

Bertsekas: *Dynamic programming and optimal control*
Chap. 4 - Problems with perfect state information

Contents:

- Linear systems and quadratic cost,
(*presentation with the DP-costume, some proofs*)
- Optimal stopping problems,
(*presentation, an example*)
- Dynamic Portfolio Analysis,
(*presentation*)
- Inventory control, (*left*)

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Linear discrete systems and quadratic cost

The system: $x_{k+1} = Ax_k + Bu_k + w_k$

Cost function: $E \left\{ x_N^T Q_N x_N + \sum_{k=0}^{N-1} (x_k^T Q x_k + u_k^T R u_k) \right\}$

The DP-algorithm:

$$J_N(x_N) = x_N^T Q_N x_N = x_N^T K_N x_N$$

$$\begin{aligned} J_k(x_k) &= \min_{u_k} E \left\{ x_k^T Q x_k + u_k^T R u_k + J_{k+1}(x_{k+1}) \right\} = \\ &= \min_{u_k} E \left\{ x_k^T Q x_k + u_k^T R u_k + J_{k+1}(Ax_k + Bu_k + w_k) \right\} \end{aligned}$$

DP- algorithm derivations I

Next last term:

$$\begin{aligned}
 J_{N-1}(x_{N-1}) &= \min_{u_{N-1}} E \left\{ x_{N-1}^T Q x_{N-1} + u_{N-1}^T R u_{N-1} + \overbrace{x_N^T K_N x_N}^{J_N} \right\} \\
 &= \min_{u_{N-1}} E \left\{ x_{N-1}^T Q x_{N-1} + u_{N-1}^T R u_{N-1} + (Ax_{N-1} + Bu_{N-1} + w_{N-1})^T K_N (Ax_{N-1} + Bu_{N-1} + w_{N-1}) \right\} = \\
 &= \min_{u_{N-1}} \left\{ x_{N-1}^T Q x_{N-1} + u_{N-1}^T R u_{N-1} + (Ax_{N-1} + Bu_{N-1})^T K_N (Ax_{N-1} + Bu_{N-1}) + E \left\{ w_{N-1}^T K_N w_{N-1} \right\} \right\} \\
 \tilde{J}_{N-1}(x) &= \min_u \left\{ x^T \underbrace{(Q + A^T K_N A)}_{Q_{xx}} x + x^T \underbrace{A^T K_N B}_{Q_{xu}} u + u^T \underbrace{B^T K_N A}_{Q_{xu}^T} x + u^T \underbrace{(R + B^T K_N B)}_{Q_{uu}} u \right\}
 \end{aligned}$$

Noise is independent of the states and the control signal and has mean value = 0

$$J(x, u) = x^T Q_{xx} x + x^T Q_{xu} u + u^T Q_{xu}^T x + u^T Q_{uu} u$$

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DP- algorithm derivations II

Minimise:

$$\begin{aligned}
 J(x, u) &= u^T Q_{uu} u + x^T Q_{xu} u + u^T Q_{xu}^T x + x^T Q_{xx} x = \\
 &= (u + Q_{uu}^{-1} Q_{xu}^T x)^T Q_{uu} (u + Q_{uu}^{-1} Q_{xu}^T x) - x^T (Q_{uu}^{-1} Q_{xu}^T)^T Q_{uu} (Q_{uu}^{-1} Q_{xu}^T) x + x^T Q_{xx} x \\
 u^* &= -Q_{uu}^{-1} Q_{xu}^T x
 \end{aligned}$$

With index and noise:

$$\begin{aligned}
 J_{N-1}(x_{N-1}) &= x_{N-1}^T K_{N-1} x_{N-1} + E \left\{ w_{N-1}^T K_N w_{N-1} \right\} \\
 J_0(x_0) &= x_0^T K_0 x_0 + \sum_{i=0}^{N-1} E \left\{ w_i^T K_{i+1} w_i \right\}
 \end{aligned}$$

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DP- algorithm derivations III

$K_{N-1} = f(K_N)$: Riccati-equation

$$\begin{aligned} K_{N-1} &= Q_{xx} - Q_{xu} Q_{uu}^{-1} Q_{xu}^T = Q + A^T K_N A - A^T K_N B (R + B^T K_N B)^{-1} B^T K_N A \\ &= A^T \left(K_N - K_N B (B^T K_N B + R)^{-1} B^T K_N \right) A + Q \end{aligned}$$

Gives the losses and the control:

$$J_0(x_0) = x_0^T K_0 x_0 + \sum_{i=0}^{N-1} E\{w_i^T K_{i+1} w_i\}$$

$$u_k^* = -(R + B^T K_{k+1} B)^{-1} B^T K_{k+1} A x_k$$

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DP- algorithm derivations IV

$$K_{N-1} = A^T \left(K_N - K_N B (B^T K_N B + R)^{-1} B^T K_N \right) A + Q$$

Index change: $P_k = K_{N-k}$

$$P_{k+1} = A^T \left(P_k - P_k B (B^T P_k B + R)^{-1} B^T P_k \right) A + Q$$

$$x_N^T K_N x_N \Leftrightarrow x_N^T P_0 x_N \quad \text{final step loss}$$

$$x_0^T K_0 x_0 \Leftrightarrow x_0^T P_N x_0 \quad \text{total loss}$$

$x_0^T P_k x_0$: Gives the loss from state x_0 in a k-step control

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Proposition 4.1

$$P_{k+1} = A^T \left(P_k - P_k B (B^T P_k B + R)^{-1} B^T P_k \right) A + Q$$

(A, B) controllable (A, C) observable, $Q = C^T C$

(a) $\exists P \geq 0 : \forall P_0 \geq 0 \Rightarrow \lim_{k \rightarrow \infty} P_k = P$

where P is the unique solution of

$$P = A^T \left(K - P B (B^T P B + R)^{-1} B^T K \right) A + Q$$

within the class of pos. semidef. sym. matrices

(b) The closed system is stable

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Convergence of the Riccati equation I

Proof:

I) Convergence of P_k in the case $P_0=0, P_k(0) :$

No final loss

Given the system:

$$x_{i+1} = Ax_i + Bu_i, \quad i = 0, 1, \dots, k-1$$

(The noise does not effect the L and the P_k)

Minimize :

$$\sum_{i=0}^{k-1} (x_i^T Q x_i + u_i^T R u_i)$$

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Convergence of the Riccati equation II

For any control sequence:

$$x_0^T P_k(0)x_0 = \min_{u_i} \sum_{i=0}^{k-1} (x_i^T Q x_i + u_i^T R u_i)$$

$$\leq \min_{u_i} \sum_{i=0}^k (x_i^T Q x_i + u_i^T R u_i) = x_0^T P_{k+1}(0)x_0$$

Giving: $x_0^T P_k(0)x_0$ is monotonically increasing

Controllability gives: $x_0^T P_k(0)x_0$ is bounded from above

Then the sequence $\{P_k(0)\}$ converges,

$$\lim_{k \rightarrow \infty} P_k(0) = P \quad (\text{can be shown element by element})$$

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Stability I

Proof:

II) Stability

For : $k \rightarrow \infty$

$$x_0^T P x_0 = \sum_{i=0}^{\infty} (x_i^T Q x_i + u_i^T R u_i) = x_0^T Q x_0 + u_0^T R u_0 + \sum_{i=1}^{\infty} (x_i^T Q x_i + u_i^T R u_i) =$$

$$= x_0^T (Q + L^T R L) x_0 + x_1^T P x_1$$

Gives:

$$P = Q + L^T R L + D^T P D, \quad \text{where } D = A + B L$$

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Stability II

For any k:

$$x_k^T P x_k - x_k^T (Q + L^T R L) x_k = x_k^T D^T P D x_k$$

$$x_k^T P x_k - x_k^T (Q + L^T R L) x_k = x_{k+1}^T P x_{k+1}$$

$$x_0^T P x_0 - \sum_{i=0}^k x_i^T (Q + L^T R L) x_i = x_{k+1}^T P x_{k+1} \quad (I)$$

$0 \leq RHS < x_0^T P x_0$ and with $R > 0$ and $Q = C^T C$ we get:

$$\lim_{k \rightarrow \infty} C x_k = 0 \quad \text{and} \quad \lim_{k \rightarrow \infty} L x_k$$

The observability assumption gives: $\lim_{k \rightarrow \infty} x_k = 0$

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Continuation of prop 4.1

Proof:

III) Positive definiteness of P

IV) Arbitrary initial matrix P_0

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Random systems I

$$x_{k+1} = A_k x_k + B_k u_k + w_k$$

$$\begin{aligned} J_k(x_k) &= \min_{u_k} E_{w_k, A_k, B_k} \{x_k^T Q x_k + u_k^T R u_k + J_{k+1}(x_{k+1})\} = \\ &= \min_{u_k} E_{w_k, A_k, B_k} \{x_k^T Q x_k + u_k^T R u_k + J_{k+1}(A x_k + B u_k + w_k)\} \end{aligned}$$

$$K_{N-1} = E\{A^T K_N A\} - E\{A^T K_N B\} \{R + E\{B^T K_N B\}\}^{-1} E\{B^T K_N A\} + Q_{N-1}$$

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Random systems II

$$P_{k+1} = \tilde{F}(P_k) = \frac{E\{A^2\}P_k R}{E\{B^2\}P_k + R} + Q + \frac{TP_k^2}{E\{B^2\}P_k + R}$$

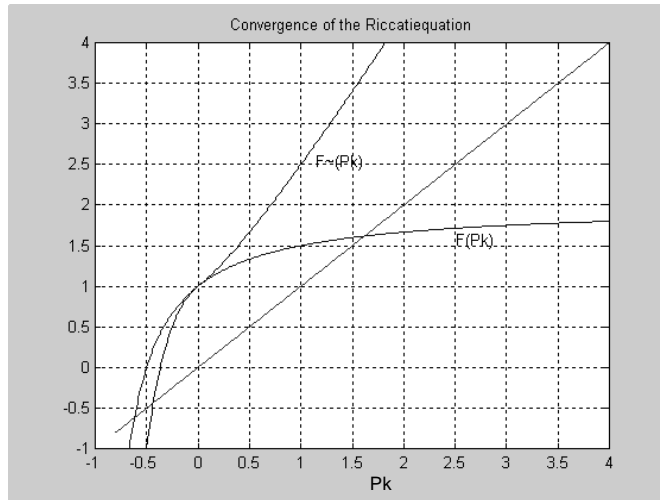
$$T = E\{A^2\}E\{B^2\} - E^2\{A\}E^2\{B\}$$

Uncertainty threshold principle:

$$T > T_{divergence} \Leftrightarrow \text{Riccati equation does not converge}$$

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Random systems III



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Optimal stopping problem I

Asset selling: w (random offer), $u = \{u^1 \quad u^2\}$ (sell, do not sell)
 r (revenue)

Given system:

$$x_{k+1} = \begin{cases} T & \text{if } x_k = T, \text{ or if } x_k \neq T \text{ and } u_k = u^1 \text{ (sell),} \\ w_k & \text{otherwise} \end{cases}$$

$$E_{w_k} \left\{ g_N(x_N) + \sum_{k=0}^{N-1} g_k(x_k, u_k w_k) \right\}$$

$k=0,1,\dots,N-1$

$$g_N(x_N) = \begin{cases} x_N & \text{if } x_N \neq T, \\ 0 & \text{otherwise,} \end{cases} \quad g_k(x_k, u_k w_k) = \begin{cases} (1+r)^{N-k} x_k, & \text{if } x_k \neq T \text{ and } u_k \neq u^1 \text{ (sell)} \\ 0 & \text{otherwise} \end{cases}$$

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Optimal stopping problem II

The DP-algorithm:

$$J_N(x_N) = \begin{cases} x_N & \text{if } x_N \neq T, \\ 0 & \text{otherwise,} \end{cases}$$

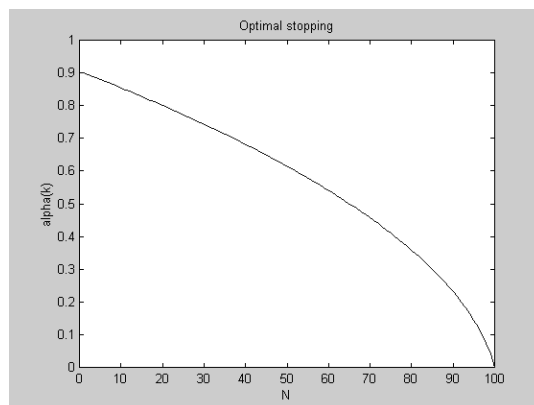
$$J_k(x_k) = \begin{cases} \max[(1+r)^{N-k} x_k, E\{J_{k+1}(w_k)\}] & \text{if } x_k \neq T, \\ 0 & \text{otherwise} \end{cases}$$

Define :

$$\alpha_k = \frac{E\{J_{k+1}(w_k)\}}{(1+r)^{N-k}} \quad \begin{array}{ll} x_k < \alpha_k & \text{do not sell} \\ x_k > \alpha_k & \text{sell} \end{array}$$

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Optimal stopping problem α



Can be shown :

$$\alpha_k \geq \alpha_{k+1}, \quad \text{for all } k$$

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Optimal stopping problem example

$$r = 0, w - \text{constant distribution : } \begin{aligned} p(w = 0) &= 0.5 \\ p(w = 0.5) &= 0.25 \\ p(w = 1) &= 0.25 \end{aligned}$$

$$J_N(x_N) = x_N = w$$

$$\begin{aligned} J_{N-1}(x_{N-1}) &= \max[x_{N-1}, E\{J_N(x_N)\}] \\ &= \max[w, E\{w\}] \\ &= \max\left[w, \frac{1}{2} \cdot \frac{1}{4} + 1 \cdot \frac{1}{4}\right] \\ &= \max\left[w, \frac{3}{8}\right] \end{aligned}$$

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Optimal stopping problem example cont.

$$\begin{aligned} J_{N-2}(x_{N-2}) &= \max[x_{N-2}, E\{J_{N-1}(x_{N-1})\}] \\ &= \max\left[w, E\left\{\max\left[w, \frac{3}{8}\right]\right\}\right] \\ &= \max\left[w, \frac{3}{8} \cdot \frac{1}{2} + \frac{1}{2} \cdot \frac{1}{4} + 1 \cdot \frac{1}{4}\right] \\ &= \max\left[w, \frac{9}{16}\right] \end{aligned}$$

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More optimal stopping problems

Asset buying: w (random price), $u = \{u^1 \quad u^2\}$ (buy, do not buy)

Correlated prices: include a model

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Dynamic Portfolio Analysis I

x_0 - initial wealth

n - risky assets

e_i - random rates of return, $i=1,2,\dots,n$.

s - rate of return, riskless asset

Wealth difference equation:

$$x_1 = s(x_0 - u_1 - \dots - u_n) + \sum_{i=1}^n e_i u_i = sx_0 + \sum_{i=1}^n (e_i - s)u_i$$

$$\max_{u_1, \dots, u_n} [E\{U(x_1)\}]$$

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Dynamic Portfolio Analysis II

If $-\frac{U'(x)}{U''(x)} = a + bx$

then $u^i(x) = \alpha^i (a + bx)$

Admissible $U(x)$:

exponential: $e^{-\frac{x}{a}}$, $b = 0$

logarithmic: $\ln(x + a)$, $b = 1$

power: $(1/(b-1))(a + bx)^{1-(1/b)}$, $b \neq 0$, $b \neq 1$