# Shortest Paths & Wrapping Up Dynamic Programming

## Shortest Paths: Cyclic Graphs

- **Problem.** Find the cost of the shortest path from s to any node v in a directed graph G
- G can have cycles with non-negative cost (but assuming no negative cycles for now)
- Subproblem:
  - D(v, i): (optimal) cost of shortest path from s to v using at most i edges

### Shortest Paths: Cyclic Graphs

- Subproblem. D(v, i): cost of shortest path from s to v using at most i edges
- Base cases?
  - D(s, i) = 0 for any i
  - $D(v,0) = \infty$  for any  $v \neq s$
- Final answer/output for shortest path cost to node *v*?

• D(v, n - 1), why?

# Shortest Paths: Cyclic Graphs

- How many edges can be on a shortest path between two nodes?
- Can there be a cycle on a shortest path?
  - We assumed no negative cycles
  - What about a positive cycle?
  - What about a cycle of cost 0?
    - Can remove them without hurting cost
- Thus, we can assume shortest paths are simple
  - Max number of edges on a simple path?
  - *n* 1

- Subproblem. D(v, i): cost of shortest path from s to v using at most i edges
- Base cases?
  - D(s, i) = 0 for any i
  - $D(v,0) = \infty$  for any  $v \neq s$
- Output D(v, n 1)
- How do we formulate the recurrence?
  - Case 1. Shortest path to v uses  $\leq i 1$  edges
  - Case 2. Shortest path to v uses exactly *i* edges

- Subproblem. D(v, i): cost of shortest path from s to v using at most i edges
- Base cases?
  - D(s, i) = 0 for any i
  - $D(v,0) = \infty$  for any  $v \neq s$
- Output D(v, n 1)
- Recurrence:

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

Called the Bellman-Ford-Moore algorithm

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- Memoization: Two-dimensional array
- Evaluation order:
  - $i: 1 \rightarrow n-1$
  - Vertices can be evaluated in any order
- Analysis
  - Space?
  - Running time?

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- Memoization: Two-dimensional array
- Evaluation order:
  - $i: 1 \rightarrow n-1$
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- Analysis
  - Space?  $O(n^2)$  entries in table
  - Running time?  $O(n^3)$ 
    - Each entry in table takes O(n) to compute
    - $O(n^2)$  entries

#### Bellman-Ford: Improved Analysis

• Recurrence for D(v, i)

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

- 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

- This is at most O(n + m) = O(m) for  $m \ge n 1$  (assuming G is connected)
- To fill *n* rows, overall running time is O(nm)

#### Bellman-Ford-Moore Correctness

- Lemma. (Correctness) d[v, i] is the cost of a shortest path from *s* to *v* using at most *i* edges
- Proof. [By induction on i]
  - Base case: i = 0
    - d[s, i] = 0 for all  $i, d[u, 0] = \infty$  for  $u \neq s$
  - Induction hypothesis:
    Assume that d[v, i] is the cost of a shortest path from s to v using at most i edges
  - Inductive step: prove for i + 1
  - **Observe**: d[v, i] never increases (only goes down)

#### **Bellman-Ford-Moore Correctness**

- Let *P* be the **shortest**  $s \sim v$  path with at most i + 1 edges.
- Let (u, v) be last edge on P, and Q be the subpath from  $s \thicksim u$
- Then Q has at most i edges, and must be shortest  $s \thicksim u$  path
- By inductive hypothesis, d[u, i] = w(Q)
- We have  $d[v, i + 1] = \min\{d[v, i], d[u, i] + w[u, v]\}$ 
  - d[u, i] + w[u, v] = w(Q) + w[u, v] = w(P)
  - Thus,  $d[v, i+1] \le w(P)$
  - d[v, i + 1] cannot be strictly less than w(P)
  - d[v, i + 1] is based on an actual path to v in the algorithm
  - Thus, d[v, i + 1] = w(P)

# Extracting Shortest Path

- Once we have the shortest path table, we can extract the actual shortest path in O(m) time
  - Consider edges with  $d[v, i] = d[u, i 1] + w_{uv}$
- Or we can do extra booking-keeping during the dynamic program to store pointers to path
  - Maintain pred[v, i] that points to node leading to v
    on shortest path s ~ v using at most i edges

# Improving Space

- Observation. d[-, i] only depends on d[-, i-1]
  - Use a one dimensional array d[v], which stores the cost of the shortest s v path found so far
  - Maintain pred[v] that points to node leading to v on shortest path s ~ v found so far
  - Keep improving estimate ( $i \rightarrow 1, ..., n-1$  now acts like a counter)
  - (Optimization) If no estimate d[v] changes during an iteration, we can just stop

### **Bellman-Ford-Moore Algorithm**

- Initialize:
  - For each node  $v \neq s$ : d[v]  $\leftarrow \infty$ , pred[v]  $\leftarrow$  null
- Initialize:  $d[s] \leftarrow 0$
- For i = 1 to n 1 # no of passes
  - For each node v
    - For each edge  $(v, w) \in E$ :
      - If d[w] > d[v] + w[v, w]:
        - d[w] ← d[v] +w[v, w]
        - pred[w] ← v

# Detecting a Negative Cycle

- **Problem.** Given a weighted directed graph with edge weights  $w_e$  find if it contains a negative cycle
- Let us solve a slightly different problem first
- Given a graph G and source s, find if there is negative cycle on a  $s \leadsto v$  path for any node v
- Suppose there is a negative cycle on a  $s \leadsto v$  path

. Then 
$$\lim_{i \to \infty} D(v, i) = -\infty$$

- If D(v, n) = D(v, n 1) for every node v then no negative cycles exits! Why?
  - Table values converge  $\implies$  shortest  $s \leadsto v$  path exists

# Detecting a Negative Cycle

- Lemma. If D(v, n) < D(v, n-1) then any shortest  $s \sim v$  path contains a negative cycle.
- Proof. [By contradiction]
  - Since D(v, n) < D(v, n − 1), the shortest s ~ v</li>
    path has exactly n edges
  - By pigeonhole principle, the path must contain a repeated node— let the cycle be  ${\cal W}$
  - If W has non-negative weight, removing it would give us a shortest path with less than n edges  $\Rightarrow \leftarrow$

# Detecting a Negative Cycle

- Now we know how to detect negative cycles on a shortest path from s to some node v
- How do we solve the problem in general (that is, given a graph does it have any negative cycle?)
- Idea: Problem reduction!
  - Given graph G, add a source s and connect it to all vertices in G with edge weight 0
  - Let the new graph be  $G^\prime$
  - G has a negative cycle iff G' has a negative cycle!

# More DP: Dividing Work

- Suppose we have to scan through a shelf of books, and this task can be split between k workers
- We do not want to reorder/rearrange the books, so instead we divide the shelf into k regions
- Each worker is assigned one of the regions
- What is the fairest way to divide the shelf up?



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- Each worker is assigned one of the regions
- What is the fairest way to divide the shelf up?
- If the books are equal length, we can just partition into equal sizes regions
- What if books are not equal size?
  - How can we find the fairest partition of work?

## The 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
  - Suppose k = 3, where should we partition to minimize the maximum sum over all ranges?

## The Linear Partition Problem

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  - Suppose k = 3, where should we partition to minimize the maximum sum over all ranges?
    100 200 300 400 500 | 600 700 | 800 900

### **Recursive Formulation**

- Notice that the kth partition starts after we place the (k-1)th "divider"
- Let us consider an optimal solution, where can it have the last divider?
  - Between some elements, suppose between *i*th and (i + 1)the element where  $1 \le i \le n$
  - What is the cost of placing the last divider here? Max of:

Cost of the last partition 
$$\sum_{j=i+1}^{n} s_j$$

• Cost of the optimal way to partition the elements to the "left" — this is a smaller version of the same problem!

#### **Dynamic Programming Recurrence**

- Subproblem?
  - M(i, j) be the minimum cost over all partitions of  $\{s_1, ..., s_i\}$  into j ranges
- Base cases?

• 
$$M(1, j) = s_1$$
 for all  $1 \le j \le k$   
•  $M(i, 1) = \sum_{t=1}^{i} s_t$  for all  $1 \le i \le n$ 

• Recurrence?

• 
$$M(i,j) = \min_{1 \le i' \le i} \max\{M(i',j-1), \sum_{t=i'+1}^{i} s_t\}$$

• Final solution: M(n,k)

# Running Time

• 
$$M(i,j) = \min_{1 \le i' \le i} \max\{M(i',j-1), \sum_{t=i'+1}^{i} s_t\}$$

- Final solution: M(n,k)
- Evaluation order? Row major order
- Running time?
  - Size of table:  $O(k \cdot n)$
  - How long to compute a single cell?
    - Depends on *n* other cells
  - $O(n^2 \cdot k)$  time

# Running Time

- Running time
  - Size of table:  $O(k \cdot n)$
  - How long to compute a single cell?
    - Depends on *n* other cells
  - $O(n^2 \cdot k)$  time
  - Is this a pseudo polynomial running time?
  - How big can k get?
    - At most *n* non-empty partitions of *n* elements
    - $O(n^3)$  algorithm in the worst case

# **Dynamic Programming Practice**

- Longest Common Subsequence Problem
- We are given two strings: string *A* of length *n*, and string *B* of length *m*.
- Our goal is to produce their longest common subsequence: the longest sequence of characters that appear left-to-right (but not necessarily in a contiguous block) in both strings.
- For example, consider:
  - A = abazdc
  - B = bacbad
- In this case, the LCS has length 4 and is the string abad

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  - Jeff Erickson's Algorithms Book (<u>http://jeffe.cs.illinois.edu/</u> <u>teaching/algorithms/book/Algorithms-JeffE.pdf</u>)