

C.2 The JLQG problem under complete information

C.2.1 Problem Statement

$$* (1) \quad x_{k+1} = A(y_k) x_k + B(y_k) u_k + w_k \quad k = 0, 1, 2, \dots, N-1$$

Jump-linear process model

x_k $n \times 1$ state vector

u_k $m \times 1$ control "

w_k $n \times 1$ process noise vector, white, zero-mean, W_k

$A(y_k)$ $n \times n$ $B(y_k)$ $n \times m$

* $\{y_k, k = 0, 1, \dots, N-1\}$ scalar Markov chain, finite alphabet; $S_y = \{1, 2, \dots, M\}$
 transition probability matrix P ; $P(i, j) = \Pr \{y_{k+1} = j \mid y_k = i\} = p_{ij}$; $i, j \in S_y$

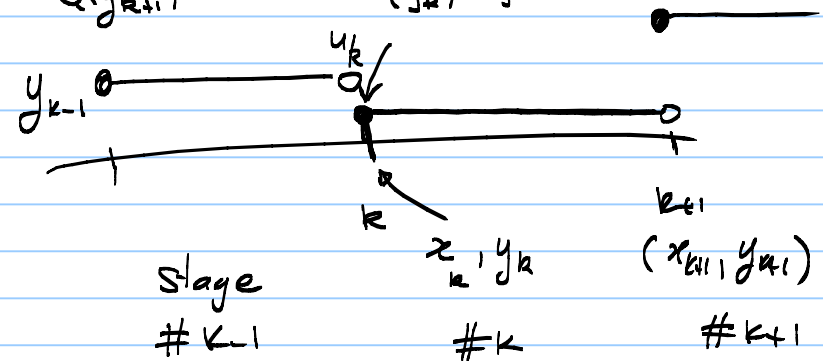
* x_0, y_k, w_k independent

Information pattern: x_k and y_k are known; $(X^k, Y^k) = \{x_\ell, y_\ell\}_{\ell=0}^k$

Cost Function

$$J = E \left\{ \sum_{k=0}^{N-1} \|x_{k+1}\|^2 Q(y_{k+1}) + \|u_k\|^2 R(y_k) \right\}$$

$$Q(y_k) \geq 0 \quad R(y_k) > 0$$



Goal: let \mathcal{U} denote the set of admissible controllers

$$\mathcal{U} = \{ \{u_k\} \mid u_k = u_k(x^k, y^k) \}$$

part history of know (x, y) .

We want to minimize J with respect to $\{u_k\} \in \mathcal{U}$, subject (i).

Notation

$$\left\{ \begin{array}{l} A(y_k) = A_k \\ B(y_k) = B_k \\ Q(y_k) = Q_k \\ R(y_k) = R_k \end{array} \right. \quad \text{denote the random variables}$$

$$x_k^L = \{x_k \dots x_L\}$$

$$y_k^L = \{y_k \dots y_L\}$$

$$u_k^L = \{u_k \dots u_L\}$$

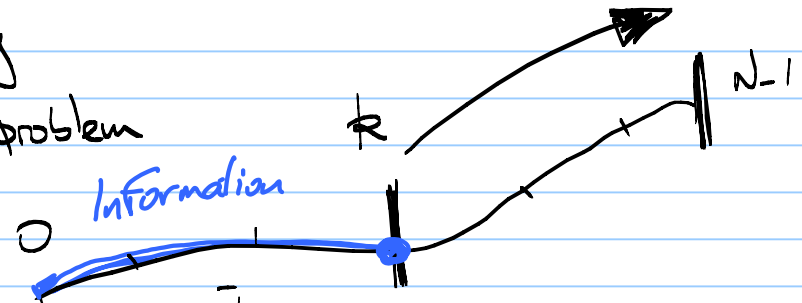
$$\left\{ \begin{array}{l} A(y_k = j) = A(j) \\ B(y_k = j) = B(j) \\ Q(y_k = j) = Q(j) \\ R(y_k = j) = R(j) \end{array} \right. \quad \begin{array}{l} \text{denote realizations} \\ j = 1, 2, \dots, \nu \end{array}$$

C.2.2. Solution via Dynamic Programming

A. Recursive formulation of the control problem

Optimal Return Function J_k^*

$$J_k^*(x^k, y^k) = \min_{u_k^{N-1}} \left[E \left\{ \sum_{i=k}^{N-1} \|x_{i+1}\|_{Q_{i+1}}^2 + \|u_i\|_{R_i}^2 \mid \underbrace{x^k, y^k}_{\text{Information}} \right\} \right]$$



goal : to formulate the above problem in a recursive manner
 main tools : - Nested Property of the Conditionnal Expectation

$$A \subseteq B \quad \text{Then} \quad E\{x \mid A\} = E\{E\{x \mid B\} \mid A\}$$

$$(x^0, y^0) \subseteq \dots \subseteq (x^k, y^k) \subseteq (x^{k+1}, y^{k+1}) \dots \subseteq (x^{N-1}, y^{N-1})$$

Fundamental Lemma of Optimal Control

the $\min_u [\]$ and $E \{ \}$ operators may be interchanged provided that the control are in the admissible set.

Consider

$$\begin{aligned}
 J_k(x^k, y^k, u^{N-1}) &= E \left\{ \sum_{i=k}^{N-1} |x_{i+1}|_{Q_{i+1}}^2 + |u_i|_{R_i}^2 \mid x^k, y^k \right\} \\
 &= E \left\{ |x_{k+1}|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 + \sum_{i=k+1}^{N-1} |x_{i+1}|_{Q_{i+1}}^2 + |u_i|_{R_i}^2 \mid x^k, y^k \right\} \\
 &= E \left\{ E \left\{ |x_{k+1}|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 \oplus \sum_{i=k+1}^{N-1} |x_{i+1}|_{Q_{i+1}}^2 + |u_i|_{R_i}^2 \mid x^{k+1}, y^{k+1} \right\} \mid x^k, y^k \right\} \\
 &= E \left\{ |x_{k+1}|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 + \underbrace{E \left\{ \sum_{i=k+1}^{N-1} |x_{i+1}|_{Q_{i+1}}^2 + |u_i|_{R_i}^2 \mid x^{k+1}, y^{k+1} \right\}}_{\equiv J_{k+1}(x^{k+1}, y^{k+1}, u^{N-1})} \mid x^k, y^k \right\}
 \end{aligned}$$

to summarize :

$$J_k(x^k, y^k, u_k^{N-1}) = E \left\{ |x|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 + J_{k+1}(x^{k+1}, y^{k+1}, u_{k+1}^{N-1}) \mid x^k, y^k \right\}$$

then,

$$J_k^*(x^k, y^k) = \min_{u_k^{N-1}} \left[J_k(x^k, y^k, u_k^{N-1}) \right]$$

$$= \min_{u_k} \min_{u_{k+1}^{N-1}} \left[E \left\{ |x|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 + J_{k+1}(x^{k+1}, y^{k+1}, u_{k+1}^{N-1}) \mid x^k, y^k \right\} \right]$$

(fundamental lemma!)

$$= \min_{u_k} \left[E \left\{ |x|_{Q_{k+1}}^2 + |u_k|_{R_k}^2 + \underbrace{\min_{u_{k+1}^{N-1}} \left[J_{k+1}(x^{k+1}, y^{k+1}, u_{k+1}^{N-1}) \right]}_{= J_{k+1}^*(x^{k+1}, y^{k+1})} \mid x^k, y^k \right\} \right]$$

Thus we achieved a Recursion for the Optimal Cost To Go.

$$J_p^* = \min_{u_k} \left[E \left[\underbrace{|x_{k+1}|^2}_{p_{k+1}} + \underbrace{|u_k|^2}_{p_k} + \underbrace{J_{k+1}^*}_{\text{cost to go}} \mid \underline{x^k, y^k} \right] \right]$$

\Rightarrow Dynamic Programming Rule . Storing @ J_{k+1}^*
FINAL STATE

B. Recursive Algorithm

Last stage $N-1$

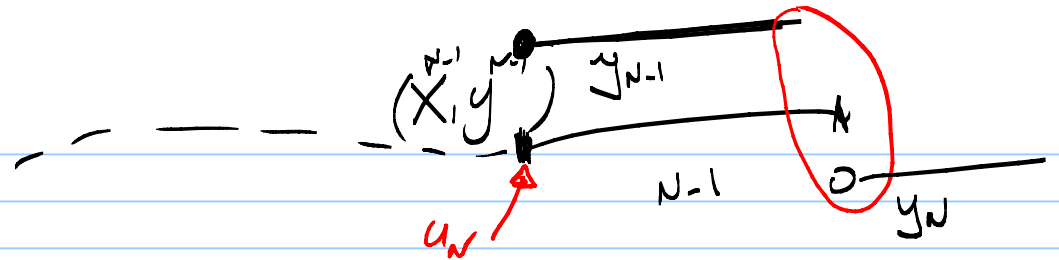
Given x^{N-1}, y^{N-1}

$$J_{N-1} = E \left\{ |x_N|^2_{\underbrace{Q_N}_{Q(y_N)}} + |u_{N-1}|^2_{\underbrace{R_{N-1}}_{R(y_{N-1})}} \mid x^{N-1}, y^{N-1} \right\} \quad (*)$$

$$J_{N-1} = E \left\{ | \underline{A_{N-1} x_{N-1}} + \underline{B_{N-1} u_{N-1}} + \underline{w_{N-1}} |^2_{Q(y_N)} + |u_{N-1}|^2_{R_{N-1}} \mid x^{N-1}, y^{N-1} \right\}$$

$$= E \left\{ (A_{N-1} x_{N-1} + B_{N-1} u_{N-1} + w_{N-1})^T Q(y_N) (A_{N-1} x_{N-1} + B_{N-1} u_{N-1} + w_{N-1}) + u_{N-1}^T R_{N-1} u_{N-1} \mid x^{N-1}, y^{N-1} \right\}$$

$$= \left\{ (A_{N-1} x_{N-1} + B_{N-1} u_{N-1})^T E \{ Q \mid x^{N-1}, y^{N-1} \} (A_{N-1} x_{N-1} + B_{N-1} u_{N-1}) + u_{N-1}^T R_{N-1} u_{N-1} \right. \\ \left. + E \{ w_{N-1}^T Q_N w_{N-1} \mid x^{N-1}, y^{N-1} \} \right\}$$



remark: 1. all the terms that are linear in w_{N-1} cancel out. why?

w_{N-1} , zero-vector, independent from x_{N-1} .

$$2. E\{Q_N | x^{N-1}, y^{N-1}\} = E\{Q(y_N) | x^{N-1}, y^{N-1}\} = E\{Q(y_N) | y_{N-1}\}$$

why? $\{y_k\}$ is MARKOV!

Notation: $\bar{Q}_N = E\{Q_N | y_{N-1}\}$

r.v. Δ — $\bar{Q}_N(y_{N-1}) = \sum_{j=1}^L Q_N(j) \Pr\{y_N=j | y_{N-1}\}$; $y_{N-1} = 1, 2, \dots, L$

realizable Δ — $\bar{Q}_N(i) = \sum_{j=1}^L Q_N(j) \underbrace{\Pr\{y_N=j | y_{N-1}=i\}}_{= p_{ij}}$; $i = 1, 2, \dots, L$

$$\bar{Q}_N(i) = \sum_{j=1}^L Q_N(j) p_{ij}$$

$i = 1, 2, \dots, L$

this is an "averaging" over the weights Q_N according to the transition probability distribution.

To sum-up:

$$J_{N-1} = \underbrace{|A_{N-1} x_{N-1} + B_{N-1} u_{N-1}|^2}_{\alpha} \underbrace{\bar{Q}_N}_{\alpha} + \underbrace{|u_{N-1}|^2}_{\alpha} \underbrace{R_{N-1}}_{\alpha} + \text{tr} (W_{N-1} \bar{Q}_N)$$

Now,

$$\min_{u_{N-1}} J_{N-1}(x_{N-1}, y_{N-1}, u_{N-1}) \mapsto u_{N-1}^*(x_{N-1}, y_{N-1})$$

$$u_{N-1}^* = - \underbrace{(B_{N-1}^T \bar{Q}_N B_{N-1} + R_{N-1})^{-1} B_{N-1}^T \bar{Q}_N A_{N-1}}_{\text{Control Gain } M_{N-1}} \cdot x_{N-1}$$

Control Gain M_{N-1}

↳ Feedback Control, Linear in x_{N-1} .

Control Gain depends on y_{N-1} ! \rightarrow validation for M_{N-1} .

$$\left\{ \begin{array}{l} \mathbb{E} \{ W_{N-1}^T Q_N(y_N) W_{N-1} \mid X^{N-1}, Y^{N-1} \} \\ \text{tr} \mathbb{E} \{ W_{N-1} W_{N-1}^T Q_N(y_N) \mid X^{N-1}, Y^{N-1} \} \\ \text{tr} \mathbb{E} \{ W_{N-1} W_{N-1}^T \mid X^{N-1}, Y^{N-1} \} \cdot \mathbb{E} \{ Q_N(y_N) \mid X^{N-1}, Y^{N-1} \} \\ \text{tr} (W_{N-1} \cdot \bar{Q}_N) \end{array} \right\}$$

$$\bar{Q}_i = \sum_{j=1}^u Q_n(j) p_{ij} \quad i = 1, 2, \dots, u \quad (= y_{N-1})$$

$$J_{N-1}^*(x_{N-1}, y_{N-1}) = |x_{N-1}|^2 S_N(y_{N-1}) + \text{tr}(w_{N-1} \bar{Q}_N)$$

$$\text{where } S_N(y) = \underbrace{A^T}_{N-1} \underbrace{\bar{Q}}_N \underbrace{A}_{N-1} - \underbrace{A^T}_{N-1} \underbrace{\bar{Q}}_{N-1} \underbrace{B}_{N-1} (\underbrace{B^T}_{N-1} \underbrace{\bar{Q}}_N \underbrace{B}_{N-1} + \underbrace{R}_{N-1})^{-1} \underbrace{B^T}_{N-1} \underbrace{\bar{Q}}_N \underbrace{A}_{N-1}$$

! for each value of x_{N-1} , there u possible values for J^* .

Secord to Last Stage:

Given x^{N-2}, y^{N-2}

$$J_{N-2} = E \left\{ |x_{N-1}|_{Q_{N-1}}^2 + |u_{N-2}|_{R_{N-2}}^2 + \underbrace{J_{N-1}^*(x_{N-1}, y_{N-1})}_{|x_{N-1}|_{S_N(y_{N-1})}^2 + \text{tr} \left(W_{N-1} \overline{Q_N}(y_{N-1}) \right)} \mid x^{N-2}, y^{N-2} \right\}$$

$$|x_{N-1}|_{S_N(y_{N-1})}^2 + \text{tr} \left(W_{N-1} \overline{Q_N}(y_{N-1}) \right)$$

$$= E \left\{ |x_{N-1}|_{\underbrace{Q_{N-1} + S_N}_{\equiv S_{N-1}(y_{N-1})}}^2 \right\}$$

$$= E \left\{ |x_{N-1}|_{S_{N-1}}^2 + |u_{N-2}|_{R_{N-2}}^2 \mid x^{N-2}, y^{N-2} \right\} + E \left\{ \text{tr} \left(W_{N-1} \overline{Q_N} \right) \mid x^{N-2}, y^{N-2} \right\}$$

min
N-2

similar to (*)

independent from u_{N-2}

Summary: The Jump-Linear Quadratic Gaussian Regulator

Backward Propagation

$$S_{N+1}(i) = 0 \quad i = 1, 2, \dots, \nu$$

a set of ν matrices S

For $k = N-1, N-2, \dots, 0$

$$S_k(y_k=i) = \sum_{j=1}^{\nu} [S_{k+1}(y_{k+1}=j) + Q(y_k=i, y_{k+1}=j)] p_{ij} \quad y_k = i = 1, 2, \dots, \nu$$

$$S_k(y_k=i) = A_k^T \bar{S}_{k+1} A_k - A_k^T \bar{S}_{k+1} B_k (B_k^T \bar{S}_{k+1} B_k + R_k)^{-1} B_k^T \bar{S}_{k+1} A_k; \quad i = 1, 2, \dots, \nu$$

$$M_k(y_k=i) = (B_k^T \bar{S}_{k+1} B_k + R_k)^{-1} B_k^T \bar{S}_{k+1} A_k \quad i = 1, 2, \dots, \nu$$

The Gains are calculated through coupled Riccati equations.

Optimal Cost :

$$J_0^*(x_0, y_0) = \|x_0\|_{S_0(y_0)}^2 + \Delta J_0(y_0) \quad y_0 = 1, 2, \dots, v$$

Gain | Computations
Cost | OFF LINE.

$$\begin{cases} \Delta J_{N-1}(y_{N-1}=i) = \text{tr}(W_{N-1} \bar{Q}_N(y_{N-1})) & i = 1, \dots, v \\ \Delta J_k(y_k=i) = \sum_{j=1}^v \Delta J_{k+1}(y_{k+1}=j) p_{ij} + \text{tr}(W_k \bar{S}_{k+1}(y_k)) \end{cases}$$

Forward Propagation :

$$\begin{cases} x_0 & \text{initial condition} \\ x_{k+1} &= A(y_k) x_k + B(y_k) u_k^* \\ u_k^* &= -M(y_k) x_k \end{cases}$$

mode dependent

State Feedback Control, Linear