell(\mathbf{x}, \mathbf{y})$  on each edge  $(\mathbf{x}, \mathbf{y}) \in \mathbf{E}$  (equivalent:  $\ell : \mathbf{E} \rightarrow \mathbb{R}$ )
- ▶ Length of path  $\mathbf{P}$  is  $\ell(\mathbf{P}) = \sum_{(\mathbf{x}, \mathbf{y}) \in \mathbf{P}} \ell(\mathbf{x}, \mathbf{y})$
- ▶  $d(\mathbf{x}, \mathbf{y}) = \min_{\mathbf{x} \rightarrow \mathbf{y} \text{ paths } \mathbf{P}} \ell(\mathbf{P})$

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Today: source  $\mathbf{v} \in \mathbf{V}$ , want to compute shortest path from  $\mathbf{v}$  to every  $\mathbf{u} \in \mathbf{V}$

- ▶  $d(\mathbf{u}) = d(\mathbf{v}, \mathbf{u})$  for all  $\mathbf{u} \in \mathbf{V}$
- ▶ Representation: “shortest path tree” out of  $\mathbf{v}$ .
- ▶ Often only care about distances – can reconstruct tree from distances.

# Bellman-Ford

# Dynamic Programming Approach

Subproblems:

- ▶  $OPT(u, i)$ : shortest path from  $v$  to  $u$  that uses at most  $i$  hops (edges)
- ▶ If no such path, set to “infinitely long” fake path.
- ▶ For simplicity, create loop (edge to and from the same node) at every node, length  $0$

# Dynamic Programming Approach

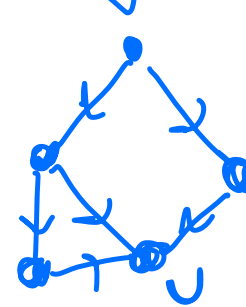
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## Theorem (Optimal Substructure)

$$\ell(OPT(u, k)) = \begin{cases} 0 & \text{if } u = v, k = 0 \\ \infty & \text{if } u \neq v, k = 0 \\ & \text{otherwise} \end{cases}$$

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Induction on  $k$ .

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$\implies OPT(x, k-1) \circ (x, u)$  is a  $v \rightarrow u$  path with at most  $k$  edges, length  $\ell(OPT(x, k-1)) + \ell(x, u)$

$\implies \ell(OPT(u, k)) \leq \min_{w:(w,u) \in E} (\ell(OPT(w, k-1)) + \ell(w, u))$

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$\geq$ : Let  $z$  be node before  $u$  in  $OPT(u, k)$ , and let  $P'$  be the first  $k-1$  edges of  $OPT(u, k)$ .  
Then

$$\begin{aligned} \ell(OPT(u, k)) &= \ell(P') + \ell(z, u) \geq \ell(OPT(z, k-1)) + \ell(z, u) \\ &\geq \min_{w:(w,u) \in E} (\ell(OPT(w, k-1)) + \ell(w, u)) \end{aligned}$$

# Bellman-Ford Algorithm

Obvious dynamic program!

$M[u, 0] = \infty$  for all  $u \in V, u \neq v$

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for( $k = 1$  to  $n - 1$ ) {  
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**Running Time:**

- ▶ Obvious:  $O(n^3)$
- ▶ Smarter:  $O(mn)$

# Bellman-Ford: Correctness

## Theorem

*After algorithm completes,  $M[u, k] = \ell(OPT(u, k))$  for all  $k \leq n - 1$  and  $u \in V$ .*

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$$\begin{aligned} M[u, k] &= \min_{w:(w,u) \in E} (M[w, k-1]) + \ell(w, u) && \text{(algorithm)} \\ &= \min_{w:(w,u) \in E} (\ell(\mathbf{OPT}(w, k-1)) + \ell(w, u)) && \text{(induction)} \\ &= \ell(\mathbf{OPT}(u, k)) && \text{(optimal substructure)} \end{aligned}$$



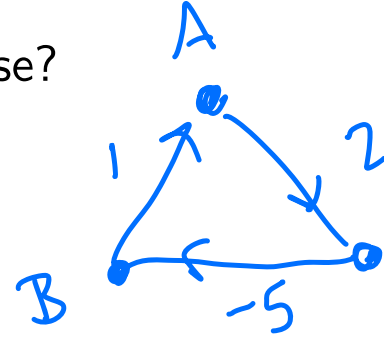
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Fun fact: best-known algorithm with negative (real) edge weights until last year!

Jeremy Fineman. *Single-Source Shortest Paths with Negative Real Weights in  $\tilde{O}(mn^{8/9})$  Time.*  
STOC '24



# Relaxations

Common primitive in shortest path algorithms

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- ▶ Use relaxations for Dijkstra's algorithm

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Intuition for  $\text{relax}(x, y)$ : can we improve  $\hat{d}(y)$  by going through  $x$ ?

```
relax( $x, y$ ) {  
    if( $\hat{d}(y) > \hat{d}(x) + \ell(x, y)$ ) {  
         $\hat{d}(y) = \hat{d}(x) + \ell(x, y)$   
         $y.\text{parent} = x$   
    }  
}
```

# Bellman-Ford as Relaxations

```
for( $i = 1$  to  $n$ ) {  
  foreach( $u \in V$ ) {  
    foreach(edge ( $x, u$ )) {  
      relax( $x, u$ )  
    }  
  }  
}
```

# Bellman-Ford as Relaxations

```
for(i = 1 to n) {  
    foreach(u ∈ V) {  
        foreach(edge (x, u)) {  
            relax(x, u)  
        }  
    }  
}
```

Not precisely the same: freezing/parallelism

# Dijkstra's Algorithm

# High Level

Intuition: “greedy starting at  $v$ ”

- ▶ BFS but with edge lengths: use priority queue (heap) instead of queue!

Pros: faster than Bellman-Ford (super fast with appropriate data structures)

Cons: Doesn't work with negative edge weights.



# Dijkstra's Algorithm

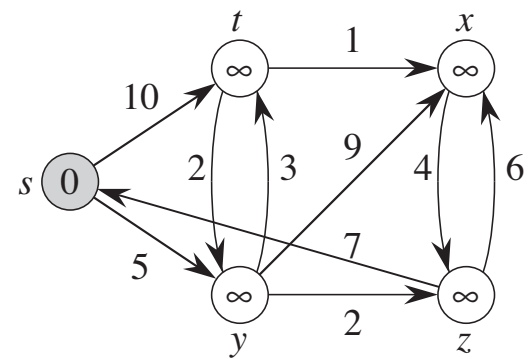
$T = \emptyset$

$\hat{d}(v) = 0$

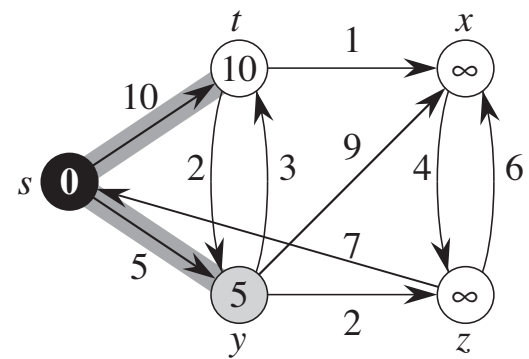
$\hat{d}(u) = \infty$  for all  $u \neq v$

```
while(not all nodes in  $T$ ) {  
    let  $u$  be node not in  $T$  with minimum  $\hat{d}(u)$   
    Add  $u$  to  $T$   
    foreach edge  $(u, x)$  with  $x \notin T$  {  
        relax( $u, x$ )  
    }  
}
```

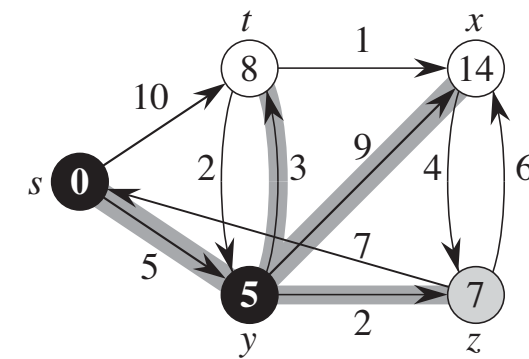
# Dijkstra Example



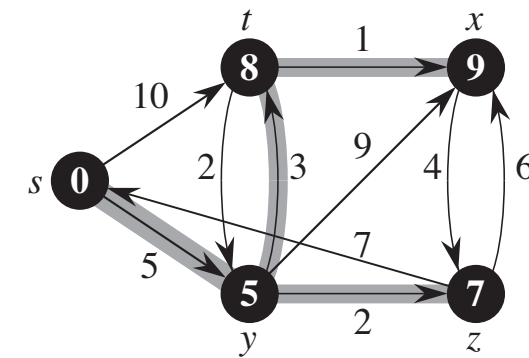
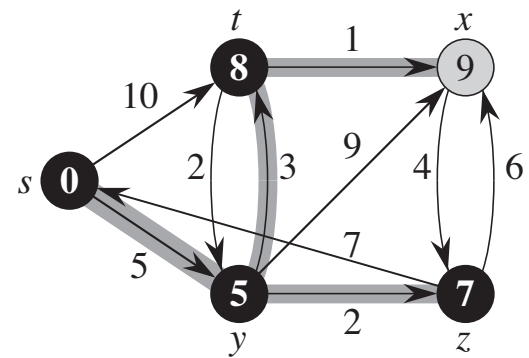
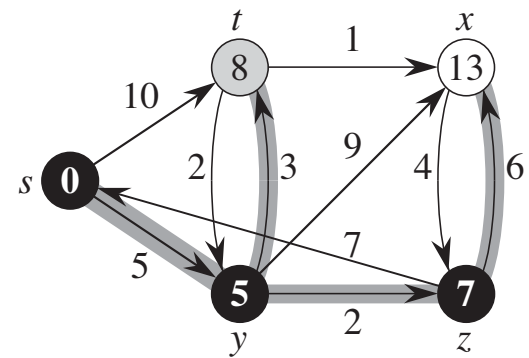
(a)



(b)



(c)



# Dijkstra Correctness

## Theorem

*Throughout the algorithm:*

1.  $\mathcal{T}$  is a shortest-path tree from  $\mathbf{v}$  to the nodes in  $\mathcal{T}$ , and
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**Proof.** Induction on  $|\mathcal{T}|$  (iterations of algorithm)

**Base Case:** After first iteration (when  $|\mathcal{T}| = 1$ ), added  $\mathbf{v}$  to  $\mathcal{T}$  with  $\hat{d}(\mathbf{v}) = d(\mathbf{v}) = 0$  ✓

## Correctness: Inductive Step (Sketch)

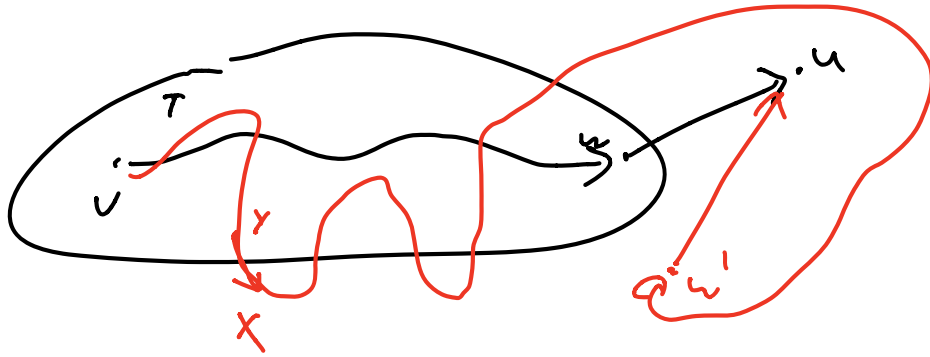
Consider iteration when  $\mathbf{u}$  added to  $\mathbf{T}$ , let  $\mathbf{w} = \mathbf{u}.\mathbf{parent}$

$$\implies \hat{d}(\mathbf{u}) = \hat{d}(\mathbf{w}) + \ell(\mathbf{w}, \mathbf{u}) = d(\mathbf{w}) + \ell(\mathbf{w}, \mathbf{u}) \text{ (induction)}$$

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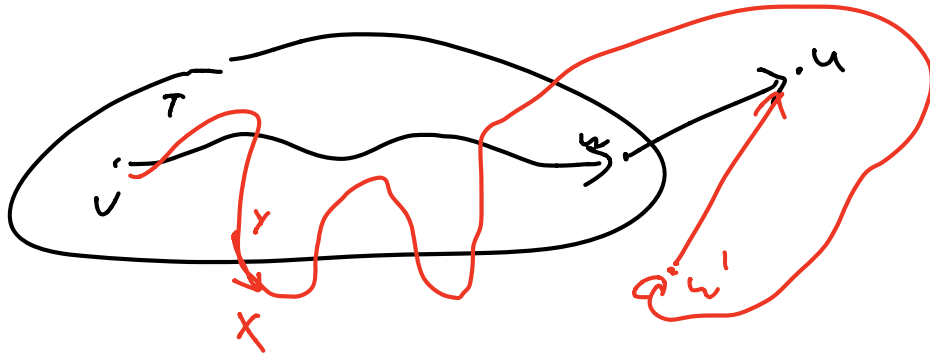


- ▶ Red path  $P$  actual shortest path, black path found by Dijkstra
- ▶  $w'$  predecessor of  $u$  on  $P$ . Can't be in  $T$ .
  - ▶ If it was, would have  $\hat{d}(w') = d(w')$  by induction, would have relaxed  $(w', u)$ , so would have  $w' = u.\text{parent}$
- ▶  $x$  first node of  $P$  outside  $T$ , previous node  $y$

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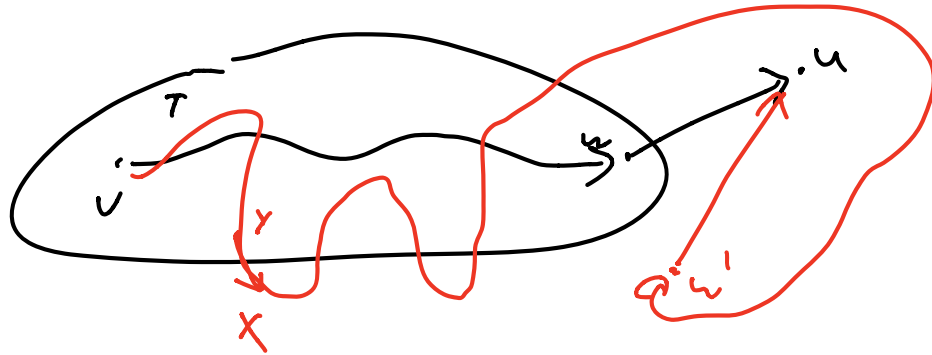
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Contradiction! Algorithm would have chosen  $x$  next, not  $u$ .

# Running Time

Algorithm needs to:

- ▶ Select node with minimum  $\hat{d}$  value  $n$  times
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Fibonacci Heap:

- ▶ Insert, Decrease-Key  $O(1)$  amortized
- ▶ Extract-Min  $O(\log n)$  amortized

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