

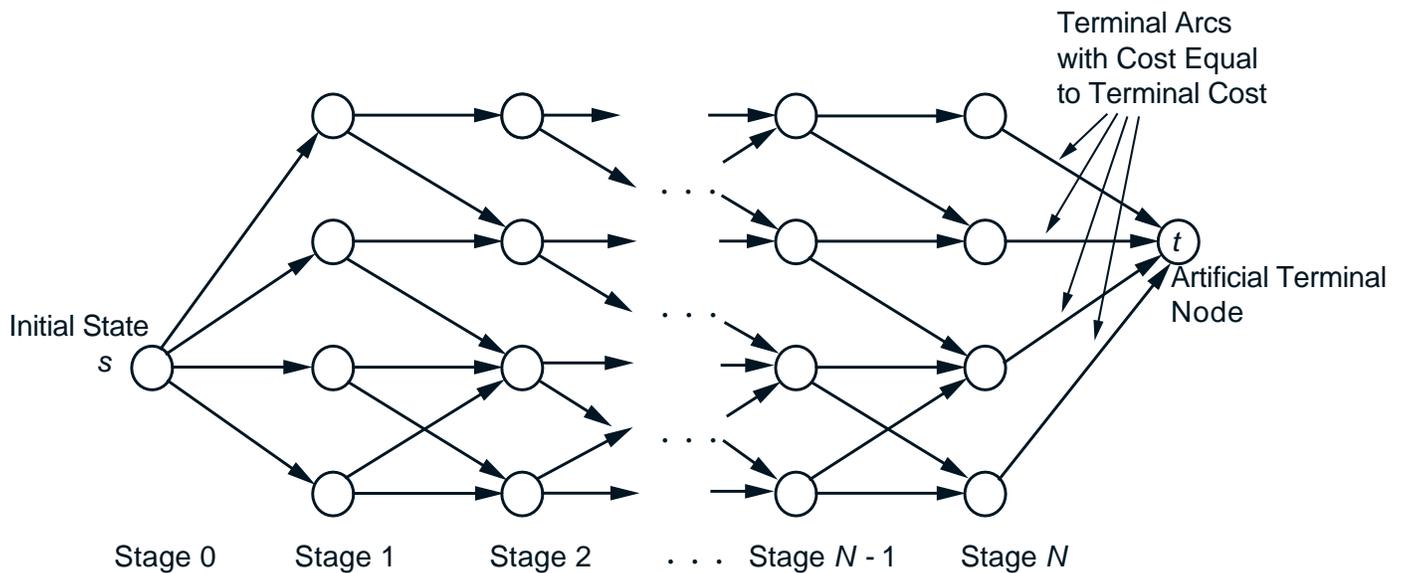
# 6.231 DYNAMIC PROGRAMMING

## LECTURE 3

### LECTURE OUTLINE

- Deterministic finite-state DP problems
- Backward shortest path algorithm
- Forward shortest path algorithm
- Shortest path examples
- Alternative shortest path algorithms

# DETERMINISTIC FINITE-STATE PROBLEM



- States  $\langle == \rangle$  Nodes
- Controls  $\langle == \rangle$  Arcs
- Control sequences (open-loop)  $\langle == \rangle$  paths from initial state to terminal states
- $a_{ij}^k$ : Cost of transition from state  $i \in S_k$  to state  $j \in S_{k+1}$  at time  $k$  (view it as “length” of the arc)
- $a_{it}^N$ : Terminal cost of state  $i \in S_N$
- Cost of control sequence  $\langle == \rangle$  Cost of the corresponding path (view it as “length” of the path)

# BACKWARD AND FORWARD DP ALGORITHMS

- DP algorithm:

$$J_N(i) = a_{it}^N, \quad i \in S_N,$$

$$J_k(i) = \min_{j \in S_{k+1}} [a_{ij}^k + J_{k+1}(j)], \quad i \in S_k, \quad k = 0, \dots, N-1$$

The optimal cost is  $J_0(s)$  and is equal to the length of the shortest path from  $s$  to  $t$

- Observation: An optimal path  $s \rightarrow t$  is also an optimal path  $t \rightarrow s$  in a “reverse” shortest path problem where the direction of each arc is reversed and its length is left unchanged

- Forward DP algorithm (= backward DP algorithm for the reverse problem):

$$\tilde{J}_N(j) = a_{sj}^0, \quad j \in S_1,$$

$$\tilde{J}_k(j) = \min_{i \in S_{N-k}} [a_{ij}^{N-k} + \tilde{J}_{k+1}(i)], \quad j \in S_{N-k+1}$$

The optimal cost is  $\tilde{J}_0(t) = \min_{i \in S_N} [a_{it}^N + \tilde{J}_1(i)]$

- View  $\tilde{J}_k(j)$  as **optimal cost-to-arrive** to state  $j$  from initial state  $s$

# A NOTE ON FORWARD DP ALGORITHMS

- There is no forward DP algorithm for **stochastic** problems
- Mathematically, for stochastic problems, we cannot restrict ourselves to open-loop sequences, so the shortest path viewpoint fails
- Conceptually, in the presence of uncertainty, the concept of “optimal-cost-to-arrive” at a state  $x_k$  does not make sense. For example, it may be impossible to guarantee (with prob. 1) that any given state can be reached
- By contrast, even in stochastic problems, the concept of “optimal cost-to-go” from any state  $x_k$  makes clear sense

# GENERIC SHORTEST PATH PROBLEMS

- $\{1, 2, \dots, N, t\}$ : nodes of a graph ( $t$ : the *destination*)
- $a_{ij}$ : cost of moving from node  $i$  to node  $j$
- Find a shortest (minimum cost) path from each node  $i$  to node  $t$
- **Assumption: All cycles have nonnegative length.** Then an optimal path need not take more than  $N$  moves
- We formulate the problem as one where we require exactly  $N$  moves but **allow degenerate moves** from a node  $i$  to itself with cost  $a_{ii} = 0$

$J_k(i)$  = opt. cost of getting from  $i$  to  $t$  in  $N - k$  moves

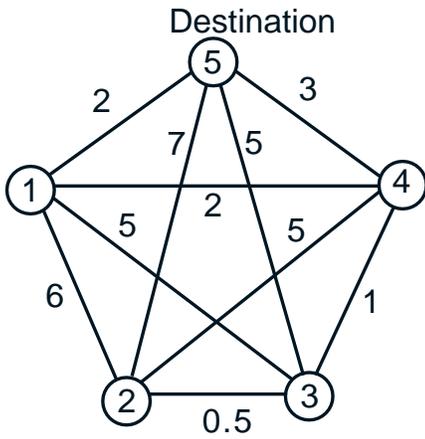
$J_0(i)$ : Cost of the optimal path from  $i$  to  $t$ .

- DP algorithm:

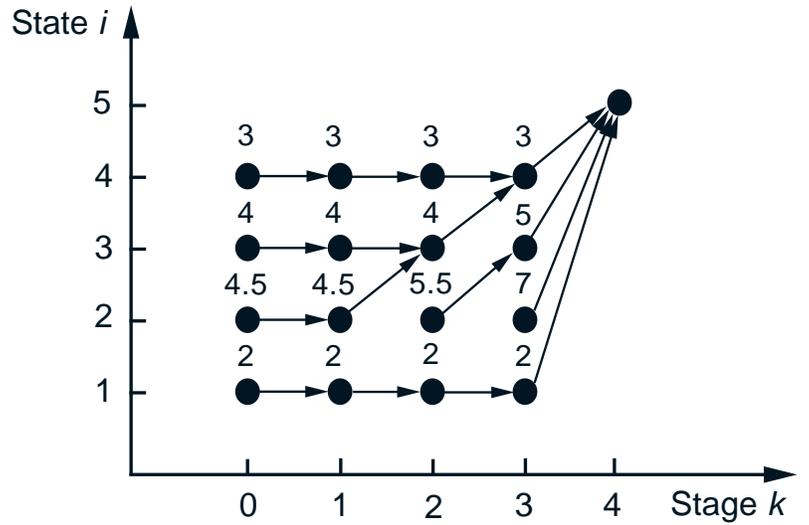
$$J_k(i) = \min_{j=1, \dots, N} [a_{ij} + J_{k+1}(j)], \quad k = 0, 1, \dots, N-2,$$

with  $J_{N-1}(i) = a_{it}$ ,  $i = 1, 2, \dots, N$

# EXAMPLE



(a)



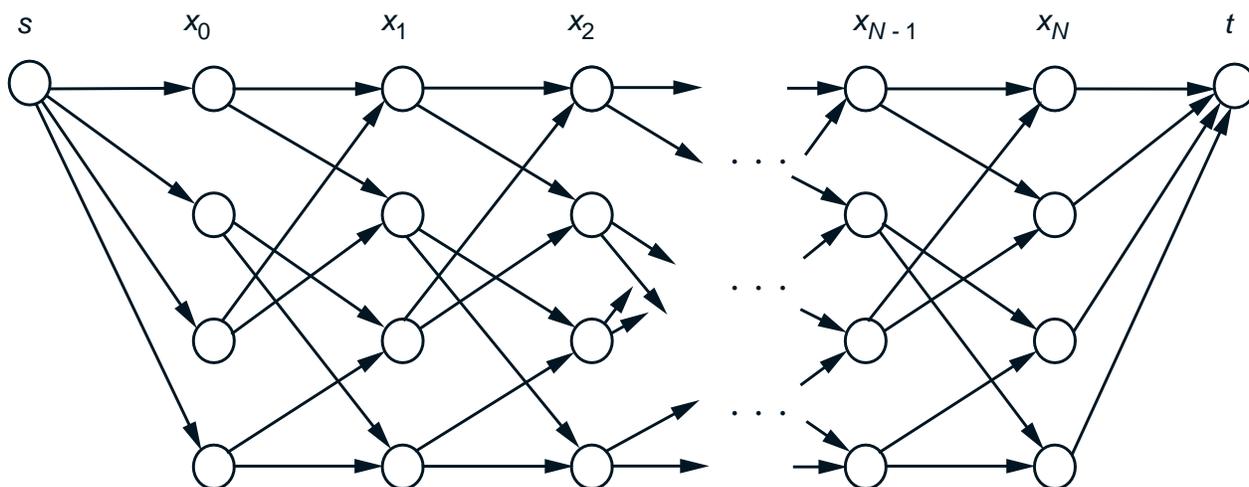
(b)

$$J_{N-1}(i) = a_{it}, \quad i = 1, 2, \dots, N,$$

$$J_k(i) = \min_{j=1, \dots, N} [a_{ij} + J_{k+1}(j)], \quad k = 0, 1, \dots, N-2.$$

# ESTIMATION / HIDDEN MARKOV MODELS

- Markov chain with transition probabilities  $p_{ij}$
- State transitions are hidden from view
- For each transition, we get an (independent) observation
- $r(z; i, j)$ : Prob. the observation takes value  $z$  when the state transition is from  $i$  to  $j$
- **Trajectory estimation problem:** Given the observation sequence  $Z_N = \{z_1, z_2, \dots, z_N\}$ , what is the “most likely” state transition sequence  $\hat{X}_N = \{\hat{x}_0, \hat{x}_1, \dots, \hat{x}_N\}$  [one that maximizes  $p(X_N | Z_N)$  over all  $X_N = \{x_0, x_1, \dots, x_N\}$ ].



## VITERBI ALGORITHM

- We have

$$p(X_N | Z_N) = \frac{p(X_N, Z_N)}{p(Z_N)}$$

where  $p(X_N, Z_N)$  and  $p(Z_N)$  are the unconditional probabilities of occurrence of  $(X_N, Z_N)$  and  $Z_N$

- Maximizing  $p(X_N | Z_N)$  is equivalent with maximizing  $\ln(p(X_N, Z_N))$
- We have (using the “multiplication rule” for cond. probs)

$$p(X_N, Z_N) = \pi_{x_0} \prod_{k=1}^N p_{x_{k-1}x_k} r(z_k; x_{k-1}, x_k)$$

so the problem is equivalent to

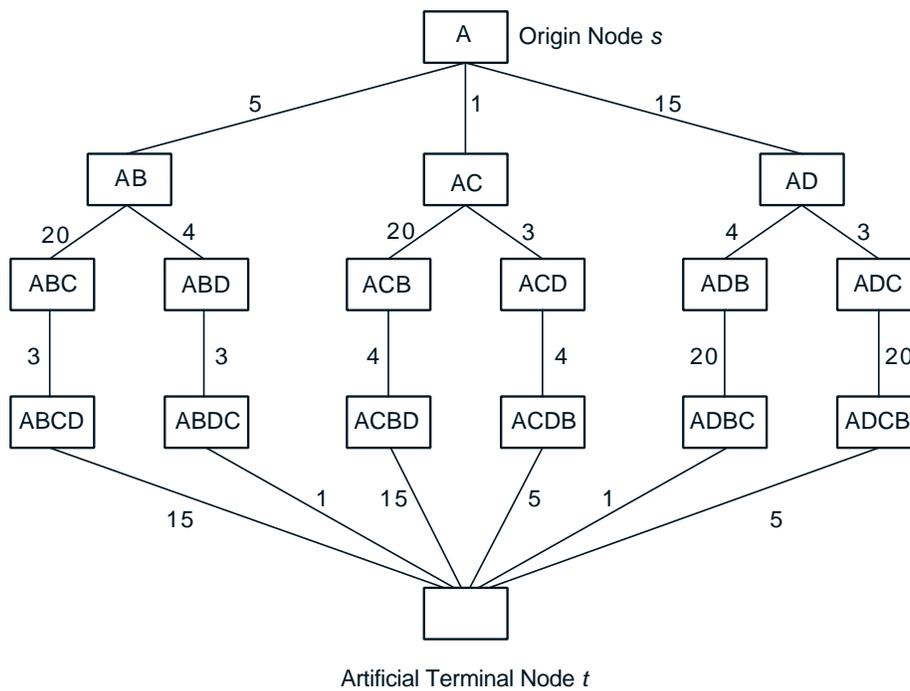
$$\text{minimize } -\ln(\pi_{x_0}) - \sum_{k=1}^N \ln(p_{x_{k-1}x_k} r(z_k; x_{k-1}, x_k))$$

over all possible sequences  $\{x_0, x_1, \dots, x_N\}$ .

- This is a shortest path problem.

# GENERAL SHORTEST PATH ALGORITHMS

- There are many nonDP shortest path algorithms. They can all be used to solve deterministic finite-state problems
- They may be preferable than DP if they avoid calculating the optimal cost-to-go of **EVERY** state
- Essential for problems with **HUGE** state spaces.
- Combinatorial optimization is prime example (e.g., **scheduling/traveling salesman**)



	5	1	15
5		20	4
1	20		3
15	4	3	

## LABEL CORRECTING METHODS

- Given: Origin  $s$ , destination  $t$ , lengths  $a_{ij} \geq 0$ .
- Idea is to progressively discover shorter paths from the origin  $s$  to every other node  $i$
- **Notation:**
  - $d_i$  (label of  $i$ ): Length of the shortest path found (initially  $d_s = 0$ ,  $d_i = \infty$  for  $i \neq s$ )
  - UPPER: The label  $d_t$  of the destination
  - OPEN list: Contains nodes that are currently active in the sense that they are candidates for further examination (initially  $\text{OPEN} = \{s\}$ )

### Label Correcting Algorithm

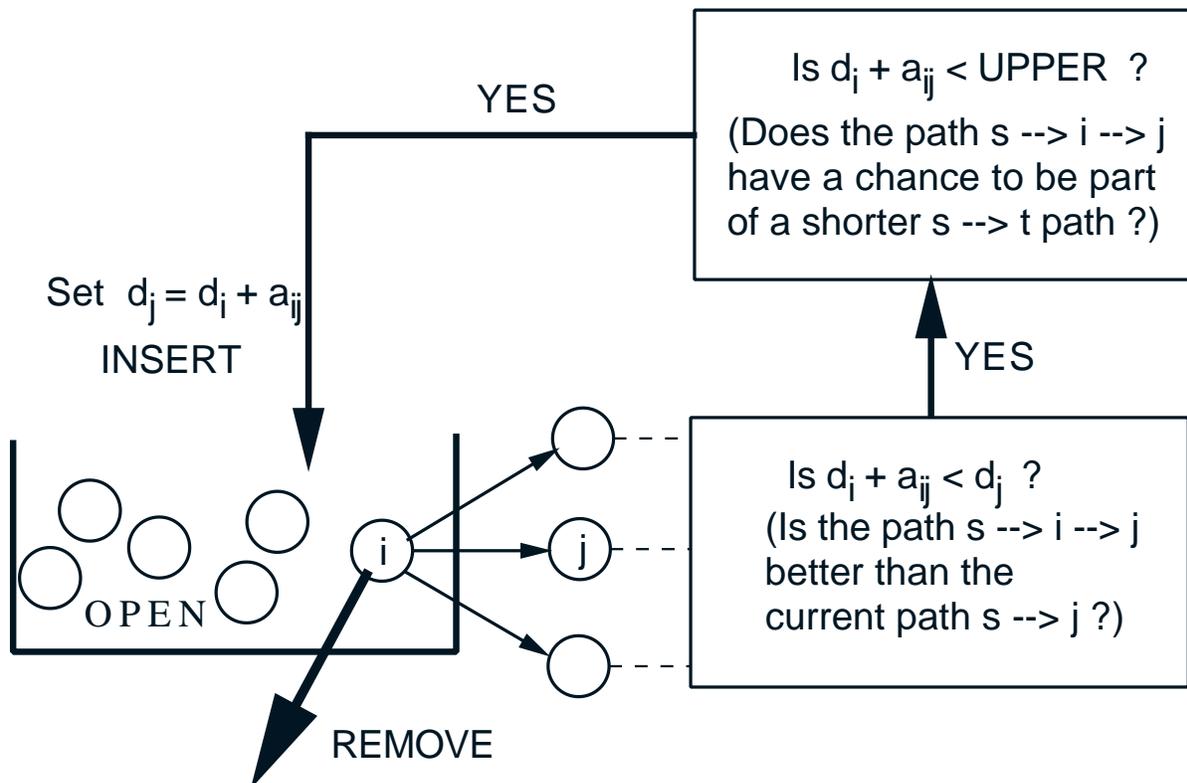
**Step 1 (Node Removal):** Remove a node  $i$  from OPEN and for each child  $j$  of  $i$ , do step 2

**Step 2 (Node Insertion Test):** If  $d_i + a_{ij} < \min\{d_j, \text{UPPER}\}$ , set  $d_j = d_i + a_{ij}$  and set  $i$  to be the parent of  $j$ . In addition, if  $j \neq t$ , place  $j$  in OPEN if it is not already in OPEN, while if  $j = t$ , set UPPER to the new value  $d_i + a_{it}$  of  $d_t$

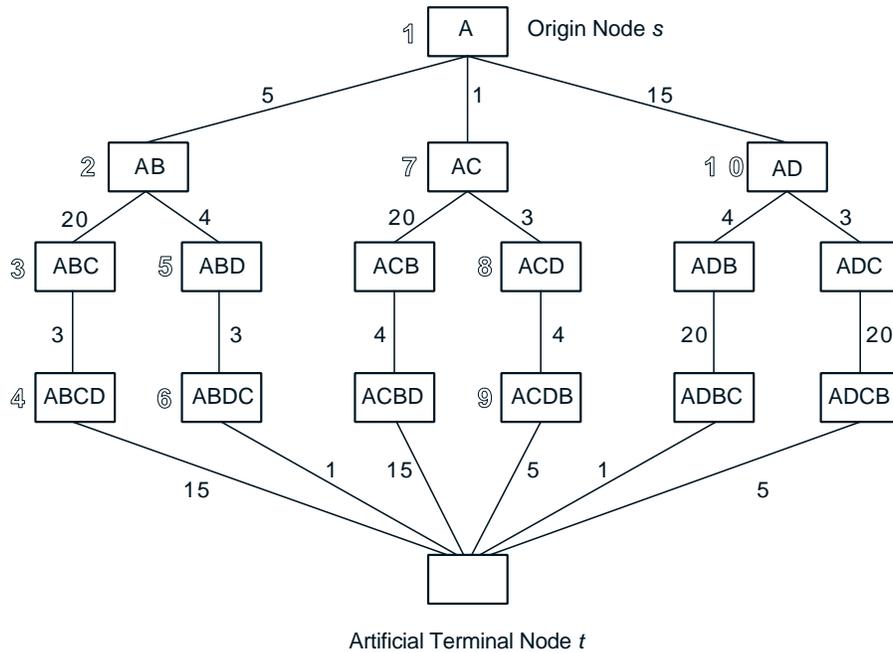
**Step 3 (Termination Test):** If OPEN is empty, terminate; else go to step 1

# VISUALIZATION/EXPLANATION

- Given: Origin  $s$ , destination  $t$ , lengths  $a_{ij} \geq 0$
- $d_i$  (label of  $i$ ): Length of the shortest path found thus far (initially  $d_s = 0$ ,  $d_i = \infty$  for  $i \neq s$ ). The label  $d_i$  is implicitly associated with an  $s \rightarrow i$  path
- UPPER: The label  $d_t$  of the destination
- OPEN list: Contains “active” nodes (initially  $\text{OPEN} = \{s\}$ )



# EXAMPLE



Iter. No.	Node Exiting OPEN	OPEN after Iteration	UPPER
0	-	1	$\infty$
1	1	2, 7, 10	$\infty$
2	2	3, 5, 7, 10	$\infty$
3	3	4, 5, 7, 10	$\infty$
4	4	5, 7, 10	43
5	5	6, 7, 10	43
6	6	7, 10	13
7	7	8, 10	13
8	8	9, 10	13
9	9	10	13
10	10	Empty	13

- Note that **some nodes never entered OPEN**

# VALIDITY OF LABEL CORRECTING METHODS

**Proposition:** If there exists at least one path from the origin to the destination, the label correcting algorithm terminates with UPPER equal to the shortest distance from the origin to the destination

**Proof:** (1) Each time a node  $j$  enters OPEN, its label is decreased and becomes equal to the length of some path from  $s$  to  $j$

(2) The number of possible distinct path lengths is finite, so the number of times a node can enter OPEN is finite, and the algorithm terminates

(3) Let  $(s, j_1, j_2, \dots, j_k, t)$  be a shortest path and let  $d^*$  be the shortest distance. If  $\text{UPPER} > d^*$  at termination, UPPER will also be larger than the length of all the paths  $(s, j_1, \dots, j_m)$ ,  $m = 1, \dots, k$ , throughout the algorithm. Hence, node  $j_k$  will never enter the OPEN list with  $d_{j_k}$  equal to the shortest distance from  $s$  to  $j_k$ . Similarly node  $j_{k-1}$  will never enter the OPEN list with  $d_{j_{k-1}}$  equal to the shortest distance from  $s$  to  $j_{k-1}$ . Continue to  $j_1$  to get a contradiction

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