# Semicontractive Dynamic Programming

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#### Contents of the Lecture Series

- Semicontractive Examples.
- Semicontractive Analysis for Stochastic Optimal Control.
- Extensions to Abstract DP Models.
- Applications to Stochastic Shortest Path and Other Problems.
- Algorithms.

### Outline of this Lecture

- Abstract Dynamic Programming
- Results Overview
- Semicontractive Models
- Semicontractive Analysis

# Abstract Dynamic Programming: A Unifying Methodological Framework

### Main Objective

- Unification of the core theory and algorithms of total cost sequential decision problems
- Simultaneous treatment of a variety of problems: stochastic optimal control, Markovian decision problems (MDP), sequential games, sequential minimax, multiplicative cost, risk-sensitive, etc

# Methodology

- Define a problem by its "mathematical signature": the mapping defining the optimality/Bellman equation
- Structure of this mapping (monotonicity, contraction, "semicontractive" properties, etc) determines the analytical and algorithmic theory of the problem
- Fixed point theory: An important connection

# Abstract DP Mappings

- State and control spaces: X, U
- Control constraint:  $u \in U(x)$
- Stationary policies:  $\mu: X \mapsto U$ , with  $\mu(x) \in U(x)$  for all x

## Monotone Mappings

• Abstract monotone mapping  $H: X \times U \times E(X) \mapsto \Re$ 

$$J \leq J'$$
  $\Longrightarrow$   $H(x, u, J) \leq H(x, u, J'), \forall x, u$ 

where E(X) is the set of functions  $J: X \mapsto [-\infty, \infty]$ 

• Mappings  $T_{\mu}$  and T

$$(T_{\mu}J)(x) = H(x, \mu(x), J), \qquad \forall \ x \in X, \ J \in R(X)$$
$$(TJ)(x) = \inf_{\mu} (T_{\mu}J)(x) = \inf_{u \in U(x)} H(x, u, J), \qquad \forall \ x \in X, \ J \in R(X)$$

## Stochastic Optimal Control Mapping: A Special Case

$$H(x, u, J) = E\{g(x, u, w) + \alpha J(f(x, u, w))\}$$

### **Abstract Problem Formulation**

#### Abstract DP Problem

• Given an initial function  $\bar{J} \in R(X)$  and policy  $\mu$ , define

$$J_{\mu}(x) = \limsup_{N \to \infty} (T_{\mu}^{N} \bar{J})(x), \qquad x \in X$$

• Find  $J^*(x) = \inf_{\mu} J_{\mu}(x)$  and an optimal  $\mu$  attaining the infimum

#### **Notes**

• Theory revolves around fixed point properties of mappings  $T_{\mu}$  and T:

$$J_{\mu}=T_{\mu}J_{\mu}, \qquad J^*=TJ^*$$

These are generalized forms of Bellman's equation

- Algorithms are special cases of fixed point algorithms
- We restrict attention (initially) to issues involving only stationary policies

# Examples With a Dynamic System $x_{k+1} = f(x_k, \mu(x_k), w_k)$

### Stochastic Optimal Control

$$\begin{split} \bar{J}(x) &\equiv 0, \qquad (T_{\mu}J)(x) = E_{w}\big\{g(x,\mu(x),w) + \alpha J\big(f(x,\mu(x),w)\big)\big\} \\ J_{\mu}(x_{0}) &= \limsup_{N \to \infty} \; E_{w_{0},w_{1},\dots}\left\{\sum_{k=0}^{N} \alpha^{k} g\big(x_{k},\mu(x_{k}),w_{k}\big)\right\} \end{split}$$

### Minimax - Sequential Games

$$\begin{split} \bar{J}(x) &\equiv 0, \qquad (T_{\mu}J)(x) = \sup_{w \in W(x)} \left\{ g(x,u,w) + \alpha J(f(x,u,w)) \right\} \\ J_{\mu}(x_0) &= \limsup_{N \to \infty} \sup_{w_0,w_1,\dots} \sum_{k=0}^N \alpha^k g(x_k,\mu(x_k),w_k) \end{split}$$

#### Multiplicative Cost Problems

$$\begin{split} \bar{J}(x) &\equiv 1, \qquad (T_{\mu}J)(x) = E_{w}\big\{g(x,\mu(x),w)J\big(f(x,\mu(x),w)\big)\big\} \\ J_{\mu}(x_{0}) &= \limsup_{N \to \infty} \ E_{w_{0},w_{1},\dots}\left\{\prod_{k=0}^{N} g\big(x_{k},\mu(x_{k}),w_{k}\big)\right\} \end{split}$$

# Examples With a Markov Chain: Transition Probs. $p_{i_k,i_{k+1}}(u_k)$

#### Finite-State Markov and Semi-Markov Decision Processes

$$\bar{J}(x) \equiv 0, \qquad (T_{\mu}J)(i) = \sum_{i=1}^{n} p_{ij}(\mu(i)) (g(i,\mu(i),j) + \alpha_{ij}(\mu(i))J(j))$$

$$J_{\mu}(i_0) = \limsup_{N \to \infty} E\left\{ \sum_{k=0}^{N} \left( \alpha_{i_0} \big( \mu(i_0) \big) \cdots a_{i_k i_{k+1}} \big( \mu(i_k) \big) \right) g(i_k, \mu(i_k), i_{k+1}) \right\}$$

where  $\alpha_{ij}(u)$  are state and control-dependent discount factors

### Risk-Sensitive Shortest Path: Exponential Cost with Termination State t

$$J_{\mu}(x_0) = \limsup_{N \rightarrow \infty} \ E\left\{e^{g\left(i_0, \mu(i_0), i_1\right) + \dots + g\left(i_N, \mu(i_N), i_{N+1}\right)}\right\}$$

$$\bar{J}(x) \equiv 1, \qquad (T_{\mu}J)(i) = p_{it}(\mu(i))e^{g(i,\mu(i),t)} + \sum_{i=1}^{n} p_{ij}(\mu(i))e^{g(i,\mu(i),j)}J(j)$$

# Models Classified According to Properties of $\mathcal{T}_{\mu}$

### Contractive (C)

All  $T_{\mu}$  are contractions within the set of bounded functions B(X), w.r.t. a common (weighted) sup-norm and contraction modulus (e.g., discounted problems)

### Monotone Increasing (I) and Monotone Decreasing (D)

 $\bar{J} \leq T_{\mu}\bar{J}$  (e.g., negative DP problems)

 $ar{J} \geq T_{\mu}ar{J}$  (e.g., positive DP problems)

#### Semicontractive (SC)

 $T_{\mu}$  has "contraction-like" properties for some  $\mu$  - to be discussed (e.g., SSP problems)

### Semicontractive Nonnegative (SC<sup>+</sup>)

Semicontractive, and in addition  $\bar{J} \geq 0$  and

$$J \ge 0 \implies H(x, u, J) \ge 0, \ \forall x, u$$

(e.g., affine monotonic, exponential/risk-sensitive problems)

# Bellman's Equation

### Bellman's Equation:

 $J_{\mu} = T_{\mu}J_{\mu}$  and  $J^* = TJ^*$  hold often (but not always) under our assumptions

### Bellman's Equation: Cases (C), (I), and (D)

 $J_{\mu}=T_{\mu}J_{\mu}$  and  $J^{*}=TJ^{*}$  always hold

### Bellman's Equation: Case (SC)

 $J_{\mu}=T_{\mu}J_{\mu}$  holds only for  $\mu$ : "regular"

 $\hat{J}$ , the "restricted optimal" cost function, solves Bellman's Eq. under our assumptions. We may have  $J^* \neq \hat{J}$ 

# Uniqueness of Solution of Bellman's Equations

### Case (C)

T is a contraction within B(X) and  $J^*$  is its unique fixed point

### Cases (I), (D)

T has multiple fixed points (some partial results hold)

### Case (SC)

 $\hat{J}$  is the unique fixed point of T within a subset of  $J \in R(X)$  with "regular" behavior

### Case (SC<sup>+</sup>)

 $J^*$  is the unique positive (or nonnegative) fixed point of T

# Optimality Conditions (A Complicated Story)

### Cases (C), (I), and (SC - under one set of assumptions)

 $\mu^*$  is optimal if and only if  $T_{\mu^*}J^* = TJ^*$ 

#### Case (SC - under another set of assumptions)

A "regular"  $\mu^*$  is optimal if and only if  $T_{\mu^*}J^*=TJ^*$ 

### Case (D)

 $\mu^*$  is optimal if and only if  $T_{\mu^*}J_{\mu^*}=TJ_{\mu^*}$ 

# Convergence of Value Iteration: $J_{k+1} = TJ_k$

### Case (C)

 $T^k J \to J^*$  for all  $J \in B(X)$ 

### Case (D)

 $T^k ar{J} o J^*$ 

### Case (I)

 $T^k \bar{J} o J^*$  under additional "compactness" conditions

### Case (SC)

 $T^kJ \to \hat{J}$  and possibly  $T^kJ \to J^*$  for all  $J \in R(X)$  within a set of "regular" behavior

#### Case (SC+)

 $T^k J \to J^*$  for all J > 0 (or  $J \ge 0$  under some conditions)

# Policy Iteration: $T_{\mu^{k+1}}J_{\mu^k}=TJ_{\mu^k}$ (A Complicated Story)

#### Classical Form of Exact PI

- $\bullet$  (C): Convergence starting with any  $\mu$
- (SC): Convergence starting with a "regular"  $\mu$  (not if "irregular"  $\mu$  arise)
- (I), (D): Convergence fails

### Optimistic/Modified PI (Combination of VI and PI)

- (C): Convergence starting with any  $\mu$
- (SC): Convergence starting with any  $\mu$  after a substantial modification in the policy evaluation step: Solving an "optimal stopping" problem instead of a linear equation
- (D): Convergence starting with initial condition  $\bar{J}$
- (I): Convergence may fail (special conditions required)

### Asynchronous Optimistic/Modified PI (Combination of VI and PI)

- (C): Fails in the standard form. Works after a substantial modification
- (SC): Works after a substantial modification
- (D), (I): Convergence may fail (special conditions required)

# Results Overview: Approximate DP

### Approximate $J_{\mu}$ and $J^*$ within a subspace spanned by basis functions

- Aim for approximate versions of value iteration, and policy iteration
- Very large and complex problems has been addressed
- Simulation-based algorithms are common
- No mathematical model is necessary (a computer simulator of the controlled system is sufficient)
- Abstract DP applies when cost approximation is based on the aggregation method (then the aggregate DP model has the required monotonicity property)

### Case (C)

- A wide variety of additional results thanks to the underlying contraction property
- Approximate value iteration and Q-learning
- Approximate policy iteration, pure and optimistic/modified

### Cases (I), (D), (SC)

Hardly any results available. Some results for stochastic shortest path problems

### Semicontractive Abstract Problem Formulation

• Abstract monotone mapping  $H: X \times U \times E(X) \mapsto \Re$ 

$$J \leq J'$$
  $\Longrightarrow$   $H(x, u, J) \leq H(x, u, J'), \quad \forall x, u$ 

where E(X) is the set of functions  $J: X \mapsto [-\infty, \infty]$ 

• Mappings  $T_{\mu}$  and T

$$(T_{\mu}J)(x) = H(x, \mu(x), J), \qquad \forall \ x \in X, \ J \in R(X)$$
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#### Abstract DP Problem

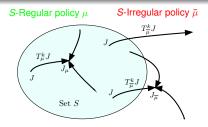
• Given an initial function  $\bar{J} \in R(X)$  and policy  $\mu$ , define

$$J_{\mu}(x) = \limsup_{N \to \infty} (T_{\mu}^{N} \bar{J})(x), \qquad x \in X$$

• Find  $J^*(x) = \inf_{\mu} J_{\mu}(x)$  and an optimal  $\mu$  attaining the infimum

# Semicontractive Models: Regular Policies

Key idea: We have a set of functions  $S \subset E(X)$ , which we view as the "domain of regularity"



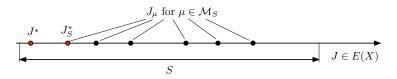
### Definition of S-Regular Policy

Given a set of functions  $S \subset E(X)$ , we say that a stationary policy  $\mu$  is S-regular if:

- ullet  $J_{\mu}\in \mathcal{S}$  and  $J_{\mu}=\mathcal{T}_{\mu}J_{\mu}$
- ullet  $T_{\mu}^k J o J_{\mu}$  for all  $J \in \mathcal{S}$

A policy that is not S-regular is called S-irregular.

## S-Regular Restricted Problem



### Given a set $S \subset E(X)$

- Consider the restricted optimization problem: Minimize  $J_{\mu}$  over  $\mu$  in the set  $\mathcal{M}_{\mathcal{S}}$  of all S-regular policies
- Let  $J_S^*$  be the optimal cost function over S-regular policies only:

$$J_{\mathcal{S}}^*(x) = \inf_{\mu \in \mathcal{M}_{\mathcal{S}}} J_{\mu}(x), \qquad x \in X$$

• Since the set of S-regular policies is a subset of the set of all policies,

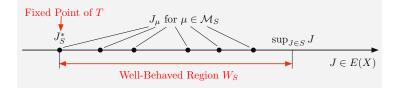
$$J^* \leq J_S^*$$

### Well-Behaved Region Theorem

Given a set  $S \subset E(X)$  consider

$$J_{\mathcal{S}}^*(x) = \inf_{\mu \in \mathcal{M}_{\mathcal{S}}} J_{\mu}(x), \qquad x \in X$$

where  $\mathcal{M}_{\mathcal{S}}$  is the set of all S-regular policies



### Proposition

Assume that  $J_S^*$  is a fixed point of T. Then:

- (Uniqueness of fixed point)  $J_S^*$  is the only fixed point of T within the set  $W_S = \{J \in E(X) \mid J_S^* \leq J \leq \tilde{J} \text{ for some } \tilde{J} \in S\}$
- (VI convergence)  $T^kJ \to J_S^*$  for every  $J \in W_S$
- (Optimality condition) If  $\mu^*$  is S-regular,  $J_S^* \in S$ , and  $T_{\mu^*}J_S^* = TJ_S^*$ , then  $\mu^*$  is  $\mathcal{M}_S$ -optimal. Conversely, if  $\mu^*$  is  $\mathcal{M}_S$ -optimal, then  $T_{\mu^*}J_S^* = TJ_S^*$ .

# How do we Show that $J_S^*$ is a Fixed Point of T?

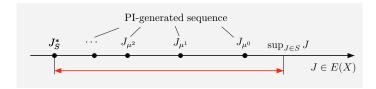
### A PI-Based Approach

- The approach applies when S is "well-behaved" with respect to PI: roughly, starting from an S-regular policy  $\mu^0$ , PI generates S-regular policies
- The significance of S-regularity is that  $\{J_{\mu^k}\}$  is monotonically nonincreasing,

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

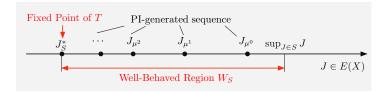
so it has a limit  $J_{\infty}$ 

• It is natural to expect that  $J_{\infty}$  will be equal to  $J_{S}^{*}$  and will be a fixed point of T



We introduce weak and strong PI properties and obtain corresponding weaker and stronger results for  $J_S^*$  to be a fixed point of T

## Weak PI Property Theorem



We say that S has the weak PI property if there exists a sequence of S-regular policies  $\{\mu^k\}$  generated by PI.

#### Assume:

- The weak PI property
- A "continuity from above" property for H: For each sequence  $\{J_m\} \subset E(X)$  with  $J_m \downarrow J$  for some  $J \in E(X)$ , we have

$$H(x, u, J) = \lim_{m \to \infty} H(x, u, J_m), \quad \forall x \in X, u \in U(x)$$

Then  $J_S^*$  is the only fixed point of T within  $W_S$ , and VI converges to  $J_S^*$  starting from within  $W_S$ .

# The Strong PI Property

We say that S has the strong PI property if the weak PI property holds, and PI generates exclusively S-regular policies, when started with an S-regular policy

## Verifying the Strong PI Property for $S \subset R(X)$

S has the strong PI property if:

- There exists at least one S-regular policy
- The set

$$\{u \in U(x) \mid H(x, u, J) \leq \lambda\}$$

is compact for every  $J \in S$ ,  $x \in X$ , and  $\lambda \in \Re$ .

• For every  $J \in S$  and S-irregular policy  $\mu$ , there exists a state  $x \in X$  such that

$$\limsup_{k\to\infty} (T^k_\mu J)(x) = \infty$$

(so S-irregular policies cannot be optimal)

# Strong PI Property Theorem

Assume the conditions of the preceding slide hold (so that the strong PI property also holds), and also that  $J_s^* \in S$ . Then:

- $J_S^*$  is the unique fixed point of T within S
- We have  $T^k J \to J_S^*$  for every J in the well-behaved region  $W_S$
- Every policy  $\mu$  that satisfies  $T_{\mu}J_{S}^{*}=TJ_{S}^{*}$  is  $\mathcal{M}_{S}$ -optimal and there exists at least one such policy

### Note the stronger conclusions:

- $J_S^*$  is the unique fixed point of T within S (not just from within  $W_S$ )
- ullet An optimality condition and existence of an  $\mathcal{M}_{\mathcal{S}}$ -optimal policy

# A Stronger Assumption for Stronger Conclusions

The conditions for verifying the strong PI property hold:

- S ⊂ R(X)
- There exists at least one S-regular policy
- The set  $\{u \in U(x) \mid H(x,u,J) \leq \lambda\}$  is compact for every  $J \in S$ ,  $x \in X$ , and  $\lambda \in \Re$
- For every  $J \in S$  and S-irregular policy  $\mu$ , there exists a state  $x \in X$  such that

$$\limsup_{k\to\infty}\,(T^k_\mu J)(x)=\infty$$

and also:

- S contains  $\bar{J}$ , and has the property that if  $J_1, J_2$  are two functions in S, then S contains all functions J with  $J_1 \leq J \leq J_2$
- The function  $J_S^* = \inf_{\mu \in \mathcal{M}_S} J_\mu$  belongs to S
- For each sequence  $\{J_m\} \subset S$  with  $J_m \uparrow J$  for some  $J \in S$ ,

$$\lim_{m\to\infty}H(x,u,J_m)=H(x,u,J)\,,\qquad\forall\;x\in X,\;u\in U(x)$$

• For each function  $J \in S$ , there exists a function  $J' \in S$  such that  $J' \leq J$  and J' < TJ'

# A Stronger Theorem for $S \subset R(X)$

### Proposition: Under the preceding assumption

- J\* is the unique fixed point of T within the set S
- We have  $T^k J \to J^*$  for all  $J \in S$
- ullet  $\mu$  is optimal if and only if  $T_{\mu}J^*=TJ^*$ , and there exists an optimal S-regular  $\mu$
- For any  $J \in S$ , if  $J \leq TJ$  we have  $J \leq J^*$ , and if  $J \geq TJ$  we have  $J \geq J^*$
- If in addition for each  $\{J_m\} \subset E(X)$  with  $J_m \downarrow J$  for some  $J \in E(X)$ ,

$$H(x, u, J) = \lim_{m \to \infty} H(x, u, J_m), \quad \forall x \in X, u \in U(x)$$

then every sequence  $\{\mu^k\}$  generated by the PI algorithm starting from an S-regular policy  $\mu^0$  satisfies  $J_{\mu^k} \downarrow J^*$ 

