# 6.231 DYNAMIC PROGRAMMING

# LECTURE 17

# LECTURE OUTLINE

- Undiscounted problems
- Stochastic shortest path problems (SSP)
- Proper and improper policies
- Analysis and computational methods for SSP
- Pathologies of SSP
- SSP under weak conditions

#### UNDISCOUNTED PROBLEMS

- System:  $x_{k+1} = f(x_k, u_k, w_k)$
- Cost of a policy  $\pi = \{\mu_0, \mu_1, \ldots\}$

$$J_{\pi}(x_0) = \limsup_{N \to \infty} \mathop{E}_{\substack{w_k \\ k=0,1,\dots}} \left\{ \sum_{k=0}^{N-1} g(x_k, \mu_k(x_k), w_k) \right\}$$

Note that  $J_{\pi}(x_0)$  and  $J^*(x_0)$  can be  $+\infty$  or  $-\infty$ 

• Shorthand notation for DP mappings

$$(TJ)(x) = \min_{u \in U(x)} E_w \left\{ g(x, u, w) + J(f(x, u, w)) \right\}, \ \forall \ x$$
$$(T_\mu J)(x) = E_w \left\{ g(x, \mu(x), w) + J(f(x, \mu(x), w)) \right\}, \ \forall \ x$$

- T and  $T_{\mu}$  need not be contractions in general, but their monotonicity is helpful (see Ch. 4, Vol. II of text for an analysis).
- SSP problems provide a "soft boundary" between the easy finite-state discounted problems and the hard undiscounted problems.
  - They share features of both.
  - Some nice theory is recovered thanks to the termination state, and special conditions.

### SSP THEORY SUMMARY I

- As before, we have a cost-free term. state t, a finite number of states  $1, \ldots, n$ , and finite number of controls.
- Mappings T and  $T_{\mu}$  (modified to account for termination state t). For all  $i = 1, \ldots, n$ :

$$(T_{\mu}J)(i) = g(i,\mu(i)) + \sum_{j=1}^{n} p_{ij}(\mu(i))J(j),$$

$$(TJ)(i) = \min_{u \in U(i)} \left[ g(i, u) + \sum_{j=1}^{n} p_{ij}(u)J(j) \right],$$

or 
$$T_{\mu}J = g_{\mu} + P_{\mu}J$$
 and  $TJ = \min_{\mu}[g_{\mu} + P_{\mu}J]$ .

- Definition: A stationary policy  $\mu$  is called proper, if under  $\mu$ , from every state i, there is a positive probability path that leads to t.
- Important fact: (To be shown) If  $\mu$  is proper,  $T_{\mu}$  is contraction w. r. t. some weighted sup-norm

$$\max_{i} \frac{1}{v_{i}} |(T_{\mu}J)(i) - (T_{\mu}J')(i)| \le \rho_{\mu} \max_{i} \frac{1}{v_{i}} |J(i) - J'(i)|$$

• T is similarly a contraction if all  $\mu$  are proper (the case discussed in the text, Ch. 7, Vol. I).

## SSP THEORY SUMMARY II

- The theory can be pushed one step further. Instead of all policies being proper, assume that:
  - (a) There exists at least one proper policy
  - (b) For each improper  $\mu$ ,  $J_{\mu}(i) = \infty$  for some i
- Example: Deterministic shortest path problem with a single destination t.
  - States <=> nodes; Controls <=> arcs
  - Termination state <=> the destination
  - Assumption (a) <=> every node is connected to the destination
  - Assumption (b)  $\ll$  all cycle costs > 0
- Note that T is not necessarily a contraction.
- The theory in summary is as follows:
  - $-J^*$  is the unique solution of Bellman's Eq.
  - $\mu^*$  is optimal if and only if  $T_{\mu^*}J^* = TJ^*$
  - VI converges:  $T^kJ \to J^*$  for all  $J \in \Re^n$
  - PI terminates with an optimal policy, if started with a proper policy

### SSP ANALYSIS I

- For a proper policy  $\mu$ ,  $J_{\mu}$  is the unique fixed point of  $T_{\mu}$ , and  $T_{\mu}^{k}J \to J_{\mu}$  for all J (holds by the theory of Vol. I, Section 7.2)
- Key Fact: A  $\mu$  satisfying  $J \geq T_{\mu}J$  for some  $J \in \mathbb{R}^n$  must be proper true because

$$J \ge T_{\mu}^{k} J = P_{\mu}^{k} J + \sum_{m=0}^{k-1} P_{\mu}^{m} g_{\mu}$$

since  $J_{\mu} = \sum_{m=0}^{\infty} P_{\mu}^{m} g_{\mu}$  and some component of the term on the right blows up as  $k \to \infty$  if  $\mu$  is improper (by our assumptions).

• Consequence: T can have at most one fixed point within  $\Re^n$ .

Proof: If J and J' are two fixed points, select  $\mu$  and  $\mu'$  such that  $J = TJ = T_{\mu}J$  and  $J' = TJ' = T_{\mu'}J'$ . By preceding assertion,  $\mu$  and  $\mu'$  must be proper, and  $J = J_{\mu}$  and  $J' = J_{\mu'}$ . Also

$$J = T^k J \le T^k_{\mu'} J \to J_{\mu'} = J'$$

Similarly,  $J' \leq J$ , so J = J'.

### SSP ANALYSIS II

- We first show that T has a fixed point, and also that PI converges to it.
- Use PI. Generate a sequence of proper policies  $\{\mu^k\}$  starting from a proper policy  $\mu^0$ .
- $\mu^1$  is proper and  $J_{\mu^0} \geq J_{\mu^1}$  since

$$J_{\mu^0} = T_{\mu^0} J_{\mu^0} \ge T J_{\mu^0} = T_{\mu^1} J_{\mu^0} \ge T_{\mu^1}^k J_{\mu^0} \ge J_{\mu^1}$$

- Thus  $\{J_{\mu k}\}$  is nonincreasing, some policy  $\bar{\mu}$  is repeated and  $J_{\bar{\mu}} = TJ_{\bar{\mu}}$ . So  $J_{\bar{\mu}}$  is fixed point of T.
- Next show that  $T^k J \to J_{\bar{\mu}}$  for all J, i.e., VI converges to the same limit as PI. (Sketch: True if  $J = J_{\bar{\mu}}$ , argue using the properness of  $\bar{\mu}$  to show that the terminal cost difference  $J J_{\bar{\mu}}$  does not matter.)
- To show  $J_{\bar{\mu}} = J^*$ , for any  $\pi = \{\mu_0, \mu_1, \ldots\}$

$$T_{\mu_0}\cdots T_{\mu_{k-1}}J_0\geq T^kJ_0,$$

where  $J_0 \equiv 0$ . Take  $\limsup as k \to \infty$ , to obtain  $J_{\pi} \geq J_{\bar{\mu}}$ , so  $\bar{\mu}$  is optimal and  $J_{\bar{\mu}} = J^*$ .

### SSP ANALYSIS III

• Contraction Property: If all policies are proper (cf. Section 7.1, Vol. I),  $T_{\mu}$  and T are contractions with respect to a weighted sup norm.

**Proof:** Consider a new SSP problem where the transition probabilities are the same as in the original, but the transition costs are all equal to -1. Let  $\hat{J}$  be the corresponding optimal cost vector. For all  $\mu$ ,

$$\hat{J}(i) = -1 + \min_{u \in U(i)} \sum_{j=1}^{n} p_{ij}(u) \hat{J}(j) \le -1 + \sum_{j=1}^{n} p_{ij} (\mu(i)) \hat{J}(j)$$

For  $v_i = -\hat{J}(i)$ , we have  $v_i \geq 1$ , and for all  $\mu$ ,

$$\sum_{j=1}^{n} p_{ij}(\mu(i)) v_j \le v_i - 1 \le \rho v_i, \qquad i = 1, \dots, n,$$

where

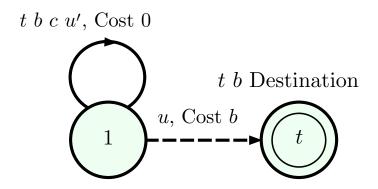
$$\rho = \max_{i=1,...,n} \frac{v_i - 1}{v_i} < 1.$$

This implies  $T_{\mu}$  and T are contractions of modulus  $\rho$  for norm  $||J|| = \max_{i=1,...,n} |J(i)|/v_i$  (by the results of earlier lectures).

## SSP ALGORITHMS

- All the basic algorithms have counterparts under our assumptions; see the text (Ch. 3, Vol. II)
- "Easy" case: All policies proper, in which case the mappings T and  $T_{\mu}$  are contractions
- Even with improper (infinite cost) policies all basic algorithms have satisfactory counterparts
  - VI and PI
  - Optimistic PI
  - Asynchronous VI
  - Asynchronous PI
  - Q-learning analogs
- \*\* THE BOUNDARY OF NICE THEORY \*\*
- Serious complications arise under any one of the following:
  - There is no proper policy
  - There is improper policy with finite cost  $\forall i$
  - The state space is infinite and/or the control space is infinite [infinite but compact U(i) can be dealt with]

# PATHOLOGIES I: DETERM. SHORTEST PATHS



- Two policies, one proper (apply u), one improper (apply u')
- Bellman's equation is

$$J(1) = \min[J(1), b]$$

Set of solutions is  $(-\infty, b]$ .

- Case b > 0,  $J^* = 0$ : VI does not converge to  $J^*$  except if started from  $J^*$ . PI may get stuck starting from the inferior proper policy
- Case b < 0,  $J^* = b$ : VI converges to  $J^*$  if started above  $J^*$ , but not if started below  $J^*$ . PI can oscillate (if started with u' it generates u, and if started with u it can generate u')

### PATHOLOGIES II: BLACKMAILER'S DILEMMA

- Two states, state 1 and the termination state t.
- At state 1, choose  $u \in (0,1]$  (the blackmail amount demanded) at a cost -u, and move to t with prob.  $u^2$ , or stay in 1 with prob.  $1 u^2$ .
- Every stationary policy is proper, but the control set in not finite (also not compact).
- For any stationary  $\mu$  with  $\mu(1) = u$ , we have

$$J_{\mu}(1) = -u + (1 - u^2)J_{\mu}(1)$$

from which  $J_{\mu}(1) = -\frac{1}{u}$ 

- Thus  $J^*(1) = -\infty$ , and there is no optimal stationary policy.
- A nonstationary policy is optimal: demand  $\mu_k(1) = \gamma/(k+1)$  at time k, with  $\gamma \in (0, 1/2)$ .
  - Blackmailer requests diminishing amounts over time, which add to  $\infty$ .
  - The probability of the victim's refusal diminishes at a much faster rate, so the probability that the victim stays forever compliant is strictly positive.

# SSP UNDER WEAK CONDITIONS I

• Assume there exists a proper policy, and  $J^*$  is real-valued. Let

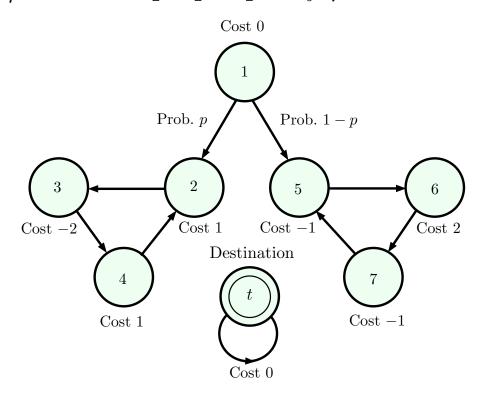
$$\hat{J}(i) = \min_{\mu: \text{ proper}} J_{\mu}(i), \qquad i = 1, \dots, n$$

Note that we may have  $\hat{J} \neq J^*$  [i.e.,  $\hat{J}(i) \neq J^*(i)$  for some i].

- It can be shown that  $\hat{J}$  is the unique solution of Bellman's equation within the set  $\{J \mid J \geq \hat{J}\}$
- Also VI converges to  $\hat{J}$  starting from any  $J \geq \hat{J}$
- The analysis is based on the  $\delta$ -perturbed problem: adding a small  $\delta > 0$  to g. Then:
  - All improper policies have infinite cost for some states in the  $\delta$ -perturbed problem
  - All proper policies have an additional  $O(\delta)$  cost for all states
  - The optimal cost  $J_{\delta}^*$  of the  $\delta$ -perturbed problem converges to  $\hat{J}$  as  $\delta \downarrow 0$
- There is also a PI method that generates a sequence  $\{\mu^k\}$  with  $J_{\mu^k} \to \hat{J}$ . Uses sequence  $\delta_k \downarrow 0$ , and policy evaluation based on the  $\delta_k$ -perturbed problems with  $\delta_k \downarrow 0$ .

### SSP UNDER WEAK CONDITIONS II

•  $J^*$  need not be a solution of Bellman's equation! Also  $J_{\mu}$  for an improper policy  $\mu$ .



• For p = 1/2, we have

$$J_{\mu}(1) = 0$$
,  $J_{\mu}(2) = J_{\mu}(5) = 1$ ,  $J_{\mu}(3) = J_{\mu}(7) = 0$ ,  $J_{\mu}(4) = J_{\mu}(6) = 2$ ,

Bellman Eq. at state 1,  $J_{\mu}(1) = \frac{1}{2} (J_{\mu}(2) + J_{\mu}(5))$ , is violated.

• References: Bertsekas, D. P., and Yu, H., 2015. "Stochastic Shortest Path Problems Under Weak Conditions," Report LIDS-2909; Math. of OR, to appear. Also the on-line updated Ch. 4 of the text.

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