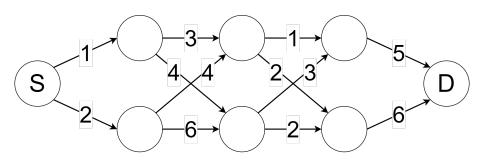
Lecture 1: Dynamic Programming (DP)

Course: Reinforcement Learning Theory Instructor: Lei Ying Department of EECS University of Michigan, Ann Arbor

A Deterministic DP Example

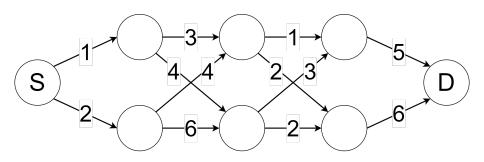


Find the shortest path from S to D.

Exclusive search (forward search):

number of possible paths $=2\times2\times2=8$

A Deterministic DP Example



Find the shortest path from S to $\mathsf{D}.$

DP (backward search):

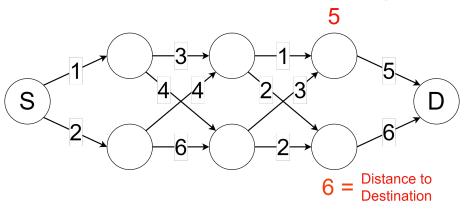
start from the destination

Deterministic DP Example

Find the shortest path from S to D.

DP: backward search.

- Calculate the shortest distance from a current node to destination D.
- Each calculation is a comparison of two choices (numbers)

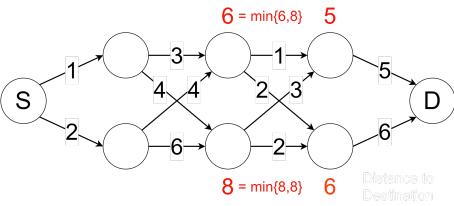


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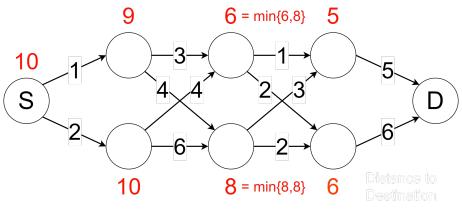


Deterministic DP Example

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DP: backward search.

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Deterministic DP

The computational complexity of exclusive search versus DP. Suppose the problem has T stages. Then

- Exclusive search: exponential in T
- ullet Dynamic programming: linear in T

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Dynamic Programming Principle

 $\mathcal{N}(j)$: set of outgoing neighbors of node j c(j,k) : distance of edge from node j to node k (denoted by (j,k))

$$d(j,i) = \min_{k \in \mathcal{N}(j)} c(j,k) + d(k,i)$$

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 $\bullet \ \text{``} \leq \mathsf{proof''} \colon \mathsf{a} \ \mathsf{shortest} \ \mathsf{path} \ j \ \mathsf{to} \ i \ \mathsf{has} \ \mathsf{to} \ \mathsf{go} \ \mathsf{through} \ \mathcal{N}(j),$

$$d(j,i) \le c(j,k) + d(k,i) \quad \forall k \in \mathcal{N}(j)$$

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• " \geq proof": if $P_{j \to i}$ (path from j to i) is a shortest path and goes through $k^* \in \mathcal{N}(j)$, the subpath to i from k^* on $P_{j \to i}$ is a shortest path from k^* to i,

$$d(j,i) = c(j,k^*) + d(k^*,i) \ge \min_{k \in \mathcal{N}(j)} c(j,k) + d(k,i).$$

We therefore conclude: $d(j, i) = \min_{k \in \mathcal{N}(j)} c(j, k) + d(k, i)$.

System equation:

$$x_{k+1} = f_k(x_k, u_k), \quad k = 0, 1, \dots, N-1$$

 x_k : system state at time k, u_k : control at time k

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 x_k : system state at time k, u_k : control at time k

In the shortest path problem,

 x_k : on the top or bottom node at stage k

 u_k : move up or down at stage k

For given initial state x_0 , the cost over control sequence $(u_0, u_1, \ldots, u_{N-1})$ is defined to be

$$J(x_0; u_0, \dots, u_{N-1}) = g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k)$$

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Optimal cost and optimal control:

$$J^*(x_0) = \min_{u_0, \dots, u_{N-1}} J(x_0; u_0, \dots, u_{N-1})$$

Finite horizon deterministic problem

Backward computation:

$$J_N^*(x_N) = g_N(x_N). (trivial)$$

In the shortest path problem, we have

$$g_N(x_N) = 0.$$

Finite horizon deterministic problem

Backward computation:

$$J_N^*(x_N) = g_N(x_N). (trivial)$$

According to the DP principle,

$$J_{N-1}^*(x_{N-1}) = \min_{u_{N-1}} \left(g_{N-1}(x_{N-1}, u_{N-1}) + J_N^*(f(x_{N-1}, u_{N-1})) \right),$$

where we assume $f_k(\cdot) = f(\cdot)$ for all K. And in general,

$$J_k^*(x_k) = \min_{u_k} \left(g_k(x_k, u_k) + J_{k+1}^*(f(x_k, u_k)) \right).$$

Reference

 Chapter 1.1 of Dimitri P. Bertsekas, Reinforcement Learning and Optimal Control, Athena Scientific, 2019. Slides and lectures available at https://web.mit.edu/dimitrib/www/RLbook.html

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