

# Introduction to Algorithms and Data Structures

Dynamic Programming - The Bellman-Ford Algorithm for  
Shortest Paths

# Shortest Paths in Graphs (Lecture 17)

- **Input:** A directed graph  $G = (V, E)$ , and a designated node  $s$  in  $V$ . We also assume that every node  $u$  in  $V$  is reachable from  $s$ . We are also given a length  $\ell_e > 0$  for every edge  $e$  in  $E$ .
- **Output:** For every node  $u$  in  $V$ , a shortest path  $s \sim u$  from  $s$  to  $u$ .

# Shortest Paths in Graphs (today)

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- **Motivation:** e.g., Financial Networks

positive costs (*costs* of transactions)

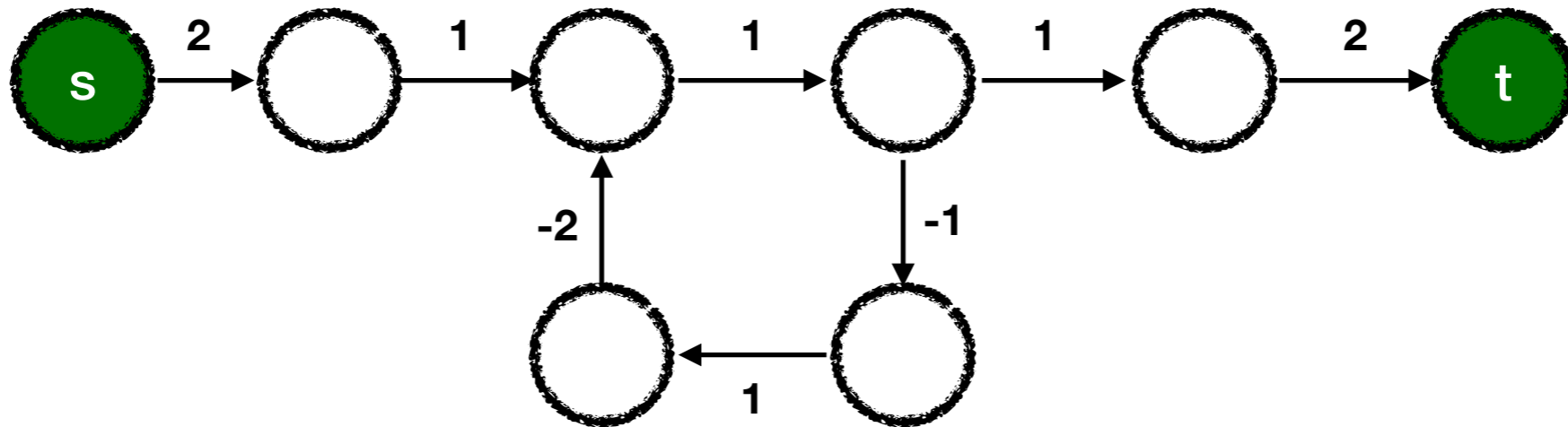
negative costs (*profits* of transactions)

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$$\sum_{(u,v) \in P} c_{uv}$$

# Negative Cycles

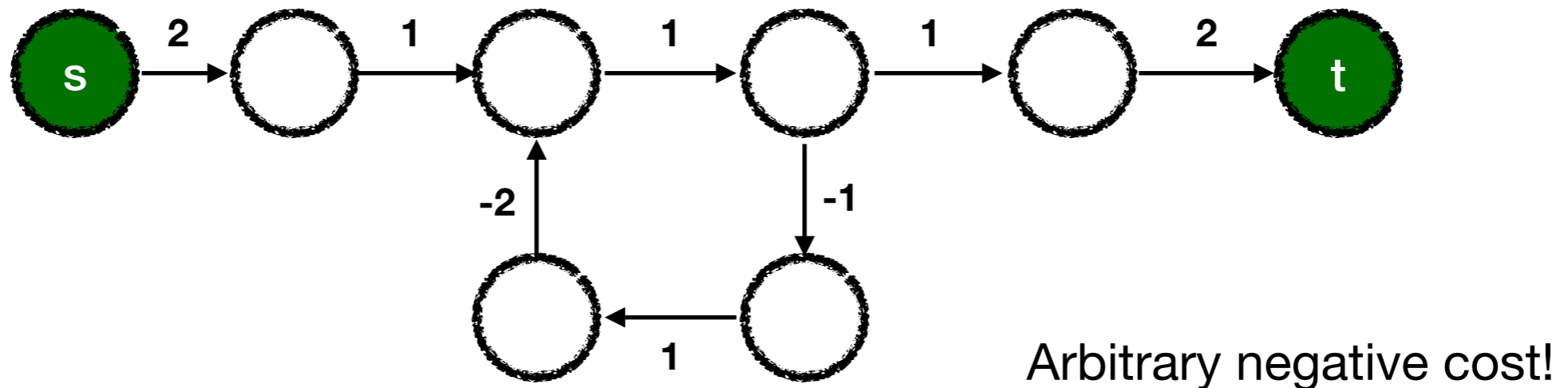
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# Shortest Paths in Graphs

- **Input:** A directed graph  $G = (V, E)$ , and designated nodes  $s, t$  in  $V$ . We also assume that every node  $u$  in  $V$  is reachable from  $s$ , and *that the graph does not have any negative cycles*. We are also given a cost  $c_e \in \mathbb{R}$  for every edge  $e$  in  $E$ .
- **Output:** A shortest path  $s \sim t$  from  $s$  to  $t$ . In other words, a path  $P$  that minimises 
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# Why not Dijkstra?

# Dijkstra's Algorithm

- For every node  $v \in V - S$ , we determine the shortest path that can be constructed by traveling along a path  $s \sim u$  for  $u \in S$ , followed by  $(u, v)$ .

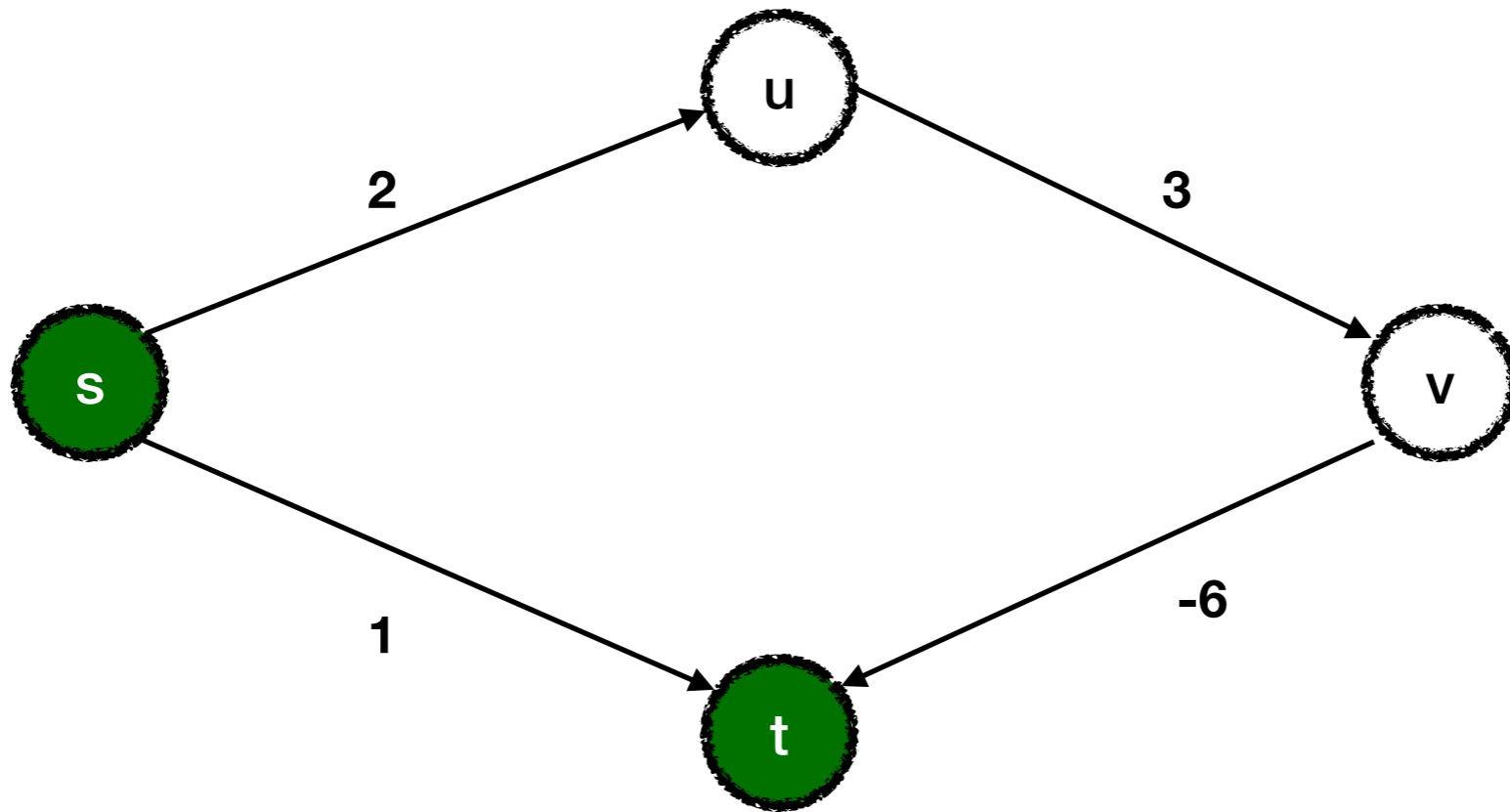
- In other words, we choose node  $v \in V - S$  such that

$$d'(v) = \min_{e=(u,v):u \in S} d(u) + \ell_e$$

- Add  $v$  to  $S$  and define  $d(v) = d'(v)$ .

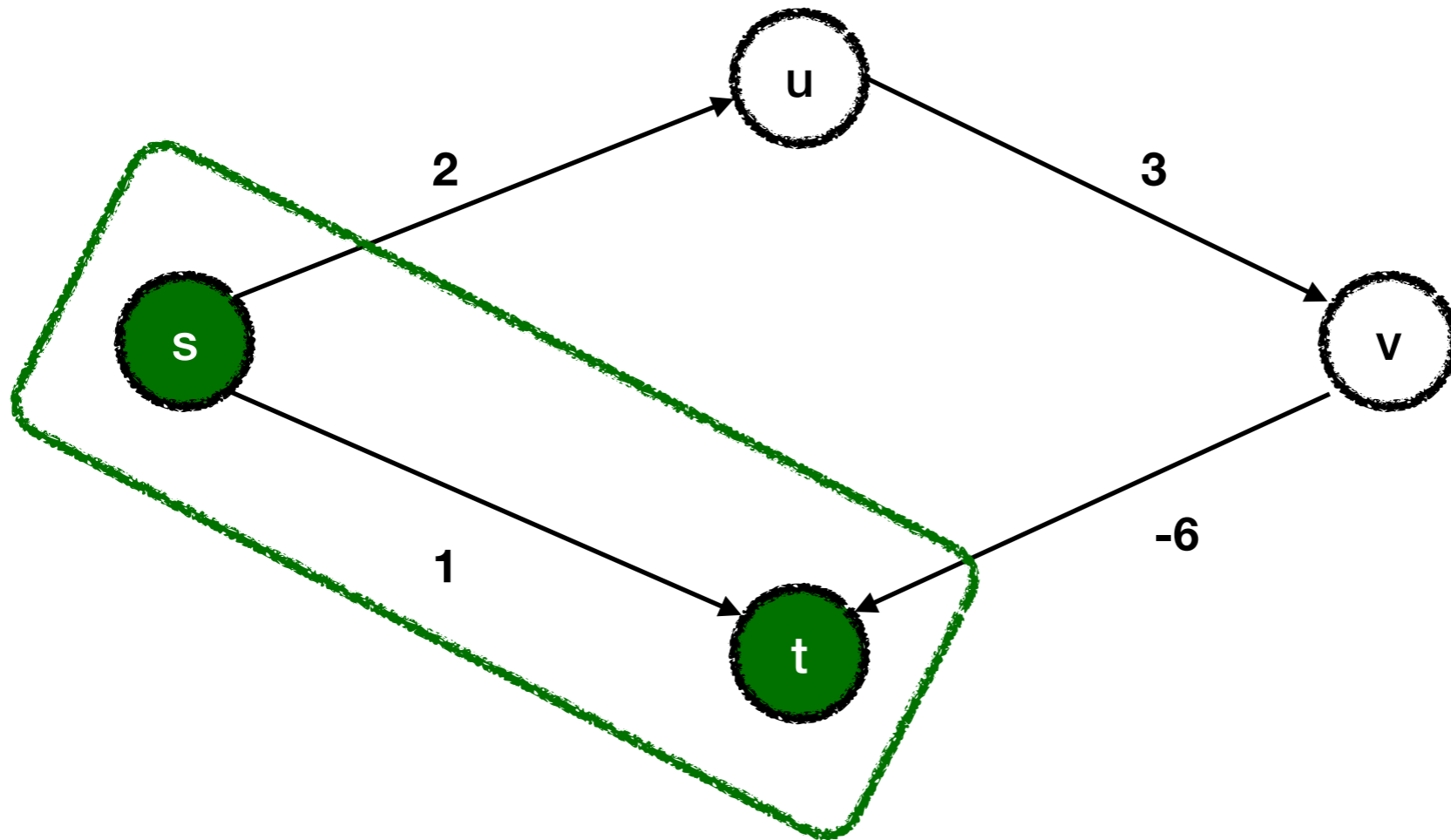
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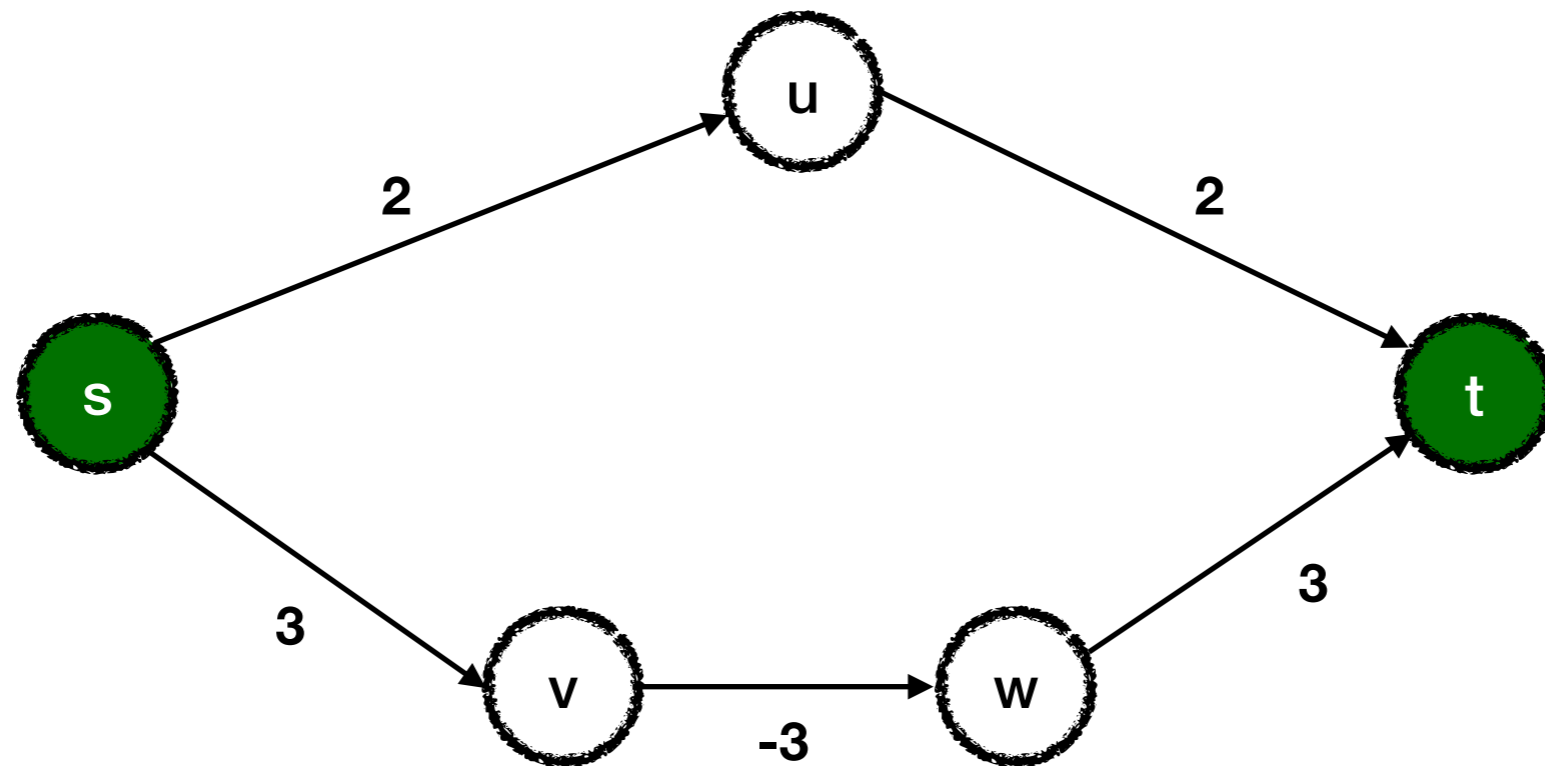


# Maybe modified Dijkstra?

- **Idea:** “Get rid” of the negative costs by adding a large number  $M$  to all the edge costs.

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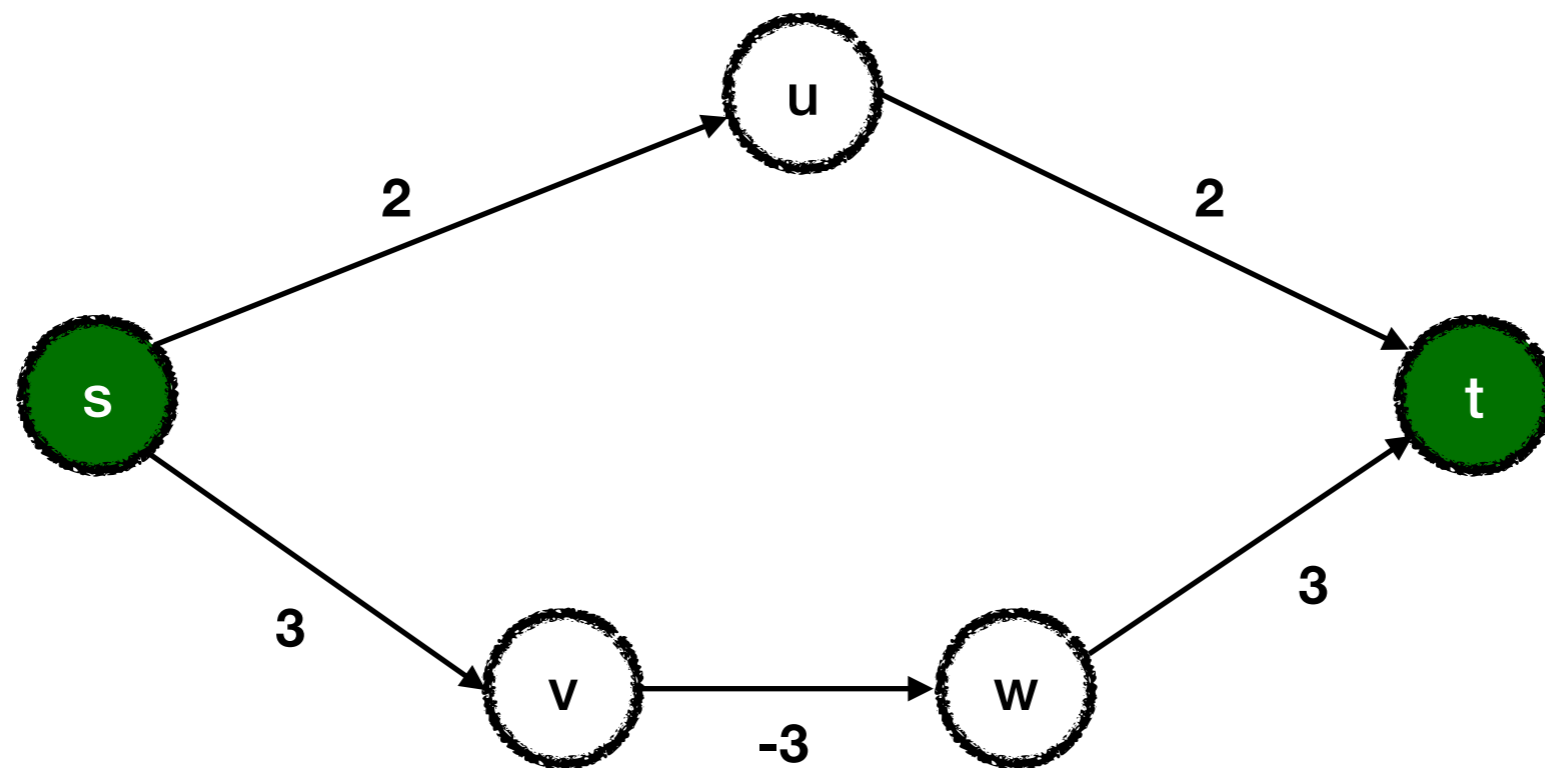
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The shortest path changes!

# A dynamic programming approach

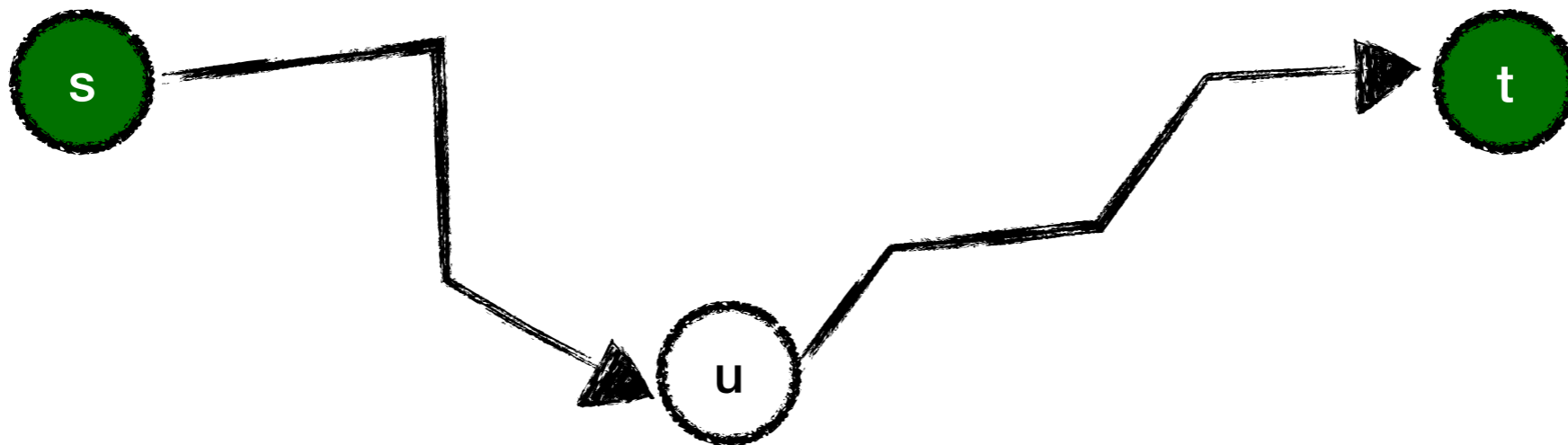
- The algorithm that we will present next was developed by Bellman (1958) and Ford (1956).
- Note that Dijkstra's algorithm was published in 1959.

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Let's look at a shortest path  $s \sim t$  from  $s$  to  $t$ .

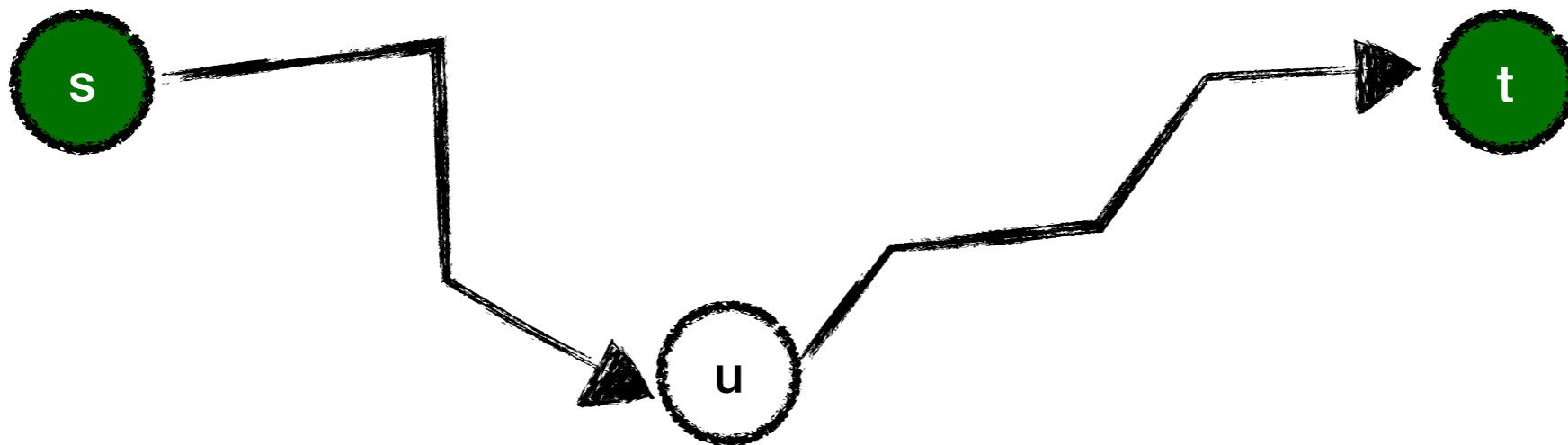
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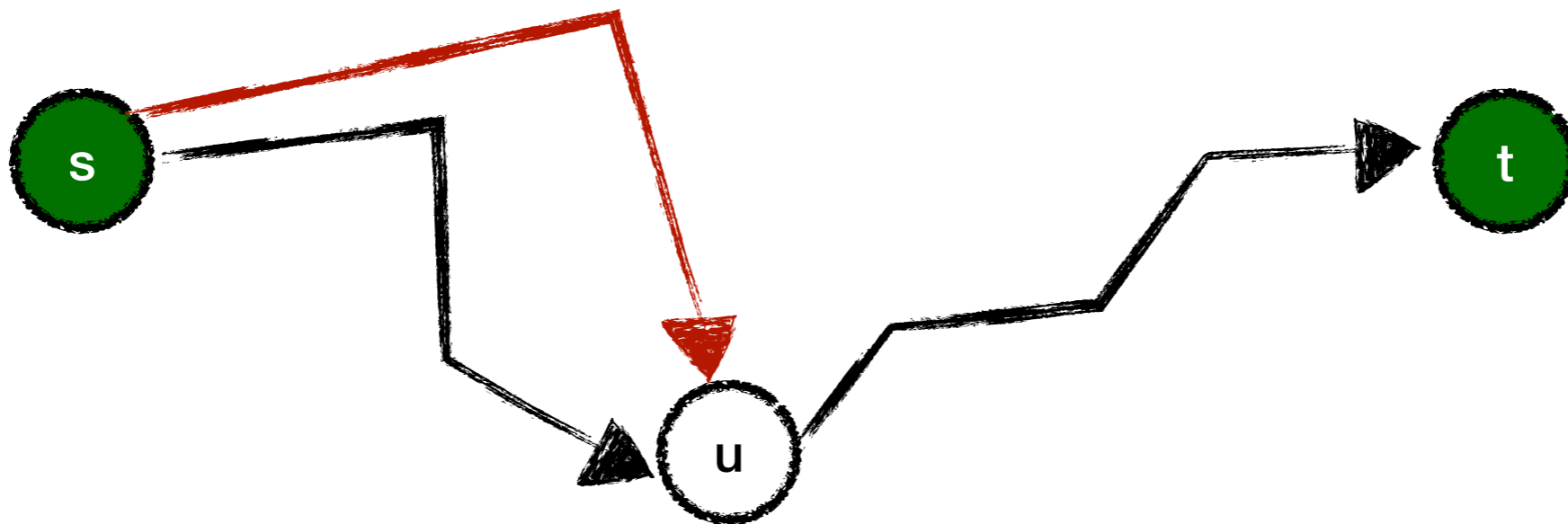
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This consists of a shortest path  $s \sim u$  from  $s$  to  $u$ , and a shortest path  $u \sim t$  from  $u$  to  $t$  (why?).

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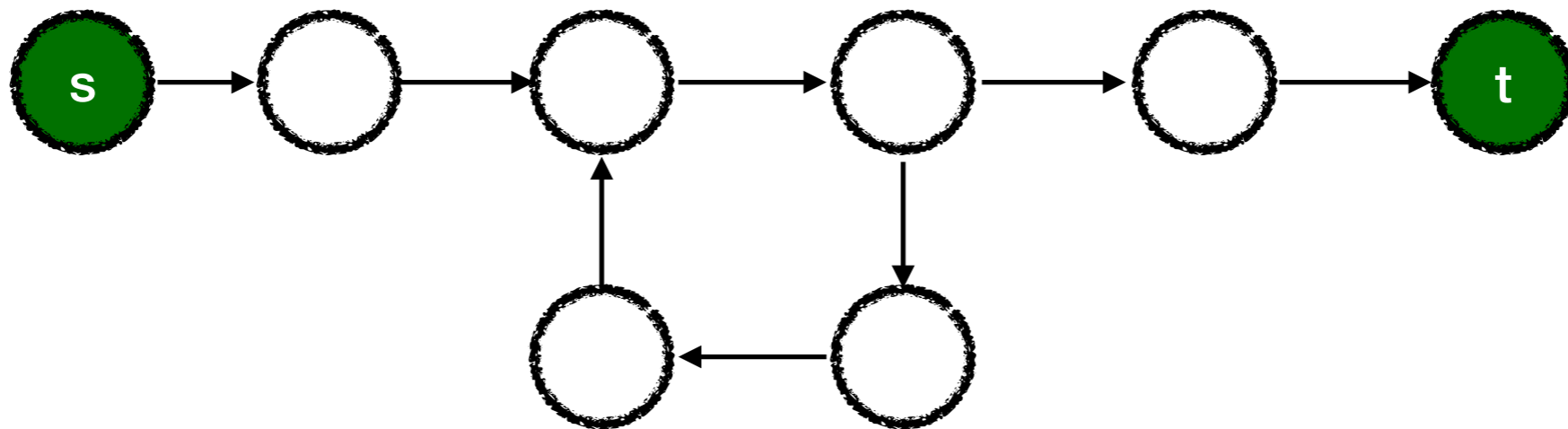
# Simple Observation

- **Observation:** If a graph *does not have any negative cycles*, then there is a shortest path  $s \sim t$  from  $s$  to  $t$  that is simple, i.e., it does not repeat any nodes.



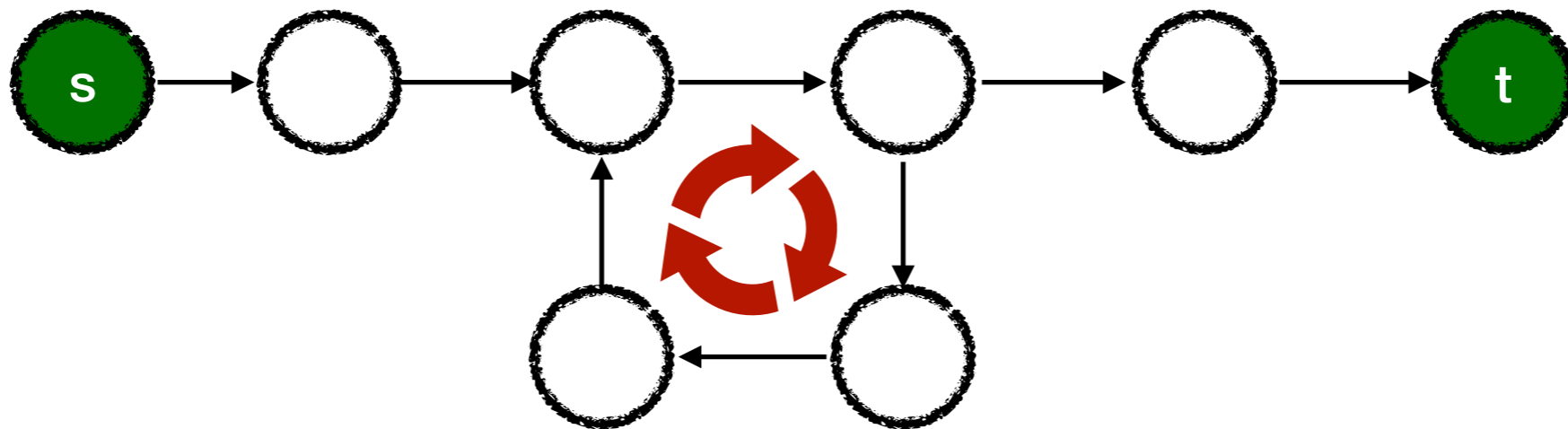
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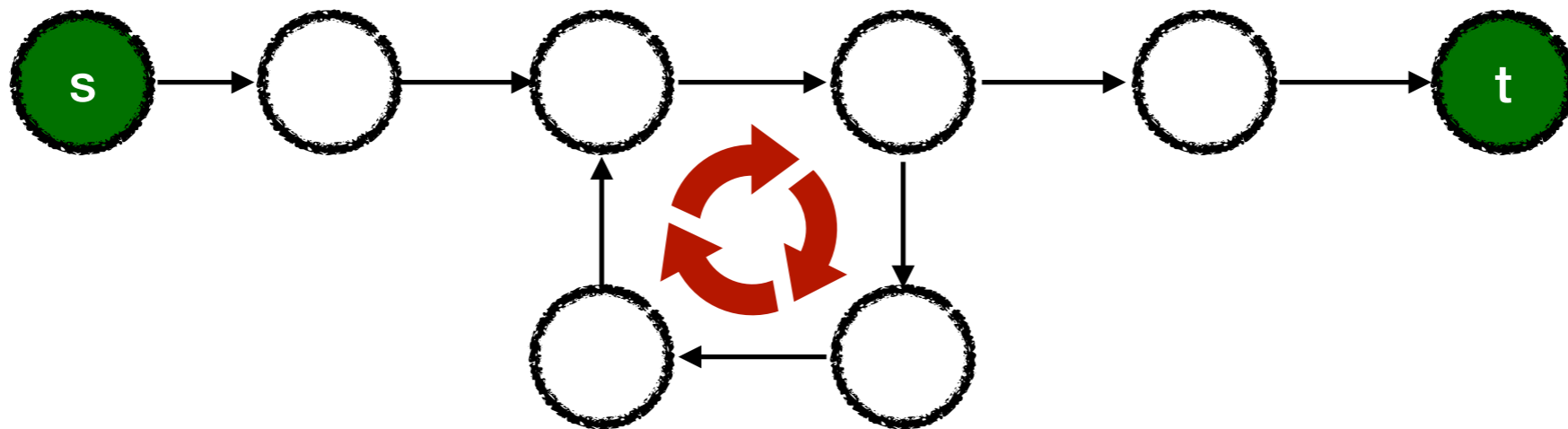
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Adding the cycle cannot make the path shorter!

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**Subset Sum:**  $OPT(i,w)$  was the value of the optimal solution on the first  $i$  items and weight  $w$ .

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- We could try something similar for the “first”  $i$  nodes.
  - Could be made to work, but it seems complicated.
  - Instead, we will use the *number of edges*, rather than the set of nodes or edges.

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- Let  $\text{OPT}(i, v)$  denote the minimum cost of a path  $v \sim t$  from node  $v$  to  $t$  that uses at most  $i$  edges.

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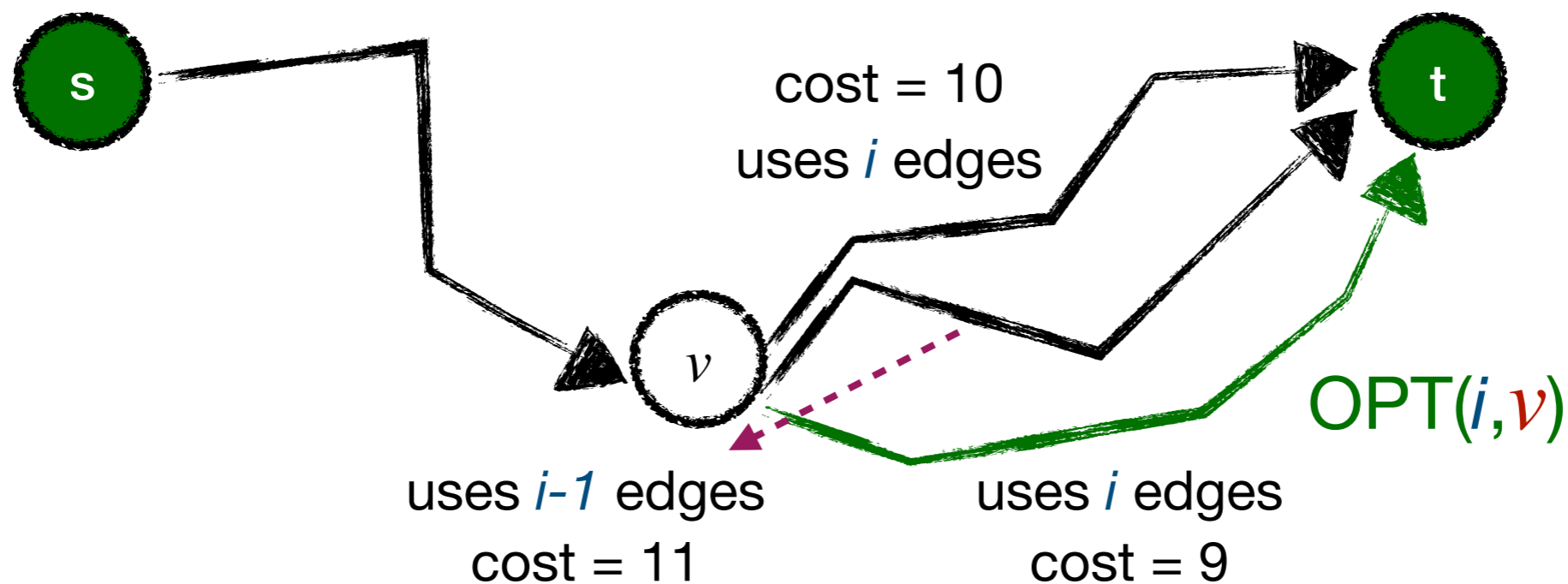
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- This looks more like Dijkstra, but the former one is used in KT, because it fits better some of the other applications presented in the book.

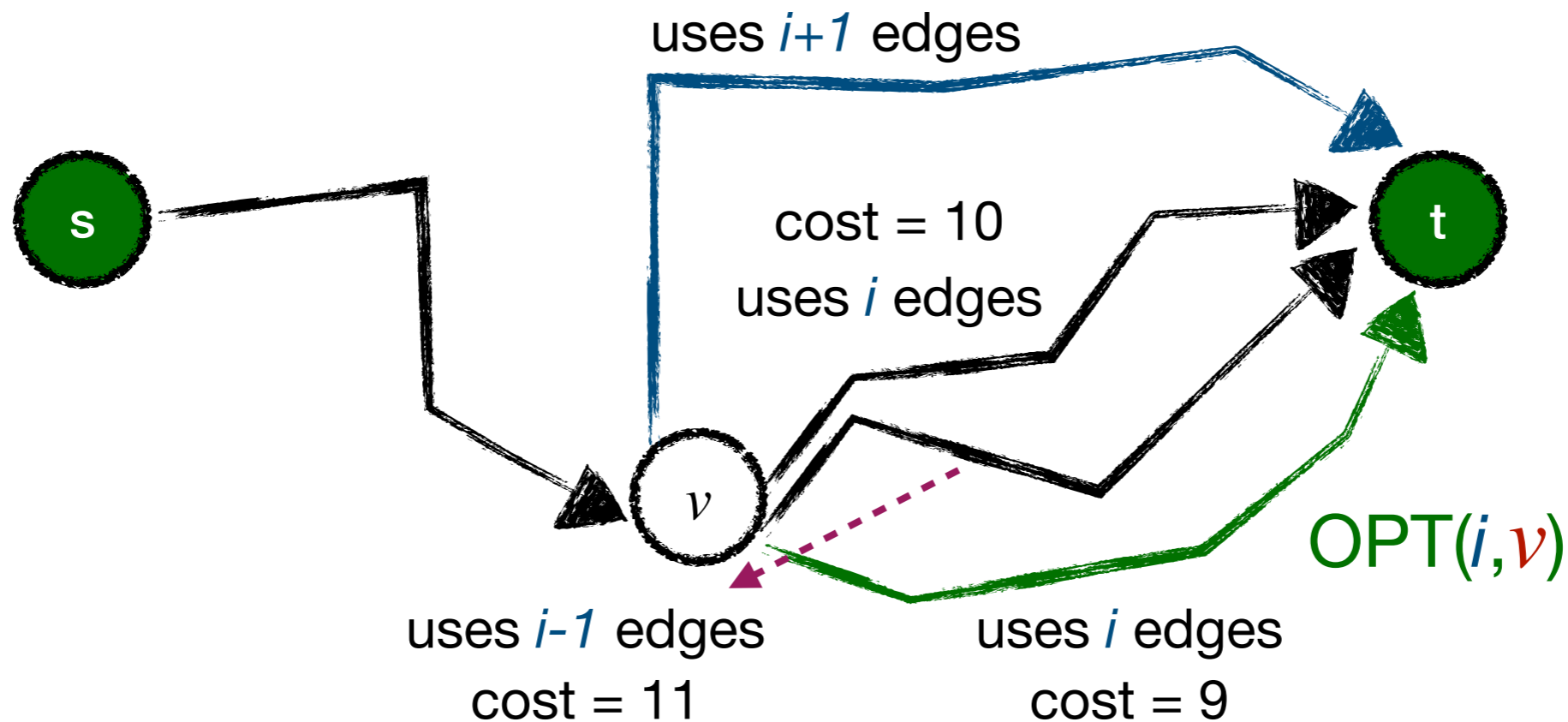
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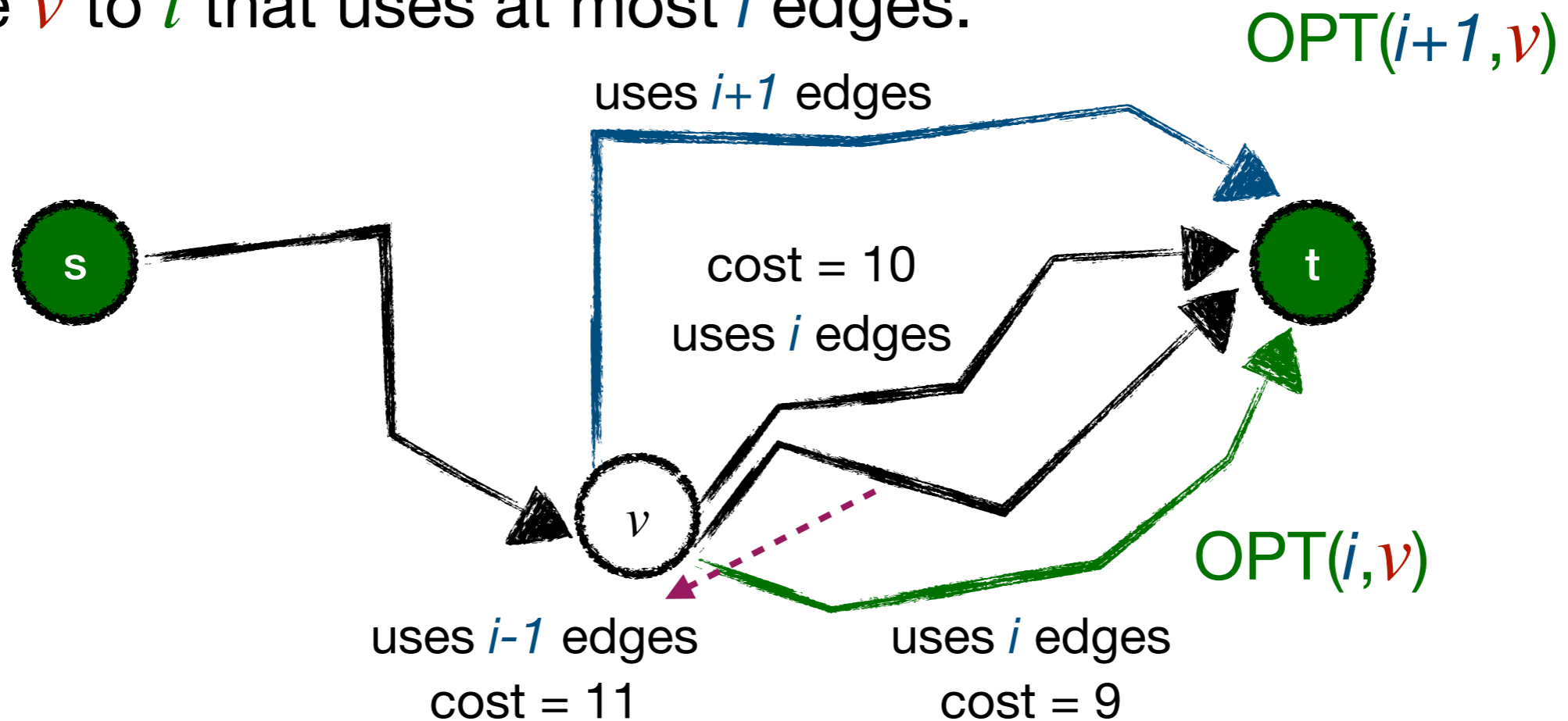
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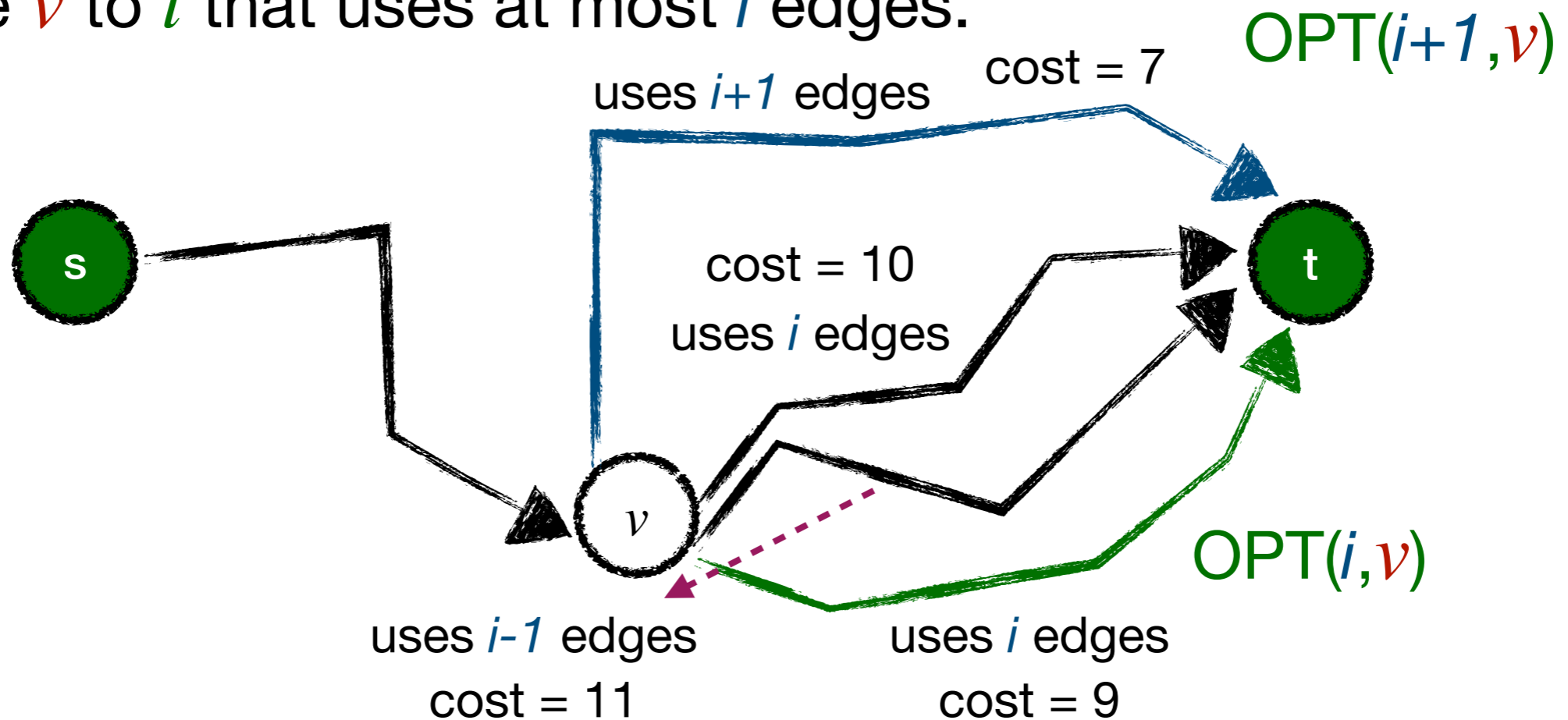
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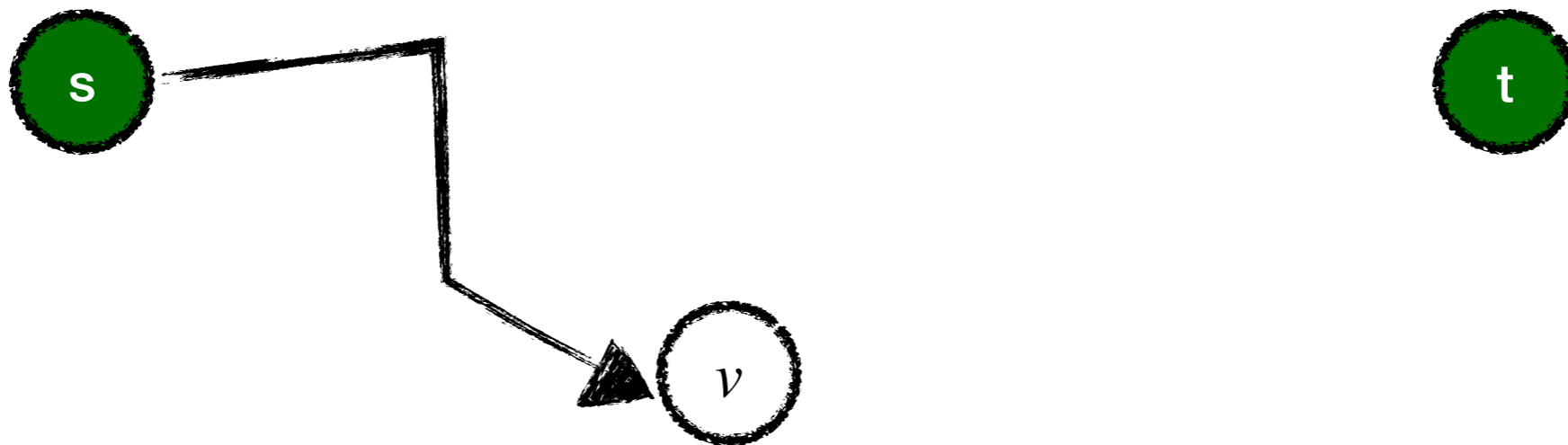
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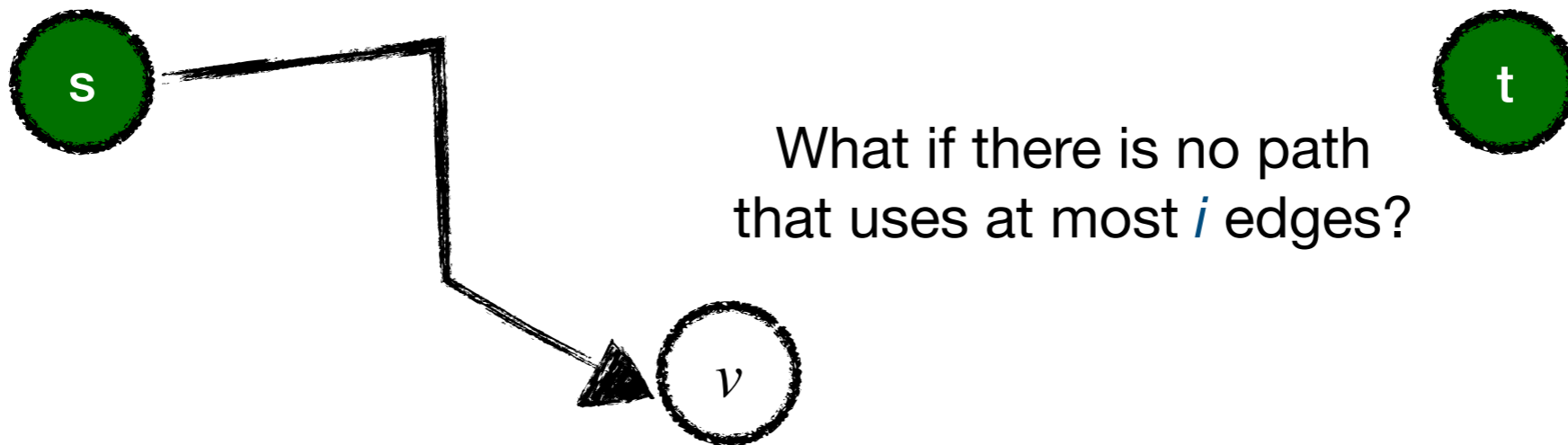
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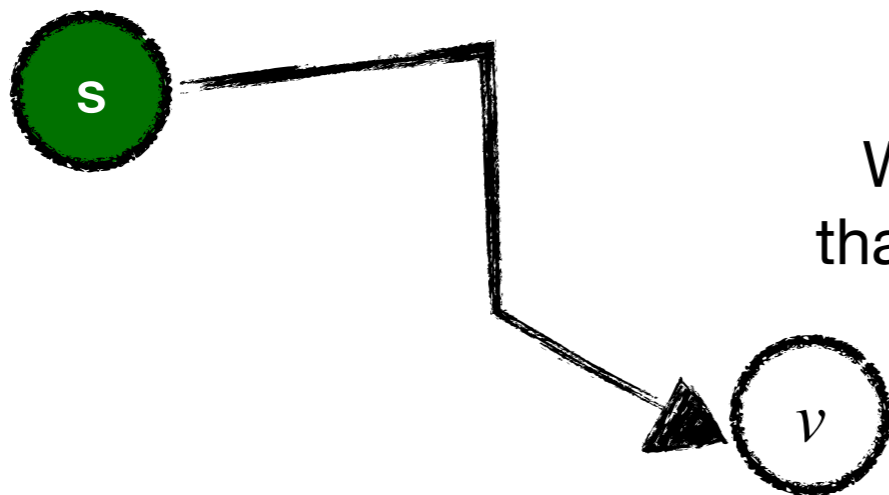
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What if there is no path that uses at most  $i$  edges?

$$\text{OPT}(i, v) = \infty$$

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  - $\text{OPT}(n-1, s)$



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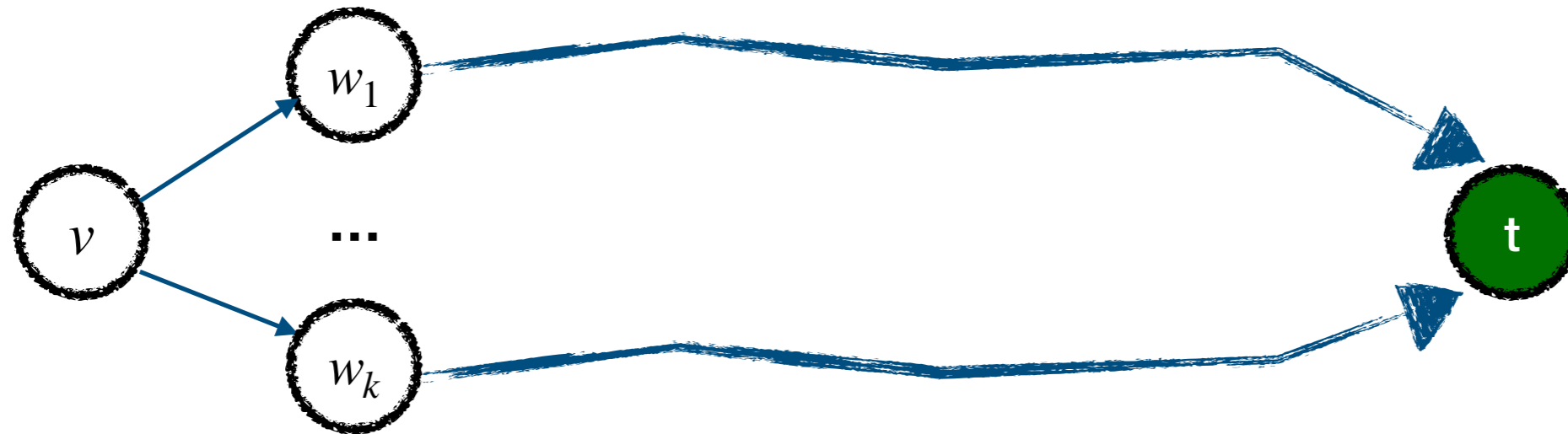
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# The Bellman-Ford Algorithm

**ShortestPath** ( $G, s, t$ ).

\\* Let  $n = |V|$  \*\

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

Initialise  $M[0, t] = 0$ , and  $M[0, v] = \infty$  for all other  $v \in V$ .

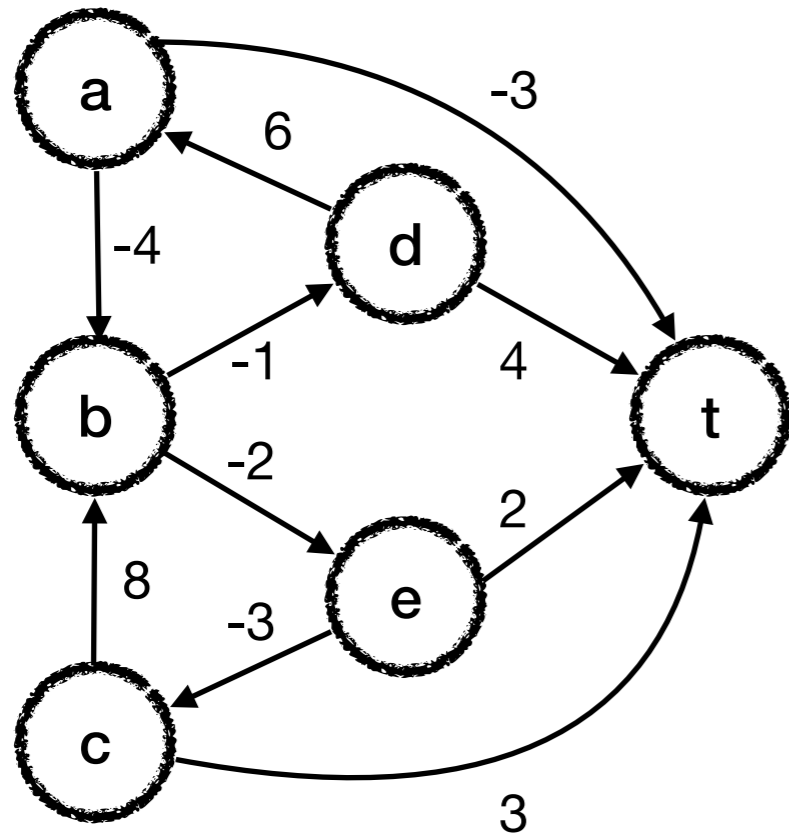
For  $i = 1, 2, \dots, n-1$

For  $v \in V$

$$M(i, v) = \min \{ M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w)) \}$$

Return  $M(n-1, s)$

# Example



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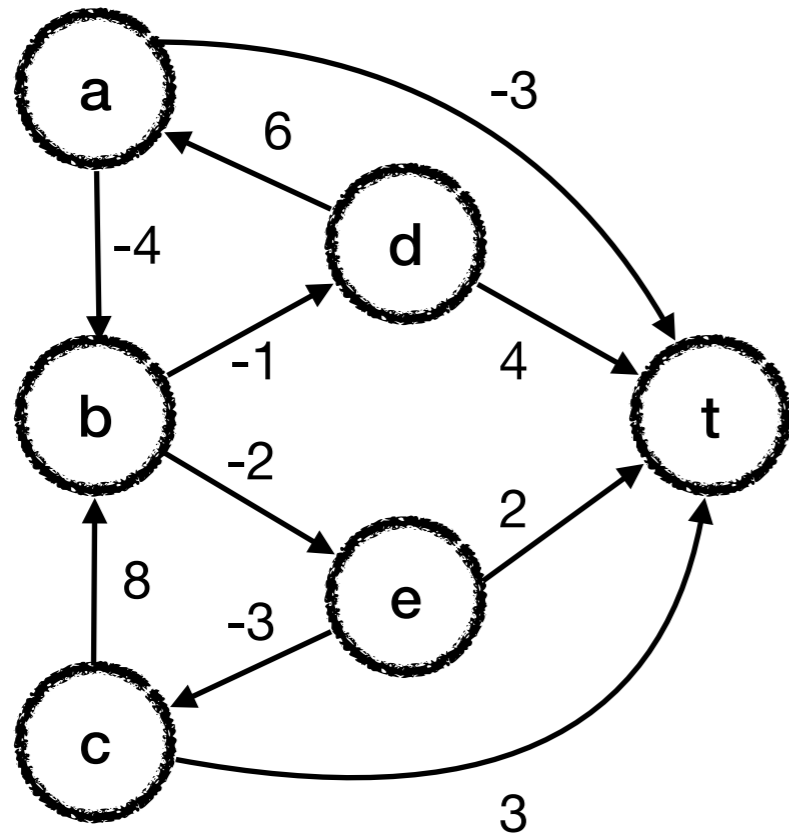
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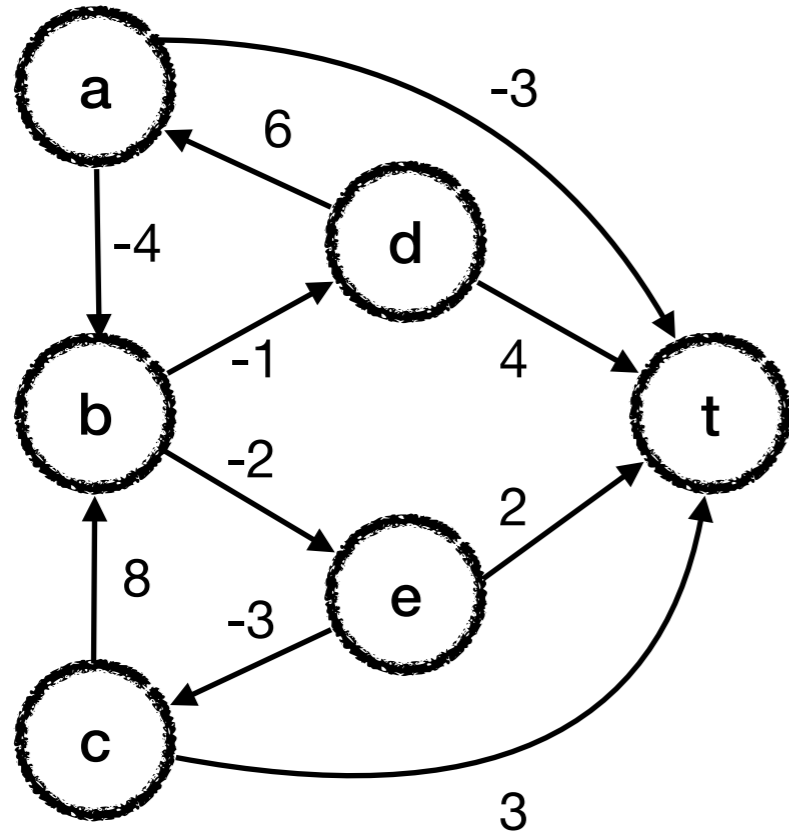
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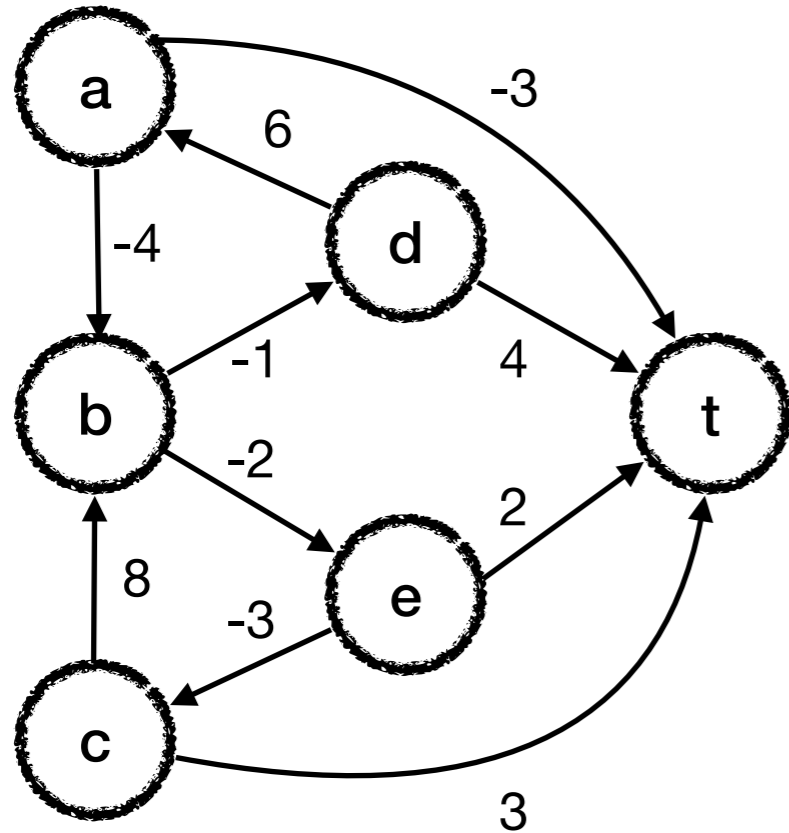
For  $i = 1, 2, \dots, n-1$

For  $v \in V$

$$M(i, v) = \min\{M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w))\}$$

Return  $M(n-1, s)$

# Example



	0	1	2	3	4	5
t	0					
a	∞					
b	∞					
c	∞					
d	∞					
e	∞					

**ShortestPath** ( $G, s, t$ ).

\\* Let  $n = |V|$  \\*

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

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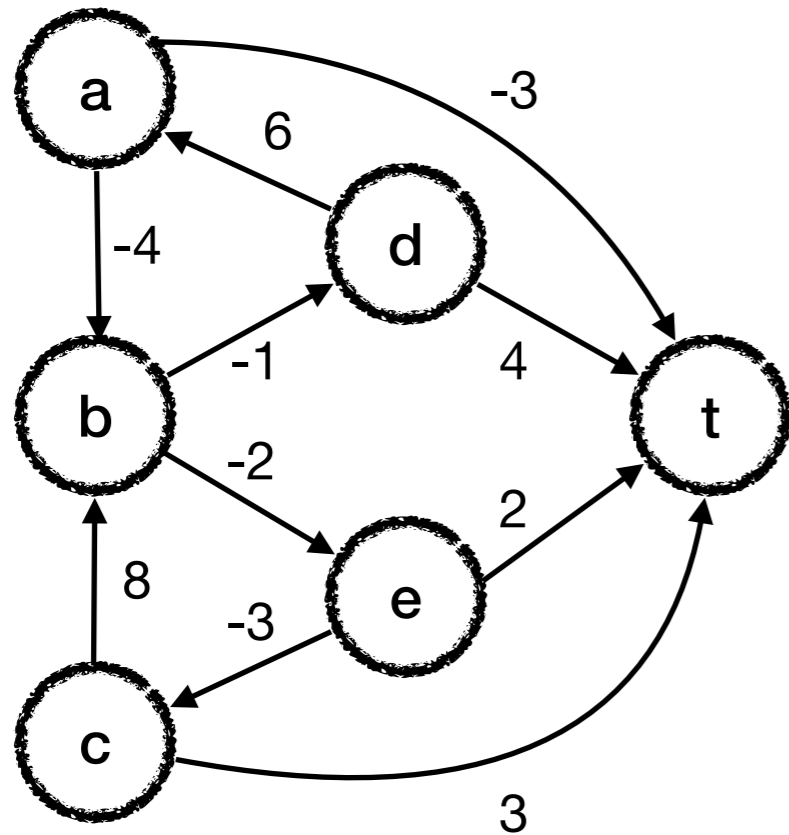
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# Example



	0	1	2	3	4	5
t	0					
a	∞					
b	∞					
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d	∞					
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ShortestPath ( $G, s, t$ ).

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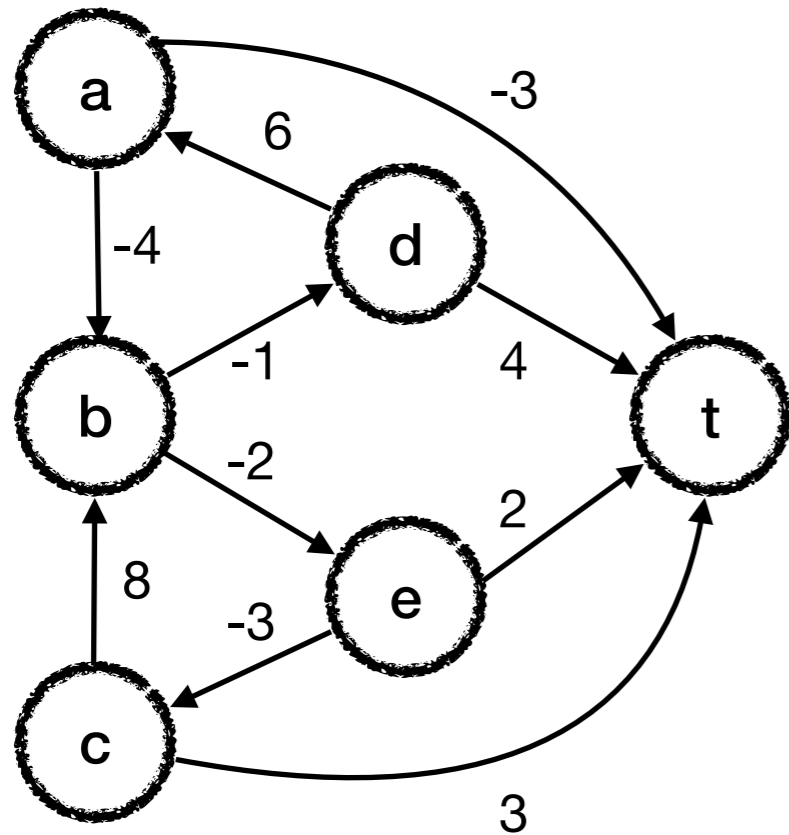
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Return  $M(n-1, s)$

$$M(1, t) = \min\{M(0, t), \min_{w \in N(t)} (0 + M(0, w))\}$$

# Example



	0	1	2	3	4	5
t	0	0				
a	∞					
b	∞					
c	∞					
d	∞					
e	∞					

**ShortestPath** ( $G, s, t$ ).

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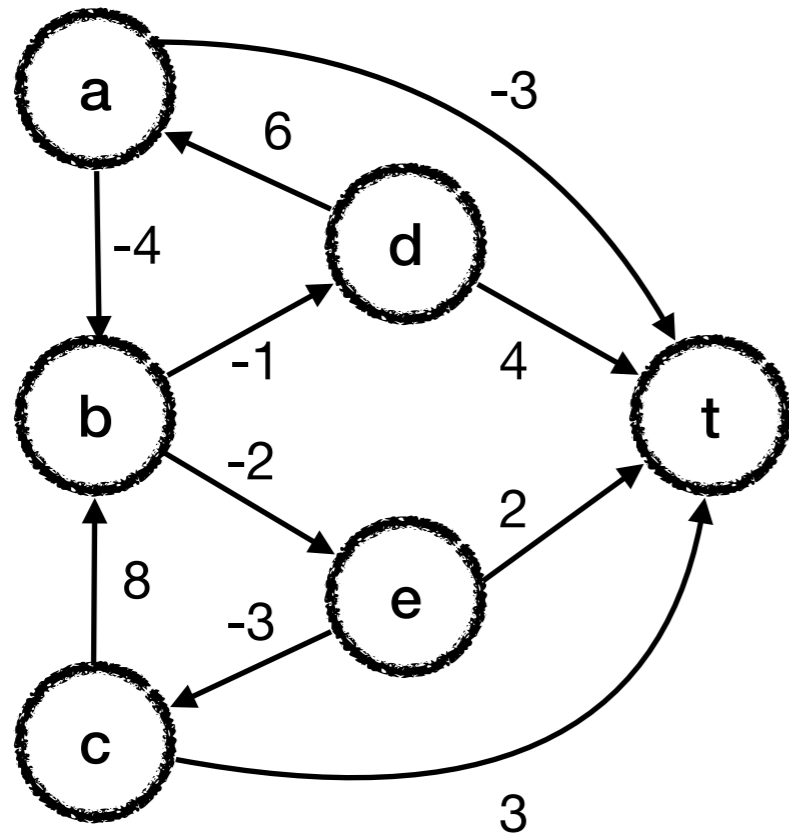
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# Example



	0	1	2	3	4	5
t	0	0				
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b	∞					
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d	∞					
e	∞					

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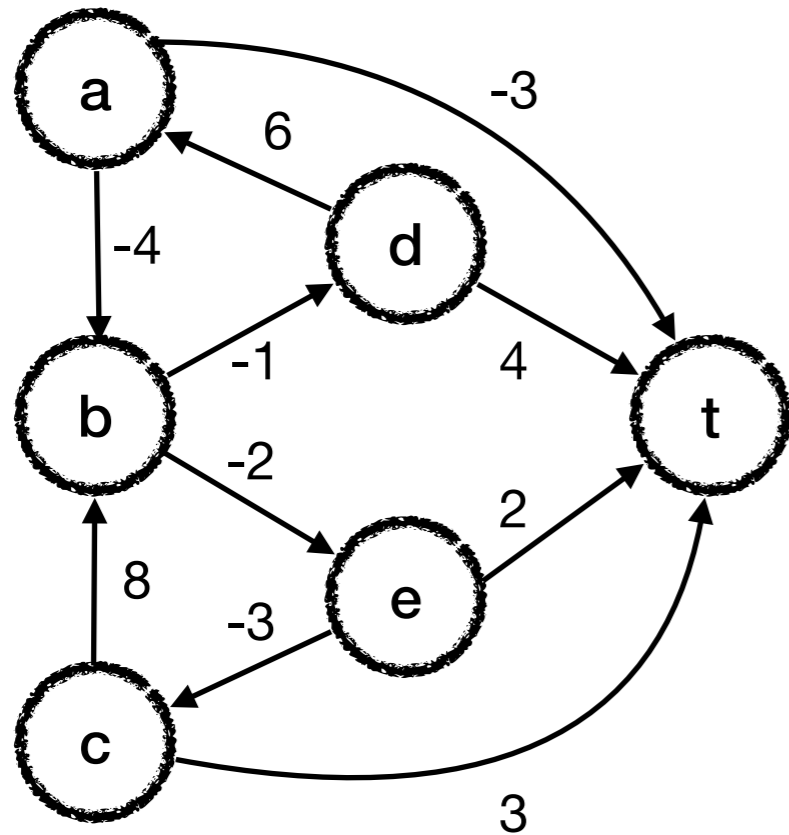
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# Example



	0	1	2	3	4	5
t	0	0				
a	∞					
b	∞					
c	∞					
d	∞					
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ShortestPath ( $G, s, t$ ).

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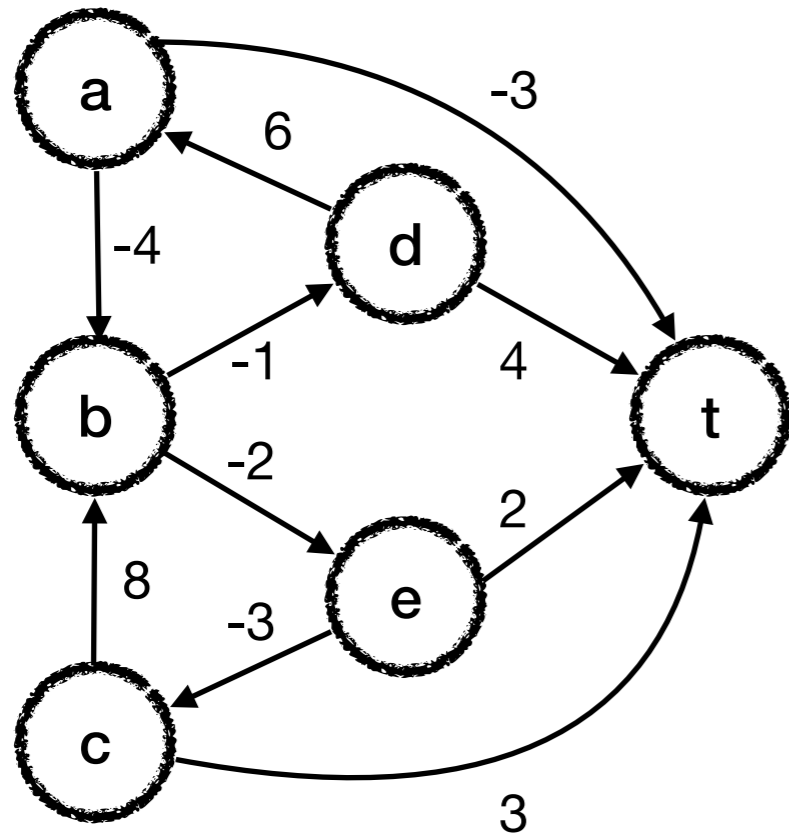
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Return  $M(n-1, s)$

$$M(1, a) = \min\{M(0, a), \min_{w \in N(a)} (c_{aw} + M(0, w))\}$$

# Example



	0	1	2	3	4	5
t	0	0				
a	∞					
b	∞					
c	∞					
d	∞					
e	∞					

ShortestPath ( $G, s, t$ ).

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For  $v \in V$

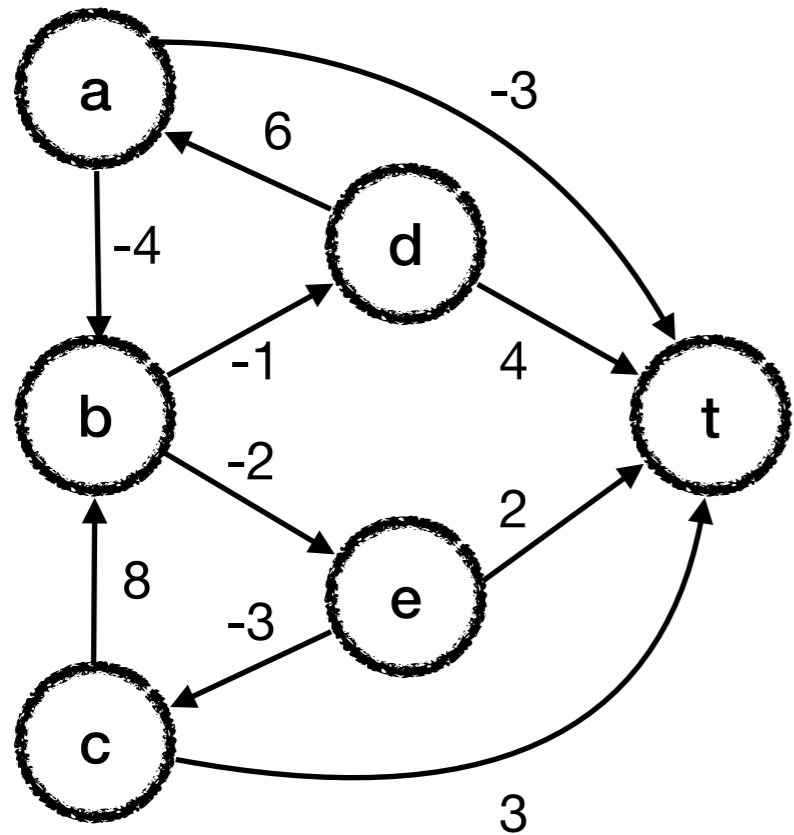
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Return  $M(n-1, s)$

$$M(1, a) = \min\{M(0, a), \min_{w \in N(a)} (c_{aw} + M(0, w))\}$$

$$M(1, a) = c_{at} + M(0, t)$$

# Example



↓

	0	1	2	3	4	5
t	0	0				
a	∞	-3				
b	∞					
c	∞					
d	∞					
e	∞					

→

## ShortestPath ( G, s, t ).

\\* Let  $n = |V|$  \\*

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

Initialise  $M[0, t] = 0$ , and  $M[0, v] = \infty$  for all other  $v \in V$ .

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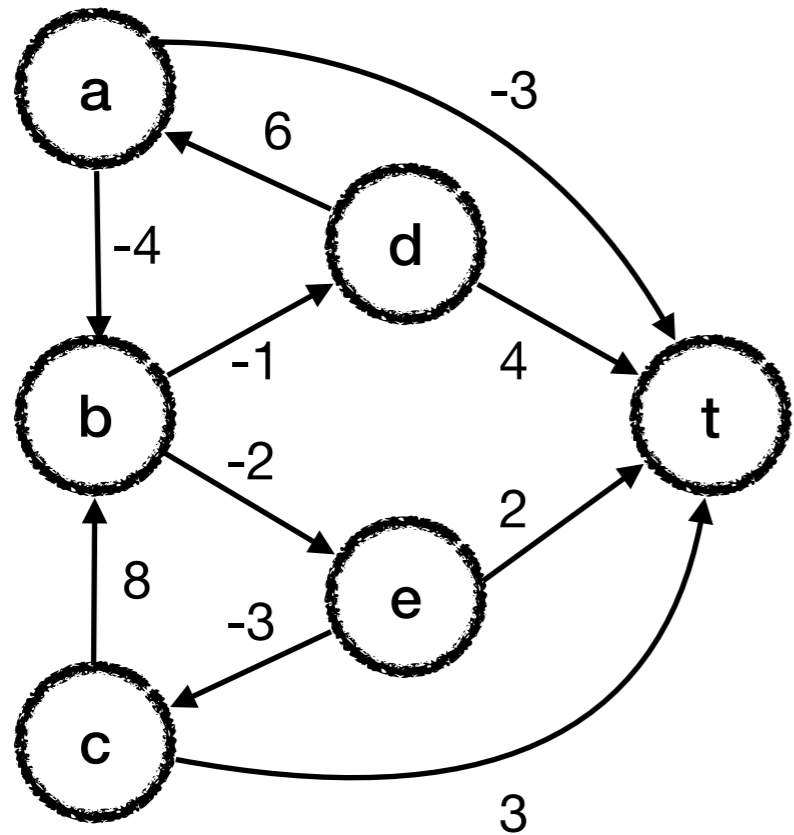
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Return  $M(n-1, s)$





# Example



	0	1	2	3	4	5
t	0	0				
a	∞	-3				
b	∞					
c	∞					
d	∞					
e	∞					

**ShortestPath** ( $G, s, t$ ).

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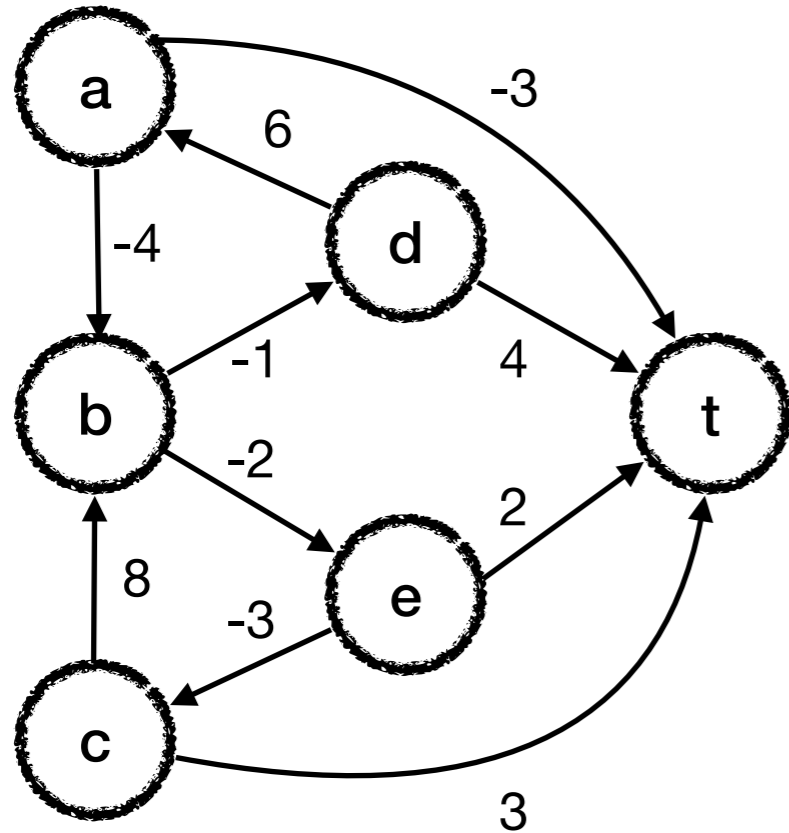
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Return  $M(n-1, s)$



# Example



	0	1	2	3	4	5
t	0	0				
a	∞	-3				
b	∞					
c	∞					
d	∞					
e	∞					

ShortestPath ( $G, s, t$ ).

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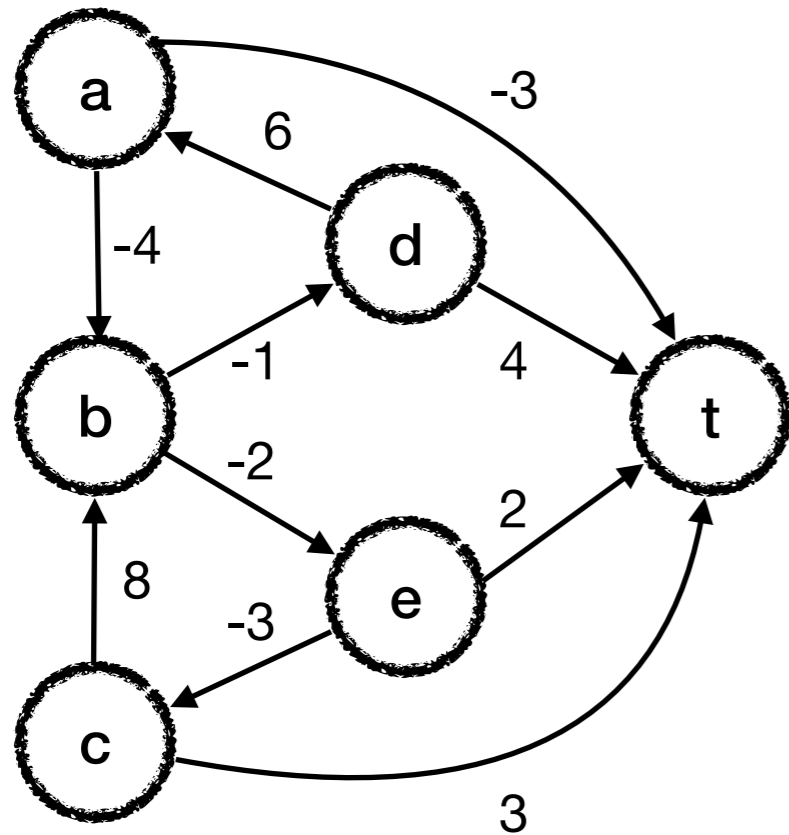
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Return  $M(n-1, s)$

$$M(1, b) = \min\{M(0, b), \min_{w \in N(b)} (c_{bw} + M(0, w))\}$$



# Example



	0	1	2	3	4	5
t	0	0				
a	∞	-3				
b	∞					
c	∞					
d	∞					
e	∞					

ShortestPath ( $G, s, t$ ).

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Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

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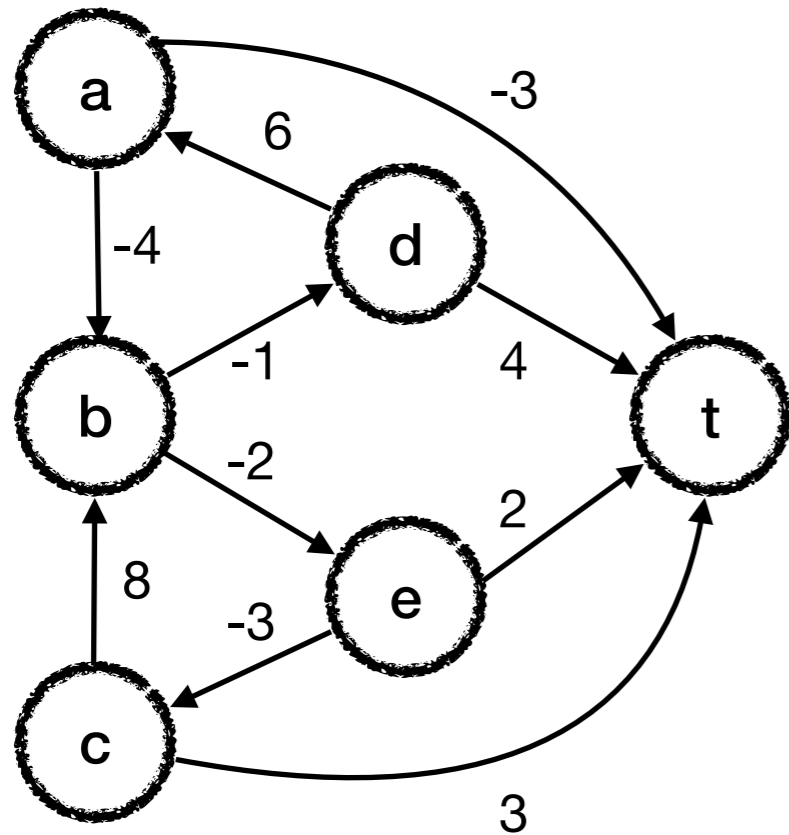
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$$M(1, b) = \infty$$

# Example



	0	1	2	3	4	5
t	0	0				
a	$\infty$	-3				
b	$\infty$	$\infty$				
c	$\infty$					
d	$\infty$					
e	$\infty$					

ShortestPath ( $G, s, t$ ).

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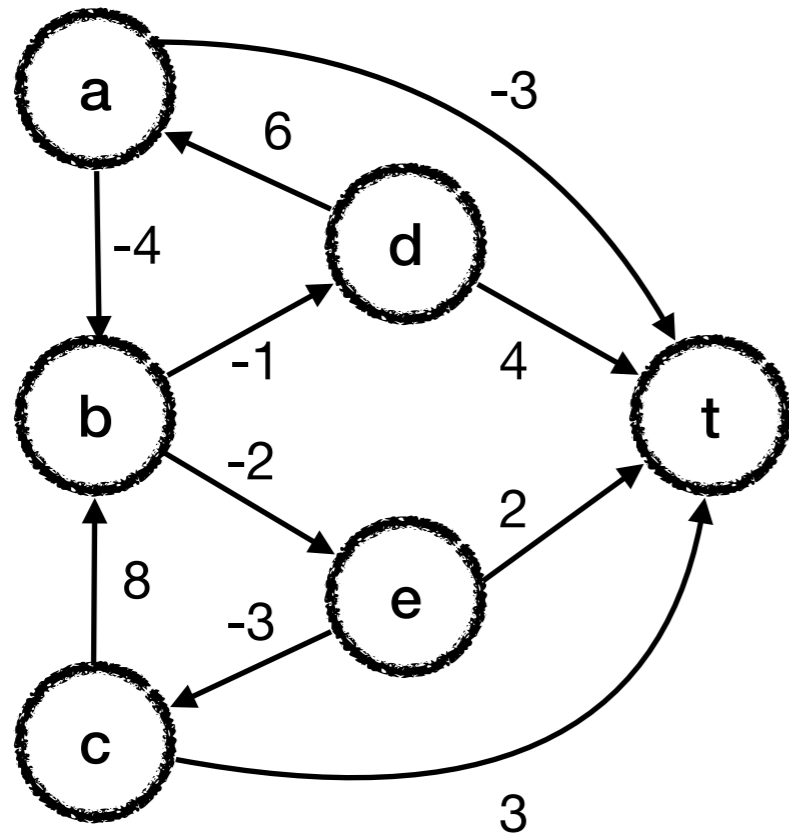
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$$M(1, b) = \infty$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4		
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		



**ShortestPath** ( $G, s, t$ ).

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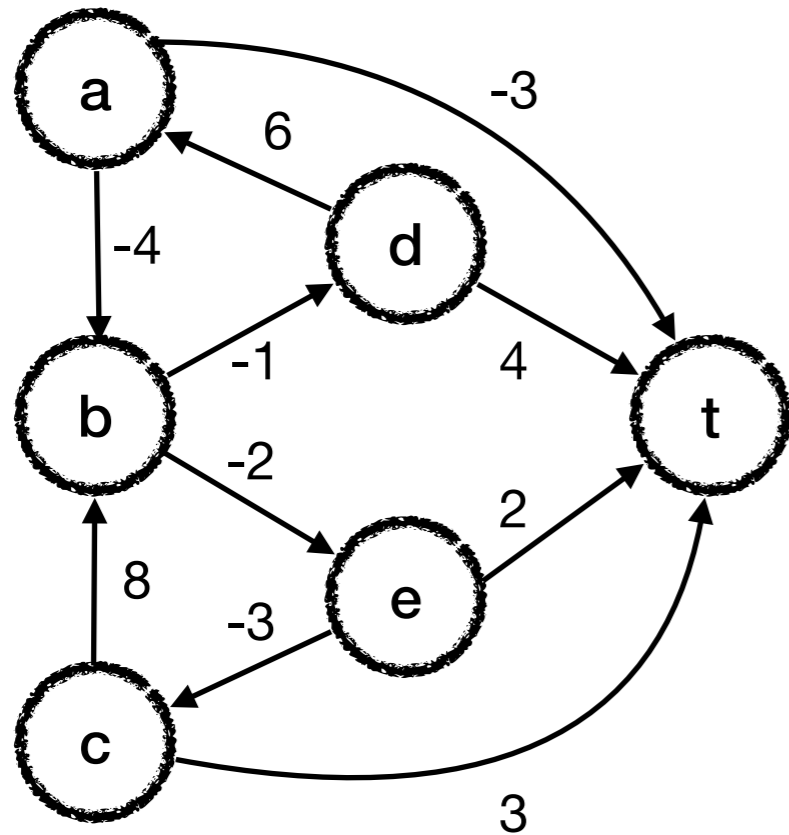
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Return  $M(n-1, s)$



# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4		
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		

ShortestPath ( $G, s, t$ ).

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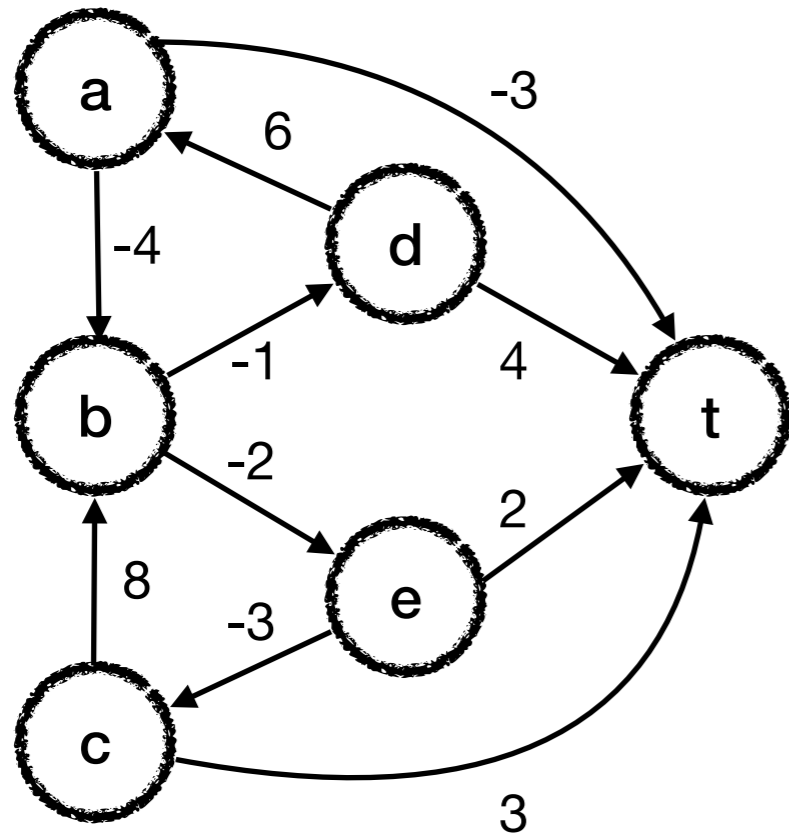
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Return  $M(n-1, s)$

$$M(4, a) = \min\{M(3, a), \min_{w \in N(a)} (c_{aw} + M(3, w))\}$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4		
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		

ShortestPath ( $G, s, t$ ).

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For  $i = 1, 2, \dots, n-1$

For  $v \in V$

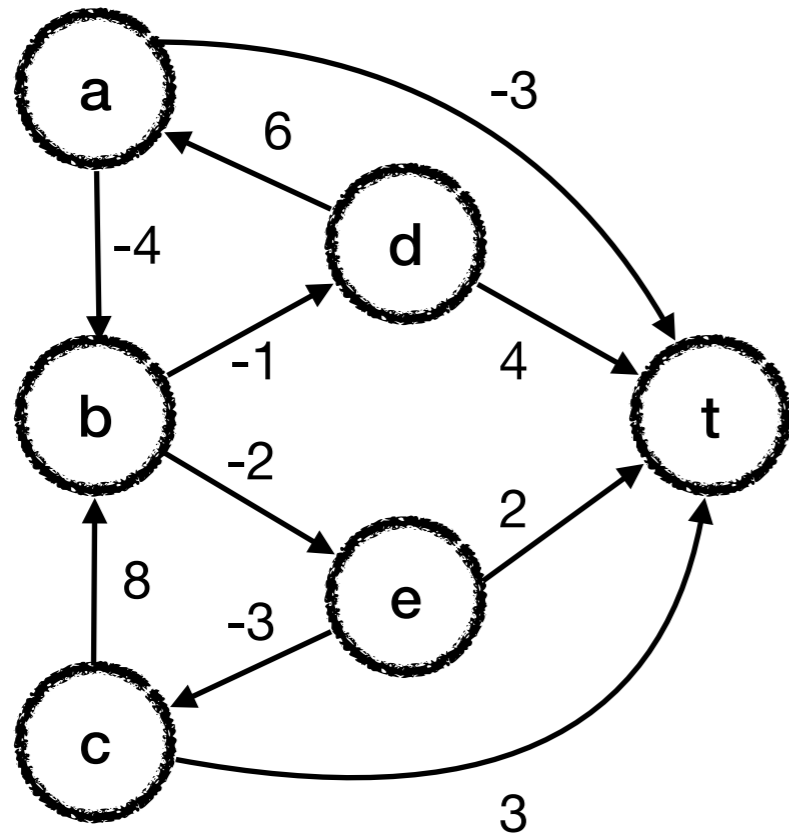
$$M(i, v) = \min\{M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w))\}$$

Return  $M(n-1, s)$

$$M(4, a) = \min\{M(3, a), \min_{w \in N(a)} (c_{aw} + M(3, w))\}$$

$$c_{ab} + M(3, b) = -6$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4		
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		

ShortestPath ( $G, s, t$ ).

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Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

Initialise  $M[0, t] = 0$ , and  $M[0, v] = \infty$  for all other  $v \in V$ .

For  $i = 1, 2, \dots, n-1$

For  $v \in V$

$$M(i, v) = \min\{M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w))\}$$

Return  $M(n-1, s)$

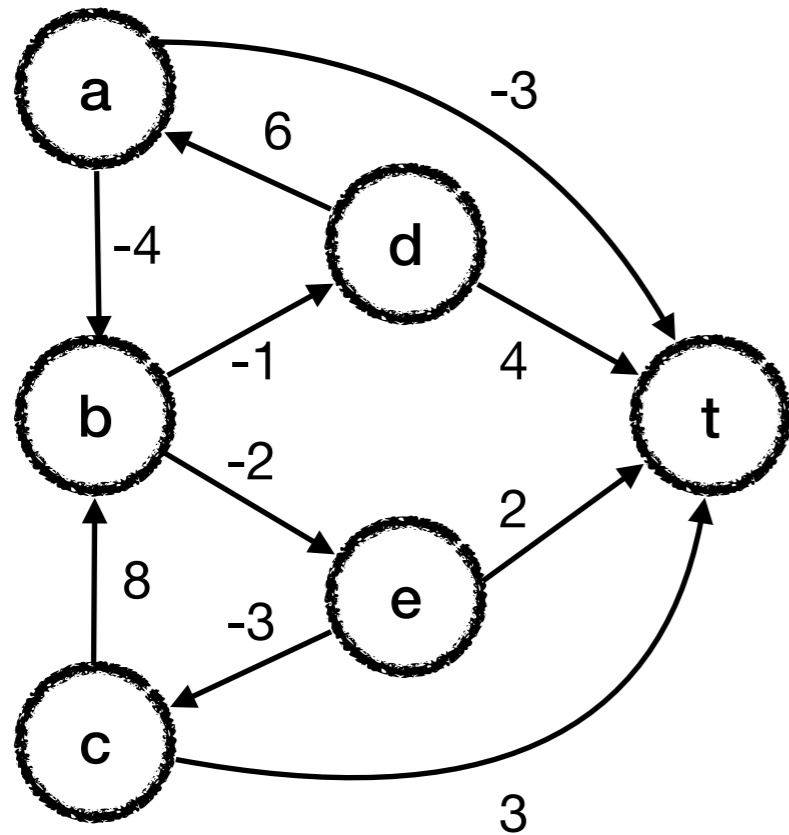
$$M(4, a) = \min\{M(3, a), \min_{w \in N(a)} (c_{aw} + M(3, w))\}$$

$$c_{ab} + M(3, b) = -6$$

$$c_{at} + M(3, t) = -3$$



# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4	-6	
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		



**ShortestPath** ( $G, s, t$ ).

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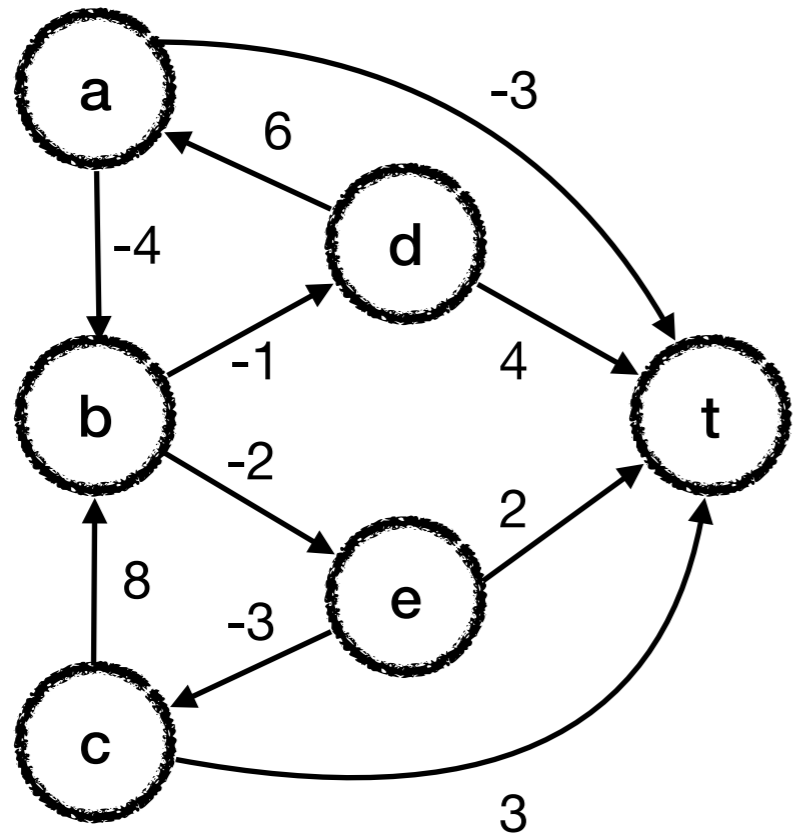
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Return  $M(n-1, s)$



# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4	-6	
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		



**ShortestPath** ( $G, s, t$ ).

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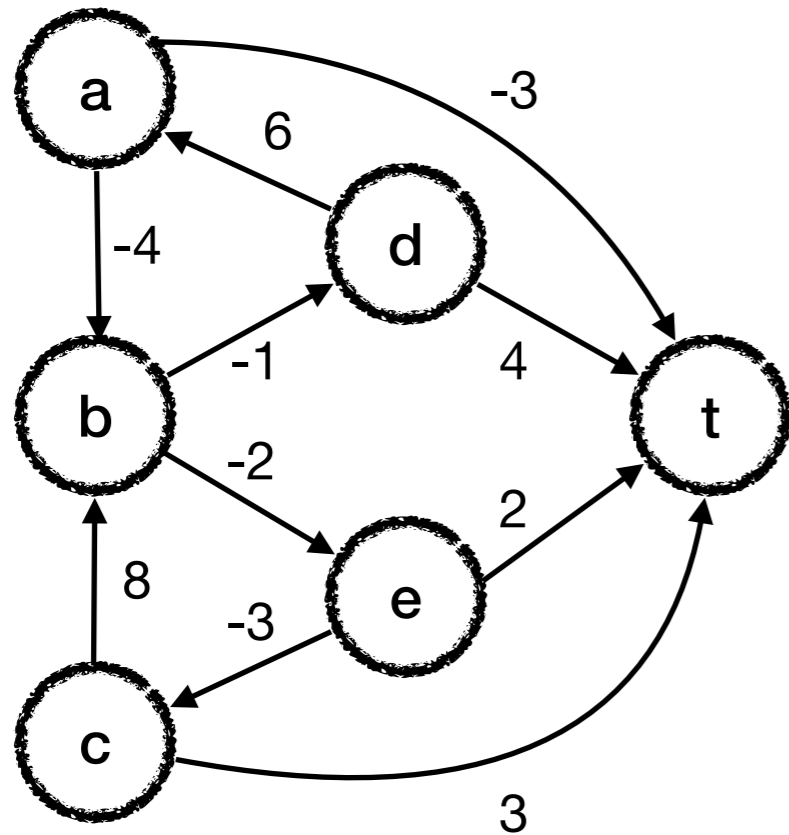
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Return  $M(n-1, s)$



# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	$\infty$	-3	-3	-4	-6	
b	$\infty$	$\infty$	0	-2		
c	$\infty$	3	3	3		
d	$\infty$	4	3	3		
e	$\infty$	2	0	0		

ShortestPath ( $G, s, t$ ).

\\* Let  $n = |V|$  \\*

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

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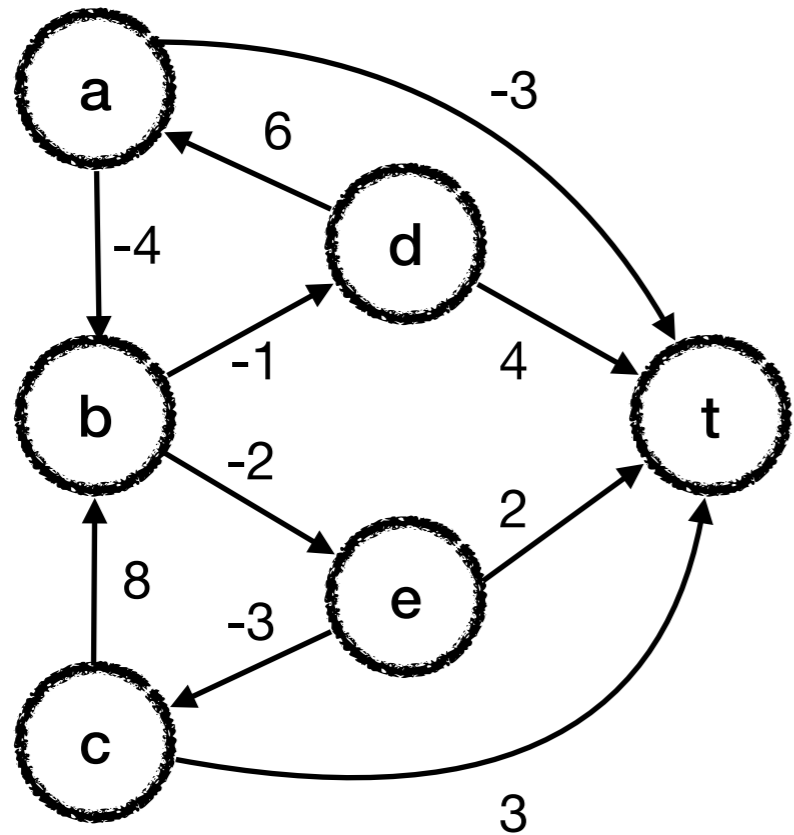
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Return  $M(n-1, s)$

$$M(4, b) = \min\{M(3, b), \min_{w \in N(b)} (c_{bw} + M(3, w))\}$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4	-6	
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		



ShortestPath ( G, s, t ).

\\* Let  $n = |V|$  \\*

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

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For  $i = 1, 2, \dots, n-1$

For  $v \in V$

$$M(i, v) = \min\{M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w))\}$$

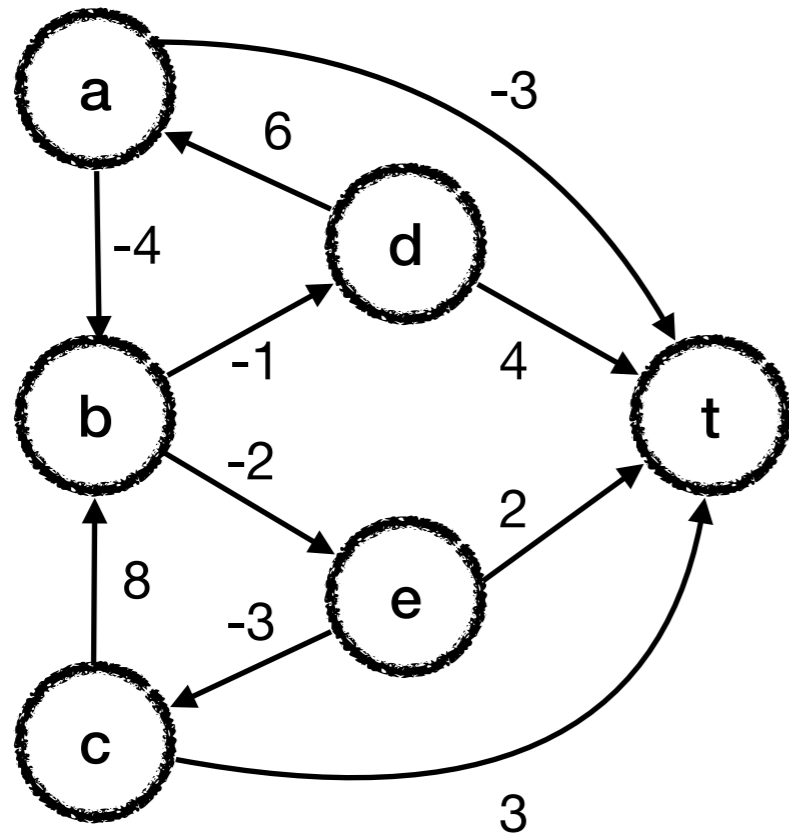
Return  $M(n-1, s)$

$$M(4, b) = \min\{M(3, b), \min_{w \in N(b)} (c_{bw} + M(3, w))\}$$



$$c_{bd} + M(3, d) = -1 + 3$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	∞	-3	-3	-4	-6	
b	∞	∞	0	-2		
c	∞	3	3	3		
d	∞	4	3	3		
e	∞	2	0	0		

ShortestPath ( $G, s, t$ ).

\\* Let  $n = |V|$  \\*

Define 2-D Array  $M[0, \dots, n-1, s, v_1, v_2, \dots, t]$

Initialise  $M[0, t] = 0$ , and  $M[0, v] = \infty$  for all other  $v \in V$ .

For  $i = 1, 2, \dots, n-1$

For  $v \in V$

$$M(i, v) = \min\{M(i-1, v), \min_{w \in N(v)} (c_{vw} + M(i-1, w))\}$$

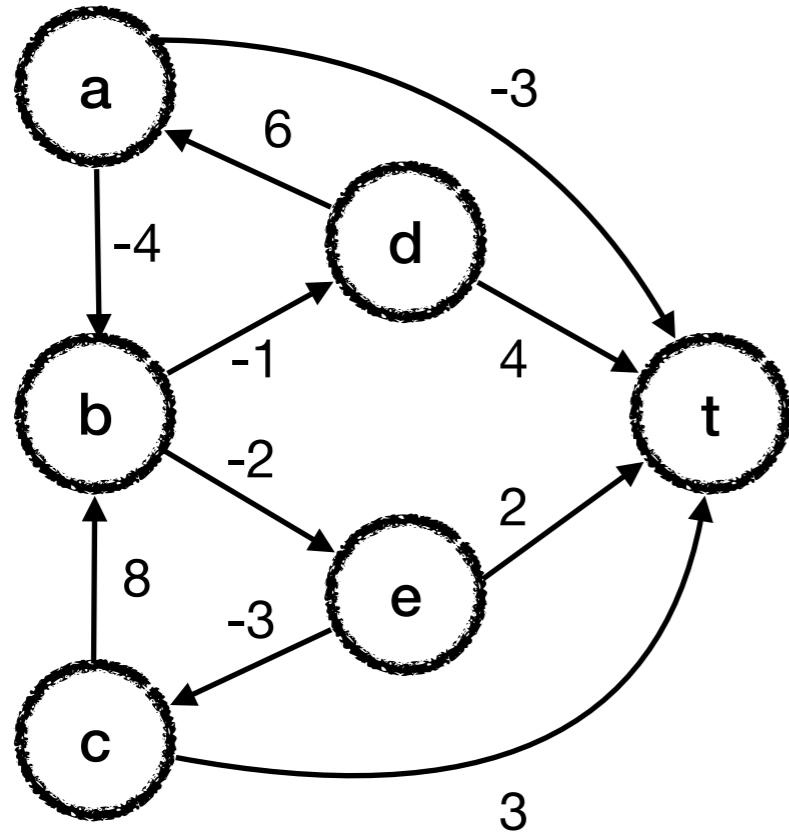
Return  $M(n-1, s)$

$$M(4, b) = \min\{M(3, b), \min_{w \in N(b)} (c_{bw} + M(3, w))\}$$

$$c_{bd} + M(3, d) = -1 + 3$$

$$c_{be} + M(3, e) = -2 + 0$$

# Example



	0	1	2	3	4	5
t	0	0	0	0	0	
a	$\infty$	-3	-3	-4	-6	
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c	$\infty$	3	3	3		
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e	$\infty$	2	0	0		



**ShortestPath** ( $G, s, t$ ).

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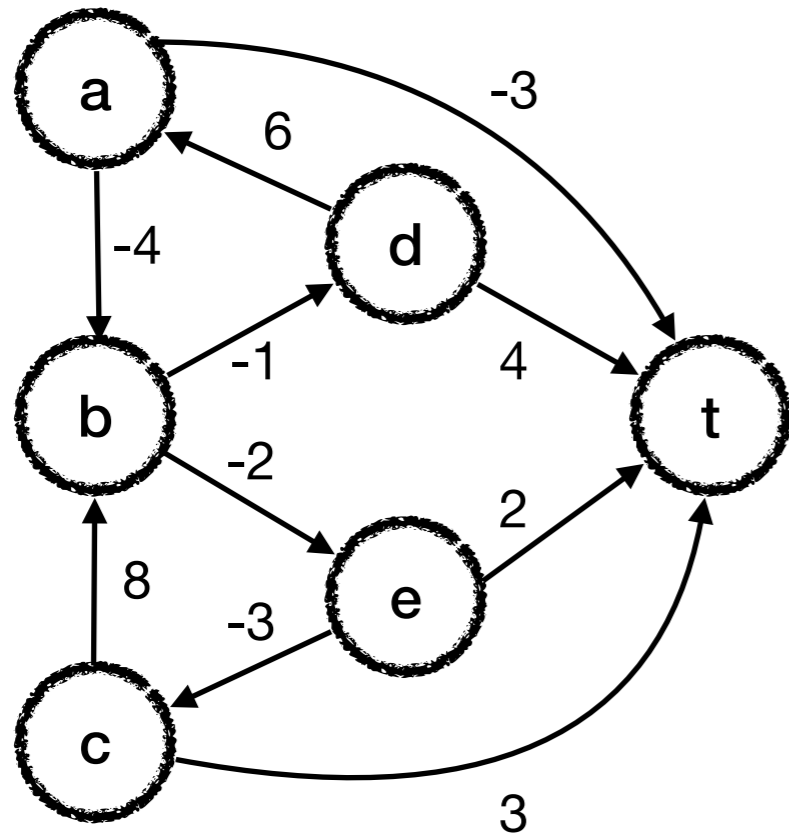
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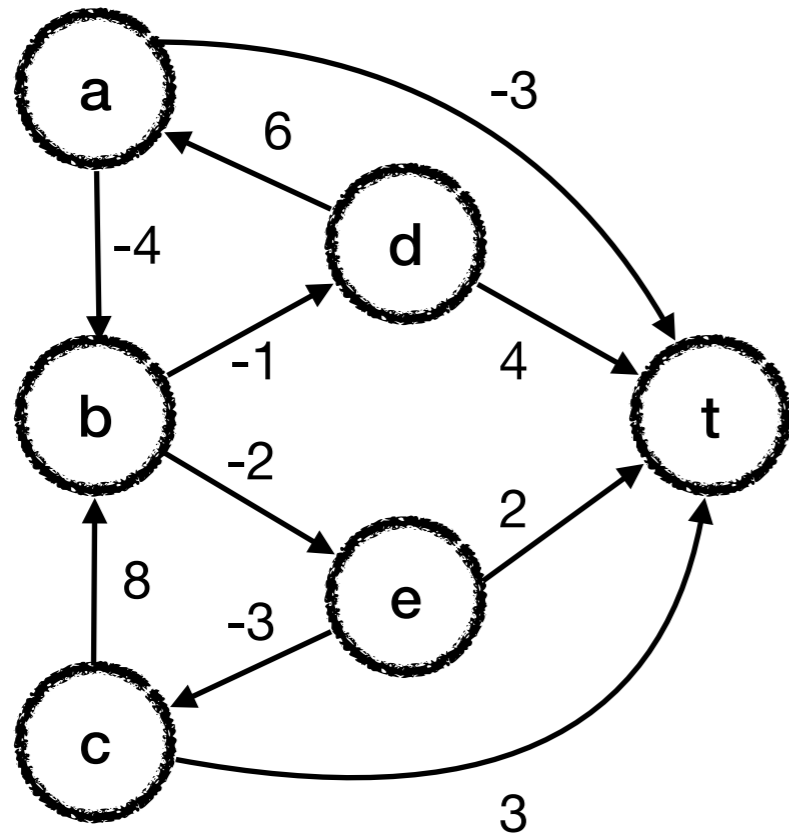
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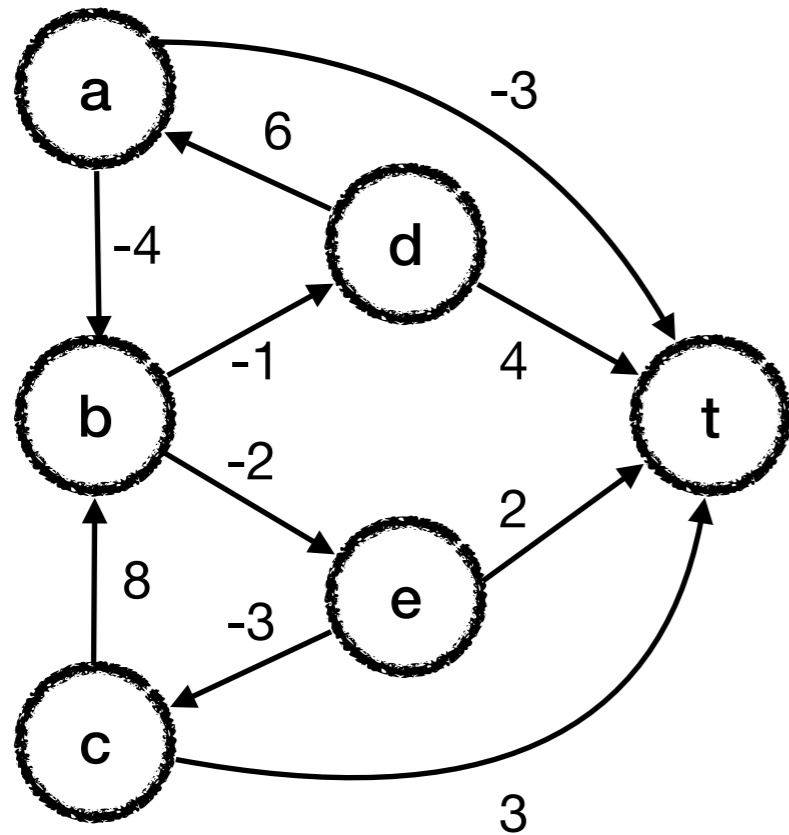
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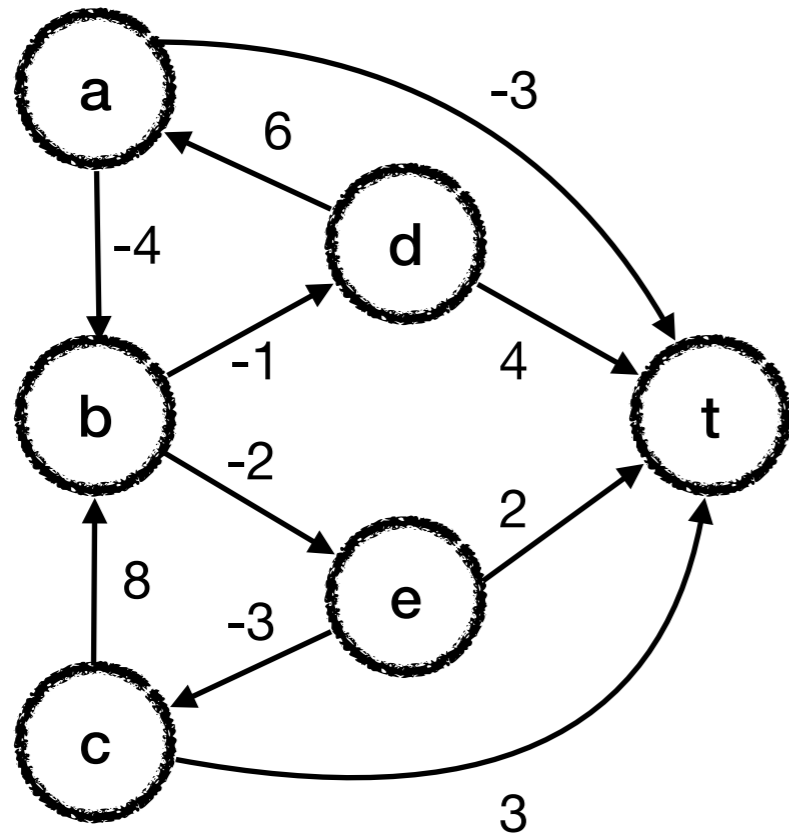
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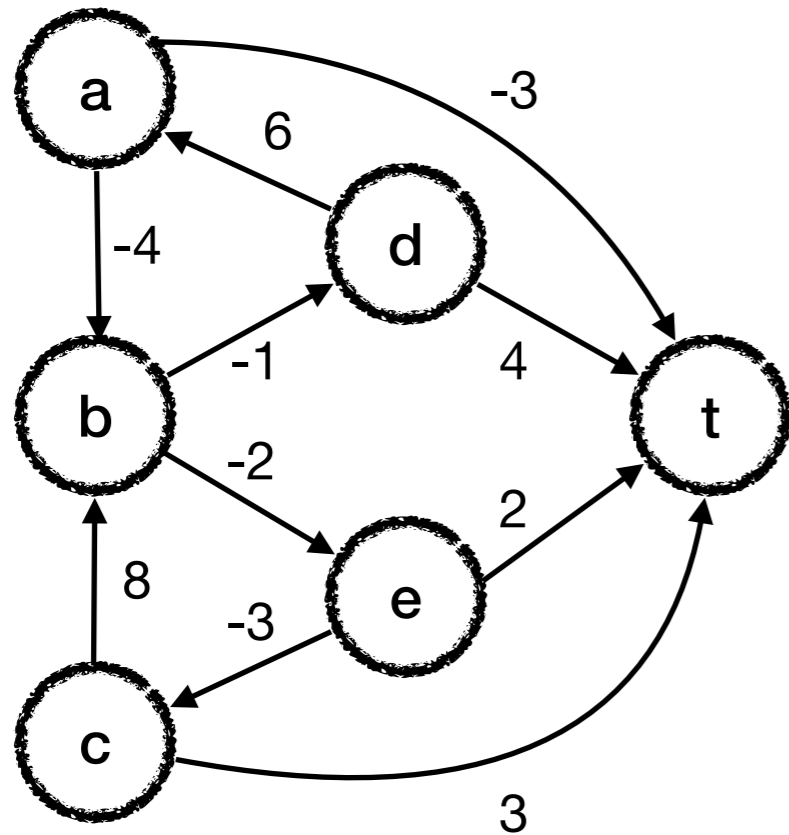
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Next we consider  $M(4, a)$ , etc.

# Running Time

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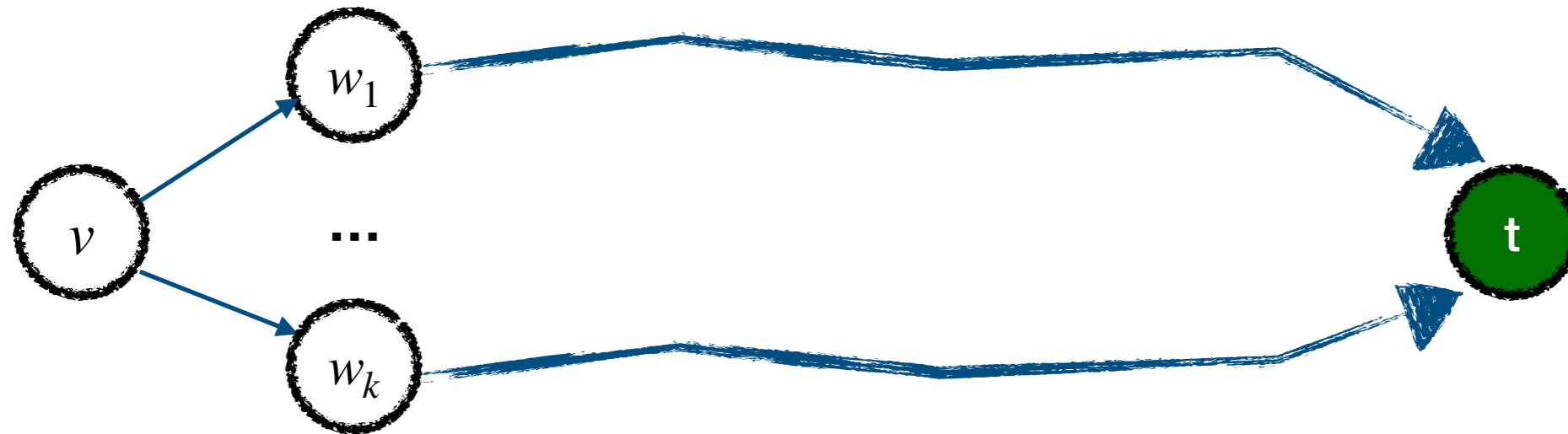
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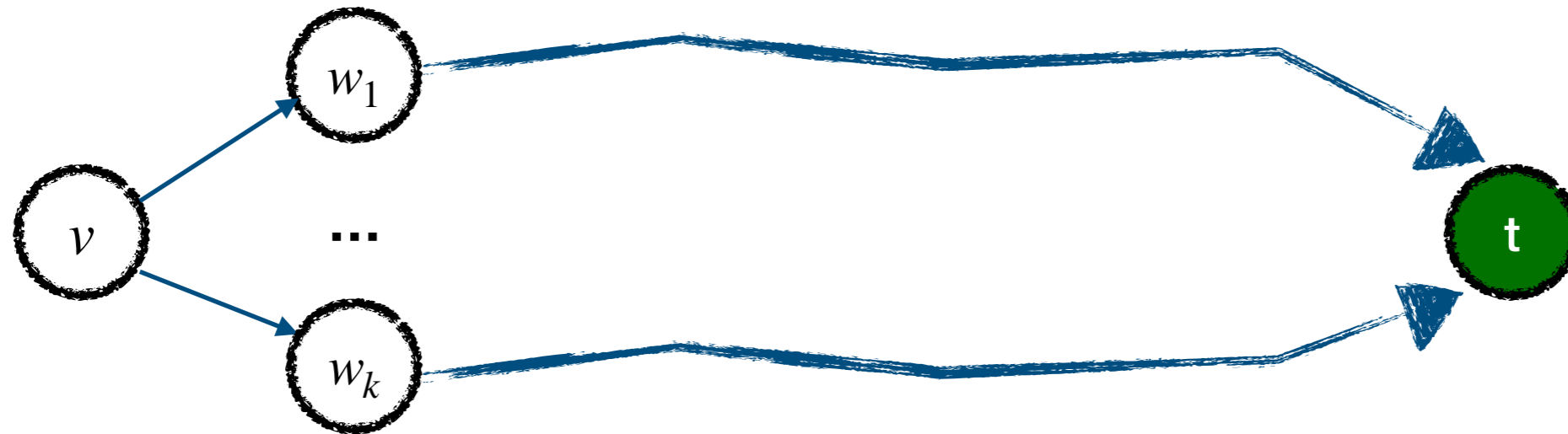
Overall:  $O(n^3)$

# Improved Analysis



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$w \in N(v)$

Suffices to only check  $w$  such that  $(v, w) \in E$ .

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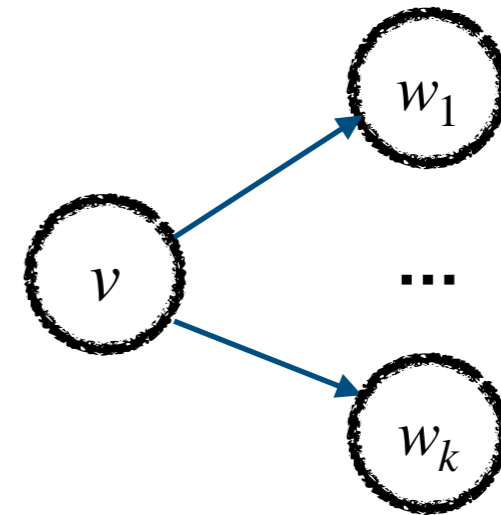
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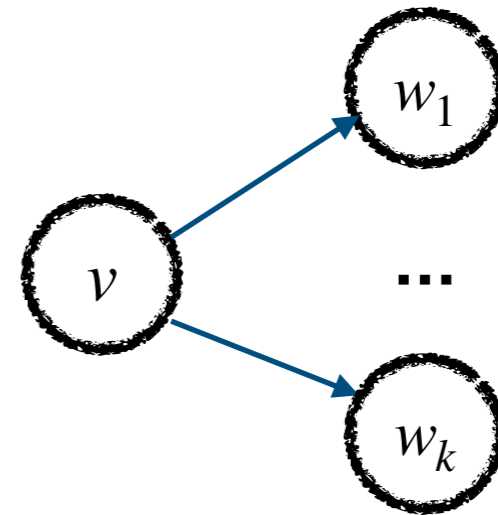
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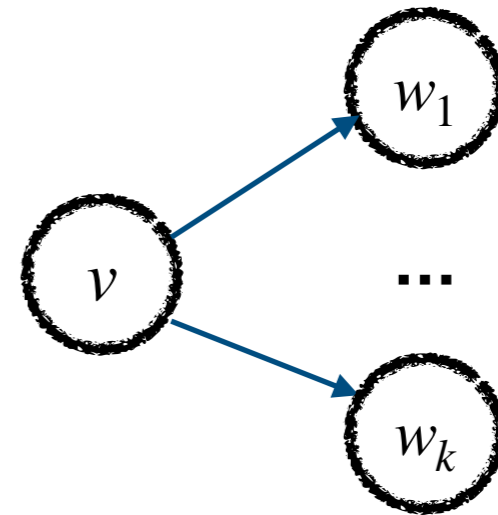
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$$\sum_{v \in V} n_v = m$$

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Overall:  $O(nm)$

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- That works, however more work is needed to recover the shortest paths!

# Shortest Paths in Graphs

- **Input:** A directed graph  $G = (V, E)$ , and designated nodes  $s, t$  in  $V$ . We also assume that every node  $u$  in  $V$  is reachable from  $s$ , and *that the graph does not have any negative cycles*. We are also given a cost  $c_e \in \mathbb{R}$  for every edge  $e$  in  $E$ .
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*What if the graph has negative cycles? Can we at least detect that?*

# Detecting Negative Cycles

- Can be done in time  $O(mn)$ .
- It is in fact usually included as a part of the Bellman-Ford algorithm.
- We will not cover this here, see KT 6.10 for the details if you are interested.

# Reading and References

- Kleinberg and Tardos 6.8.
- CLRS 22.1.
- Roughgarden 18.1, 18.2.
- The Bellman-Ford visualiser:  
[https://algorithms.discrete.ma.tum.de/graph-algorithms/spp-bellman-ford/index\\_en.html](https://algorithms.discrete.ma.tum.de/graph-algorithms/spp-bellman-ford/index_en.html)