

# CSE 421 Winter 2025

## Lecture 14: DP3

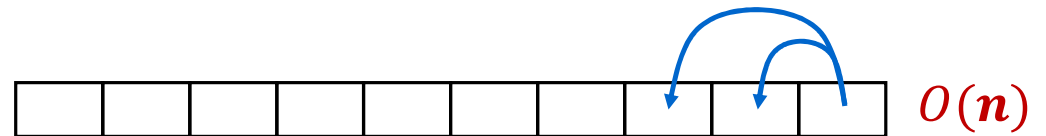
Nathan Brunelle

<http://www.cs.uw.edu/421>

# Dynamic Programming Patterns

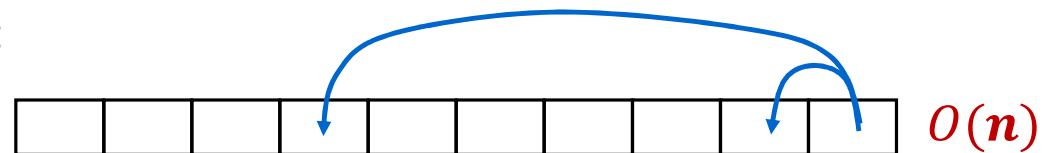
Fibonacci pattern:

- 1-D,  $O(1)$  immediately prior
- $O(1)$  space



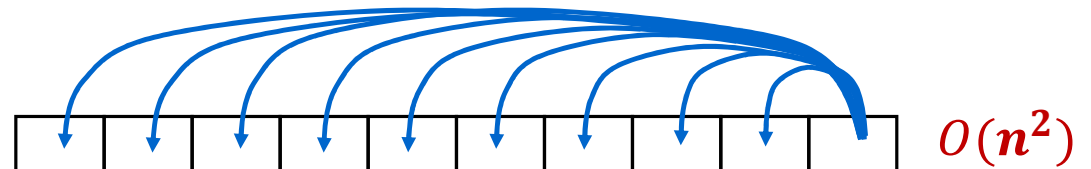
Weighted interval scheduling pattern:

- 1-D,  $O(1)$  arbitrary prior
- $O(n)$  space



Longest increasing subsequence pattern:

- 1-D, all  $n - 1$  prior
- $O(n)$  space



# String Similarity

## How similar are two strings?

- **ocurrance**
- **occurrence**

Clearly a better matching

Maybe a better matching

- depends on cost of gaps vs mismatches

o c u r r a n c e -

o c c u r r e n c e

6 mismatches, 1 gap

o c - u r r a n c e

o c c u r r e n c e

1 mismatch, 1 gap

o c - u r r - a n c e

o c c u r r e - n c e

0 mismatches, 3 gaps

# Edit Distance

## Applications:

- Basis for Unix `diff`.
- Speech recognition.
- Computational biology.
- autocorrect

**Edit distance:** [Levenshtein 1966, Needleman-Wunsch 1970]

- Gap penalty  $\delta$ ; mismatch penalty  $\alpha_{pq}$  if symbol  $p$  is replaced by symbol  $q$ .
- **Cost** = gap penalties + mismatch penalties.

C T G A C C T A C C T

- C T G A C C T A C C T

C C T G A C T A C A T

C C T G A C - T A C A T

$$\alpha_{TC} + \alpha_{GT} + \alpha_{AG} + 2\alpha_{CA}$$

$$2\delta + \alpha_{CA}$$

# Sequence Alignment

## Sequence Alignment:

**Given:** Two strings  $X = x_1x_2 \dots x_m$  and  $Y = y_1y_2 \dots y_n$

**Find:** “Alignment” of  $X$  and  $Y$  of minimum edit cost.

**Defn:** An **alignment**  $M$  of  $X$  and  $Y$  is a set of ordered pairs  $x_i-y_j$  s.t. each symbol of  $X$  and  $Y$  occurs in at most one pair with no “crossing pairs”.

The pairs  $x_i-y_j$  and  $x_{i'}-y_{j'}$  **cross** iff  $i < i'$  but  $j > j'$ .

$$\text{cost}(M) = \underbrace{\sum_{(x_i, y_j) \in M} \alpha_{x_i y_j}}_{\text{mismatch}} + \underbrace{\sum_{i: x_i \text{ unmatched}} \delta + \sum_{j: y_j \text{ unmatched}} \delta}_{\text{gap}}$$

Note: if  $x_i = y_j$  then  $\alpha_{x_i y_j} = 0$

### Example:

**CTACCG vs TACATG**

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$		$x_6$
C	T	A	C	C	-	G
	T	A	C	A	T	G
	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$

$$M = \{x_2-y_1, x_3-y_2, x_4-y_3, x_5-y_4, x_6-y_6\}$$

# Edit Distance – Four Steps

1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
  - For each such option, what does the subproblem look like? How do we use it?
2. Choose a memory structure.
  - Figure out the possible values of all parameters in the recursive calls.
  - How many subproblems (options for last choice) are there?
  - What are the parameters needed to identify each?
  - How many different values could there be per parameter?
3. Specify an order of evaluation.
  - Want to guarantee that the necessary subproblem solutions are in memory when you need them.
  - With this step: a “Bottom-up” (iterative) algorithm
  - Without this step: a “Top-down” (recursive) algorithm
4. See if there’s a way to save space
  - Is it possible to reuse some memory locations?

# Step 1: Identify Recursive Structure

Consider the last two indices  $x_i$  and  $y_j$   
Options for what to do with them:

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
C	T	A	C	C	G
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$
T	A	C	A	T	G

Option 1:  
Match them

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
C	T	A	C	C	G
T	A	C	A	T	G
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$

We use up one index from  $x$  and  $y$   
Accrue a mismatch penalty  
 $OPT(i-1, j-1) + \alpha_{x_i y_j}$

Option 2:  
Don't match  $x_i$

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	
	C	T	A	C	C	G
T	A	C	A	T	G	-
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	

We use up one index from  $x$  only  
Accrue a gap penalty  
 $OPT(i-1, j) + \delta$

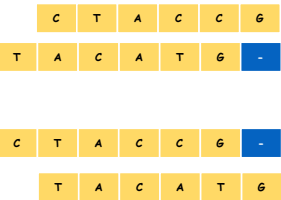
Option 3:  
Don't match  $y_i$

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	
C	T	A	C	C	G	-
	T	A	C	A	T	G
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	

We use up one index from  $y$  only  
Accrue a gap penalty  
 $OPT(i, j-1) + \delta$

$$OPT(i, j) = \begin{cases} j \cdot \delta & \text{if } i = 0 \\ i \cdot \delta & \text{if } j = 0 \\ \min \begin{cases} OPT(i-1, j-1) + \alpha_{x_i y_j} \\ OPT(i-1, j) + \delta \\ OPT(i, j-1) + \delta \end{cases} & \text{otherwise} \end{cases}$$

# Edit Distance – Four Steps



1. Formulate the answer with a recursive structure
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  - Is it possible to reuse some memory locations?



# Step 2: Identify Memory Structure

$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$
C	T	A	C	C	G
$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$
T	A	C	A	T	G

$$OPT(i, j) = \begin{cases} j \cdot \delta & \text{if } i = 0 \\ i \cdot \delta & \text{if } j = 0 \\ \min \begin{cases} OPT(i-1, j-1) + \alpha_{x_i y_j} \\ OPT(i-1, j) + \delta \\ OPT(i, j-1) + \delta \end{cases} & \text{otherwise} \end{cases}$$

- How many parameters?
  - 2
- What does each represent?
  - The number of items in each sequence
- How many different values?
  - Length of sequence  $x$  for  $i$
  - Length of sequence  $y$  for  $j$
  - $n \cdot m$  overall

	$y_1$	$y_2$	$y_3$	$y_4$	$y_5$	$y_6$	$y_7$	$y_8$
$x_1$								
$x_2$								
$x_3$								
$x_4$								
$x_5$								
$x_6$								

# Top-Down Sequence Alignment

**align( $i, j$ ):**

if OPT[ $i$ ][ $j$ ] not blank: // Check if we've solved this already

return OPT[ $i$ ][ $j$ ]

if  $i \cdot j == 0$ : // Check if this is a base case

**solution** =  $(i + j) \cdot \delta$

OPT[ $i$ ][ $j$ ] = **solution** // Always save your solution before returning

return **solution**

match = align( $i - 1, j - 1$ ) // solve each subproblem

gapx = align( $i - 1, j$ ) // solve each subproblem

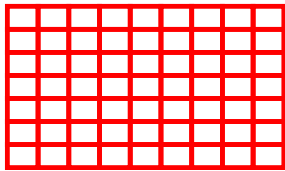
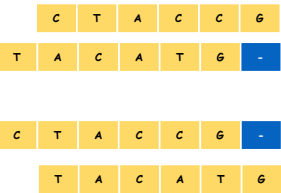
gapy = align( $j, i - 1$ ) // solve each subproblem

**solution** = min(match +  $\alpha_{x_i y_j}$ , gapx +  $\delta$ , gapy +  $\delta$ ) // Pick the subproblem to use

OPT[ $i$ ][ $j$ ] = **solution** // Always save your solution before returning

return **solution**

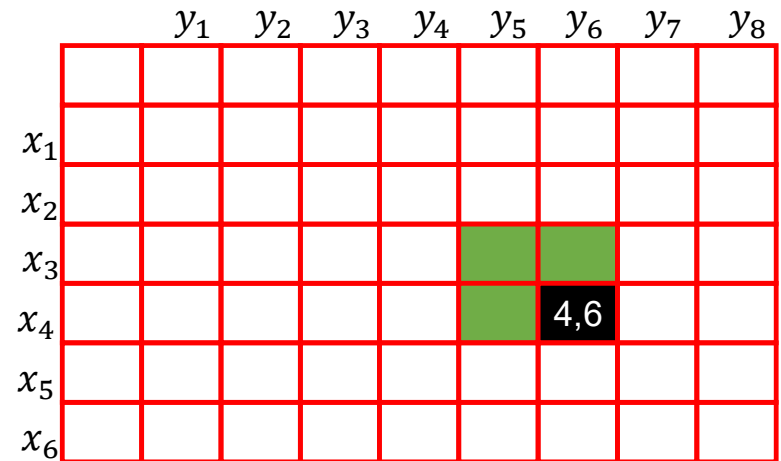
# Edit Distance – Four Steps



1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
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# Step 3: Identify Order of Evaluation

$$OPT(i, j) = \begin{cases} j \cdot \delta & \text{if } i = 0 \\ i \cdot \delta & \text{if } j = 0 \\ \min \begin{cases} OPT(i-1, j-1) + \alpha_{x_i y_j} \\ OPT(i-1, j) + \delta \\ OPT(i, j-1) + \delta \end{cases} & \text{otherwise} \end{cases}$$

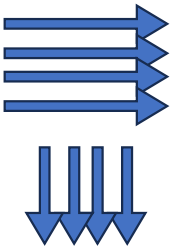


Any of these orders will work:

Each index depends on 3 others:

1. The one above it:  $(i - 1, j)$
2. The one to its left:  $(i, j - 1)$
3. The one to its upper left:  $(i - 1, j - 1)$

- Top-to-bottom, then left-to-right
- Left-to-right, then top-to-bottom
- Diagonally



# Bottom-Up Sequence Alignment

**align**( $x, y$ ):

for  $i = 0$  up to  $n$ :

$\text{OPT}[i][0] = 0$  // Solve and save base cases

for  $j = 0$  up to  $m$ :

$\text{OPT}[0][j] = 0$  // Solve and save base cases

for  $i = 1$  up to  $n$ :

    for  $j = 1$  up to  $m$  :

$\text{match} = \text{OPT}[i - 1][j - 1]$  // solve each subproblem

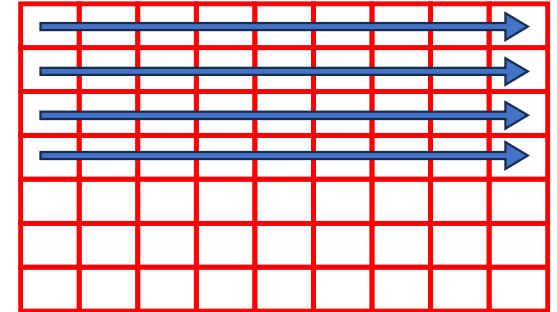
$\text{gapx} = \text{OPT}[i][j - 1]$  // solve each subproblem

$\text{gapy} = \text{OPT}[i - 1][j]$  // solve each subproblem

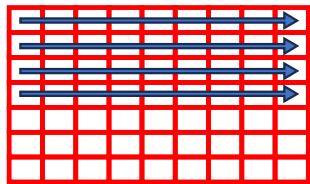
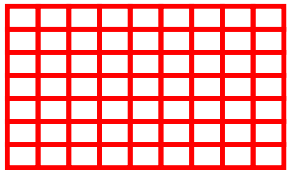
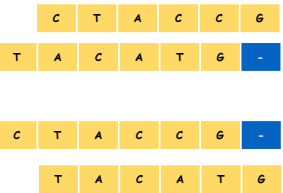
$\text{solution} = \min(\text{match} + \alpha_{x_i y_j}, \text{gapx} + \delta, \text{gapy} + \delta)$  // pick solution

$\text{OPT}[i][j] = \text{solution}$  // save solution

return  $\text{OPT}[n][m]$



# Edit Distance – Four Steps



1. Formulate the answer with a recursive structure
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Example run with **AGACATTG** and **GAGTTA**:  $\delta = \alpha_{\text{mis}} = 1$

		<b>A</b>	<b>G</b>	<b>A</b>	<b>C</b>	<b>A</b>	<b>T</b>	<b>T</b>	<b>G</b>
	0								
<b>G</b>	1								
<b>A</b>	2								
<b>G</b>	3								
<b>T</b>	4								
<b>T</b>	5								
<b>A</b>	6								









Example run with **AGACATTG** and **GAGTTA**:  $\delta = \alpha_{\text{mis}} = 1$

	A	G	A	C	A	T	T	G	
	0	1	2	3	4	5	6	7	8
G	1	1	1	2	3	4	5	6	7
A	2	1	2	1	2	3	4	5	6
G	3	2	1	2	2	3	4	5	5
T	4	3	2	2	3	3	3	4	5
T	5	4	3	3	3	4	3	3	4
A	6	5	4	3	4	3	4	4	4

Example run with **AGACATTG** and **GAGTTA**:  $\delta = \alpha_{\text{mis}} = 1$

		A	G	A	C	A	T	T	G
	0	1	2	3	4	5	6	7	8
<b>G</b>	1	1	1	2	3	4	5	6	7
<b>A</b>	2	1	2	1	2	3	4	5	6
<b>G</b>	3	2	1	2	2	3	4	5	5
<b>T</b>	4	3	2	2	3	3	3	4	5
<b>T</b>	5	4	3	3	3	4	3	3	4
<b>A</b>	6	5	4	3	4	3	4	4	4

Example run with *AGACATTG* and *GAGTTA*:  $\delta = \alpha_{\text{mis}} = 1$

		A	G	A	C	A	T	T	G
	0	1	2	3	4	5	6	7	8
G	1	1	1	2	3	4	5	6	7
A	2	1	2	1	2	3	4	5	6
G	3	2	1	2	2	3	4	5	5
T	4	3	2	2	3	3	3	4	5
T	5	4	3	3	3	4	3	3	4
A	6	5	4	3	4	3	4	4	4

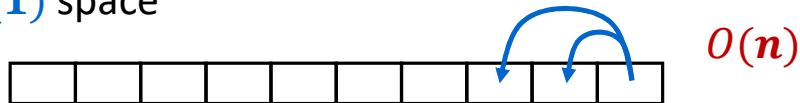
Optimal Alignment

*AGACATTG*  
*\_GAG\_TTA*

# Dynamic Programming Patterns

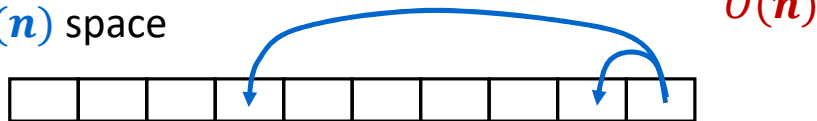
Fibonacci pattern:

- 1-D,  $O(1)$  immediately prior
- $O(1)$  space



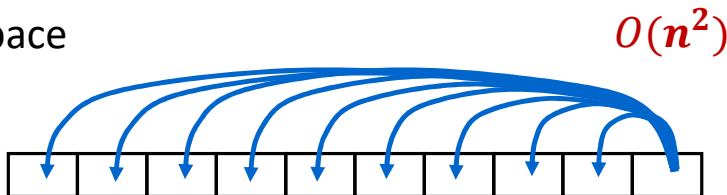
Weighted interval scheduling pattern:

- 1-D,  $O(1)$  arbitrary prior
- $O(n)$  space



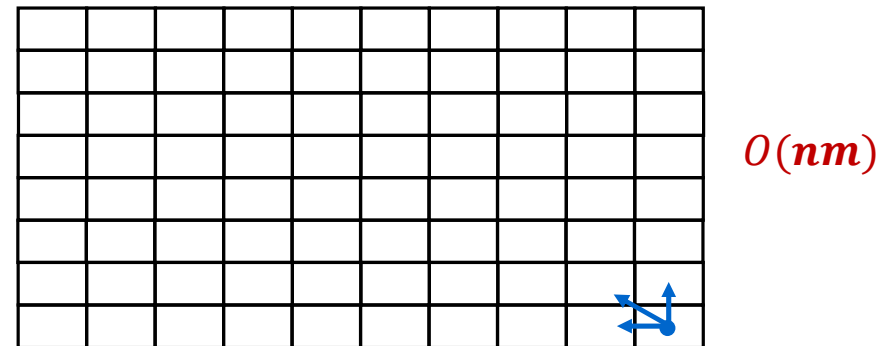
Longest increasing subsequence pattern:

- 1-D, all  $n - 1$  prior
- $O(n)$  space



Alignment pattern:

- 2-D,  $O(1)$  in previous row, above and arbitrary prior
- $O(n \cdot m)$  space



## Single-source shortest paths (332)

**Given:** an (un)directed graph  $G = (V, E)$  with each edge  $e$  having a non-negative weight  $w(e)$  and a vertex  $s$

**Find:** (length of) shortest paths from  $s$  to each vertex in  $G$

# Single-source shortest paths (Today)

**Given:** an (un)directed graph  $G = (V, E)$  with each edge  $e$  having a ~~non-negative~~ weight  $w(e)$  and a vertex  $s$

**Find:** (length of) shortest paths from  $s$  to each vertex in  $G$



# Dijkstra's Algorithm

- Maintain a set  $S$  of vertices whose shortest paths are known
  - initially  $S = \{s\}$
- Maintaining current best lengths of paths that *only go through*  $S$  to each of the vertices in  $G$ 
  - path-lengths to elements of  $S$  will be right, to  $V \setminus S$  they might not be right
- Repeatedly add vertex  $v$  to  $S$  that has the shortest path-length of any vertex in  $V \setminus S$ 
  - update path lengths based on new paths through  $v$

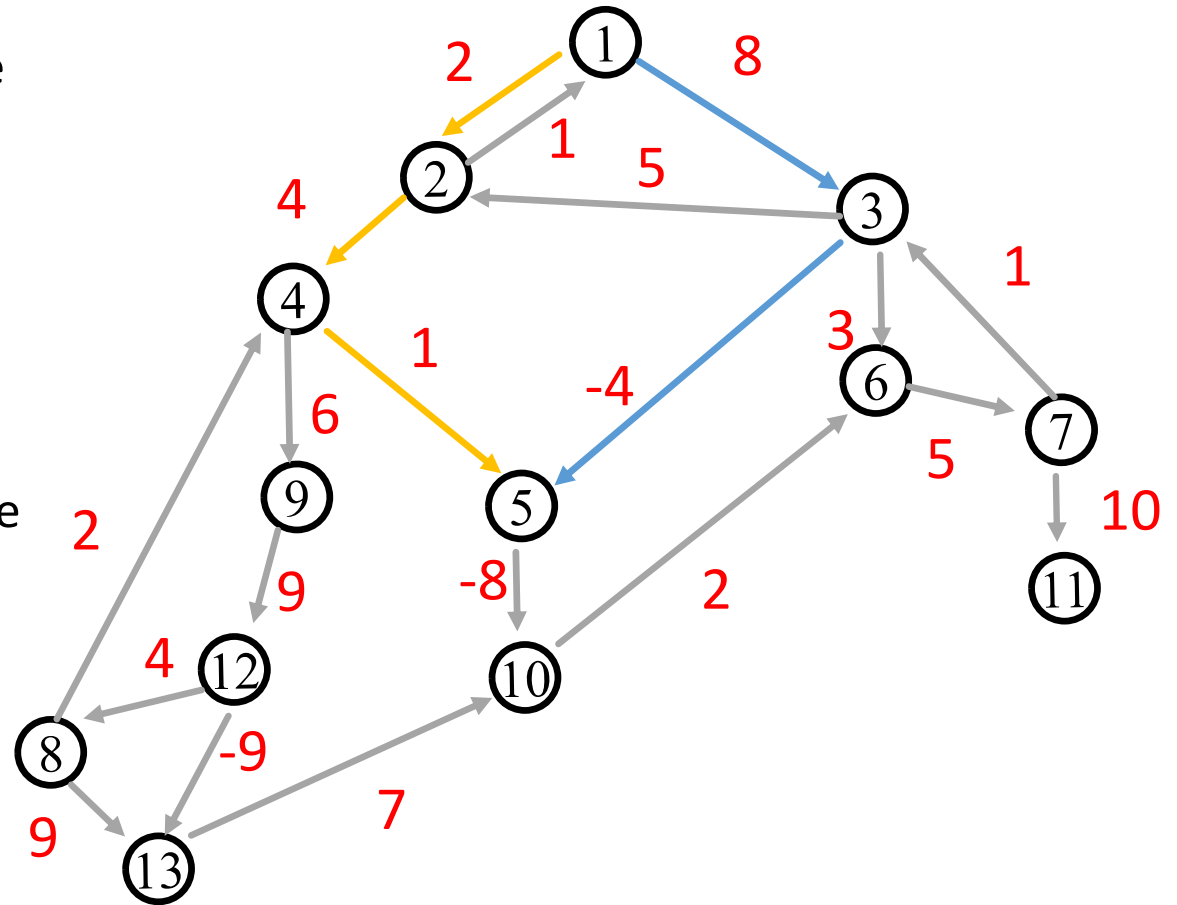
# Directed Graph with Negative Weights

Dijkstra's algorithm would not find the shortest path from 1 to 5

Shortest path is 1,3,5 which has cost 4

The path 1,2,4,5 has cost 7

Dijkstra's will "lock in" *that path* before processing node 3



# Negative Cycles

There's an issue when a graph has negative cost cycles

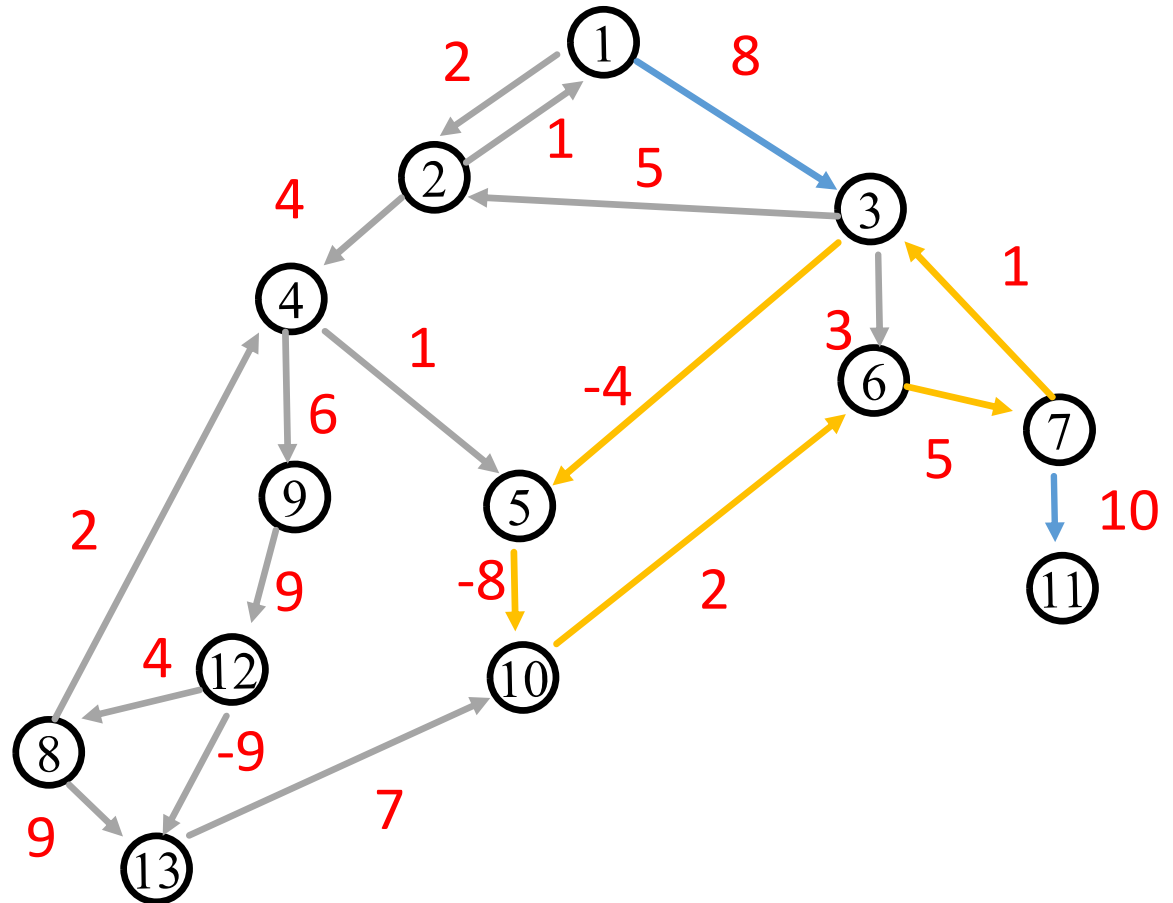
The shortest simple path to node 11 is **1,3,5,10,6,7,11** which has cost 13

The cycle **3,5,8,10,6,7,3** has cost -4

The (non-simple) path **1,3,5,8,10,6,7,3,5,10,6,7,11** has cost 9

Taking **the cycle** twice gives cost 5

No shortest path exists!



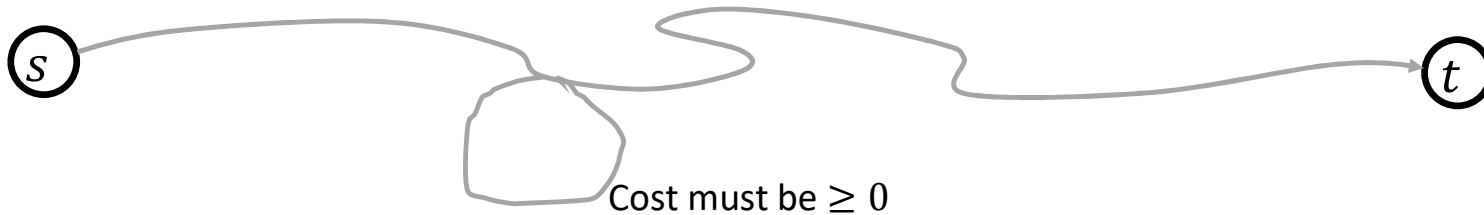
# Observations

**Claim:** A simple path has at most  $|V| - 1$  edges

**Justification:** Pigeon-hole principle. If we have  $\geq |V|$  edges then we have used at least one node at least twice

**Claim:** If a graph has no negative weight cycles then any shortest path must be simple

**Justification:** If some shortest path was not simple then there is a repeated node. The cycle involving that repeated node must have weight  $\geq 0$ . Removing that cycle from the path can't make it worse



# Single-source shortest paths, with negative edge weights

**Given:** an (un)directed graph  $G = (V, E)$  with each edge  $e$  having a weight  $w(e)$  and a vertex  $s$

**Find:** (length of) shortest paths from  $s$  to each vertex in  $G$ , or else indicate that there is a negative-cost cycle

Called the Bellman-Ford algorithm

(The original DP algorithm!)

(Also, the original shortest path algorithm!)

# Bellman Ford– Four Steps

1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
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  - Is it possible to reuse some memory locations?

# Identifying Recursive Structure – False Start

Consider the shortest path from  $s$  to  $t$



This shortest path is composed of:

- The shortest path from  $s$  to the **second-to-last node** (call it  $u$ )
- The edge  $(u, t)$



$OPT(t)$  = The cost of the shortest path from  $s$  to  $t$

$$OPT(t) = \begin{cases} 0 & \text{if } s = t \\ \min_{u \in V} \{OPT(u) + w(u, t)\} & \text{o. w.} \end{cases}$$

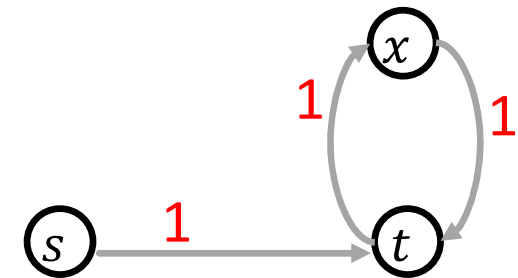
Where  $w(u, t)$  is the weight of the edge from  $u$  to  $t$  if it exists and  $\infty$  if not.

# So...What's wrong with this?

$OPT(t)$  = The cost of the shortest path from  $s$  to  $t$

$$OPT(t) = \begin{cases} 0 & \text{if } s = t \\ \min_{u \in V} \{OPT(u) + w(u, t)\} & \text{o. w.} \end{cases}$$

Where  $w(u, t)$  is the weight of the edge from  $u$  to  $t$  if it exists and  $\infty$  if not.



$$OPT(t) = \min \begin{cases} OPT(x) + 1 \\ OPT(s) + 1 \end{cases}$$

$$OPT(x) = \min \begin{cases} OPT(t) + 1 \\ OPT(s) + \infty \end{cases}$$

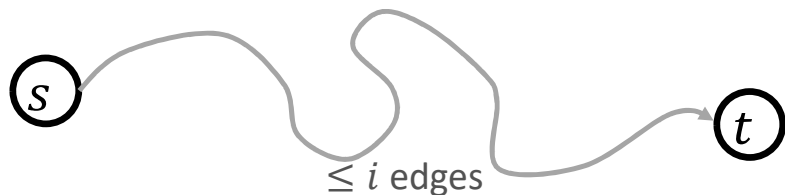
$$OPT(s) = 0$$

**We never reach a base case!**



# Identifying Recursive Structure – Correctly!

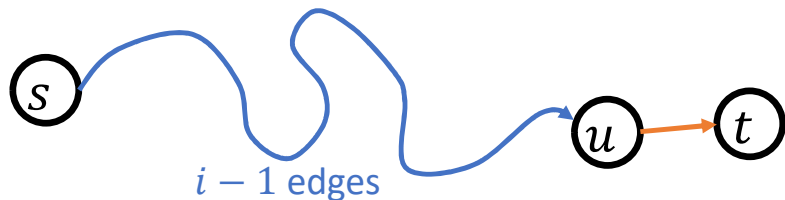
Suppose the shortest path from  $s$  to  $t$  has  $i$  or fewer edges



$OPT(i, t)$  = the weight of the shortest path from  $s$  to  $t$  with at most  $i$  edges

This shortest path will be one of these:

Option 1: the shortest path from  $s$  to some  $u$  with  $i - 1$  or fewer edges, plus the edge  $(u, t)$



$$\min_{u \in V} \{OPT(i - 1, u) + w(u, t)\}$$

Option 2: the same as shortest path from  $s$  to  $t$  with  $i - 1$  or fewer edges



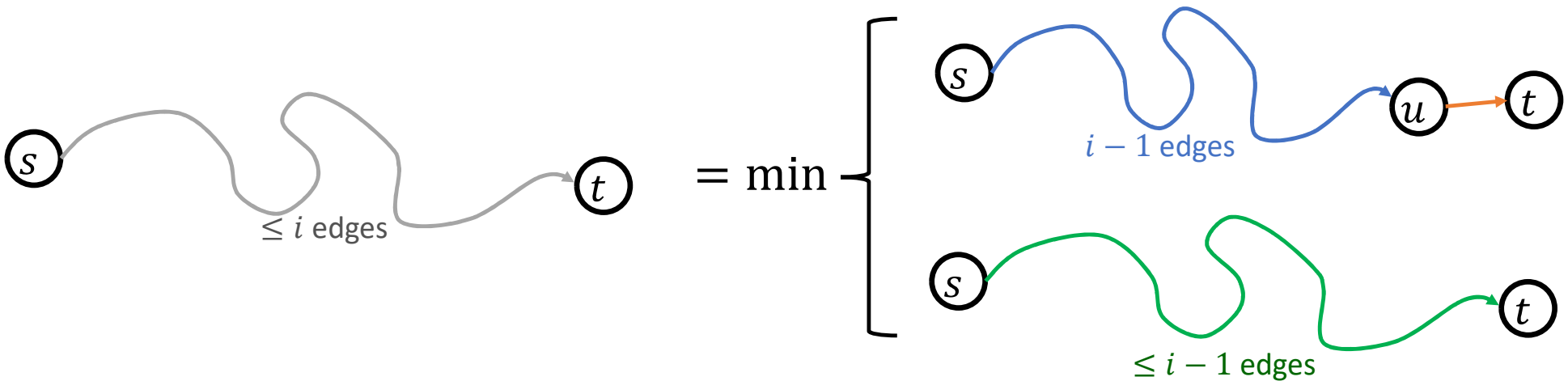
$$OPT(i - 1, t)$$

# Final Recursive Structure

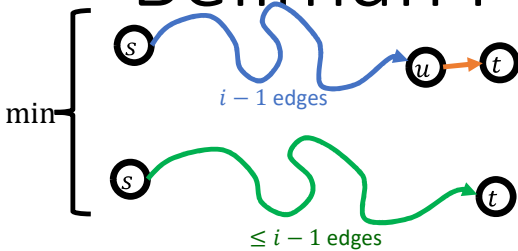
$OPT(i, t)$  = the weight of the shortest path from  $s$  to  $t$  with at most  $i$  edges

$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

Where  $w(u, t)$  is the weight of the edge from  $u$  to  $t$  if it exists and  $\infty$  if not.



# Bellman Ford– Four Steps



1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
  - For each such option, what does the subproblem look like? How do we use it?
2. Choose a memory structure.
  - Figure out the possible values of all parameters in the recursive calls.
  - How many subproblems (options for last choice) are there?
  - What are the parameters needed to identify each?
  - How many different values could there be per parameter?
3. Specify an order of evaluation.
  - Want to guarantee that the necessary subproblem solutions are in memory when you need them.
  - With this step: a “Bottom-up” (iterative) algorithm
  - Without this step: a “Top-down” (recursive) algorithm
4. See if there’s a way to save space
  - Is it possible to reuse some memory locations?

# Identifying the Memory Structure

$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. & \end{cases}$$

- How many parameters?
  - 2
- What does each represent?
  - $i$ : the length of the path
  - $t$ : a node
- How many different values?
  - $i$ :  $|V|$  (from length 0 up to  $|V| - 1$  if the path is simple)
  - $t$ :  $|V|$  (one value per node)

	1	2	3	4	5	6	7
0							
1							
2							
3							
4							
5							
6							

# Top-Down Bellman-Ford

This algorithm correctly finds shortest paths when there are no negative-cost cycles  
How can we check for negative cost cycles?

**BF**( $i, t$ ):

if  $\text{OPT}[i][t]$  not blank: // Check if we've solved this already

return  $\text{OPT}[i][j]$

if  $i == 0$ : // Check if this is a base case

$\text{solution} = 0$  ?  $t == s$  :  $\infty$

$\text{OPT}[i][t] = \text{solution}$  // Always save your solution before returning

return  $\text{solution}$

$\text{solution} = \infty$

for each  $u \in V$ :

$\text{solution} = \min(\text{solution}, \text{BF}(i - 1, u) + w(u, t))$  // solve each subproblem, pick which to use

$\text{solution} = \min(\text{solution}, \text{BF}(i - 1, t))$  // solve each subproblem, pick which to use

$\text{OPT}[i][t] = \text{solution}$  // Always save your solution before returning

return  $\text{solution}$

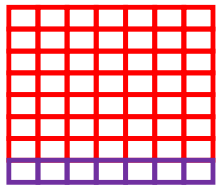
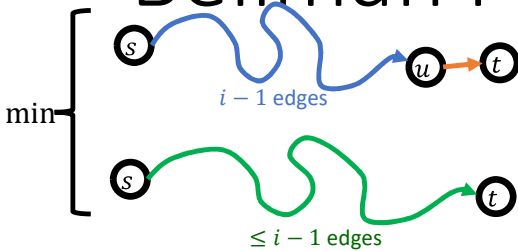
# Checking for Negative Cycles

$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

- How many parameters?
  - 2
- What does each represent?
  - $i$ : the length of the path
  - $t$ : a node
- How many different values?
  - $i$ :  $|V|+1$ 
    - a path of  $|V|$  edges is not simple, so if any  $|V|$ -edge path is shorter than one with fewer edges, there must be a negative cycle!
  - $t$ :  $|V|$  (one value per node)

	1	2	3	4	5	6	7
0							
1							
2							
3							
4							
5							
6							
7							

# Bellman Ford– Four Steps



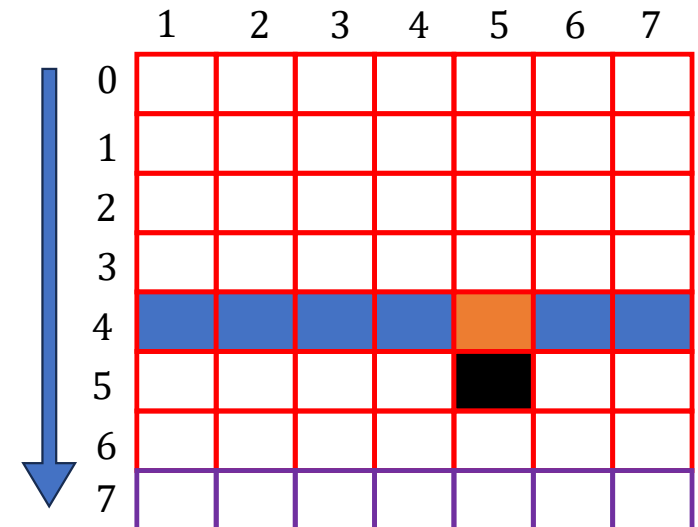
1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
  - For each such option, what does the subproblem look like? How do we use it?
2. Choose a memory structure.
  - Figure out the possible values of all parameters in the recursive calls.
  - How many subproblems (options for last choice) are there?
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  - How many different values could there be per parameter?
3. Specify an order of evaluation.
  - Want to guarantee that the necessary subproblem solutions are in memory when you need them.
  - With this step: a “Bottom-up” (iterative) algorithm
  - Without this step: a “Top-down” (recursive) algorithm
4. See if there’s a way to save space
  - Is it possible to reuse some memory locations?

# Order of Evaluations

$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

Each cell depends on every value in the previous row

Solve in order of  $i$





# Bottom-Up Bellman-Ford

**BF**( $s, t$ ):

$OPT[0][s] = 0$  // Solve and save base cases

for  $u \in V \setminus \{s\}$ :

$OPT[0][u] = \infty$  // Solve and save base cases

for  $i = 0$  up to  $|V|$ :

for  $u \in V$ :

for  $v \in \text{neighbors}(u)$ :

$OPT[i][u] = \min(OPT[i][u], OPT[i-1][v])$  // solve and pick

$OPT[i][u] = \min(OPT[i][u], OPT[i-1][u])$  // solve and pick

for  $u \in V$ :

if  $OPT[|V|][u] < OPT[|V|-1][u]$ : // check for negative cycles

return “negative cycle”

return  $OPT[s][t]$  // return the final answer

# Bottom-Up Bellman-Ford

**BF**( $s, t$ ):

$OPT[0][s] = 0$  // Solve and save base cases  $\Theta(1)$

for  $u \in V \setminus \{s\}$ :

$OPT[0][u] = \infty$  // Solve and save base cases  $\Theta(|V|)$

for  $i = 0$  up to  $|V|$ :

for  $u \in V$ :

for  $v \in \text{neighbors}(u)$ :

$\Theta(|V||E|)$

$OPT[i][u] = \min(OPT[i][u], OPT[i-1][v])$  // solve and pick

$OPT[i][u] = \min(OPT[i][u], OPT[i-1][u])$  // solve and pick

for  $u \in V$ :

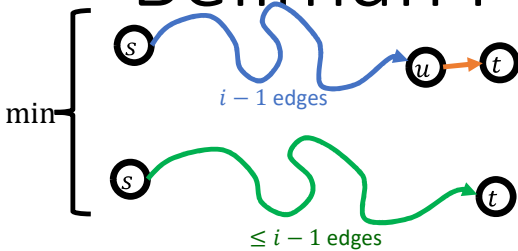
if  $OPT[|V|][u] < OPT[|V|-1][u]$ : // check for negative cycles

$\Theta(|V|)$

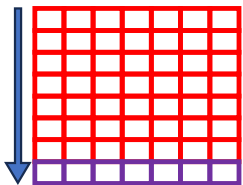
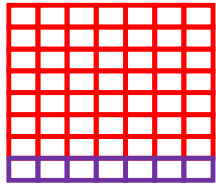
return "negative cycle"

return  $OPT[s][t]$  // return the final answer  $\Theta(1)$

# Bellman Ford– Four Steps



1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
  - For each such option, what does the subproblem look like? How do we use it?
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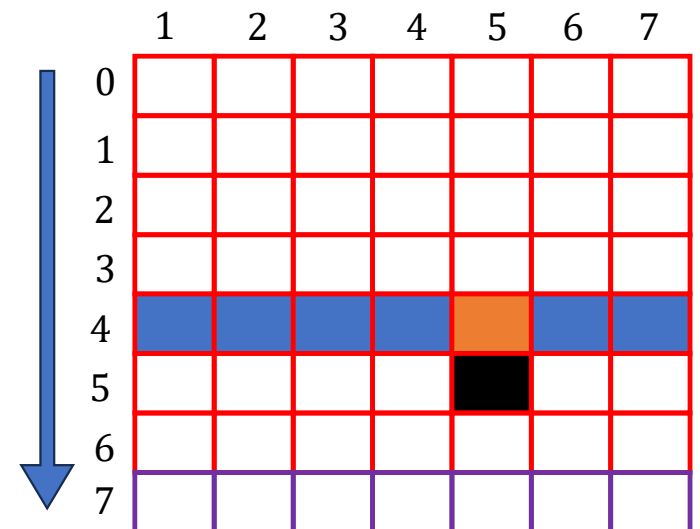


# Order of Evaluations

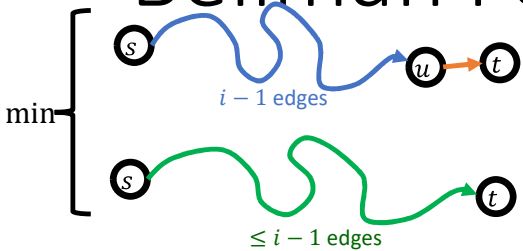
$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. & \end{cases}$$

Each cell depends *only* on values in the previous row

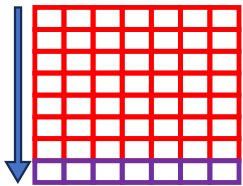
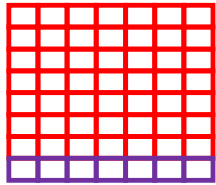
We only need two rows!



# Bellman Ford– Four Steps



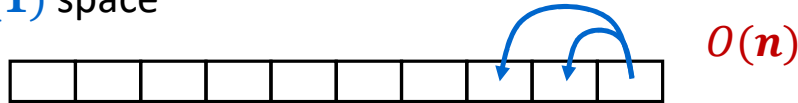
1. Formulate the answer with a recursive structure
  - What are the options for the last choice?
  - For each such option, what does the subproblem look like? How do we use it?
2. Choose a memory structure.
  - Figure out the possible values of all parameters in the recursive calls.
  - How many subproblems (options for last choice) are there?
  - What are the parameters needed to identify each?
  - How many different values could there be per parameter?
3. Specify an order of evaluation.
  - Want to guarantee that the necessary subproblem solutions are in memory when you need them.
  - With this step: a “Bottom-up” (iterative) algorithm
  - Without this step: a “Top-down” (recursive) algorithm
4. See if there’s a way to save space
  - Is it possible to reuse some memory locations?



# Dynamic Programming Patterns

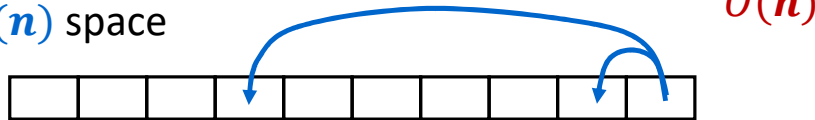
Fibonacci pattern:

- 1-D,  $O(1)$  immediately prior
- $O(1)$  space



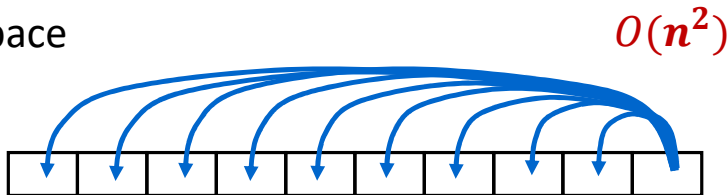
Weighted interval scheduling pattern:

- 1-D,  $O(1)$  arbitrary prior
- $O(n)$  space



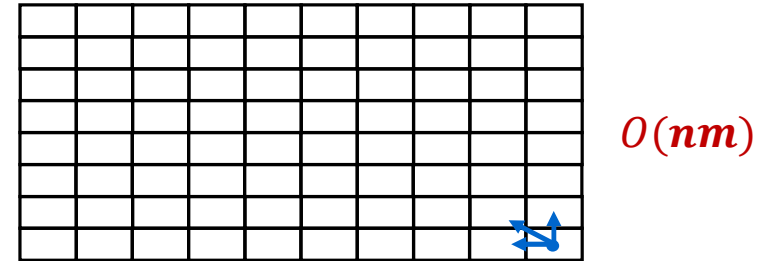
Longest increasing subsequence pattern:

- 1-D, all  $n - 1$  prior
- $O(n)$  space



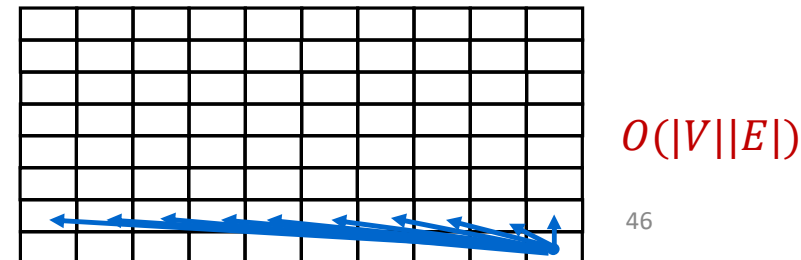
Alignment pattern:

- 2-D,  $O(1)$  in previous row, above, left, diagonal
- $O(n \cdot m)$  space

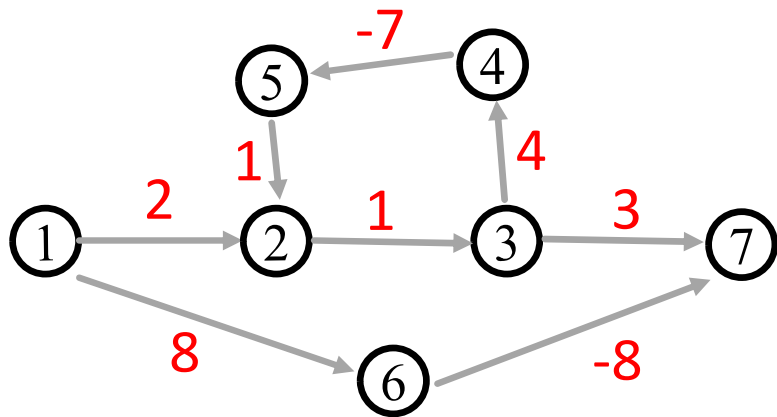


Bellman Ford pattern:

- 2-D,  $O(|V|)$  in previous row,
- $O(|V|)$  space



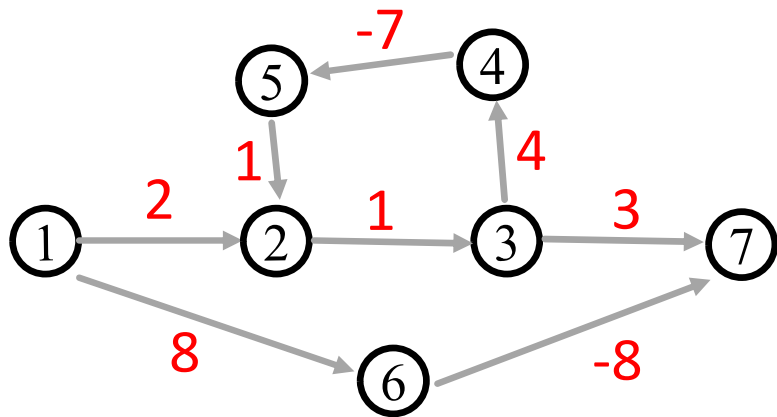
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1							
2							
3							
4							
5							
6							
7							

# Example Execution

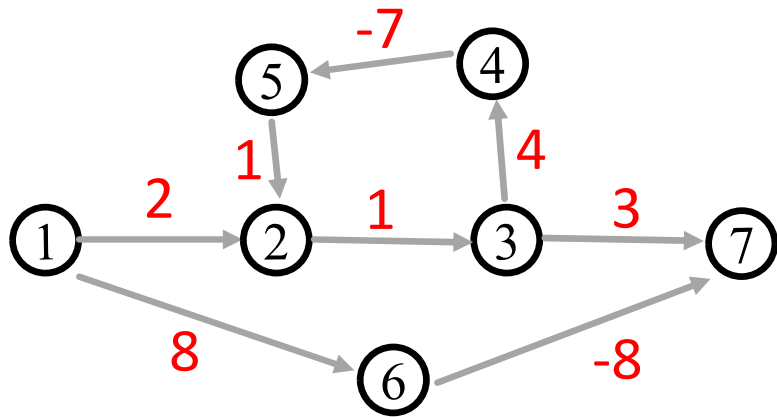


$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2							
3							
4							
5							
6							
7							



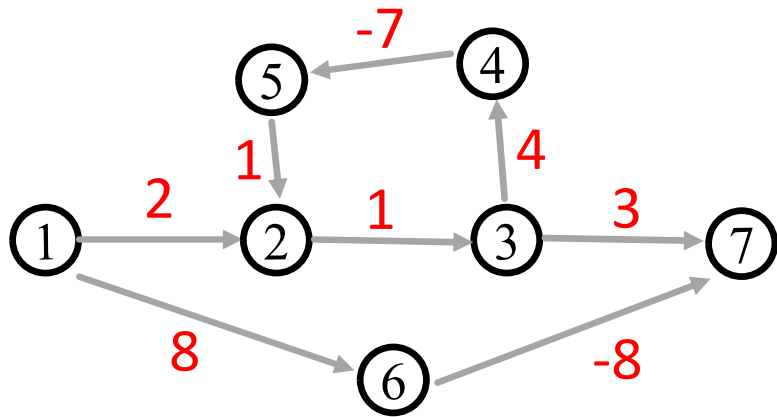
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	∞	∞	∞	∞	∞	∞
1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3							
4							
5							
6							
7							

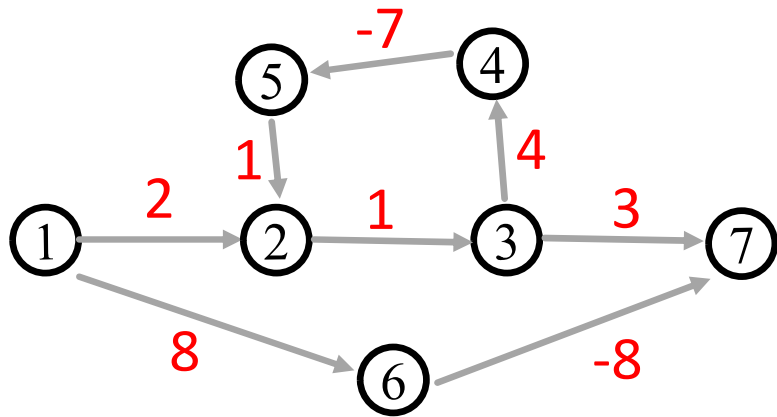
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. & \text{otherwise} \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2	0	2	3	$\infty$	$\infty$	8	0
3	0	2	3	7	$\infty$	8	0
4							
5							
6							
7							

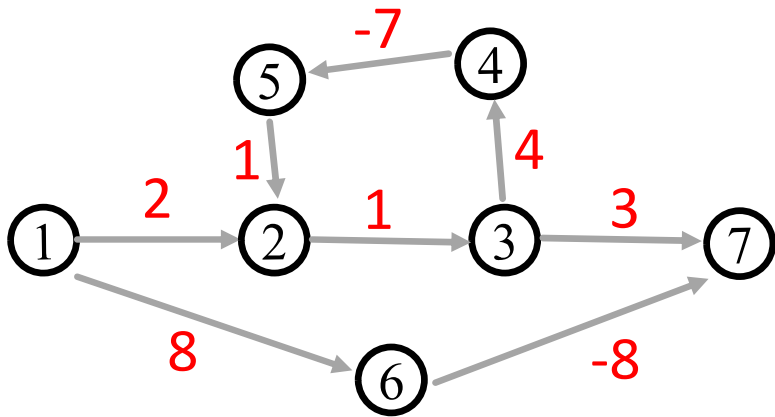
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. & \text{otherwise} \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2	0	2	3	$\infty$	$\infty$	8	0
3	0	2	3	7	$\infty$	8	0
4	0	2	3	7	0	8	0
5							
6							
7							

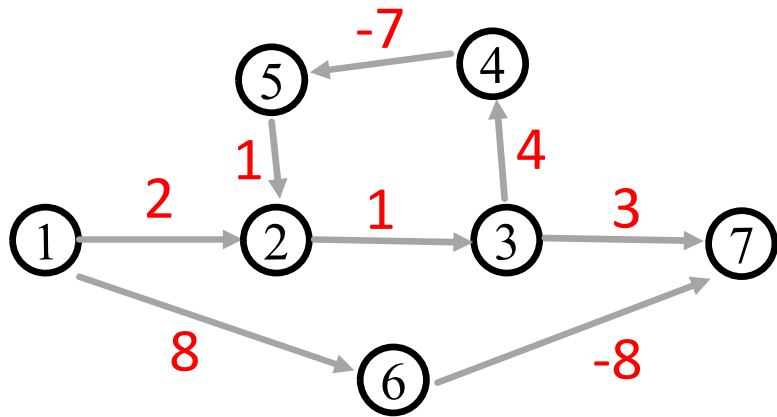
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$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	∞	∞	∞	∞	∞	∞
1	0	2	∞	∞	∞	8	∞
2	0	2	3	∞	∞	8	0
3	0	2	3	7	∞	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6							
7							

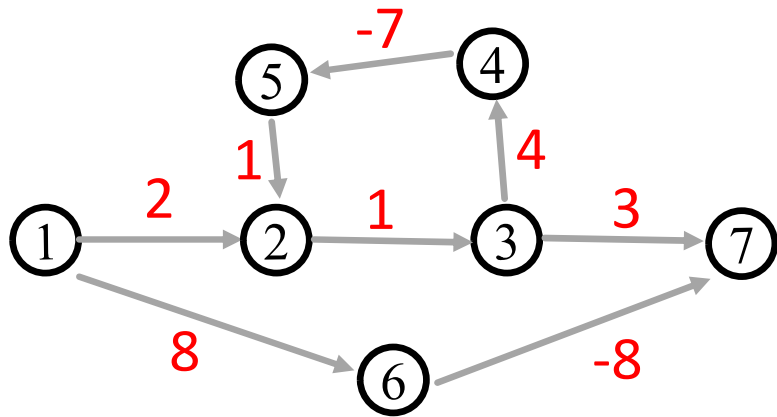
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2	0	2	3	$\infty$	$\infty$	8	0
3	0	2	3	7	$\infty$	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7							

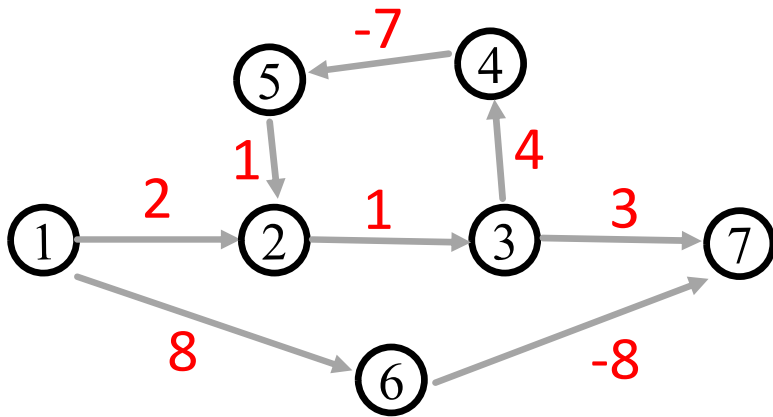
# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2	0	2	3	$\infty$	$\infty$	8	0
3	0	2	3	7	$\infty$	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7	0	1	2	3	0	8	0

# Example Execution



$$OPT(i, t) = \begin{cases} 0 & \text{if } i = 0 \text{ and } s = t \\ \infty & \text{if } i = 0 \text{ and } s \neq t \\ \min \left\{ \begin{array}{l} \min_{u \in V} \{OPT(i-1, u) + w(u, t)\} \\ OPT(i-1, t) \end{array} \right. & \text{otherwise} \end{cases}$$

	1	2	3	4	5	6	7
0	0	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$	$\infty$
1	0	2	$\infty$	$\infty$	$\infty$	8	$\infty$
2	0	2	3	$\infty$	$\infty$	8	0
3	0	2	3	7	$\infty$	8	0
4	0	2	3	7	0	8	0
5	0	1	3	7	0	8	0
6	0	1	2	7	0	8	0
7	0	1	2	3	0	8	0

Negative Cycle Found!