

MIT OpenCourseWare
<http://ocw.mit.edu>

6.231 Dynamic Programming and Stochastic Control
Fall 2008

For information about citing these materials or our Terms of Use, visit: <http://ocw.mit.edu/terms>.

6.231 DYNAMIC PROGRAMMING

LECTURE 18

LECTURE OUTLINE

- One-step lookahead and rollout for discounted problems
- Approximate policy iteration: Infinite state space
- Contraction mappings in DP
- Discounted problems: Countable state space with unbounded costs

ONE-STEP LOOKAHEAD POLICIES

- At state i use the control $\bar{\mu}(i)$ that attains the minimum in

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

where \tilde{J} is some approximation to J^* .

- Assume that $\hat{J} \leq \tilde{J} + \delta e$, for some δ , where

$$\hat{J}(i) = \min_{u \in U(i)} \left[g(i, u) + \alpha \sum_{j=1}^n p_{ij}(u) \tilde{J}(j) \right], \quad \forall i.$$

Then

$$J_{\bar{\mu}} \leq \hat{J} + \frac{\alpha \delta}{1 - \alpha} e \leq \tilde{J} + \frac{\delta}{1 - \alpha} e.$$

- Assume that $J^* - \epsilon e \leq \tilde{J} \leq J^* + \epsilon e$, for some ϵ . Then

$$J_{\bar{\mu}} \leq J^* + \frac{2\alpha\epsilon}{1 - \alpha} e.$$

APPLICATION TO ROLLOUT POLICIES

- Let μ_1, \dots, μ_M be stationary policies, and let

$$\tilde{J}(i) = \min\{J_{\mu_1}(i), \dots, J_{\mu_M}(i)\}, \quad \forall i.$$

- Then, for all i , and $m = 1, \dots, M$, we have

$$\begin{aligned} \hat{J}(i) &= \min_{u \in U(i)} \left[g(i, u) + \alpha \sum_{j=1}^n p_{ij}(u) \tilde{J}(j) \right] \\ &\leq \min_{u \in U(i)} \left[g(i, u) + \alpha \sum_{j=1}^n p_{ij}(u) \tilde{J}_{\mu_m}(j) \right] \\ &\leq J_{\mu_m}(i) \end{aligned}$$

- Taking minimum over m ,

$$\hat{J}(i) \leq \tilde{J}(i), \quad \forall i.$$

- Using the preceding slide result with $\delta = 0$,

$$J_{\bar{\mu}}(i) \leq \tilde{J}(i) = \min\{J_{\mu_1}(i), \dots, J_{\mu_M}(i)\}, \quad \forall i,$$

i.e., the rollout policy $\bar{\mu}$ improves over each μ_m .

APPROXIMATE POLICY ITERATION

- Suppose that the policy evaluation is approximate, according to,

$$\max_x |J_k(x) - J_{\mu^k}(x)| \leq \delta, \quad k = 0, 1, \dots$$

and policy improvement is approximate, according to,

$$\max_x |(T_{\mu^{k+1}} J_k)(x) - (T J_k)(x)| \leq \epsilon, \quad k = 0, 1, \dots$$

where δ and ϵ are some positive scalars.

- **Error Bound:** The sequence $\{\mu^k\}$ generated by approximate policy iteration satisfies

$$\limsup_{k \rightarrow \infty} \max_{x \in \mathcal{S}} (J_{\mu^k}(x) - J^*(x)) \leq \frac{\epsilon + 2\alpha\delta}{(1 - \alpha)^2}$$

- **Typical practical behavior:** The method makes steady progress up to a point and then the iterates J_{μ^k} oscillate within a neighborhood of J^* .

CONTRACTION MAPPINGS

- Given a real vector space Y with a norm $\|\cdot\|$ (i.e., $\|y\| \geq 0$ for all $y \in Y$, $\|y\| = 0$ if and only if $y = 0$, and $\|y + z\| \leq \|y\| + \|z\|$ for all $y, z \in Y$)
- A function $F : Y \mapsto Y$ is said to be a *contraction mapping* if for some $\rho \in (0, 1)$, we have

$$\|F(y) - F(z)\| \leq \rho \|y - z\|, \quad \text{for all } y, z \in Y.$$

ρ is called the *modulus of contraction* of F .

- For $m > 1$, we say that F is an *m-stage contraction* if F^m is a contraction.
- **Important example:** Let S be a set (e.g., state space in DP), $v : S \mapsto \mathfrak{R}$ be a positive-valued function. Let $B(S)$ be the set of all functions $J : S \mapsto \mathfrak{R}$ such that $J(s)/v(s)$ is bounded over s .
- We define a norm on $B(S)$, called the *weighted sup-norm*, by

$$\|J\| = \max_{s \in S} \frac{|J(s)|}{v(s)}.$$

- **Important special case:** The discounted problem mappings T and T_μ [for $v(s) \equiv 1$, $\rho = \alpha$].

CONTRACTION MAPPING FIXED-POINT TH.

- **Contraction Mapping Fixed-Point Theorem:** If $F : B(S) \mapsto B(S)$ is a contraction with modulus $\rho \in (0, 1)$, then there exists a unique $J^* \in B(S)$ such that

$$J^* = FJ^*.$$

Furthermore, if J is any function in $B(S)$, then $\{F^k J\}$ converges to J^* and we have

$$\|F^k J - J^*\| \leq \rho^k \|J - J^*\|, \quad k = 1, 2, \dots$$

- Similar result if F is an m -stage contraction mapping.
- This is a special case of a general result for contraction mappings $F : Y \mapsto Y$ over normed vector spaces Y that are *complete*: every sequence $\{y_k\}$ that is Cauchy (satisfies $\|y_m - y_n\| \rightarrow 0$ as $m, n \rightarrow \infty$) converges.
- The space $B(S)$ is complete (see the text for a proof).

A DP-LIKE CONTRACTION MAPPING I

- Let $S = \{1, 2, \dots\}$, and let $F : B(S) \mapsto B(S)$ be a linear mapping of the form

$$(FJ)(i) = b(i) + \sum_{j \in S} a(i, j) J(j), \quad \forall i$$

where $b(i)$ and $a(i, j)$ are some scalars. Then F is a contraction with modulus ρ if

$$\frac{\sum_{j \in S} |a(i, j)| v(j)}{v(i)} \leq \rho, \quad \forall i$$

- Let $F : B(S) \mapsto B(S)$ be a mapping of the form

$$(FJ)(i) = \min_{\mu \in M} (F_{\mu} J)(i), \quad \forall i$$

where M is parameter set, and for each $\mu \in M$, F_{μ} is a contraction mapping from $B(S)$ to $B(S)$ with modulus ρ . Then F is a contraction mapping with modulus ρ .

A DP-LIKE CONTRACTION MAPPING II

- Let $S = \{1, 2, \dots\}$, let M be a parameter set, and for each $\mu \in M$, let

$$(F_\mu J)(i) = b(i, \mu) + \sum_{j \in S} a(i, j, \mu) J(j), \quad \forall i$$

- We have $F_\mu J \in B(S)$ for all $J \in B(S)$ provided $b_\mu \in B(S)$ and $V_\mu \in B(S)$, where

$$b_\mu = \{b(1, \mu), b(2, \mu), \dots\}, \quad V_\mu = \{V(1, \mu), V(2, \mu), \dots\},$$

$$V(i, \mu) = \sum_{j \in S} |a(i, j, \mu)| v(j), \quad \forall i$$

- Consider the mapping F

$$(FJ)(i) = \min_{\mu \in M} (F_\mu J)(i), \quad \forall i$$

We have $FJ \in B(S)$ for all $J \in B(S)$, provided $b \in B(S)$ and $V \in B(S)$, where

$$b = \{b(1), b(2), \dots\}, \quad V = \{V(1), V(2), \dots\},$$

with $b(i) = \max_{\mu \in M} b(i, \mu)$ and $V(i) = \max_{\mu \in M} V(i, \mu)$.

DISCOUNTED DP - UNBOUNDED COST I

- State space $S = \{1, 2, \dots\}$, transition probabilities $p_{ij}(u)$, cost $g(i, u)$.

- Weighted sup-norm

$$\|J\| = \max_{i \in S} \frac{|J(i)|}{v_i}$$

on $B(S)$: sequences $\{J(i)\}$ such that $\|J\| < \infty$.

- **Assumptions:**

(a) $G = \{G(1), G(2), \dots\} \in B(S)$, where

$$G(i) = \max_{u \in U(i)} |g(i, u)|, \quad \forall i$$

(b) $V = \{V(1), V(2), \dots\} \in B(S)$, where

$$V(i) = \max_{u \in U(i)} \sum_{j \in S} p_{ij}(u) v_j, \quad \forall i$$

(c) There exists an integer $m \geq 1$ and a scalar $\rho \in (0, 1)$ such that for every policy π ,

$$\alpha^m \frac{\sum_{j \in S} P(x_m = j \mid x_0 = i, \pi) v_j}{v_i} \leq \rho, \quad \forall i$$

DISCOUNTED DP - UNBOUNDED COST II

- **Example:** Let $v_i = i$ for all $i = 1, 2, \dots$
- Assumption (a) is satisfied if the maximum expected absolute cost per stage at state i grows no faster than linearly with i .
- Assumption (b) states that the maximum expected next state following state i ,

$$\max_{u \in U(i)} E\{j \mid i, u\},$$

also grows no faster than linearly with i .

- Assumption (c) is satisfied if

$$\alpha^m \sum_{j \in S} P(x_m = j \mid x_0 = i, \pi) j \leq \rho i, \quad \forall i$$

It requires that for all π , the expected value of the state obtained m stages after reaching state i is no more than $\alpha^{-m} \rho i$.

- If there is bounded upward expected change of the state starting at i , there exists m sufficiently large so that Assumption (c) is satisfied.

DISCOUNTED DP - UNBOUNDED COST III

- Consider the DP mappings T_μ and T ,

$$(T_\mu J)(i) = g(i, \mu(i)) + \alpha \sum_{j \in S} p_{ij}(\mu(i)) J(j), \quad \forall i,$$

$$(TJ)(i) = \min_{u \in U(i)} \left[g(i, u) + \alpha \sum_{j \in S} p_{ij}(u) J(j) \right], \quad \forall i$$

- **Proposition:** Under the earlier assumptions, T and T_μ map $B(S)$ into $B(S)$, and are m -stage contraction mappings with modulus ρ .
- The m -stage contraction properties can be used to essentially replicate the analysis for the case of bounded cost, and to show the standard results:
 - The value iteration method $J_{k+1} = TJ_k$ converges to the unique solution J^* of Bellman's equation $J = TJ$.
 - The unique solution J^* of Bellman's equation is the optimal cost function.
 - A stationary policy μ is optimal if and only if $T_\mu J^* = TJ^*$.