

# CS2010: Data Structures and Algorithms II

## Shortest paths in graphs

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# Outline

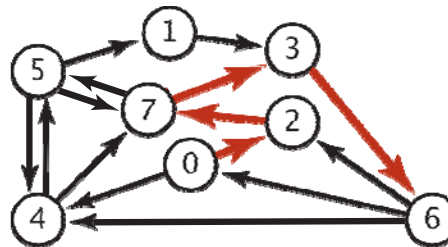
- › Shortest paths
  - Single source shortest path
    - › Topological sort – acyclic graphs but ok with negative weights
    - › Dijkstra – non negative weights but ok with cycles
    - › Bellman-Ford – non-negative cycles
  - Single-pair shortest path
    - › A\* search algorithm
  - All pairs shortest path
    - › Floyd-Warshall
- › Dynamic programming summary

## Shortest paths in an edge-weighted digraph

Given an edge-weighted digraph, find the shortest path from  $s$  to  $t$ .

edge-weighted digraph

4→5	0.35
5→4	0.35
4→7	0.37
5→7	0.28
7→5	0.28
5→1	0.32
0→4	0.38
0→2	0.26
7→3	0.39
1→3	0.29
2→7	0.34
6→2	0.40
3→6	0.52
6→0	0.58
6→4	0.93



shortest path from 0 to 6

0→2	0.26
2→7	0.34
7→3	0.39
3→6	0.52

## Shortest path variants

### Which vertices?


- **Single source:** from one vertex  $s$  to every other vertex.
- Single sink: from every vertex to one vertex  $t$ .
- Source-sink: from one vertex  $s$  to another  $t$ .
- All pairs: between all pairs of vertices.

### Restrictions on edge weights?

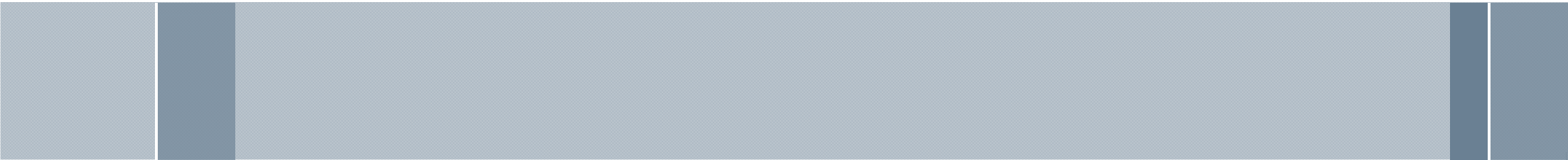
- Nonnegative weights.
- Euclidean weights.
- Arbitrary weights.

### Cycles?

- No directed cycles.
- No "negative cycles."



# Dijkstra's shortest path algorithm



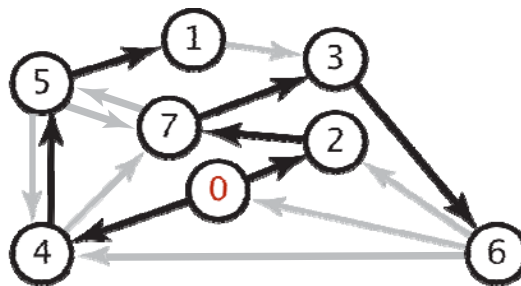
## Data structures for single-source shortest paths

**Goal.** Find the shortest path from  $s$  to every other vertex.

**Observation.** A **shortest-paths tree** (SPT) solution exists.

**Consequence.** Can represent the SPT with two vertex-indexed arrays:

- $\text{distTo}[v]$  is length of shortest path from  $s$  to  $v$ .
- $\text{edgeTo}[v]$  is last edge on shortest path from  $s$  to  $v$ .



shortest-paths tree from 0

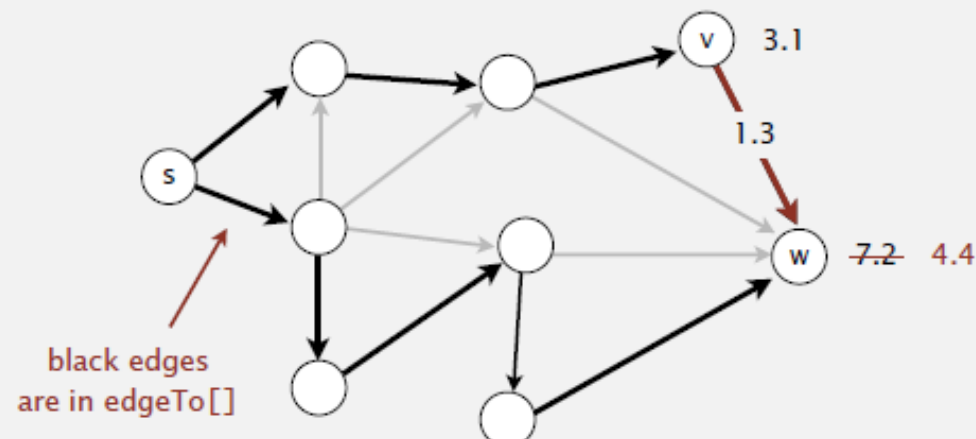
	edgeTo[]	distTo[]
0	null	0
1	5->1 0.32	1.05
2	0->2 0.26	0.26
3	7->3 0.37	0.97
4	0->4 0.38	0.38
5	4->5 0.35	0.73
6	3->6 0.52	1.49
7	2->7 0.34	0.60

parent-link representation

Relax edge  $e = v \rightarrow w$ .

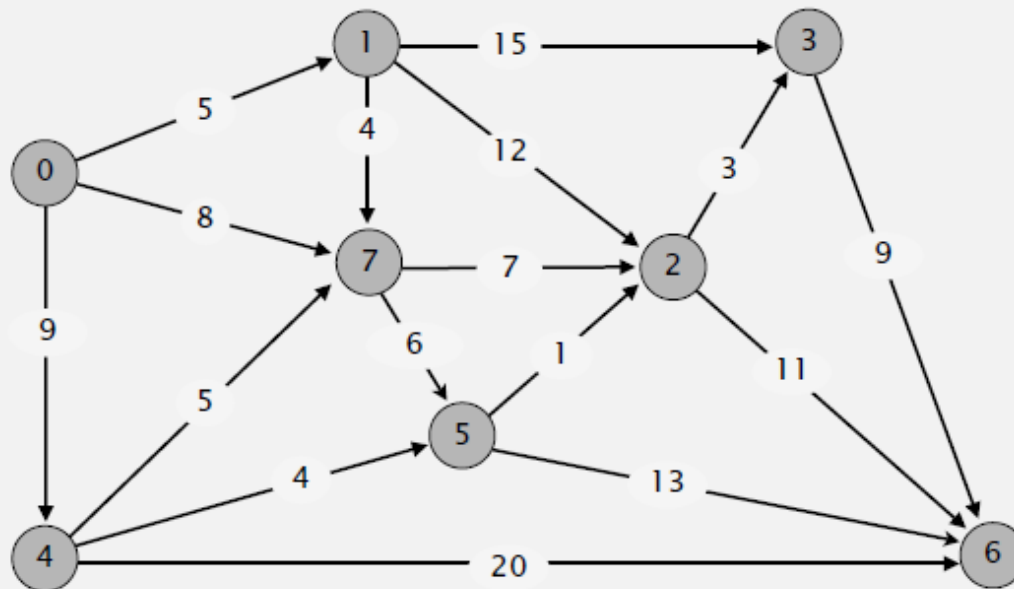
- $\text{distTo}[v]$  is length of shortest **known** path from  $s$  to  $v$ .
- $\text{distTo}[w]$  is length of shortest **known** path from  $s$  to  $w$ .
- $\text{edgeTo}[w]$  is last edge on shortest **known** path from  $s$  to  $w$ .
- If  $e = v \rightarrow w$  gives shorter path to  $w$  through  $v$ ,  
update both  $\text{distTo}[w]$  and  $\text{edgeTo}[w]$ .

$v \rightarrow w$  successfully relaxes





- Consider vertices in increasing order of distance from  $s$  (non-tree vertex with the lowest  $\text{distTo}[]$  value).
- Add vertex to tree and relax all edges pointing from that vertex.



an edge-weighted digraph

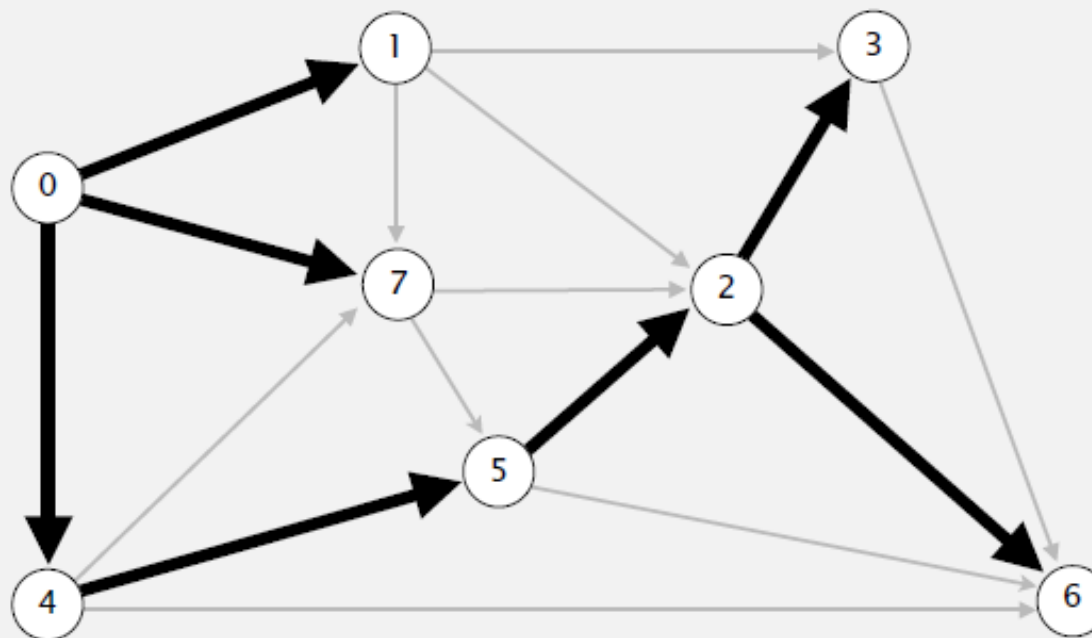
0→1	5.0
0→4	9.0
0→7	8.0
1→2	12.0
1→3	15.0
1→7	4.0
2→3	3.0
2→6	11.0
3→6	9.0
4→5	4.0
4→6	20.0
4→7	5.0
5→2	1.0
5→6	13.0
7→5	6.0



# Dijkstra Demo

[https://algs4.cs.princeton.edu/lectures/44DemoDijkstra.p  
df](https://algs4.cs.princeton.edu/lectures/44DemoDijkstra.pdf)

- Consider vertices in increasing order of distance from  $s$  (non-tree vertex with the lowest  $\text{distTo}[]$  value).
- Add vertex to tree and relax all edges pointing from that vertex.



$v$	$\text{distTo}[]$	$\text{edgeTo}[]$
0	0.0	-
1	5.0	0→1
2	14.0	5→2
3	17.0	2→3
4	9.0	0→4
5	13.0	4→5
6	25.0	2→6
7	8.0	0→7

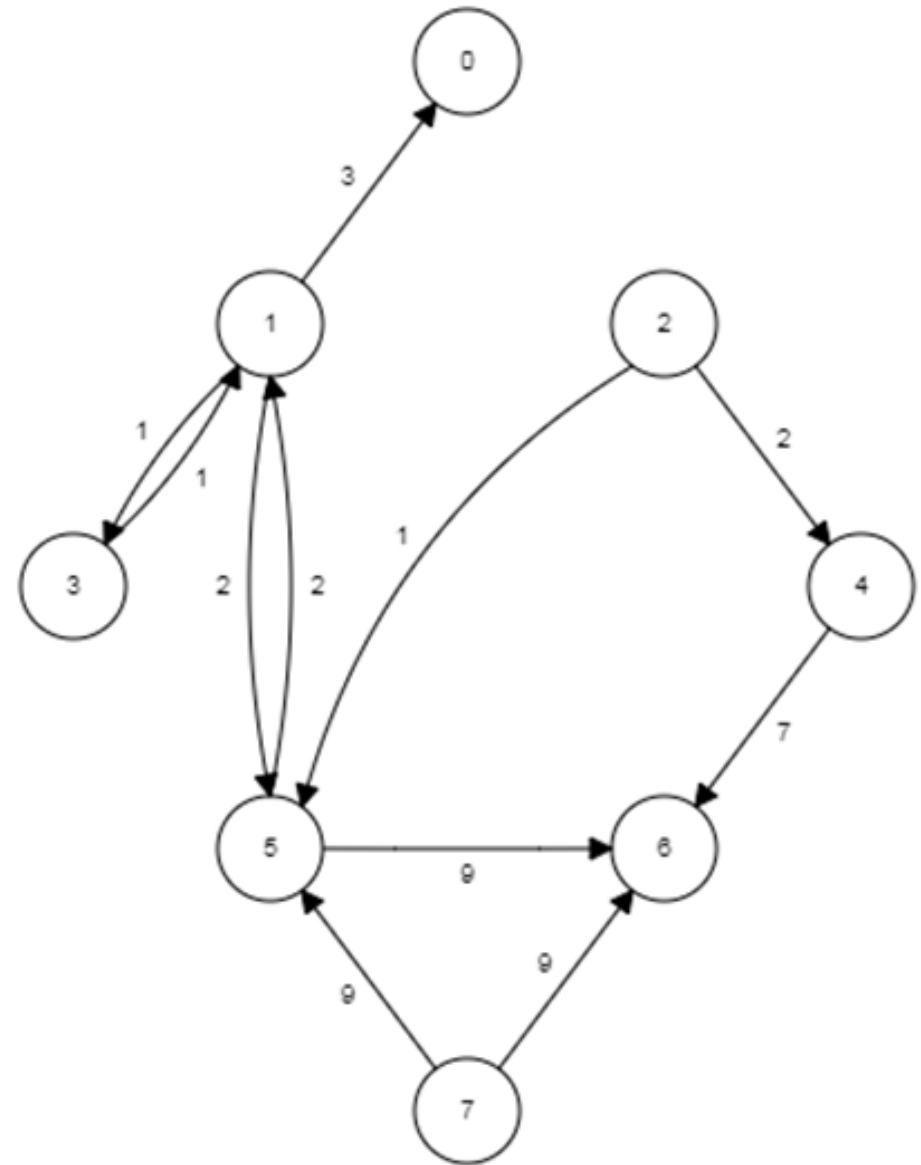
**shortest-paths tree from vertex  $s$**

# Dijkstra exercise

Start from vertex 1

v	DistTo[]	EdgeTo[]
0		
1		
2		
3		
4		
5		
6		
7		

Turning point – which vertex  
Can't be reached from 1?



# Solution

Vertex	Known	Cost	Path	
0	T	3	1	1 0
1	T	0	-1	1
2	F	INF	-1	No Path
3	T	1	1	1 3
4	F	INF	-1	No Path
5	T	2	1	1 5
6	T	11	5	1 5 6
7	F	INF	-1	No Path

# Dijkstra performance

## Dijkstra's algorithm: which priority queue?

Depends on PQ implementation:  $V$  insert,  $V$  delete-min,  $E$  decrease-key.

PQ implementation	insert	delete-min	decrease-key	total
unordered array	1	$V$	1	$V^2$
binary heap	$\log V$	$\log V$	$\log V$	$E \log V$
d-way heap	$\log_d V$	$d \log_d V$	$\log_d V$	$E \log_{dV} V$
Fibonacci heap	$1^\dagger$	$\log V^\dagger$	$1^\dagger$	$E + V \log V$

$^\dagger$  amortized

### Bottom line.

- Array implementation optimal for dense graphs.
- Binary heap much faster for sparse graphs.
- 4-way heap worth the trouble in performance-critical situations.
- Fibonacci heap best in theory, but not worth implementing.

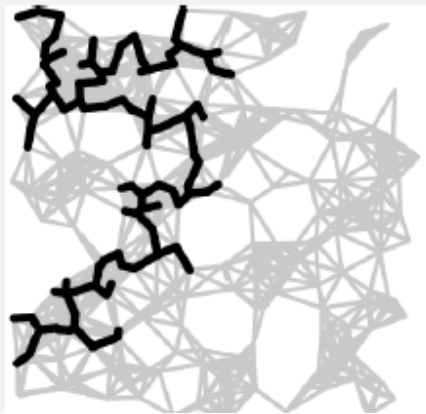


Dijkstra's algorithm seem familiar?

- Prim's algorithm is essentially the same algorithm.
- Both are in a family of algorithms that compute a spanning tree.

**Main distinction:** Rule used to choose next vertex for the tree.

- Prim: Closest vertex to the **tree** (via an undirected edge).
- Dijkstra: Closest vertex to the **source** (via a directed path).





# Dijkstra – why can't work with negative weights?

- › Example?
- › Consequence: picking the shortest candidate edge (local optimality) always ends up being correct (global optimality).
  - Greedy algorithm!
  - Wouldn't be true if used dijkstra with negative weights – use a different algorithm instead!
- › Can be modified to work with negative weights, i.e., vertex can be en-queued more than once -> exponential worst case running time though!



$A^*$



# A\* shortest path

- › Single source, single destination/goal
- › Extension of Dijkstra's algorithm
- › Uses heuristics to guide its search and achieve better performance
  - prioritizes paths that seem to be leading closer to the goal

# Heuristic function

- › solving a problem more quickly when classic methods are too slow
- › finding an approximate solution when classic methods fail to find any exact solution
- › trading optimality, completeness, accuracy, or precision for speed.
- › a function that ranks alternatives in search algorithms at each branching step based on available information to decide which branch to follow
  - Eg approximate exact solution

# Heuristic function $h(n)$

- › The 2 most important properties:
  - relatively cheap to compute
  - relatively accurate estimator of the cost to reach a goal. Usually a “good” heuristic is if  $\frac{1}{2} \text{opt}(n) < h(n) < \text{opt}(n)$
- › Admissible heuristic
  - $h(n)$  never overestimates the actual cost from  $n$  to goal


# A\*

- › uses both the actual distance from the start and the estimated distance to the goal.
- › only expands a node if it seems promising (only focuses on reaching the goal node, not every other node)
- › A guided version of Dijkstra
- › Evaluation function  $f(n) = g(n) + h(n)$  where
  - $g(n)$  = cost so far to reach  $n$
  - $h(n)$  = estimated cost from  $n$  to goal
  - $f(n)$  = estimated total cost of path through  $n$  to goal

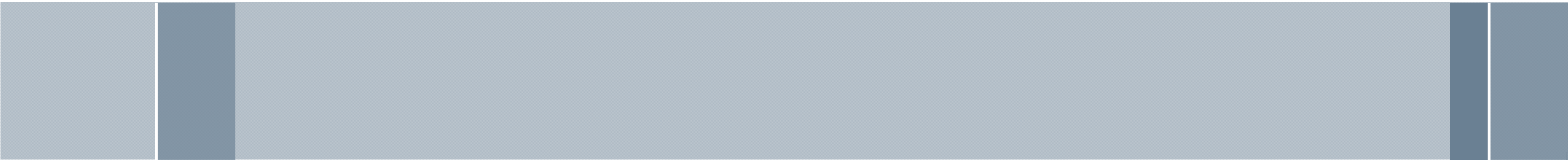


# A\*

- › How to pick a heuristic function?
  - › Domain knowledge – some information about a goal
  - › Eg in route planning:
    - Manhattan distance – on a square grid that allows 4 directions of movement
    - Diagonal distance – 8-direction square
    - Euclidean distance – any direction
  - A good example on route planning in games
- <http://theory.stanford.edu/~amitp/GameProgramming/Heuristics.html>



# Topological sort shortest path



# Shortest path in acyclic graphs

- › Is it easier than in graphs with cycles?
- › Yes! Linear time
- › Use topological sort (which only works in DAGs – directional acyclic graphs) to find shortest path
- › If we have an edge from  $x$  to  $y$ , the ordering visits  $x$  before  $y$
- › Shortest path visits/relaxes edges in topological order
- › Topological sort – identify a vertex with no incoming edges, add it to the ordered list, remove it, repeat...
  - (decrease by 1 and conquer)

# Topological sort shortest path demo

<https://algs4.cs.princeton.edu/lectures/44DemoAcyclicSP.pdf>

## So far

- › No negative weights – Dijkstra
- › No cycles – Topological sort shortest path
- › What if the graph has negative weights and cycles?
- › What about negative cycles?



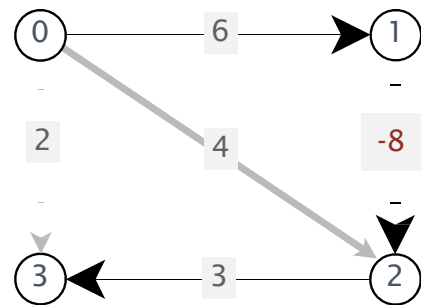
# Bellman-Ford Shortest Path Algorithm





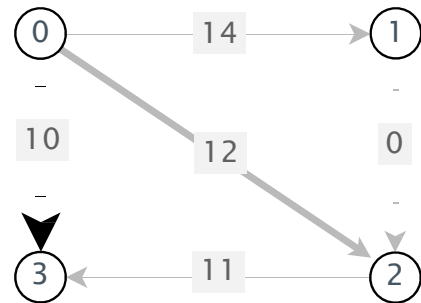
## Shortest paths with negative weights: failed attempts

**Dijkstra.** Doesn't work with negative edge weights.



Dijkstra selects vertex 3 immediately after 0.  
But shortest path from 0 to 3 is  $0 \rightarrow 1 \rightarrow 2 \rightarrow 3$ .

**Re-weighting.** Add a constant to every edge weight doesn't work.



Adding 8 to each edge weight changes the  
shortest path from  $0 \rightarrow 1 \rightarrow 2 \rightarrow 3$  to  $0 \rightarrow 3$ .

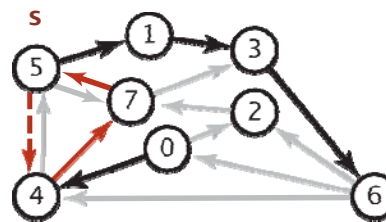
**Conclusion.** Need a different algorithm.

## Negative cycles

**Def.** A **negative cycle** is a directed cycle whose sum of edge weights is negative.

**digraph**

4→5	0.35
5→4	-0.66
4→7	0.37
5→7	0.28
7→5	0.28
5→1	0.32
0→4	0.38
0→2	0.26
7→3	0.39
1→3	0.29
2→7	0.34
6→2	0.40
3→6	0.52
6→0	0.58
6→4	0.93



**negative cycle**  $(-0.66 + 0.37 + 0.28)$

5→4→7→5

**shortest path from 0 to 6**

0→4→7→5→4→7→5...→1→3→6

**Proposition.** A SPT exists iff no negative cycles.

↖ assuming all vertices reachable from s

# Bellman-Ford algorithm

## Bellman-Ford algorithm

---

Initialize  $\text{distTo}[s] = 0$  and  $\text{distTo}[v] = \infty$  for all other vertices.

Repeat  $V$  times:

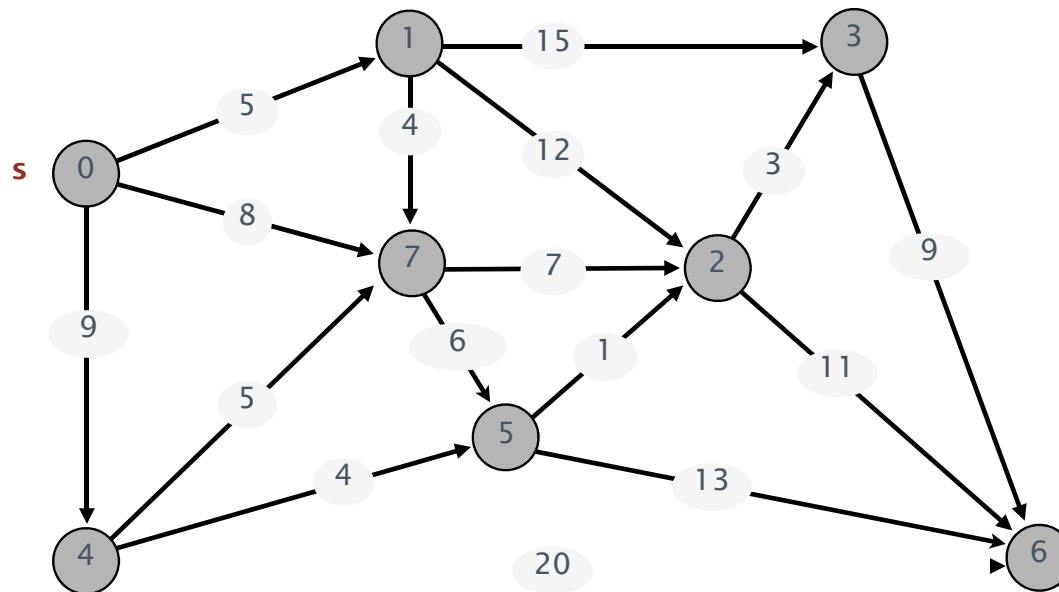
- Relax each edge.
- 

```
for (int i = 0; i < G.V(); i++)  
    for (int v = 0; v < G.V(); v++)  
        for (DirectedEdge e : G.adj(v))  
            relax(e);
```

← pass i (relax each edge)

## Bellman-Ford algorithm demo

Repeat  $V$  times: relax all  $E$  edges.



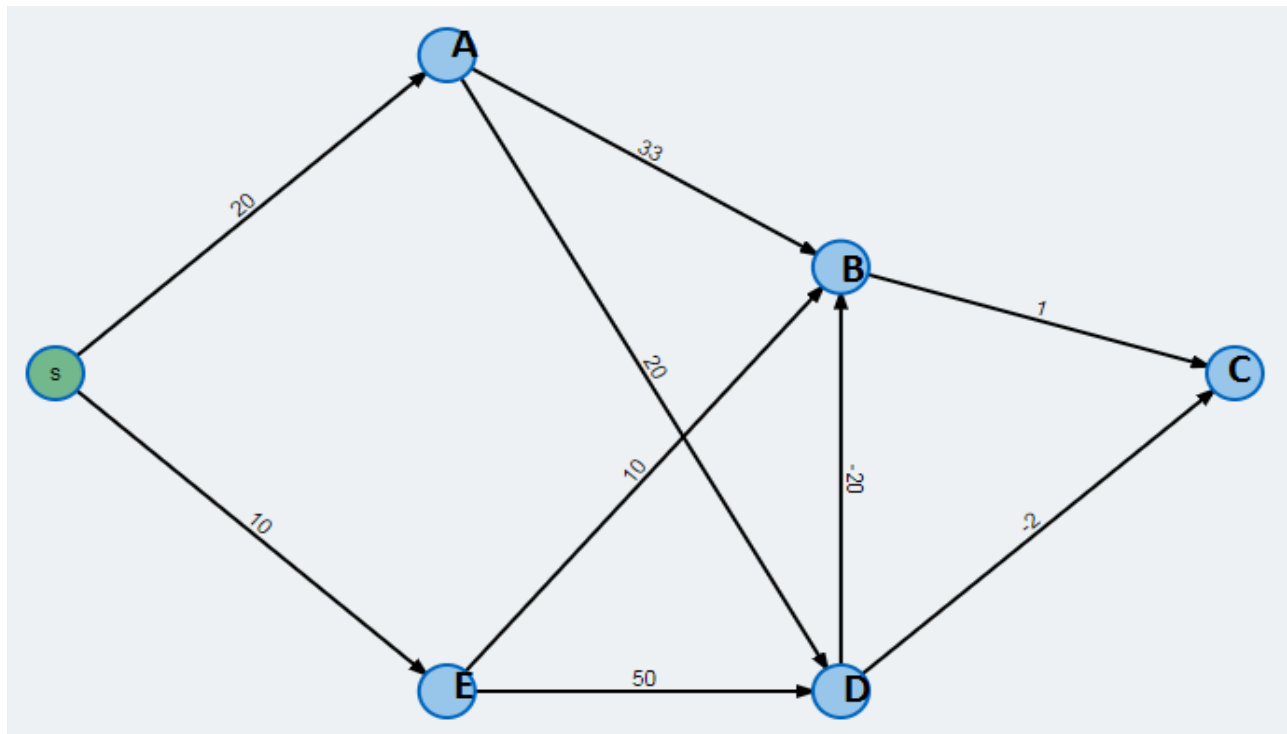
an edge-weighted digraph

0→1	5.0
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1→3	15.0
1→7	4.0
2→3	3.0
2→6	11.0
3→6	9.0
4→5	4.0
4→6	20.0
4→7	5.0
5→2	1.0
5→6	13.0
7→5	6.0
7→2	7.0

# Bellman-Ford Demo

- › <https://algs4.cs.princeton.edu/lectures/44DemoBellmanFord.pdf>
- › Only positive weights in this example – paper exercise with negative weights

# Bellman-Ford Exercise





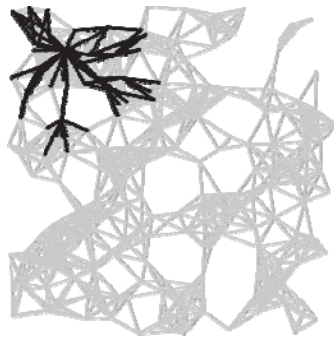
# Bellman-Ford Exercise Table

Iteration	Dist to S	A	B	C	D	E
0	0	inf	inf	inf	inf	Inf
1						
2						
3						
4						
5						

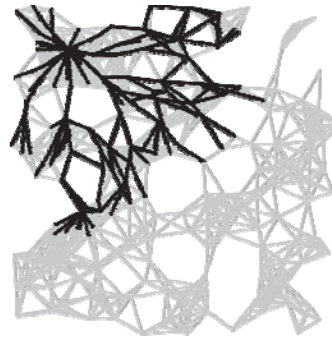
Keep track of distance and parent node eg 5 (via B) for each node for each iteration

## Bellman-Ford algorithm: visualization

passes  
4



7



10



13



SPT



## Bellman-Ford algorithm: analysis

### Bellman-Ford algorithm

---

Initialize  $\text{distTo}[s] = 0$  and  $\text{distTo}[v] = \infty$  for all other vertices.

Repeat  $V$  times:

- Relax each edge.
- 

**Proposition.** Dynamic programming algorithm computes SPT in any edge-weighted digraph with no negative cycles in time proportional to  $E \times V$ .

**Pf idea.** After pass  $i$ , found path that is at least as short as any shortest path containing  $i$  (or fewer) edges.

## Bellman-Ford algorithm: practical improvement

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**Observation.** If  $\text{distTo}[v]$  does not change during pass  $i$ , no need to relax any edge pointing from  $v$  in pass  $i+1$ .

**FIFO implementation.** Maintain **queue** of vertices whose  $\text{distTo}[]$  changed.



be careful to keep at most one copy  
of each vertex on queue (why?)

**Overall effect.**

- The running time is still proportional to  $E \times V$  in worst case.
- But much faster than that in practice.

# Single source shortest path summary

algorithm	restriction	typical case	worst case	extra space
topological sort	no directed cycles	$E + V$	$E + V$	$V$
Dijkstra (binary heap)	no negative weights	$E \log V$	$E \log V$	$V$
Bellman-Ford	no negative cycles	$E V$	$E V$	$V$
Bellman-Ford (queue-based)		$E + V$	$E V$	$V$

Remark 1. Directed cycles make the problem harder.

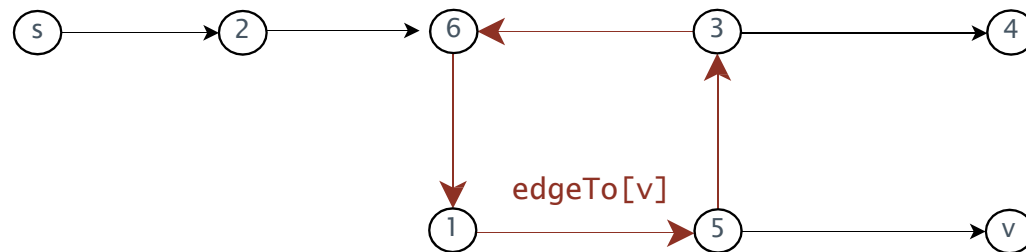
Remark 2. Negative weights make the problem harder.

Remark 3. Negative cycles makes the problem intractable.



## Finding a negative cycle

**Observation.** If there is a negative cycle, Bellman-Ford gets stuck in loop, updating `distTo[]` and `edgeTo[]` entries of vertices in the cycle.



**Proposition.** If any vertex  $v$  is updated in pass  $v$ , there exists a negative cycle (and can trace back `edgeTo[v]` entries to find it).

**In practice.** Check for negative cycles more frequently.



## Negative cycle application: arbitrage detection

**Problem.** Given table of exchange rates, is there an arbitrage opportunity?

	USD	EUR	GBP	CHF	CAD
USD	1	0.741	0.657	1.061	1.011
EUR	1.350	1	0.888	1.433	1.366
GBP	1.521	1.126	1	1.614	1.538
CHF	0.943	0.698	0.620	1	0.953
CAD	0.995	0.732	0.650	1.049	1

**Ex.** \$1,000  $\Rightarrow$  741 Euros  $\Rightarrow$  1,012.206 Canadian dollars  $\Rightarrow$  \$1,007.14497.

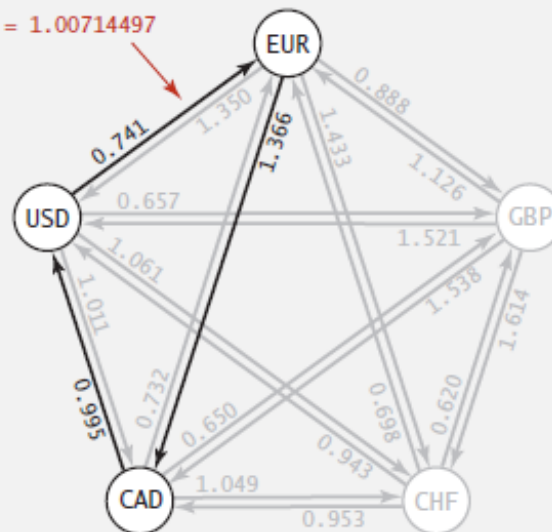
$$1000 \times 0.741 \times 1.366 \times 0.995 = 1007.14497$$

## Negative cycle application: arbitrage detection

### Currency exchange graph.

- Vertex = currency.
- Edge = transaction, with weight equal to exchange rate.
- Find a directed cycle whose product of edge weights is  $> 1$ .

$$0.741 * 1.366 * .995 = 1.00714497$$

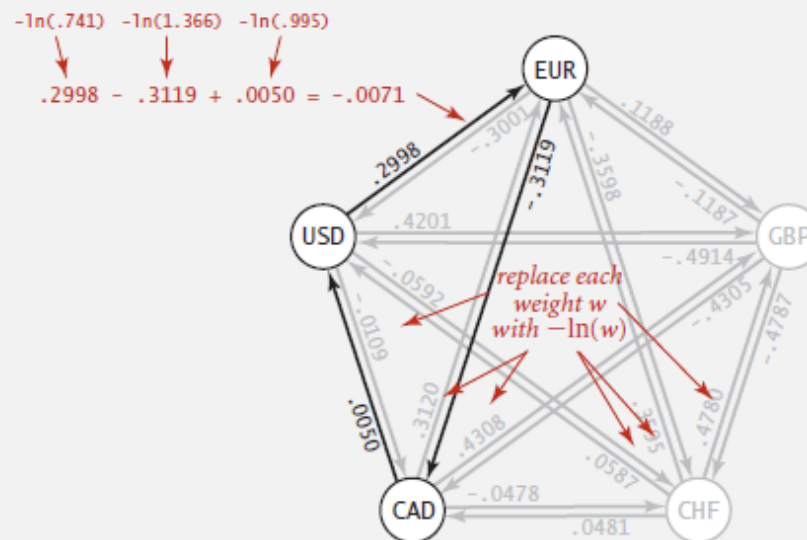


**Challenge.** Express as a negative cycle detection problem.

## Negative cycle application: arbitrage detection

Model as a negative cycle detection problem by taking logs.

- Let weight of edge  $v \rightarrow w$  be  $-\ln$  (exchange rate from currency  $v$  to  $w$ ).
- Multiplication turns to addition;  $> 1$  turns to  $< 0$ .
- Find a directed cycle whose sum of edge weights is  $< 0$  (negative cycle).



**Remark.** Fastest algorithm is extraordinarily valuable!



# Floyd-Warshall shortest path algorithm



## All-pairs shortest path

- › Run Dijkstra for each vertex?
- › Run Bellman-Ford each vertex?
- › Worst case scenario – assume fully connected graph, so  $E = V^2$
- › Dijkstra =  $V$  times  $V^2 \log V = V^3 \log V$
- › Bellman-Ford =  $V$  times  $V^3 = V^4$
- › Other options?
- › Floyd-Warshall =  $V^3$  (but  $V^2$  space)

# Floyd-Warshall all-pairs shortest path

- › For a path  $p = \{v_1, v_2, \dots, v_l\}$ , vertices  $v_2$  to  $v_{l-1}$  are intermediate vertices
- › Path consisting of a single edge has no intermediate vertices
- ›  $d_{ij}^{(k)}$  is a shortest path from  $i$  to  $j$  such that any intermediate vertices on the path are chosen from the set  $\{1, 2, \dots, k\}$  – in any order, any subset of them



# Floyd-Warshall

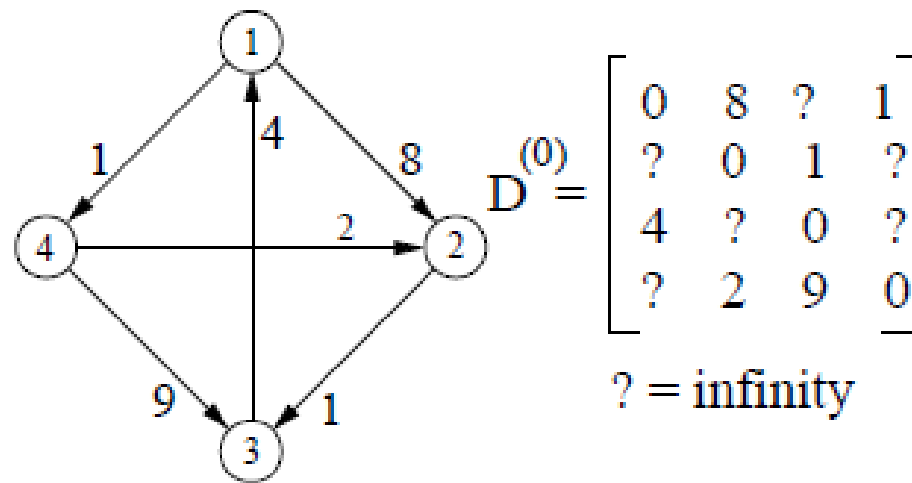
- › Assume we know  $d_{ij}^{(k-1)}$  – how do we calculate  $d_{ij}^{(k)}$
- › The path either goes through  $k$ , or it does not
  - If it does not, then shortest path  $d_{ij}^{(k)} = d_{ij}^{(k-1)}$
  - If it does, it means it passes through it exactly once, and it consists of shortest path from  $i$  to  $k$ , and then the shortest path from  $k$  to  $j$   $d_{ij}^{(k)} = d_{ik}^{(k-1)} + d_{kj}^{(k-1)}$

$$\begin{aligned}d_{ij}^{(0)} &= w_{ij}, \\d_{ij}^{(k)} &= \min \left( d_{ij}^{(k-1)}, d_{ik}^{(k-1)} + d_{kj}^{(k-1)} \right) \quad \text{for } k \geq 1.\end{aligned}$$

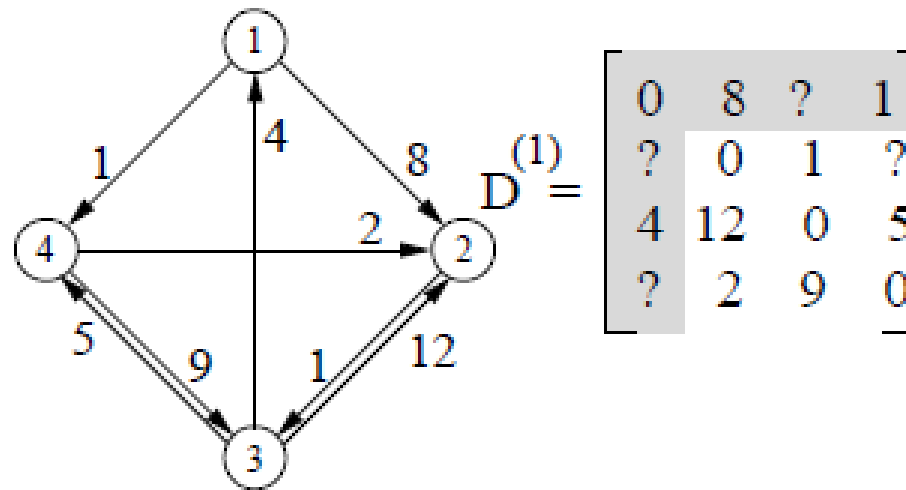
## Floyd-Warshall pseudocode

```
for  $k = 1$  to  $n$  do
  for  $i = 1$  to  $n$  do
    for  $j = 1$  to  $n$  do
      if ( $d[i, k] + d[k, j] < d[i, j]$ )
        { $d[i, j] = d[i, k] + d[k, j];$ 
          $pred[i, j] = k;$ }
return  $d[1..n, 1..n];$ 
```

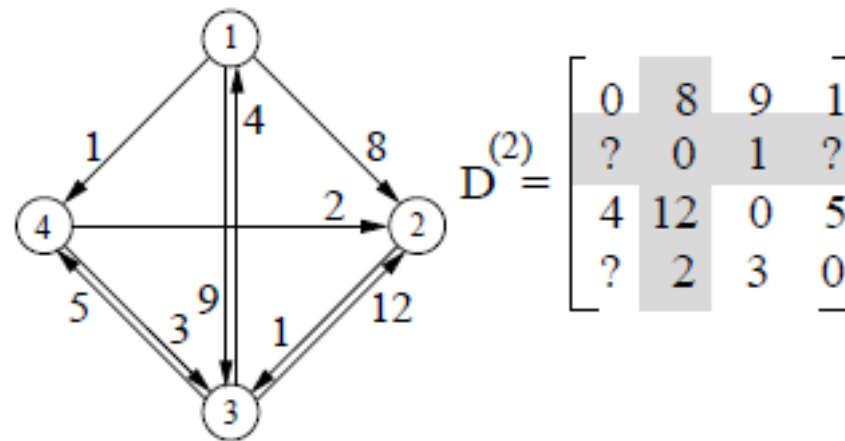
# Floyd Warshall example



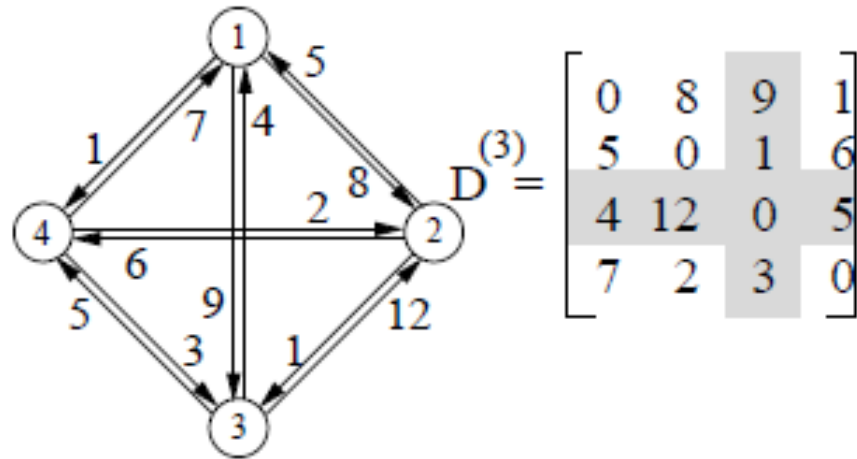
# Floyd Warshall example



# Floyd Warshall example

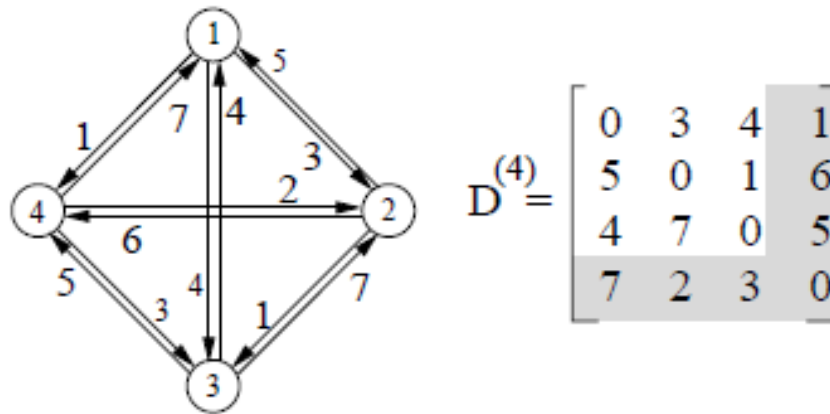


# Floyd Warshall example





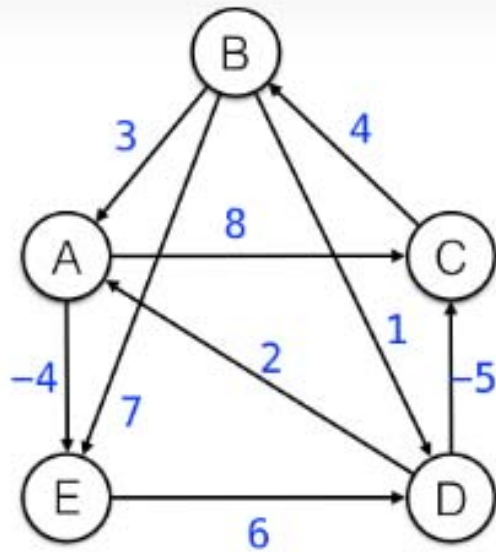
# Floyd Warshall example



# Floyd-Warshall demo

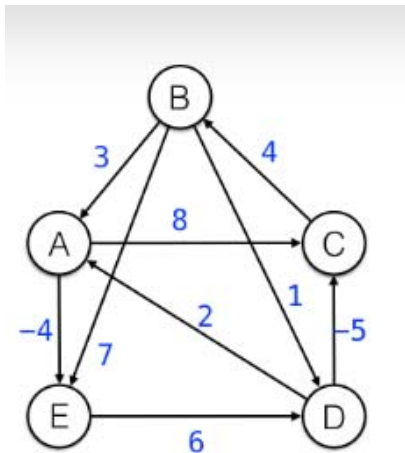
- › <https://www.cs.usfca.edu/~galles/visualization/Floyd.html>

# Floyd-Warshall exercise



$D^0$	A	B	C	D	E
A	0	3	8	INF	-4
B	INF	0	INF	1	7
C	INF	4	0	INF	INF
D	2	INF	-5	0	INF
E	INF	INF	INF	6	0

# Exercise solution



$D^5$	A	B	C	D	E
A	0	0	1	-3	-4
B	3	0	-4	1	-1
C	7	4	0	5	3
D	2	-1	-5	0	-2
E	8	5	1	6	0



# Dynamic Programming



# Dynamic programming

- › Algorithm Design, Kleinberg and Tardos, Pearson 2014
- › Introduction to Design and Analysis of Algorithms, Levitin. Pearson 2012



# Dynamic programming

- › Examples:
  - Bellman-Ford
  - Floyd-Warshall
- › Examines the full search space but implicitly, by breaking up the problem into a series of subproblems, and then building up the solution to larger and larger subproblems
- › Typically overlapping subproblems – instead of over and over calculating solutions to a subproblem, record it in a table and look up when needed
- › So why a fancy name if this is all that it's doing?
- › Richard Bellman on the Birth of Dynamic Programming, by Stuart Dreyfus  
<https://pubsonline.informs.org/doi/pdf/10.1287/opre.50.1.48.17791>

# Dynamic programming

## › Informal guidelines:

- There are only a polynomial number of subproblems
- The solution to the original problem can be easily computed from the solution of the subproblems
- There is a natural order of subproblems from smallest to largest together with easy to compute recurrence that allows building a solution to a subproblem from smaller subproblems

# Shortest paths challenges

- › <http://www.diag.uniroma1.it/challenge9/>
- › <http://www.diag.uniroma1.it/challenge9/download.shtml>