

DSC40B:  
Theoretical Foundations of Data  
Science II

Lecture 14: *Shortest Path in  
Weighted Graphs – part I*

Instructor: Yusu Wang

# Prelude

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## ▶ Previously

- ▶ Basics of graphs, representations, graph search strategies
- ▶ BFS: also leads to shortest path distance in input graph
  - ▶ Note: graph is unweighted!

## ▶ Today:

- ▶ Weighted graphs
  - ▶ where each edge has an edge weight
- ▶ Properties of shortest paths in weighted graphs
- ▶ Bellman-Ford algorithm for computing single-source shortest path for any weighted graphs



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# Weighted graphs, and shortest paths in them



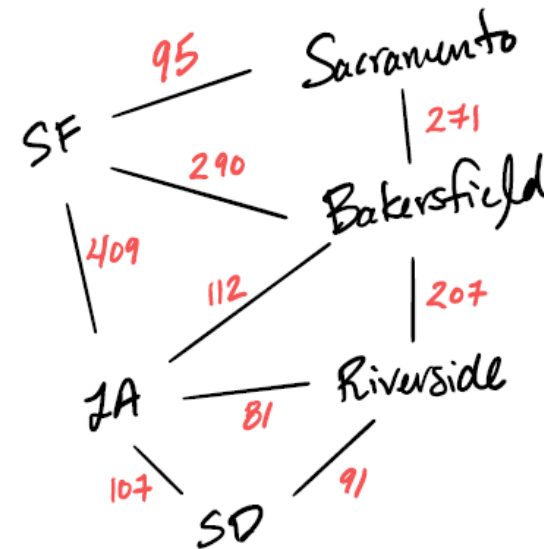
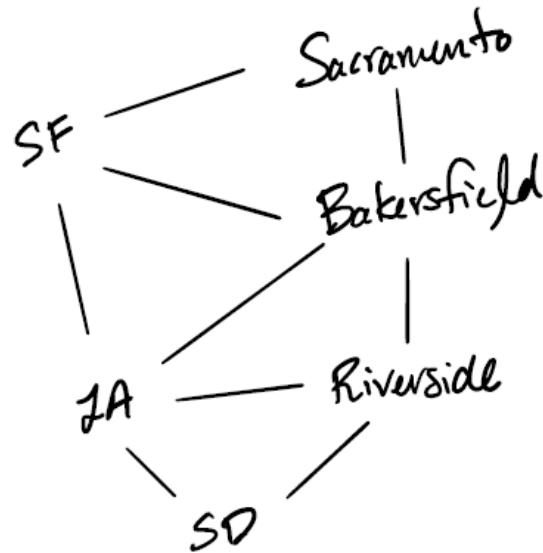
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- ▶ Unweighted graph:

- ▶  $G = (V, E)$

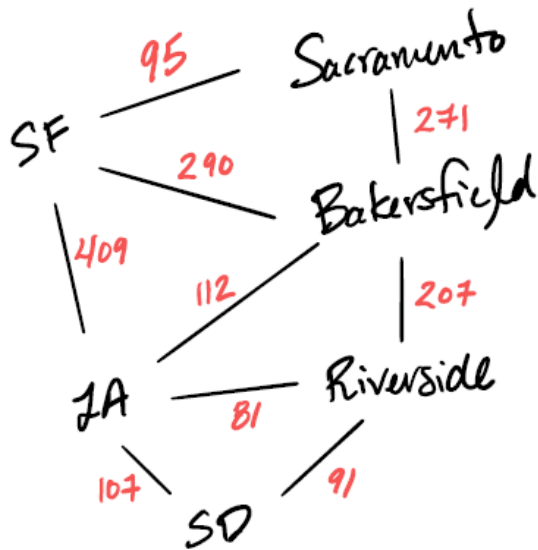
- ▶ Nodes and edges can carry meaning, and thus can carry weights as well.

- ▶ Example: transportation network



# Weighted Graph

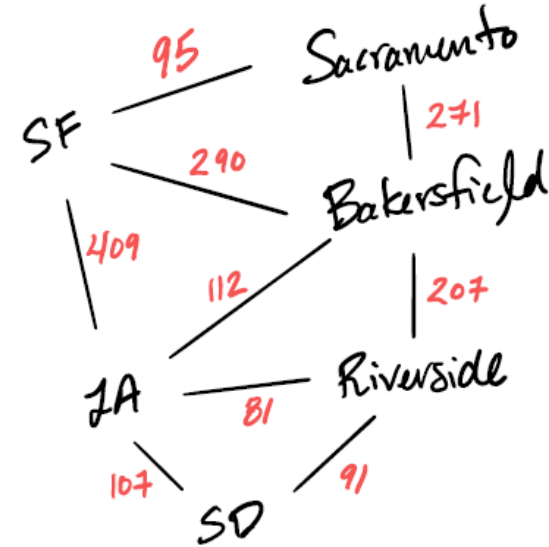
- ▶ (Edge) **weighted graph**  $G = (V, E; \omega)$ 
  - ▶ is a graph  $G = (V, E)$  together with an edge weight assignment map:  $\omega: E \rightarrow R$
  - ▶ i.e., a graph where each edge  $e$  has a weight (real value)  $\omega(e)$



- ▶ can be directed / undirected
  - ▶ weights can be positive/negative
- ▶ useful in many applications
  - ▶ strength of connection in a social network
  - ▶ distance in a transportation network
  - ▶ probability that two nodes interact in a protein-protein interaction network

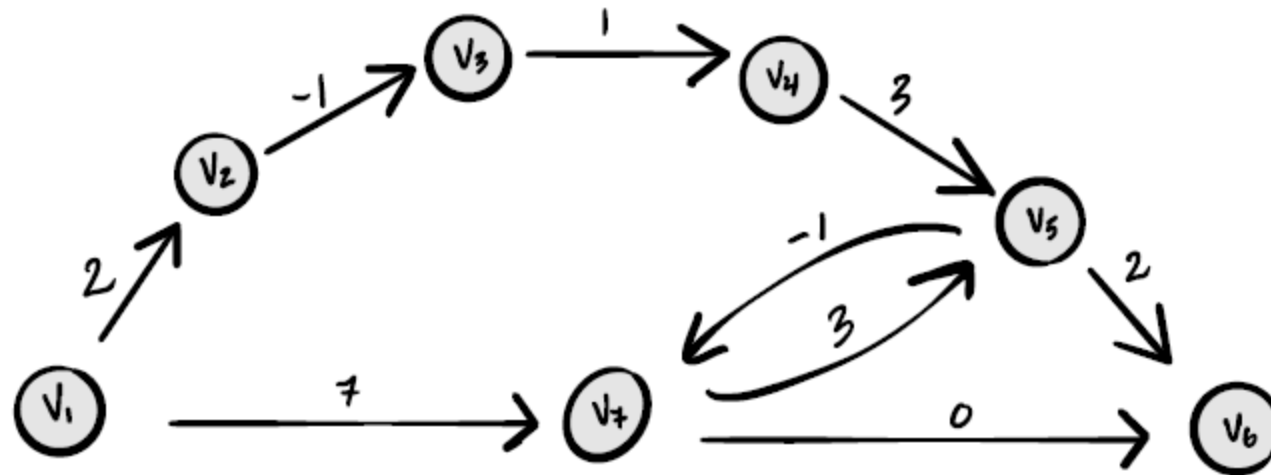
# Path lengths

- ▶ Given a path in a weighted graph, its **length** is the total weights of all edges in the path.
- ▶ Examples:
  - ▶ SF, LA, Bakersfield, Riverside
    - ▶ length = 728
  - ▶ SF, LA, Riverside
    - ▶ length = 490
  - ▶ LA, SD, Riverside, LA, SF
    - ▶ length = 688
  - ▶ LA, SF
    - ▶ length = 409
  - ▶ LA, Bakersfield, SF
    - ▶ length = 402



# Shortest Paths

- ▶ A **shortest path** from  $u$  to  $v$  is a path from  $u$  to  $v$  with minimum length.

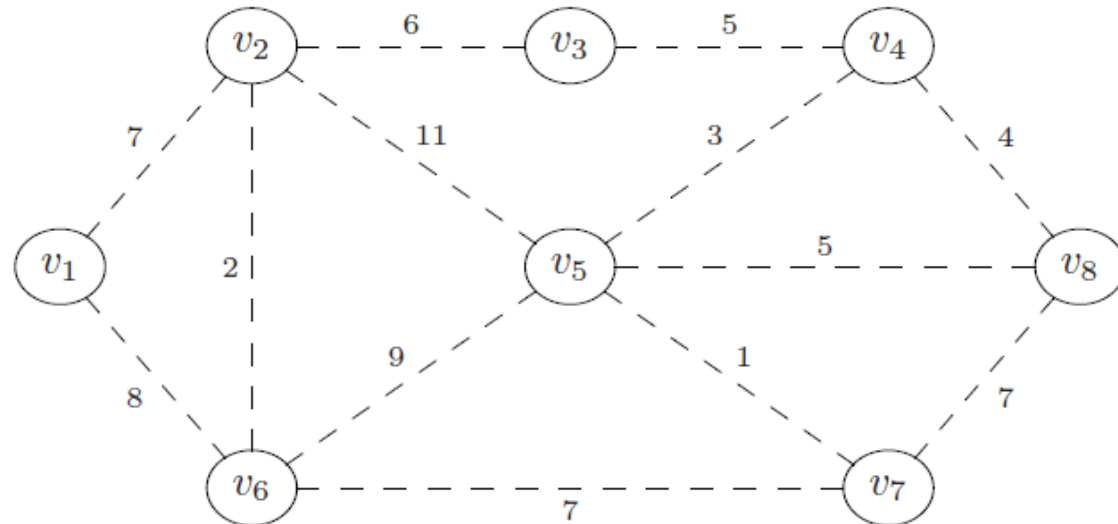


- ▶ Shortest path from  $v_1$  to  $v_6$ ?



# Shortest Paths

- ▶ A **shortest path** from  $u$  to  $v$  is a path from  $u$  to  $v$  with minimum length.
- ▶ The (shortest-path) **distance** from  $u$  to  $v$  is the length of the shortest path from  $u$  to  $v$
- ▶ A shortest path from  $u$  to  $v$  may not be unique
  - ▶ but all shortest paths from  $u$  to  $v$  have same length





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▶ An unweighted graph  $G = (V, E)$

▶ can be thought of as a weighted graph where all edges have the same unit weight, i.e.,  $\omega(e) = 1$  for any edge  $e \in E$

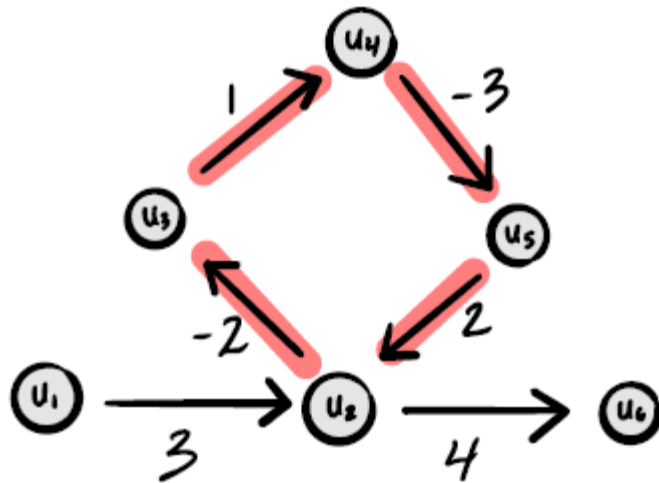
▶ Hence,

▶ BFS can compute the shortest path lengths (to the source) for an unweighted graph, or equivalently, a graph where all edges have **the same edge weights!**



# Properties of shortest paths

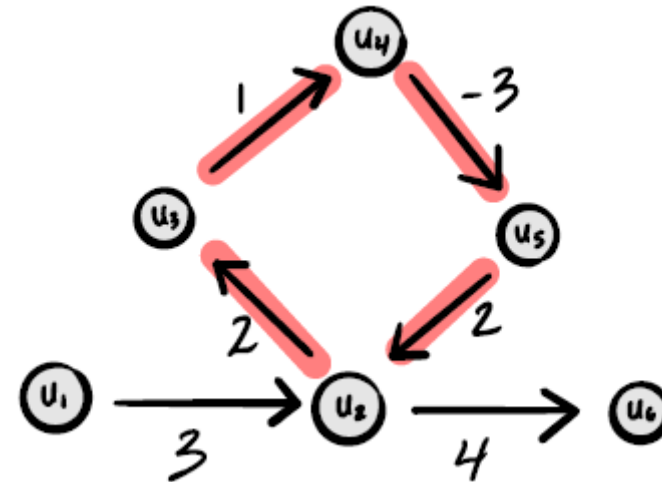
- ▶ Shortest path is not well-defined if the input graph has “**negative cycles**”
  - ▶ A **negative cycle** is a cycle whose length is negative



Negative weights are usually okay. Negative cycles make shortest path not well-defined.

# Properties of shortest paths

- ▶ Shortest path is not well-defined if the input graph has “**negative cycles**”
  - ▶ A **negative cycle** is a cycle whose length is negative
- ▶ Assume we have a graph with no negative cycle
  - ▶ Then for any pair  $u, v \in V$ , there is always a shortest path that is **simple**.
    - ▶ If a path is not simple, there is a cycle inside, then removing this cycle can only make the path length shorter



# Properties of shortest paths

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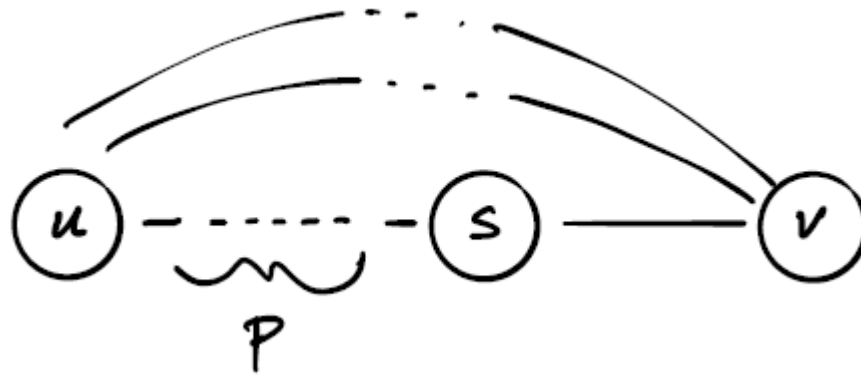
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  - ▶ Then for any pair  $u, v \in V$ , there is always a shortest path that is **simple**.
    - ▶ If a path is not simple, there is a cycle inside, then removing this cycle can only make the path length shorter
- ▶ Hence from now on, when we can assume that shortest paths are **simple**.



# Properties of shortest path

## Optimal Substructure Property (Theorem):

If  $(u_1, u_2, \dots, u_m)$  is a shortest path from  $u_1$  to  $u_m$ , then any sub-path  $(u_i, \dots, u_j)$  is also a shortest path.



# Property of shortest paths

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- ▶ From now on, let  $\delta(u, v)$  denote the (shortest path) distance from  $u$  to  $v$
- ▶ Triangle inequality:
  - ▶ Suppose  $(z, v)$  is an edge. Then
$$\delta(s, v) \leq \delta(s, z) + \omega(z, v)$$
  - ▶ If  $\delta(s, v) = \delta(s, z) + \omega(z, v)$  , then  $z$  is the predecessor of  $v$  along a shortest path from  $s$  to  $v$ 
    - ▶ that is,  $(z, v)$  is the last edge along a shortest path from  $s$  to  $v$



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Single-source shortest paths (SSSP)  
and Does BFS work for weighted graphs?



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▶ **Single-source shortest path (SSSP) problem:**

- ▶ Given a weighted graph  $G = (V, E; \omega)$ , and a source node  $s$ , compute the shortest path distance from  $s$  to all other nodes in  $V$ 
  - ▶ i.e, compute  $\delta(s, u)$  for all  $u \in V$
- ▶ Once we have an algorithm for SSSP, we can use it to solve for all-pairs shortest path problem (where we compute shortest path distance among all pairs of nodes in  $V$ )
  - ▶ by simply running SSSP once using each node as source





# Recall

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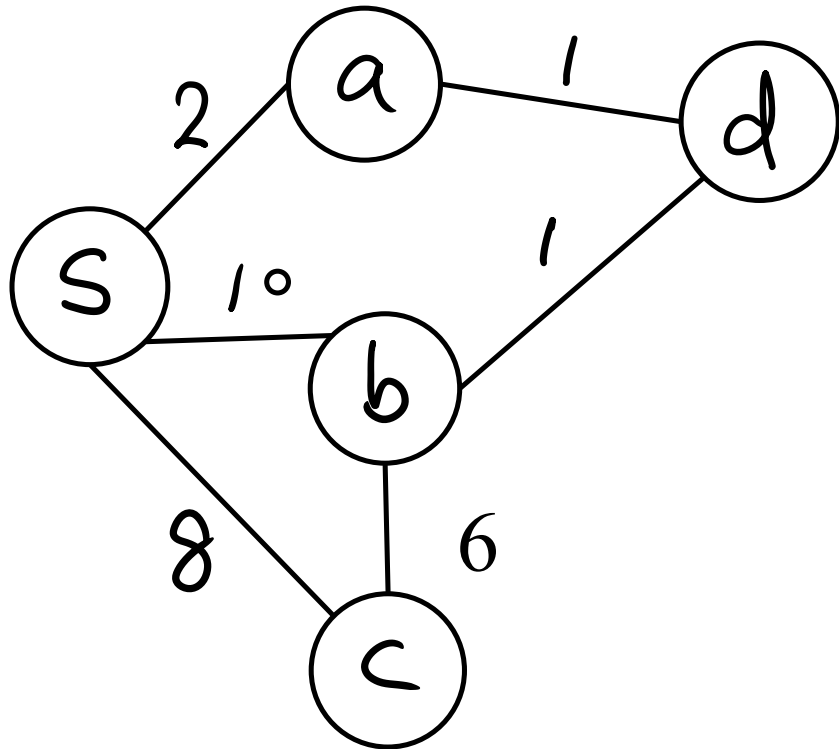
- ▶ An unweighted graph  $G = (V, E)$ 
  - ▶ can be thought of as a weighted graph where all edges have the same unit weight, i.e.,  $\omega(e) = 1$  for any edge  $e \in E$
- ▶ Hence,
  - ▶ BFS can compute the shortest path distance for an unweighted graph, or equivalently, a graph where all edges have **the same edge weights!**



# Can BFS idea work?

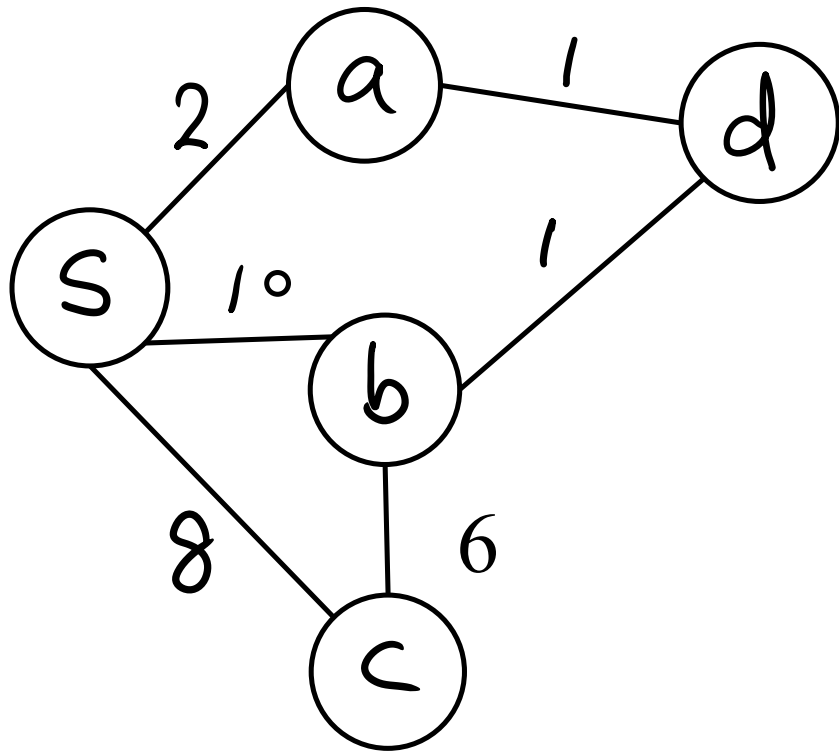
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- ▶ Not really
- ▶ Example:



# Can BFS idea work?

- ▶ Not really
- ▶ Example:



- ▶ Intuitively, what went wrong?
  - ▶ Recall BFS is a greedy algorithm and keeps exploring nodes in increasing distance to the source.
  - ▶ In BFS, at the time we explore a node  $u$ , we have found its correct distance to the source  $s$  already.
  - ▶ This however fails when edges have non-equal weights.

# Can we use BFS to solve SSSP?

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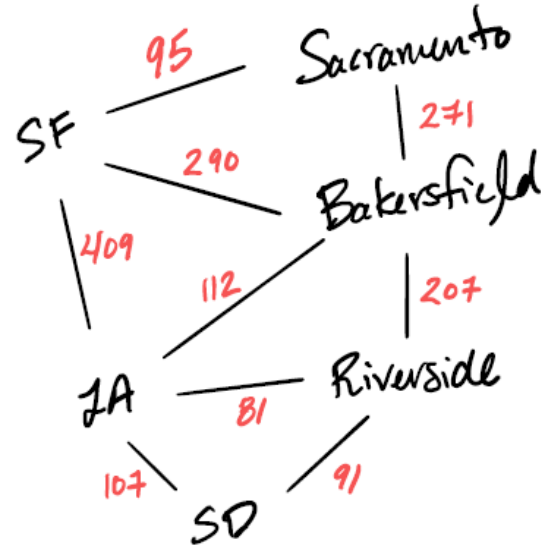
- ▶ Suppose edge weights are all positive integers
- ▶ Then here is an idea to compute SSSP:
- ▶ Input:
  - ▶  $G = (V, E; \omega)$  where  $\omega: E \rightarrow \mathbb{Z}$  gives integer weights, and a source node  $s \in V$
- ▶ Output:
  - ▶ The shortest path distance from  $s$  to all nodes in  $V$
- ▶ Approach #0:
  - ▶ Step 1: For each edge with weight  $k$ , replace it by a path with  $k$  edges, each of which has weight 1. Call the new graph  $\hat{G} = (\hat{V}, \hat{E})$ .
  - ▶ Step 2: Use BFS on the new graph  $\hat{G}$



# Problem with Approach #0

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- ▶ Only works when edges have positive integer weights
- ▶ Even for integer-weighted graphs, it can be highly inefficient.



- ▶ We need better algorithms for SSSP.



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Key operation for SSSP:  
Edge Update



# Two algorithms for SSSP

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## ▶ Bellman-Ford algorithm

- ▶ Works for any weighted graph  $G = (V, E)$
- ▶ Has time complexity  $\Theta(V \cdot E)$

## ▶ Dijkstra algorithm

- ▶ Works for graphs with **positive edge weights**
- ▶ More efficient! Has time complexity  $\Theta((V + E) \lg V)$  (which we will discuss in class), and can be made to run in  $\Theta(V \lg V + E)$  time.

## ▶ Both algorithms

- ▶ use an **update**( ) operation to keep track of shortest path estimates
- ▶ perform it repeatedly till all shortest path distances to source are round

From now on, for simplicity, we use  $V$  and  $E$  to denote  $|V|$  and  $|E|$  in time complexity.

# Estimated shortest path

- ▶ Fix the source node to be  $s$
- ▶ Both algorithms keep track of the shortest path found so far,
  - ▶ we call these **estimated shortest paths**
  - ▶ set  $u.est$  = the length of estimated shortest path source  $s$  to  $u$
- ▶ At the beginning,  $u.est = \infty$  for all nodes other than the source  $s$
- ▶ And  $s.est = 0$
- ▶ Then the algorithm will iteratively update shortest path estimates  $u.est$  when it finds better (shorter) path to reach it.





# Estimated shortest path so far

- ▶ Fix the source node to be  $s$
- ▶ Both algorithms keep track of the shortest path found so far,
  - ▶ we call these **estimated shortest paths**
  - ▶ set  $u.est$  = the length of estimated shortest path source  $s$  to  $u$
- ▶ Key: during the update process, at any moment,
  - ▶ the estimated shortest path can only improve,
  - ▶ is at least as long as the true shortest path (i.e,  $u.est \geq \delta(s, u)$ ),
  - ▶ and once it finds shortest distances, it will stay that way.
- ▶ For each node  $u$ , we will remember  $u$ 's
  - ▶ predecessor along the estimated shortest path from  $s$  to  $u$
  - ▶  $u.est$ , the current estimated distance from  $s$  to  $u$



# Updating edges

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- ▶ The way we update the estimates is via repeatedly performing “**update**( $u, v$ )” operation over an edge  $(u, v) \in E$ 
  - ▶  $v$  has current predecessor
  - ▶ is  $u$  a better predecessor for  $v$ ?
  - ▶ if yes, then we should update  $v.est$  and  $v$ 's predecessor!

- ▶ In particular:

Is the current shortest path from

source  $s \rightsquigarrow u \rightarrow v$

shorter than the current shortest path from

source  $s \rightsquigarrow v$ 's current predecessor  $\rightarrow v$  ?

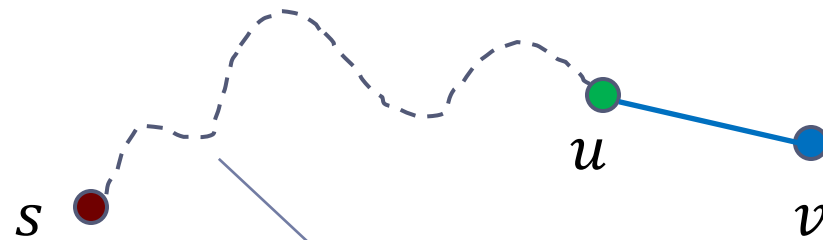
If **yes**, then we have discovered **a shorter path to  $v$** , and we change  $v$ 's predecessor and estimated distance.



# Updating edges

**update**( $u, v$ ) // where  $(u, v) \in E$  is an edge in graph

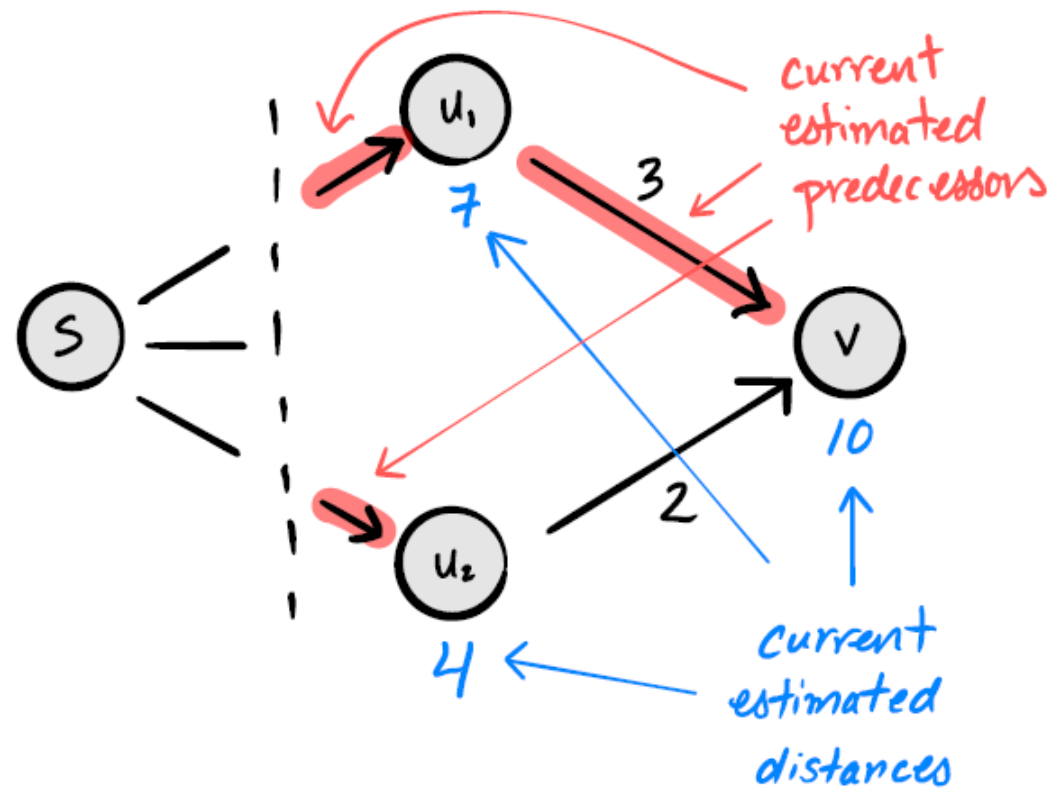
- ▶ If  $v.\text{est} > u.\text{est} + \omega(u, v)$ 
  - ▶ Then we found a better path from  $s$  to  $v$ 
    - by first going from  $s$  to  $u$ , and then go to  $v$  through edge  $(u, v)$
  - ▶ So we update  $v.\text{est} = u.\text{est} + \omega(u, v)$  and set  $u$  to be  $v$ 's predecessor
- ▶ Otherwise, we do nothing.



current estimated shortest  
path from  $s$  to  $u$

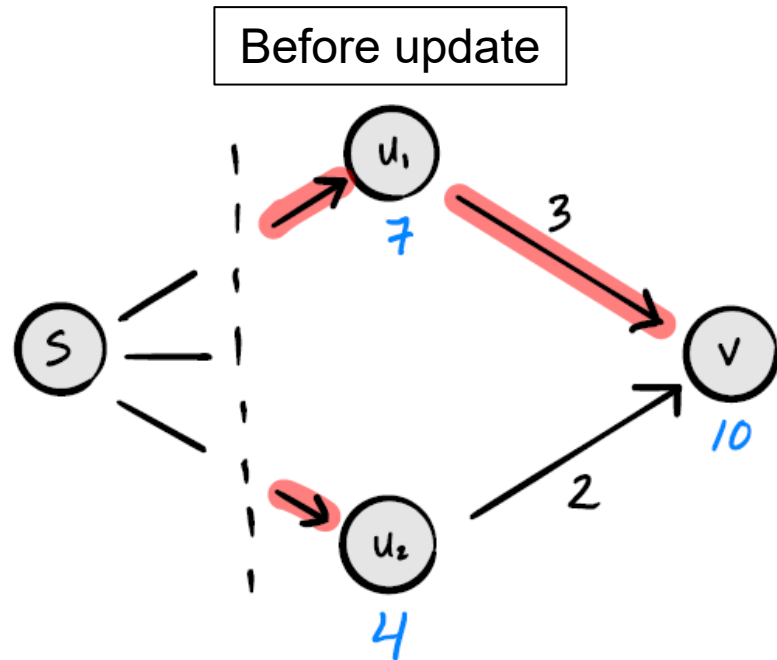
# Example

- Before **update**( $u_2, v$ )

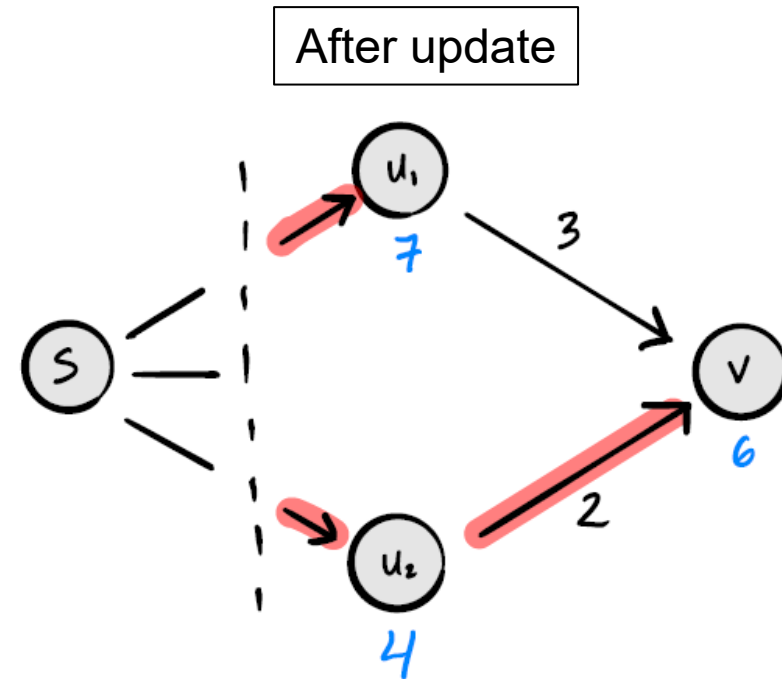


# Example

## ► **update**( $u_2, v$ )



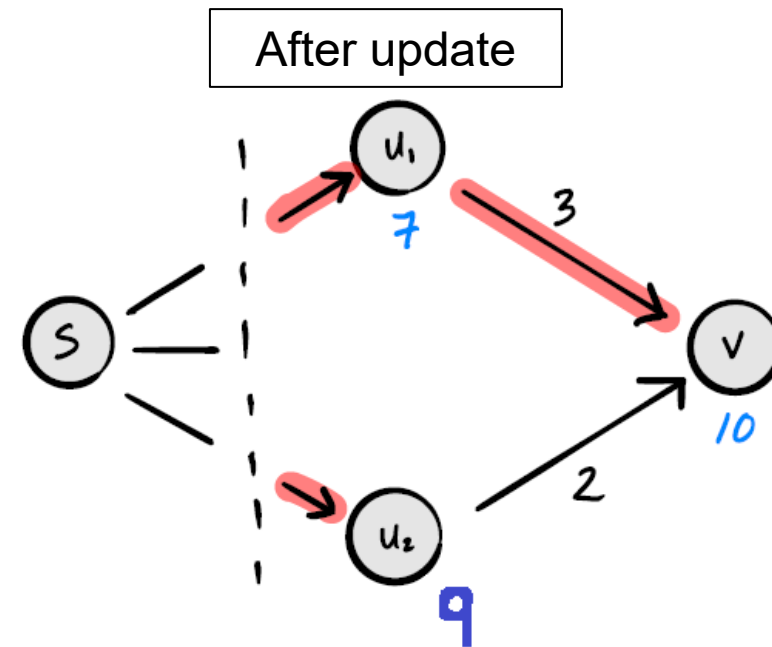
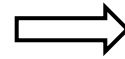
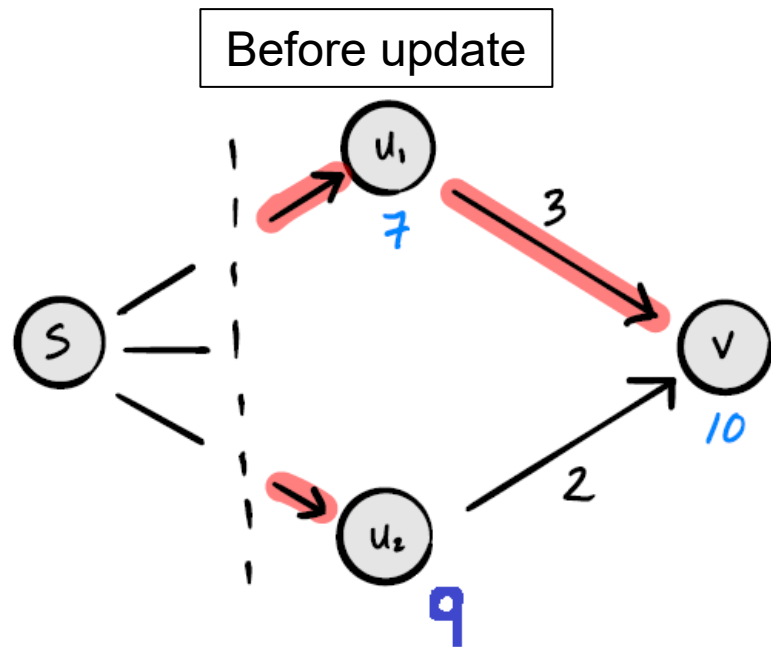
$v.est = 10$ ,  $u_2.est = 4$ ,  $\omega(u_2, v) = 2$   
 $\Rightarrow v.est > u_2.est + \omega(u_2, v)$   
 $\Rightarrow$  find a shorter path from  $s$  to  $v$  !



So we update  
 $v.est = u_2.est + \omega(u_2, v) = 6$   
and set  $v$ 's predecessor to  $u_2$

# Another Example

## ► **update**( $u_2, v$ )



Do Nothing!

$v.est = 10$ ,  $u_2.est = 9$ ,  $\omega(u_2, v) = 2$   
 $\Rightarrow v.est < u_2.est + \omega(u_2, v)$   
 $\Rightarrow$  The path from  $s$  to  $u_2$  then to  $v$  is **not shorter** than what already discovered for  $v$ !

# Implementing update() in python

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- ▶ To implement **update**(u,v) in python, let
  - ▶ **est** be a dictionary of estimated shortest path distances
  - ▶ **predecessor** be a dictionary of estimated shortest path predecessors
  - ▶ **weights** be a function which returns edge weights



# Implementing update() in python

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```
def update(u, v, weights, est, predecessor):  
    """Update edge (u,v)."""  
    if est[v] > est[u] + weights(u,v):  
        est[v] = est[u] + weights(u,v)  
        predecessor[v] = u  
        return True  
    else:  
        return False
```

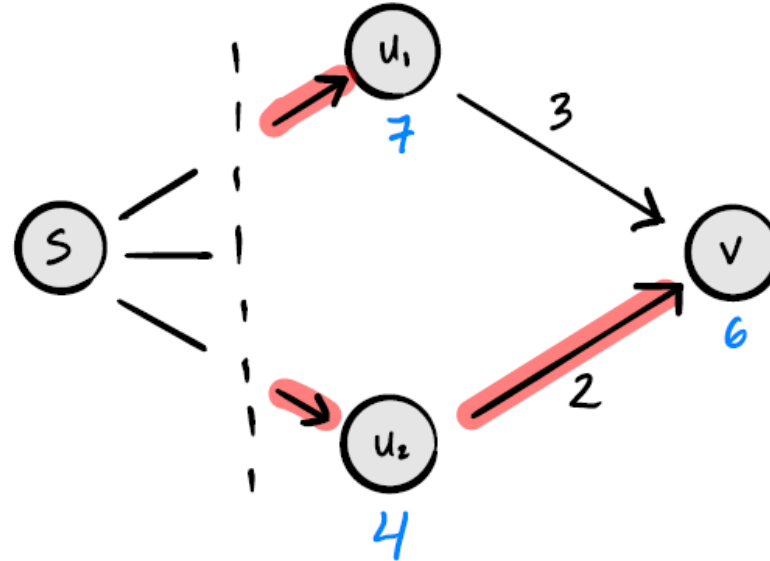
Time complexity:  $\Theta(1)$





## When does an update discover a shortest path?

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- ▶ So  $\text{update}(u_2, v)$  discovered a new estimated shortest path from  $s$  to  $v$
- ▶ Is this the shortest path?
- ▶ **Not necessarily:** We might discover a shorter path, say, reaching  $v$  through  $u_1$

# When does an update discover a shortest path?

## [Theorem Update]

Let  $u$  and  $v$  be graph nodes

Suppose:

- ▶ (a) current shortest path distance estimate  $u.est$  is correct
  - ▶ i.e.,  $u.est = \delta(s, u)$
- ▶ (b) there is a shortest path from  $s$  to  $v$  with  $u$  being  $v$ 's predecessor

Then, after **update**( $u, v$ ), the estimated shortest path distance to  $v$  is correct

- ▶ i.e., after update,  $v.est = \delta(s, v)$



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# Bellman-Ford shortest path algorithm

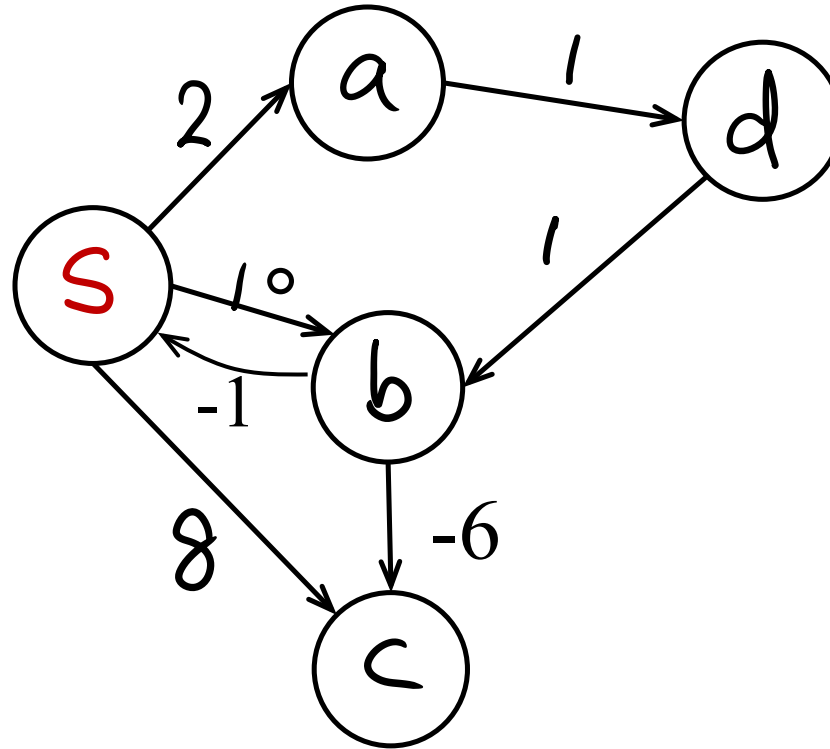


- 
- ▶ [Theorem Update] implies that if we have already computed the shortest path distance from source  $s$  for those nodes whose shortest paths from  $s$  have  $k$  hops, then we can compute those shortest paths with  $k + 1$  hops via the `update()` operations.
    - ▶ In particular, let  $u$  be the predecessor of  $v$  along some shortest path from  $s$  to  $v$ , and assume  $u.est$  is already correct (i.e,  $u.est = \delta(s, u)$ )
    - ▶ then performing `update(u,v)` will render  $v.est = \delta(s, v)$
  - ▶ [Observation]:
    - ▶ Any any moment, if  $v.est$  is already correct, then performing further `update()` on any edge will not change  $v.est$ .
- 



## More specifically

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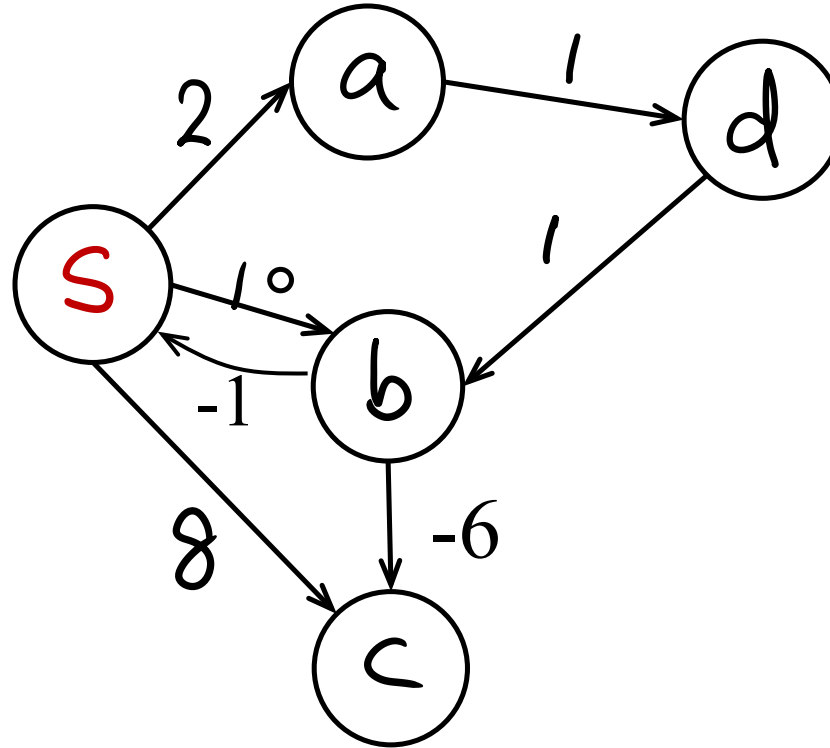


- ▶ At the beginning, we only know that  $s.est = 0$
- ▶ For all other nodes  $v \in V$ , we set  $v.est = \infty$



## More specifically

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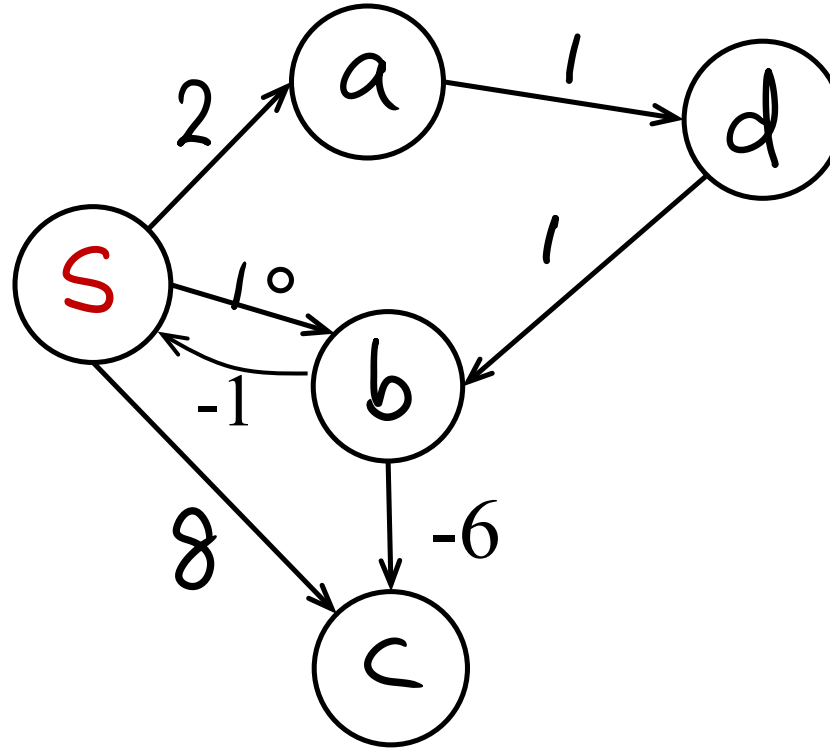


- ▶ Now perform **update** for **all edges** in  $E$
- ▶ Afterwards, all nodes whose shortest path from  $s$  has only **one** edge are now guaranteed to be estimated **correctly**!



## More specifically

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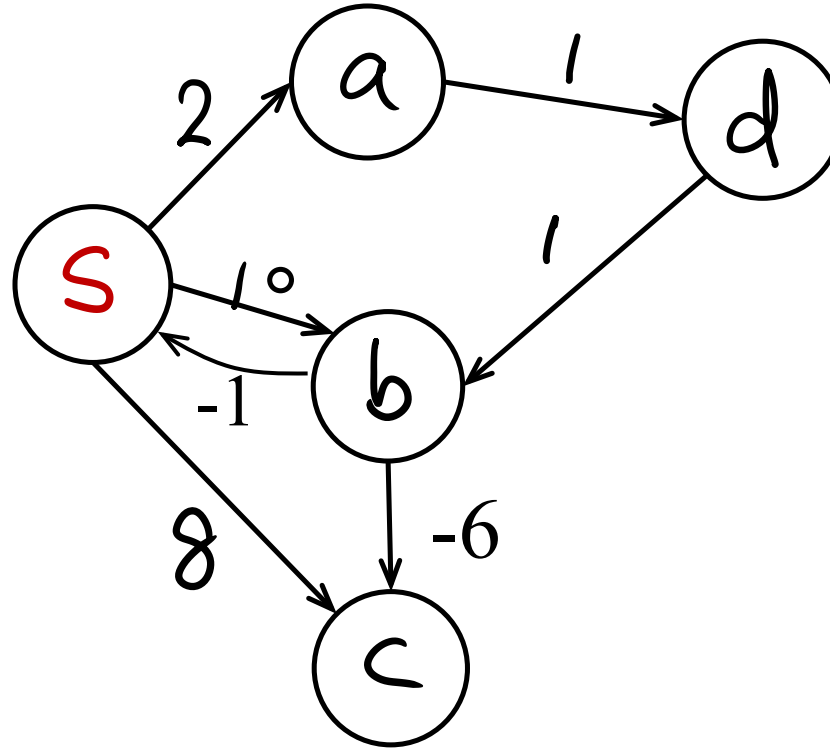


- ▶ Now perform **update** for **all edges** in  $E$  again
- ▶ Afterwards, all nodes whose shortest path from  $s$  has at most **two** edges are now guaranteed to be estimated **correctly**!



## More specifically

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- ▶ Now perform **update** for **all edges** in  $E$  **repeatedly** ...
- ▶ Afterwards, all nodes whose shortest path from  $s$  has at most **more and more** edges will be now guaranteed to be estimated **correctly**





# Loop Invariant

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- ▶ Suppose we perform “update all edges”  $k$  times
- ▶ Loop invariant:
  - ▶ Then all nodes whose shortest path from source  $s$  has  $\leq k$  edges are guaranteed to be estimated correctly.
- ▶ Note that it is possible that some nodes whose shortest path has  $> k$  edges are also estimated correctly.



- 
- ▶ How many times should we perform “update all edges”
    - ▶ in order to guarantee that we find shortest path for all nodes?
  - ▶ Note that shortest paths are **simple**
    - ▶ Hence a shortest path has at most  $V - 1$  edges in it
  - ▶ Hence after  $r = V - 1$  rounds of “update all edges”,
    - ▶ we can guarantee that the shortest path distances to **all nodes** in  $V$  are estimated correctly.

This is the idea behind Bellman-Ford Algorithm !



# Bellman-Ford Algorithm in Python

```
def bellman_ford(graph, weights, source):  
    """Assume graph is directed."""  
    est = {node: float('inf') for node in graph.nodes}  
    est[source] = 0  
    predecessor = {node: None for node in graph.nodes}  
  
    for i in range(len(graph.nodes) - 1):  
        for (u, v) in graph.edges:  
            update(u, v, weights, est, predecessor)  
  
    return est, predecessor
```

- ▶ Setup takes \_\_\_\_\_ time
- ▶ Each update takes \_\_\_\_\_ time
- ▶ There are \_\_\_\_\_ numbers of updates
- ▶ Total time complexity is \_\_\_\_\_.



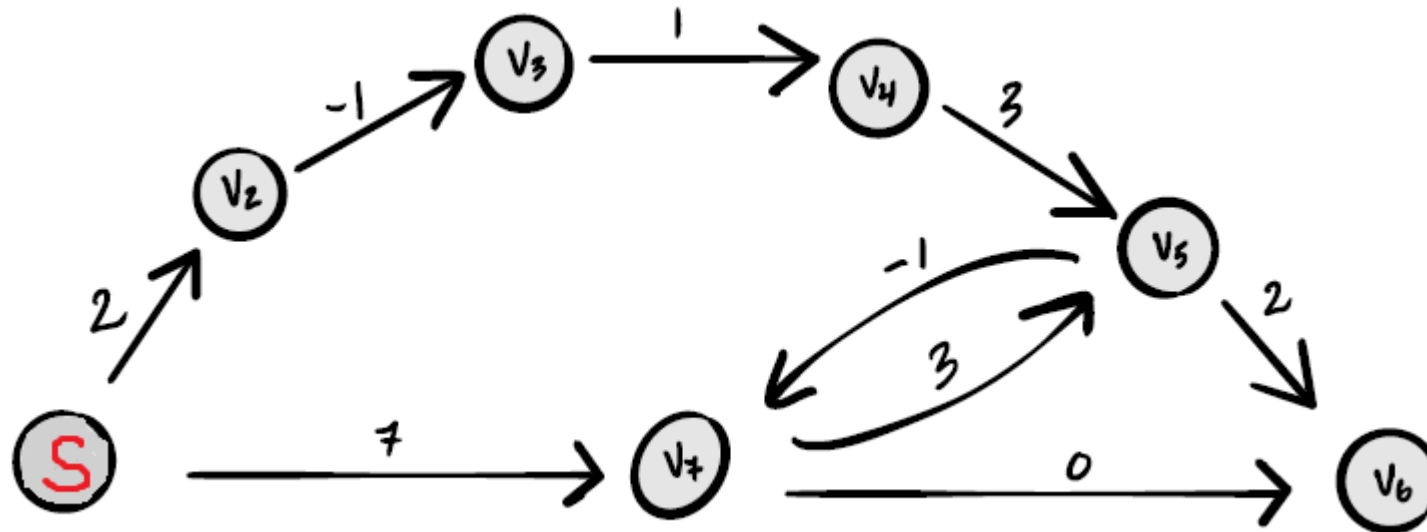
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    for i in range(len(graph.nodes) - 1):  
        for (u, v) in graph.edges:  
            update(u, v, weights, est, predecessor)  
  
    return est, predecessor
```

- ▶ Setup takes  $\Theta(V)$  time
- ▶ Each update takes  $\Theta(1)$  time
- ▶ There are  $E \cdot (V - 1)$  numbers of updates
- ▶ Total time complexity is  $\Theta(V \cdot E)$ .

# Example

- ▶ Suppose `graph.edges` returns edges in the following order:
  - ▶  $(v_3, v_4), (s, v_2), (v_2, v_3), (v_7, v_6), (v_5, v_7), (v_7, v_5), (v_4, v_5), (v_5, v_6), (v_5, v_4), (s, v_7)$



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# Early-stopping and negative cycles



# Early-stopping

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- ▶ Bellman-Ford may not need to run  $V - 1$  iterations
- ▶ If there is no distance change after a round, we can stop (called **early-stopping**)

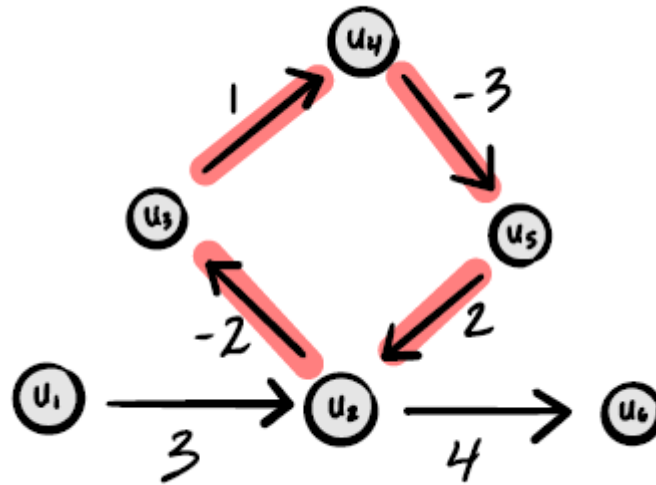
```
def bellman_ford(graph, weights, source):  
    """Early stopping version."""  
    est = {node: float('inf') for node in graph.nodes}  
    est[source] = 0  
    predecessor = {node: None for node in graph.nodes}  
  
    for i in range(len(graph.nodes) - 1):  
        any_changes = False  
        for (u, v) in graph.edges:  
            changed = update(u, v, weights, est, predecessor)  
            any_changes = changed or any_changes  
        if not any_changes:  
            break  
    return est, predecessor
```



# Negative Cycles

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- Recall: if a graph has negative cycle(s), then the shortest paths are not well-defined

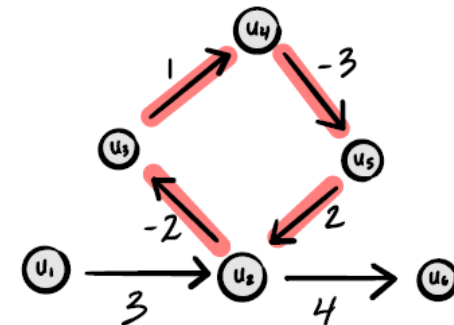




# Negative Cycles

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- ▶ Recall: if a graph has negative cycle(s), then the shortest paths are not well-defined
- ▶ If a graph does not have any negative cycle, then the estimated distances **stop changing** after  $V - 1$  iterations
  - ▶ Why?
- ▶ But if a graph has negative cycle(s), then some estimated distances **continue to decrease** even after  $V$  iterations



# Negative Cycles

---

- ▶ If a graph does not have any negative cycle, then the estimated distances **stop changing** after  $V - 1$  iterations
- ▶ But if a graph has negative cycle(s), then some estimated distances **continue to decrease** even after  $V$  iterations
- ▶ Hence Bellman-Ford can be modified to also detect negative cycles
  - ▶ Run a  $V$  iteration of “update all edges”
  - ▶ If any estimated distance is still decreasing, a negative cycle exists



# Modified Bellman-Ford with early stopping and negative cycle detection

---

```
def bellman_ford(graph, weights, source):  
    """Early stopping version, detects negative cycles."""  
    est = {node: float('inf') for node in graph.nodes}  
    est[source] = 0  
    predecessor = {node: None for node in graph.nodes}  
  
    for i in range(len(graph.nodes)):  
        any_changes = False  
        for (u, v) in graph.edges:  
            changed = update(u, v, weights, est, predecessor)  
            any_changes = changed or any_changes  
        if not any_changes:  
            break  
    # this will be True if negative cycles exist  
    contains_negative_cycles = any_changes  
    return est, predecessor, contains_negative_cycles
```



---

FIN

