Dynamic Programming IV: Shortest Path Revisited

Admin

- Additional office hours tomorrow: **12.30 - 2 pm**
- Office hours today and tomorrow:
    - Come with any questions you have
    - Or any topic that you'd want reviewed
- No lecture on Friday: 24-hour open-book midterm
    - Can be turned in latest by 10 am Sunday
    - No late work permitted on exam
- Review item: Solving recurrences with an $O()$ term
    - By definition, constants do not change as input size changes

Partitioning Books

Reading: Linked on GLOW

Partitioning Work

- Suppose we have to scan through a shelf of books, and each book has a different size
- We want to divide the shelf into k region of books, and each region is assigned one of the workers
- Order of books fixed by cataloging system: cannot reorder/ rearrange the books
- **Goal**: divide the work is a fair way among the workers

Linear Partition Problem

- **Input.** A input arrangement S of nonnegative integers $\{s_1, \ldots, s_n\}$ and an integer k
- **Problem.** Partition S into k ranges such that the **maximum sum** over all the ranges is **minimized**
- Example.
  - Consider the following arrangement

    100 200 300 400 500 600 700 800 900

  - If $k = 3$, a partition that minimizes the maximum sum:

    100 200 300 400 500 | 600 700 | 800 900

Subproblem

- **Subproblem**

$M(i, j)$ be the optimal cost of partitioning elements $s_1, s_2, \ldots, s_i$ using j partitions, where $1 \leq i \leq n$, $1 \leq j \leq k$

- **Final answer**

$M(n, k)$

Base Cases

- Let us think about which rows/columns can we fill initially
- What about the first row corresponding to item 1?
- Remember that optimal cost is max sum over all partitions
- $M(1, j)$: optimal cost of partitioning s_1 across j partitions
- For $j = 1,2,\ldots,k$ we can fill out the first column as:

$$\boxed{M(1, j) = s_1}$$

Base Cases

- Let us think about which rows/columns can we fill initially
- What about the first row corresponding to item 1?
- Remember that optimal cost is max sum over all partitions
- $M(i,\ 1)$: optimal cost of partitioning $s_1, s_2, \ldots, s_i$ using only 1 partition
- For $i = 1,2,\ldots,n$ we can fill out the first column as:

$$\boxed{M(i,\ 1) = \sum_{\ell=1}^{i} s_\ell}$$

Base Cases Summary

- For $j = 1,2,\ldots,k$ we can fill out the first column as:

$$\boxed{M(1, j) = s_1}$$

- For $i = 1,2,\ldots,n$ we can fill out the first column as:

$$\boxed{M(i, 1) = \sum_{\ell=1}^{i} s_\ell}$$

Towards a Recurrence

- Want a recurrence for $M(i, j)$
- Notice that the jth partition starts after we place the $(j-1)$st "divider"
- Where can we place the $j - 1st$ divider?
  - Suppose between i' th and $(i'+1)$st book/element, where $1 \le i' < i$
  - What is the cost of placing the last divider here?
  - Max of the cost of
    - the last partition (the sum of all elements in it)
    - the optimal way to partition the elements to the "left"

Final Recurrence

- For $2 \leq i \leq n$ and $2 \leq j \leq k$, we have:

$$\boxed{M(i,\, j) = \min_{1 \leq i' < i} \max\{M(i', j-1), \sum_{\ell = i'+1}^{i} s_t\}}$$

- **Memoization structure**: We store $M[i, j]$ values in a 2-D array or table using space $O(nk)$
- **Evaluation order**: In what order should we fill in the table?

Final Pieces

- Evaluation order.
    - To fill out $M[i, j]$, I need the previous column filled in for rows less than i, that is, $M[i', j-1]$ for all $1 \leq i' < i$
    - Can compute using column major order: column by column
- Running time?
    - Size of table (space): $O(k \cdot n)$
    - How long to compute a single cell?
        - Depends on n other cells
        - $O(n)$ time to fill in one cell

Running Time

- Running time
  - $O(n^2 \cdot k)$
- Is this a polynomial running time?
  - Not as stated, not polynomial in k
  - But lets think if we can upper bound k using n
- How big can k get?
  - At most n non-empty partitions of n elements
  - $O(n^3)$ algorithm in the worst case

Last Topic in Dynamic Programming:
Shortest Paths Revisited

Shortest Path Problem

- **Single-Source Shortest Path Problem**.
  Given a directed graph $G = (V, E)$ with edge weights w_e on each $e \in E$ and a a source node s, find the shortest path from s to to all nodes in G.

- **Negative weights**. The edge-weights $w_e$in G can be negative. (When we studied Dijkstra's, we assumed non-negative weights.)

- Let P be a path from s to t, denoted $s \rightsquigarrow t$.

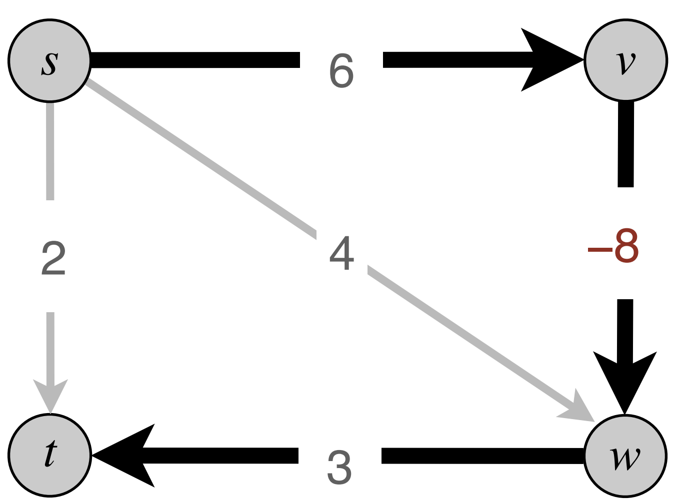
  - The **length** of P is the number of edges in P

  - The cost or weight of P is $w(P) = \sum_{e \in P} w_e$

- Goal: **cost** of the shortest path from s to all nodes

Negative Weights & Dijkstra's

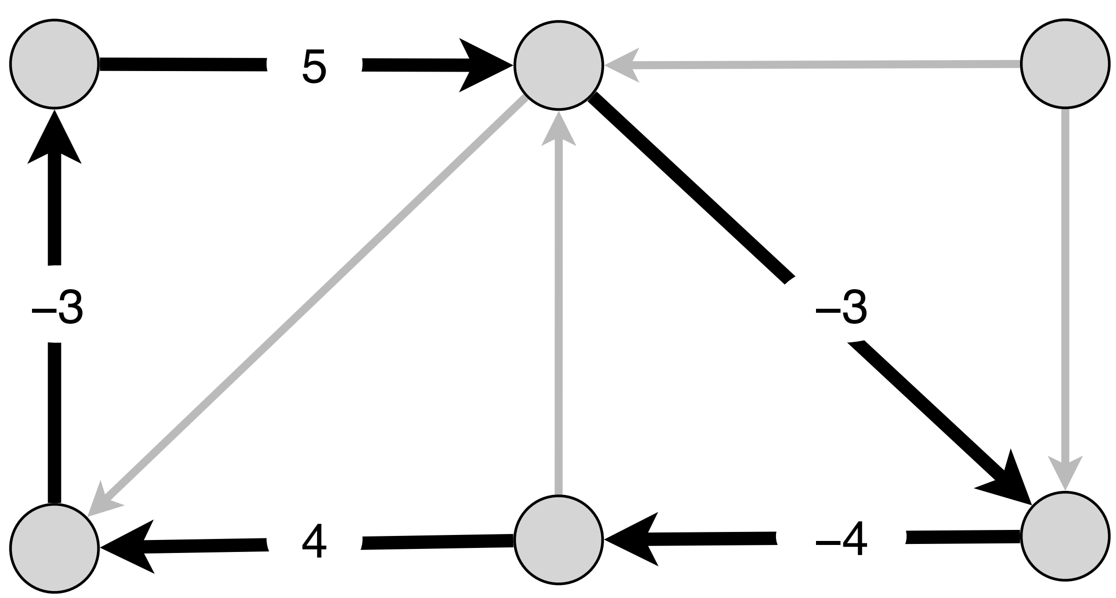
- **Dijkstra's Algorithm**. Does the greedy approach work for graphs with negative edge weights?
  - Dijkstra's will explore s's neighbor and add t, with $d[t] = w_{sv} = 2$ to the shortest path tree
  - Dijkstra assumes that there cannot be a "longer path" that has lower cost (relies on edge weights being non-negative)



Dijkstra's will find $s \to t$ as shortest path with cost 2
But the shortest path is $s \to v \to w \to t$ with cost 1

Negative Cycles

- **Definition**. A negative cycle is a directed cycle C such that the sum of all the edge weights in C is less than zero
- **Question**. How do negative cycles affect shortest path?



a negative cycle W : $\ell(W) = \sum_{e \in W} \ell_e < 0$

Negative Cycles & Shortest Paths

- **Claim.** If a path from s to some node v contains a negative cycle, then there does not exist a shortest path from s to v.

- **Proof**.
  - Suppose there exists a shortest $s \rightsquigarrow v$ path with cost d that traverses the negative cycle t times for $t \geq 0$.
  - Can construct a shorter path by traversing the cycle $t+1$ times

  $\Rightarrow\!\Leftarrow$ ∎

- **Assumption.** G has no negative cycle.

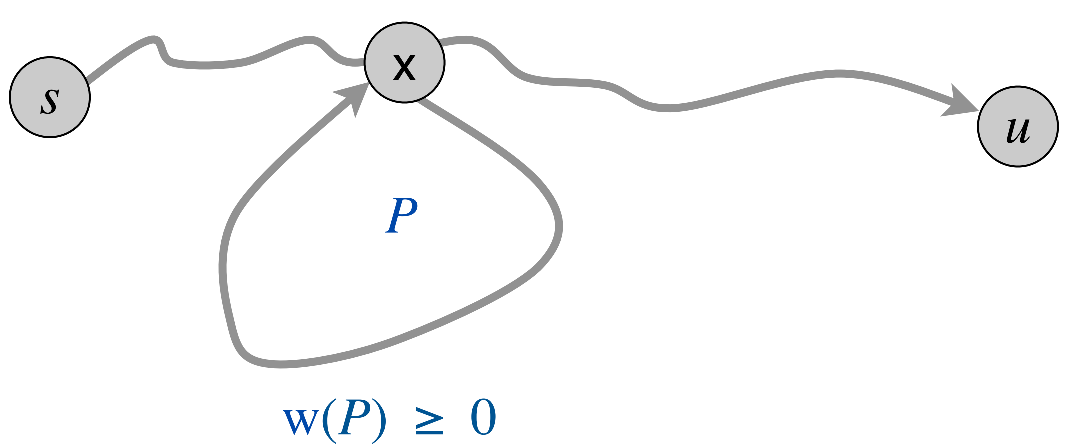
- Later in the lecture: how can we detect whether the input graph G contains a negative cycle?

Dynamic Programming Approach

- First step to a dynamic program? Recursive formulation
    - Subproblem with an "optimal substructure"
- **Structure of the problem**. With negative edge weights, the optimal cost can have any length
    - Let's keep track of **length of paths** considered so far
- How long can the shortest path from s to any node u be, assuming no negative cycle?
- **Claim**. If G has no negative cycles, then exists a shortest path from s to any node u that uses at most $n-1$ edges.

No. of Edges in Shortest Path

- **Claim.** If G has no negative cycles, then exists a shortest path from s to any node u that uses at most $n-1$ edges.
- **Proof.** Suppose there exists a shortest path from s to u made up of n or more edges
- A path of length at least n must visit at least $n+1$ nodes
- There exists a node x that is visited more than once (**pigeonhole principle**). Let P denote the portion of the path between the successive visits.
- Can remove P without increasing cost of path. ∎

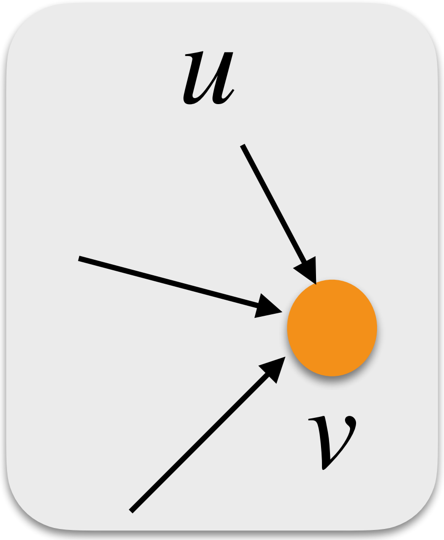


Shortest Path Subproblem

- **Subproblem**. $D[v, i]$: (optimal) cost of shortest path from s to v using $\leq i$ edges
- **Base cases**.
  - $D[s, i] = 0$ for any i
  - $D[v, 0] = \infty$ for any $v \neq s$
- **Final answer** for shortest path cost to node v
  - $D[v, n - 1]$

Recurrence

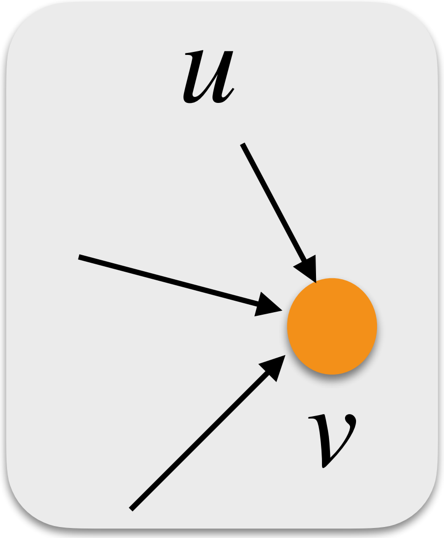
- Suppose we have found shortest paths to all nodes of length at most $i - 1$
- We are now considering shortest paths of length i
- Cases to consider for the **recurrence** of $D[v, i]$
  - **Case 1**. Shortest path to v was already found (is same as $D[v, i - 1]$)
  - **Case 2**. Shortest path to v is "longer" than paths found so far:
    - Look at all nodes u that have incoming edges to v
    - Take minimum over their distances and add w_{uv}



Bellman-Ford-Moore Algorithm

- **Recurrence.** For all nodes $v \neq s$, and for all $1 \leq i \leq n-1$,

$$\boxed{D[v,i] = \min\{D[v,i-1], \min_{(u,v)\in E} \{D[u,i-1] + w_{uv}\}\}}$$



- Called the **Bellman-Ford-Moore** algorithm

Bellman-Ford-Moore Algorithm

- **Subproblem**. $D[v, i]$: (optimal) cost of shortest path from s to v using $\leq i$ edges
- **Recurrence.**
  $$D[v, i] = \min\{D[v, i-1], \min_{(u,v)\in E} \{D[u, i-1] + w_{uv}\}\}$$
- **Memoization structure**. Two-dimensional array
- **Evaluation order**.
  - $i : 1 \rightarrow n-1$ (column major order)
  - Starting from s, the row of vertices can be in any order

Running Time

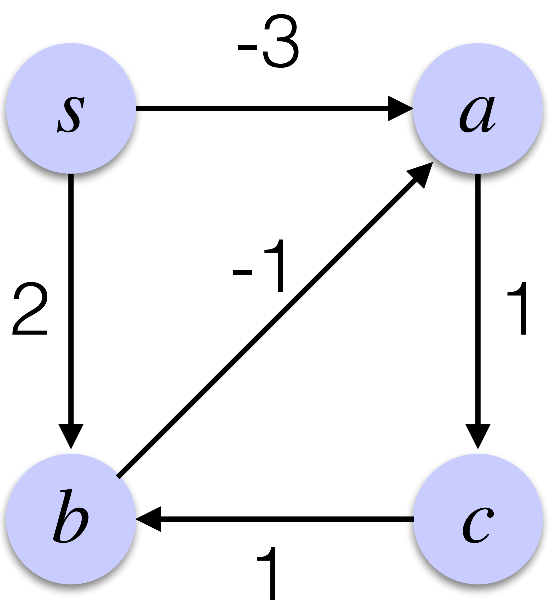
- **Recurrence**.
$$D[v,i] = \min\{D[v,i-1], \min_{(u,v)\in E} \{D[u,i-1] + w_{uv}\}\}$$
- **Naive analysis**. $O(n^3)$ time
  - Each entry takes $O(n)$ to compute, there are $O(n^2)$ entries
- **Improved analysis**. For a given i, v, $d[v,i]$ looks at each incoming edge of v
  - Takes indegree(v) accesses to the table
  - For a given i, filling $d[-,i]$ takes $\sum_{v\in V}$ indegree(v) accesses
  - At most $O(n+m) = O(m)$ accesses for connected graphs where $m \geq n-1$
- Overall running time is $O(nm)$

- **Shortest-Path Summary.** Assuming there are no negative cycles in G, we can compute the shortest path from s to all nodes in G in $O(nm)$ time using the Bellman-Ford-Moore algorithm

Dynamic Programming
Shortest Path:
Bellman-Ford-Moore Example

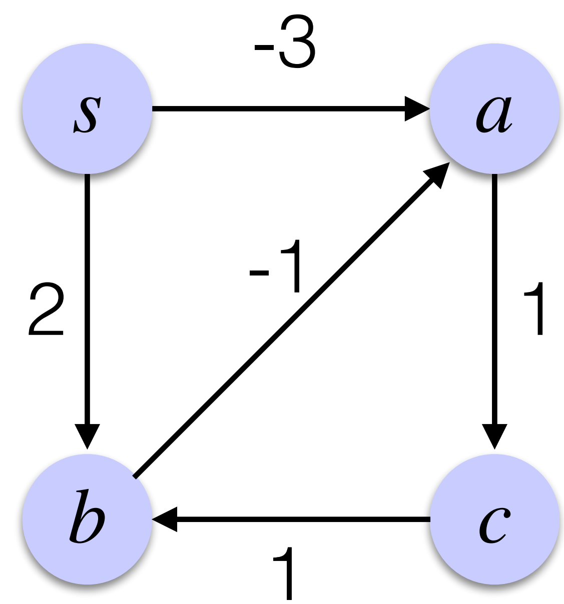
- $D[s, i] = 0$ for any i
- $D[v,0] = \infty$ for any $v \neq s$

	0	1	2	3
s	0	0	0	0
a	inf			
b	inf			
c	inf			



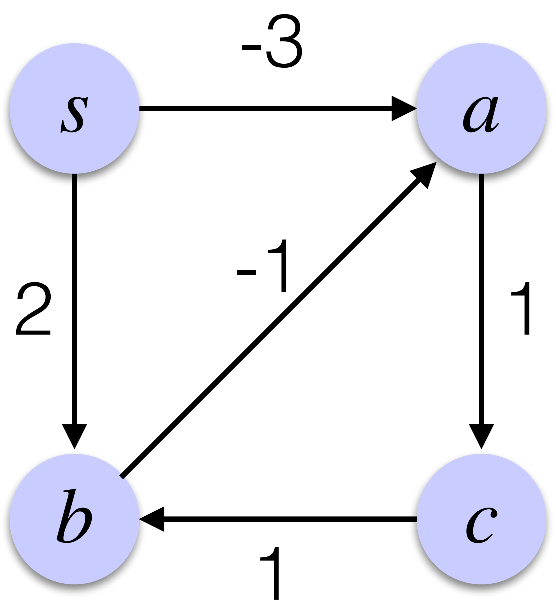
- $D[v,1] = \min\{D[v,0], \min_{u,v \in E}\{D[u,0] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf			
b	inf			
c	inf			



- $D[v,1] = \min\{D[v,0], \min_{u,v \in E}\{D[u,0] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3		
b	inf			
c	inf			



- $D[v,1] = \min\{D[v,0], \min_{u,v \in E} \{D[u,0] + w_{uv}\}$

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s	0	0	0	0
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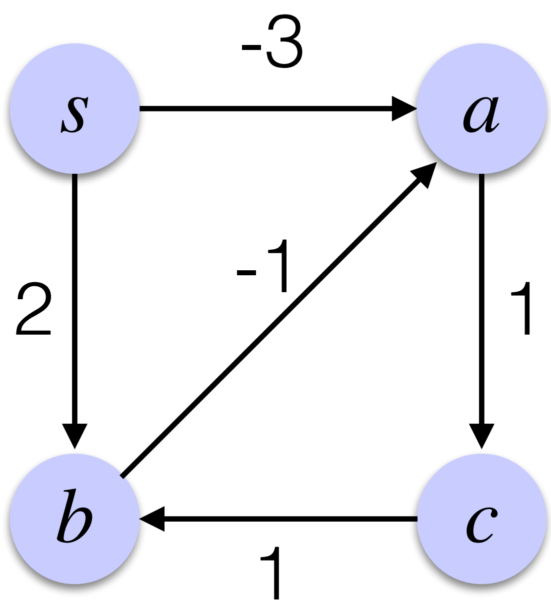
b	inf	2		
c	inf			



- $D[v,1] = \min\{D[v,0], \min_{u,v \in E} \{D[u,0] + w_{uv}\}$

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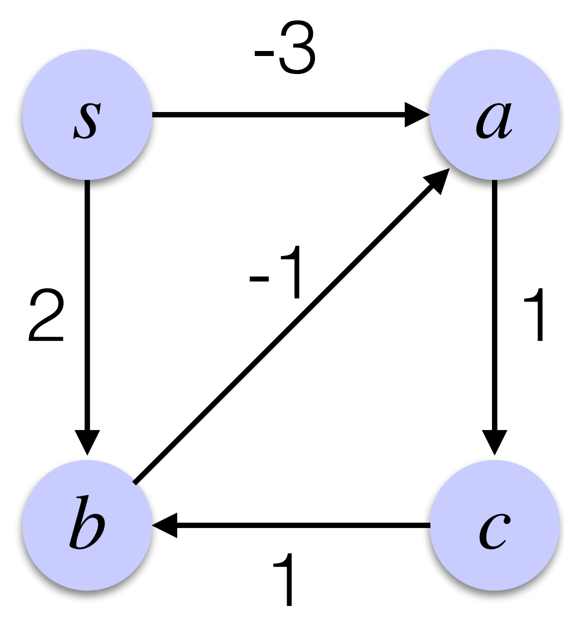
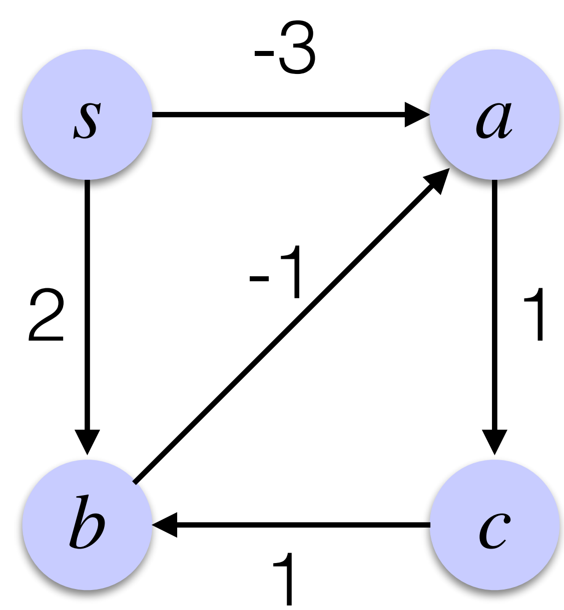


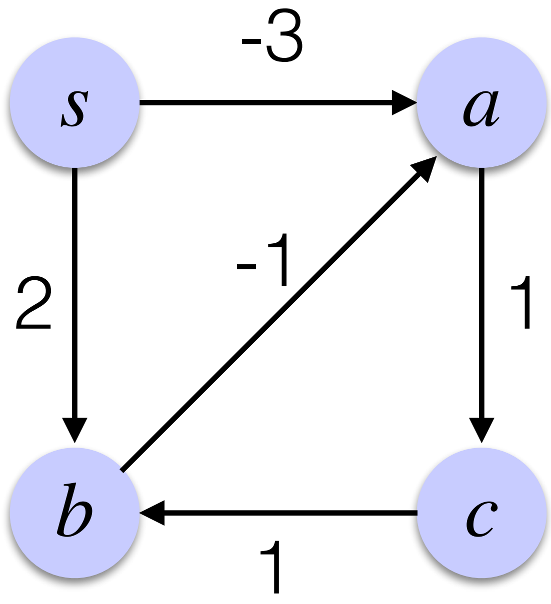
- $D[v,2] = \min\{D[v,1], \min_{u,v \in E} \{D[u,1] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3		
b	inf	2		
c	inf	inf		



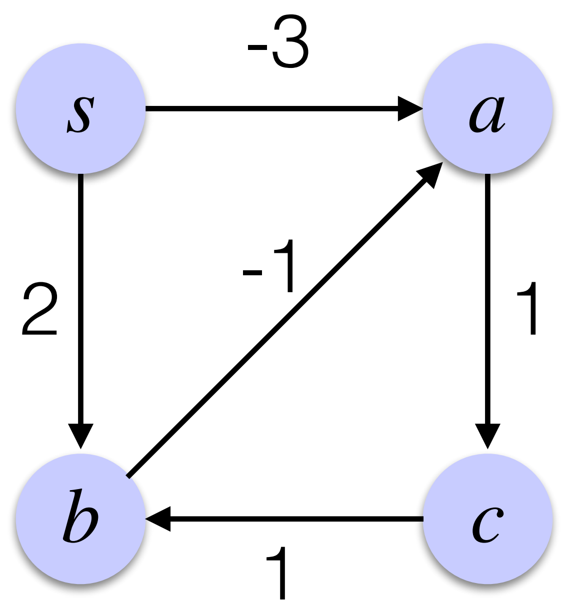
- $D[v,2] = \min\{D[v,1], \min_{u,v \in E}\{D[u,1] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	
b	inf	2		
c	inf	inf		



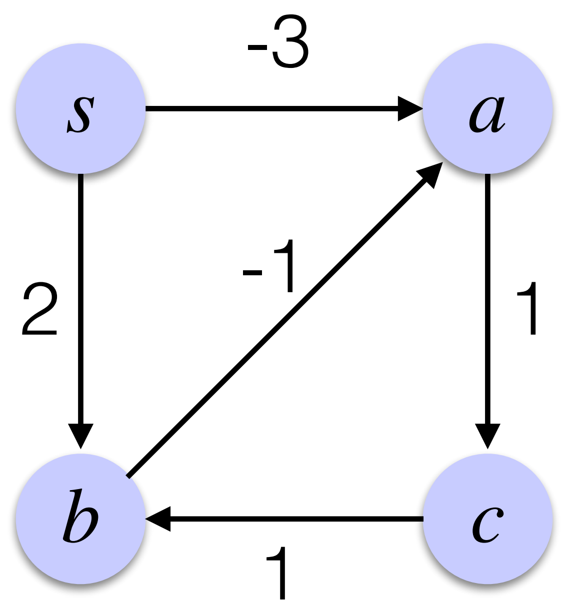
- $D[v,2] = \min\{D[v,1], \min_{u,v \in E}\{D[u,1] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	
b	inf	2	2	
c	inf	inf		



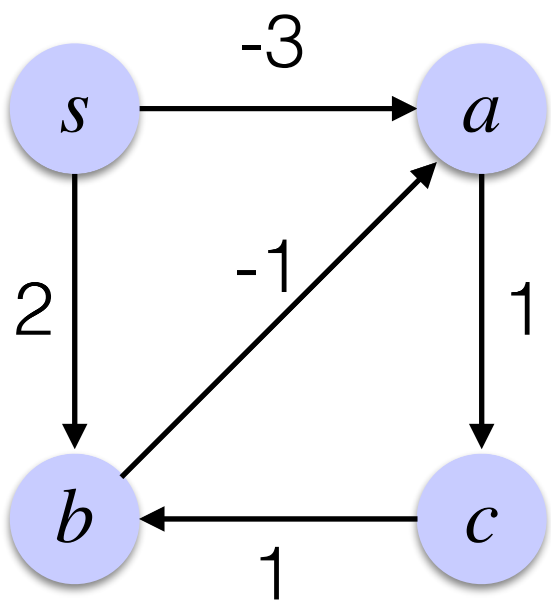
- $D[v,2] = \min\{D[v,1], \min_{u,v \in E}\{D[u,1] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	
b	inf	2	2	
c	inf	inf	-2	



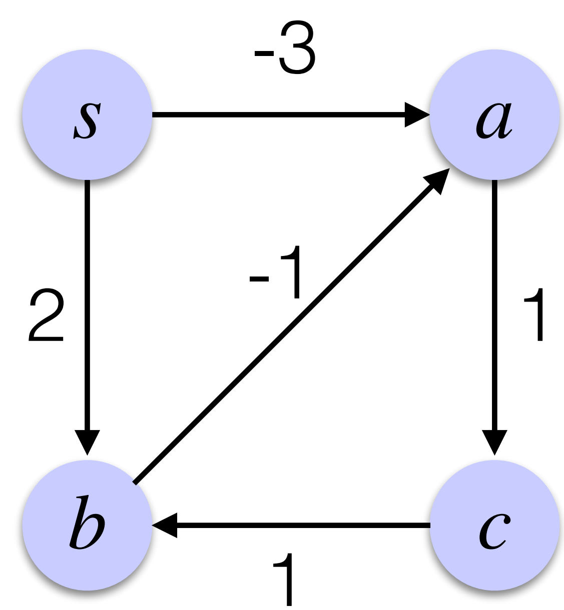
- $D[v,3] = \min\{D[v,2], \min_{u,v \in E} \{D[u,2] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	-3
b	inf	2	2	
c	inf	inf	-2	



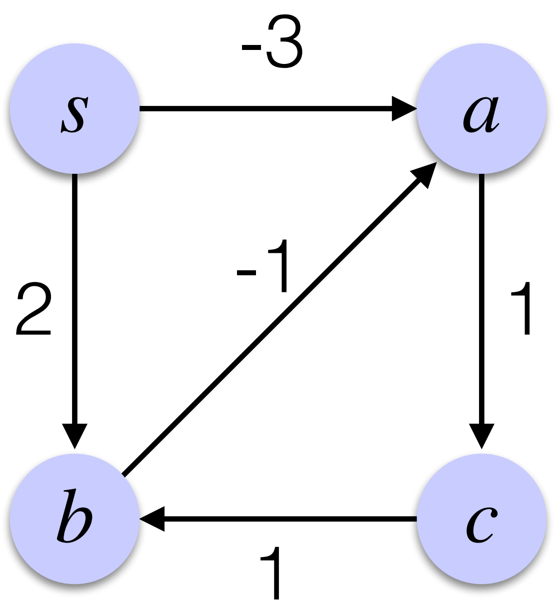
- $D[v,3] = \min\{D[v,2], \min_{u,v \in E} \{D[u,2] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	-3
b	inf	2	2	-1
c	inf	inf	-2	



- $D[v,3] = \min\{D[v,2], \min_{u,v \in E}\{D[u,2] + w_{uv}\}$

	0	1	2	3
s	0	0	0	0
a	inf	-3	-3	-3
b	inf	2	2	-1
c	inf	inf	-2	-2



Acknowledgments

- Some of the material in these slides are taken from
  - Kleinberg Tardos Slides by Kevin Wayne (https://www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/04GreedyAlgorithmsI.pdf)
  - Jeff Erickson's Algorithms Book (http://jeffe.cs.illinois.edu/teaching/algorithms/book/Algorithms-JeffE.pdf)