# DYNAMIC PROGRAMMING

(OUTLINE OF PRESENTATION)

BASIC IDEA-HISTORICAL ELEMENTS
GENERAL DISCRETE TIME STOCHASTIC CASE
LINEAR QUADRATIC WITH NOISY MEASUREMENTS
INFINITE TIME AVERAGE COST

#### BASIC IDEA-HISTORICAL ELEMENTS

• We hope that the following hold:

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f: R^3 \to R, if min f(x, y, z), has solution: x^*, y^*, z^*
then:
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\min[f(x,y,z):x,y,z] = \min[\min[\min f(x,y,z):x]:z]:y]
\min[f(x,y,z):x] \text{ has solution } \hat{x}(y,z)
\min[f(\hat{x}(y,z),y,z):z] \text{ has solution } \hat{z}(y)
\min[f(\hat{x}(y,\hat{z}(y)),y,\hat{z}(y)):y] \text{ has solution } y^*
z(y^*) = z^*, \hat{x}(y^*,z^*) = x^*
Assumptions needed!
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Caratheodory (Hamilton-Jacobii) for Cont.Time, (War) Operations Research, (Programming/Optimization: Linear, Nonlinear, Dynamic), Differential Games (Tenet of Transition) R.Isaacs/RAND,R.Bellman,Computers

- 1. For infima the interchanges are OK but for minima we need assumptions.
- 2. Order of minimization dictated by convenience. For example a known time/space ordering of actions or calculations.
- 3. In Stochastic cases we also have the interchange of conditional expectations and minima as well.
- 4. Discrete time. Continuous time. Partially ordered parameters.
- 4. Theoretical difficulties for both discrete and continuous time.
- 5. We focus on discrete time.

#### Discrete Time Stochastic Model

$$\begin{aligned} x_{k+1} &= f_k\left(x_k, u_k, w_k\right), k = 0, 1, 2, ..., N \\ z_k &= h_k\left(x_k, u_{k-1}, v_k\right), k = 1, 2, ..., N, z_0 = h_0\left(x_0, v_0\right) \\ v_k &\sim P(v_k \mid x_k, ..., x_0, u_{k-1}, ..., u_0, w_{k-1}, ..., w_0, v_{k-1}, ..., v_0) \\ w_k &\sim P(w_k \mid x_k, u_k) \\ I_k &= \{z_0, z_1, ..., z_k, u_0, ... u_{k-1}\} \\ I_0 &= \{z_0\} \\ u_k &= \mu_k\left(I_k\right) \in U_k \\ \pi &= (\mu_0, ..., \mu_N) \\ \min J_\pi &= E\{g_{N+1}(x_{N+1}) + \sum_{k=0}^N g_k\left(x_k, \mu_k\left(I_k\right), w_k\right)\} \\ \text{new state:} I_{k+1} &= (I_k, z_{k+1}, u_k), I_0 = z_0 \end{aligned}$$

# Dynamic Programming Algorithm

Assuming that the interchanges of minima and conditional expectations are OK, we have:

$$\min J_{\pi} = \min_{\mu_0} E\{g_0 + ... + \min_{\mu_{N-1}} E\{g_{N-1} + \min_{\mu_N} E\{g_{N+1} + g_N / I_N\} / I_{N-1}\} ... / I_0\}$$

#### Cases to be worked out

CASE 1. (pages 28-32,in D.P.Bertsekas)

$$x_{k+1} = \max(0, x_k + u_k - w_k), x_k, u_k, w_k \in \{0, 1, 2, ...\}, x_k + u_k \le 2, U_k(x_k) = [0, 2 - x_k]$$

 $w_{k:}$ : are independent random variables (iid), with

 $w_k = 0, 1, 2$ , with probabilities: 0.1, 0.7, 0.2, respectively

x<sub>0</sub>:given number

$$J=E\left[\sum_{k=0}^{N-1} c u_k + H(x_k + u_k - w_k)\right]$$

$$c = 1, H(\theta) = \max(0, \theta) + 3\max(0, -\theta), N = 3$$

CASE 2.LQG Full State Measurements, (pages 148-154, in D.P.Bertsekas)

$$X_{k+1} = Ax_k + Bu_k + w_k, k = 0, 1, ..., N - 1, I_k = \{x_0, x_1, ..., x_k\}$$

$$J = E\{x_N Q x_N + \sum_{k=0}^{N-1} (x_k Q x_k + u_k R u_k)\}$$

 $x_0, w_k$  are 0-mean finite variance, for example ind. Gaussian

 $Q \ge 0,R > 0$ , symmetric

CASE 3. LQG Partial State Measurements, (pages 229-236, in D.P.Bertsekas)

As in Case 2 but with:  $I_k = \{z_0, z_1, ..., z_k\}, z_k = Cx_k + v_k$ 

v,w,x,ind.0-mean finite variance, for example ind. Gaussian

## Infinite Time Average Cost (pages 421-435 in D.P.Bertsekas)

We will consider: Average Cost, Infinite Time, Stationary Model and Policies

$$x_k \in S = \{1, 2, ..., n\}, u_k \in C_i = \{1, 2, ..., M_i\}, I_k = \{x_0, x_1, ..., x_k\}, \text{ but stationary } \rightarrow u_k = \mu(x_k)$$
  
State evolution  $p_{ij}(u) = P(x_{k+1} = j / x_k = i, u_k = u)$ 

$$x_k = i$$
, and  $u_k = u$  give cost  $g(i, u)$ ,  $J(x_0) = \lim_{N \to +\infty} (1/N) E[\sum_{k=0}^{N-1} g(x_k, u_k)]$ 

Example: 
$$P_{\mu}(u) = \begin{pmatrix} p_{11}(u_1) & p_{12}(u_1) & p_{13}(u_1) \\ p_{21}(u_2) & p_{22}(u_2) & p_{23}(u_2) \\ p_{31}(u_3) & p_{32}(u_3) & p_{33}(u_3) \end{pmatrix}, n = 3, u_1 \in C_1, u_2 \in C, u_3 \in C_3, g_{\mu} = \begin{bmatrix} g(1, u_1) \\ g(2, u_2) \\ g(3, u_3) \end{bmatrix}$$

$$u_i = \mu(i), J_{\mu} = \lim_{N \to \infty} \frac{1}{N} \left[ \sum_{k=0}^{N-1} (P_{\mu})^k g_{\mu} \right]$$

Simplifying Assumption: The whole State Space is a Single Ergodic Class for any Policy

# ROLE OF INFORMATION: NESTEDNESS, NONCLASSICAL INFORMATION PATTERNS MATERIAL CHOSEN FROM THE FOLLOWING:

• Withenhausen's paper and Ho and Chu's papers

• InformationTheory model with Gaussian channel (Ho Kastner Wong)

Game Theory Information Patterns (Basar and Olsder)

## **REFERENCES**

- 1. D.P.Bertsekas,"Dynamic Programming and Optimal Control", Athena Scientific, 2005.
- 2.H.Witsenhausen,"Acounterexample in stochastic optimal Control"SIAM JOC, Vol.6, No.1, pp.131-147,1968.
- 3.Ho&Chu "Team Decision Theory and Information structures in Optimal Control problems-Part I,II",IEEE-AC -17,No.1,pp.15-22 and 22-28,Feb.1972.
- 4.T.Basar&G.J.Olsder,"Dynamic Noncooperative Game Theory",SIAM Classics.
- 5.C.Caratheodory,"Calculus of Variations and Partial Differential Equations",Chelsea.
- 6.R.Bellman,"Dynamic Programming"Princeton Univ.Press.

### Homework

1. From D.P.Bertsekas, problems: 1.1,1.14,

2. In conjunction with the papers of Ho and Chu, study/discuss a three stage scalar LQG problem and compare the solutions of the following three cases with:

$$I_0 = \{z_0\}, I_1 = \{\varepsilon_0 z_0, \varepsilon_1 z_1\}, I_2 = \{z_0, \varepsilon_2 z_1, \varepsilon_3 z_2\}$$

Case 1. All the  $\varepsilon_i$ 's are nonzero.

Case 2. 
$$\varepsilon_0 = 0$$
,  $\varepsilon_i \neq 0$ ,  $i = 1, 2, 3$ 

Case 3. 
$$\varepsilon_0 \rightarrow 0, \varepsilon_i \neq 0, i = 1, 2, 3$$

3. Solve using Dynamic Program ming  $x_{i+1} = x_i - u_i$ , i = 0, 1, 2, 3 min  $\sum_{i=0}^{3} (x_{i+1}^2 + 2u_i^2)$   $x_0 = 5$ ,  $u_i \in \{0, 1, 2\}$