



Quiz 1

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# Solutions

Duration:	45 minutes
Number of Problems:	2
Permitted Aids:	None. Use only the prepared sheets for your solutions.

## Problem 1

Given is the following system equation

$$x_{k+1} = x_k + 2x_{k-2}^2 - x_{k-3} + 3u_k^2 - u_{k-1} + w_k u_k x_k$$

with  $x_k, u_k, w_k \in \mathbb{R}$  and  $w_k \sim P(\cdot \mid x_k, u_k)$ .

To apply the Dynamic Programming algorithm, the system must be reformulated into the basic problem format:

$$\tilde{x}_{k+1} = \tilde{f}_k(\tilde{x}_k, u_k, w_k)$$

with  $\tilde{x}_k = [\tilde{x}_{k,1}, \dots, \tilde{x}_{k,m}]^T \in \mathbb{R}^m$  being the augmented state.

- a) What dimension m does the augmented state  $\tilde{x}_k$  have?
- b) Please circle the correct representation of the augmented state  $\tilde{x}_k$ .

$$\begin{split} \tilde{x}_{k} &= \begin{bmatrix} x_{k} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k-1} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\ u_{k} \end{bmatrix} \qquad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-2} \\ x_{k-3} \\ u_{k} \\$$

c) Rewrite the given system in the form  $\tilde{x}_{k+1} = \tilde{f}_k(\tilde{x}_k, u_k, w_k)$  using the augmented state  $\tilde{x}_k = [\tilde{x}_{k,1}, \dots, \tilde{x}_{k,m}]^T$ .

## Solution 1

**a**) 5

$$\mathbf{b} \quad \tilde{x}_{k} = \begin{bmatrix} x_{k} \\ x_{k-1} \\ x_{k-2} \\ x_{k-3} \\ u_{k-1} \end{bmatrix} = \begin{bmatrix} \tilde{x}_{k,1} \\ \tilde{x}_{k,2} \\ \tilde{x}_{k,3} \\ \tilde{x}_{k,4} \\ \tilde{x}_{k,5} \end{bmatrix}$$
$$\mathbf{c} \quad \tilde{x}_{k+1} = \begin{bmatrix} \tilde{x}_{k,1} + 2\tilde{x}_{k,3}^{2} - \tilde{x}_{k,4} + 3u_{k}^{2} - \tilde{x}_{k,5} + w_{k}u_{k}\tilde{x}_{k,1} \\ & \tilde{x}_{k,1} \\ & \tilde{x}_{k,2} \\ & \tilde{x}_{k,3} \\ & u_{k} \end{bmatrix}$$

## Problem 2

Consider the system

$$x_{k+1} = x_k + u_k + w_k, \qquad k = 0, 1,$$

with initial state  $x_0 = 0$ . The disturbance  $w_k$  takes values -1 and 1 with equal probability. The cost for the above system is given by

$$(x_2 - x_2^*)^2 + (x_1 - x_1^*)^2 + u_1^2 + u_0^2$$

with  $x_1^* = 2$  and  $x_2^* = 1$ .

- **a)** Assume a discrete input  $u_k, u_k \in \{-1, 0, 1\}$  for k = 0, 1:
  - i) Find all states  $x_k$  that can be reached from  $x_0 = 0$  in stage 1 (k = 1) and in stage 2 (k = 2).
  - ii) Calculate the optimal cost-to-go  $J_0(x_0)$  and the optimal policy  $\{\mu_0^*(x_0), \mu_1^*(x_1)\}$ .
  - iii) Will the optimal policy be affected by adding  $(x_0 x_0^*)^2$ ,  $x_0^* = 1$ , to the cost? If so, how?
- **b)** Assume a continuous input  $u_k, u_k \in [-1, 1]$  for k = 0, 1:
  - i) Calculate the optimal cost-to-go  $J_1(x_1)$  and the optimal policy  $\mu_1^*(x_1)$  for  $x_1 = 2, 1, -2$ .

## Solution 2

- a) Discrete input case:
  - i) State evolution for k = 1 and 2: For k=1 and  $x_0 = 0$ ,

$$\{ u_0 = 1, w_0 = 1 \} \quad \Rightarrow \quad x_1 = 2 \\ \{ u_0 = 0, w_0 = 1 \} \quad \Rightarrow \quad x_1 = 1 \\ \{ u_0 = 1, w_0 = -1 \} \text{ or } \{ u_0 = -1, w_0 = 1 \} \quad \Rightarrow \quad x_1 = 0 \\ \{ u_0 = 0, w_0 = -1 \} \quad \Rightarrow \quad x_1 = -1 \\ \{ u_0 = -1, w_0 = -1 \} \quad \Rightarrow \quad x_1 = -2 \end{cases}$$

Similarly for k = 2,

$$\begin{array}{rcl} x_1 = 2 & \Rightarrow & x_2 \in \{4, 3, 2, 1, 0\} \\ x_1 = 1 & \Rightarrow & x_2 \in \{3, 2, 1, 0, -1\} \\ x_1 = 0 & \Rightarrow & x_2 \in \{2, 1, 0, -1, -2\} \\ x_1 = -1 & \Rightarrow & x_2 \in \{1, 0, -1, -2, -3\} \\ x_1 = -2 & \Rightarrow & x_2 \in \{0, -1, -2, -3, -4\}. \end{array}$$

This implies:

$$x_1 \in \{2, 1, 0, -1, -2\}$$
 and  $x_2 \in \{4, 3, 2, 1, 0, -1, -2, -3, -4\}.$ 

ii) Optimal cost-to-go and the optimal policy: Calculate the terminal cost  $J_2(x_2) = (x_2 - x_2^*)^2$ , for all possible states at k = 2.

$$\begin{aligned} J_2(4) &= 9 & J_2(3) = 4 & J_2(2) = 1 \\ J_2(1) &= 0 & J_2(0) = 1 & J_2(-1) = 4 \\ J_2(-2) &= 9 & J_2(-3) = 16 & J_2(-4) = 25. \end{aligned}$$

Now, using the the Dynamic Programming Algorithm for k = 1,

$$J_1(x_1) = \min_{u_1 \in \{-1,0,1\}} E_{w_1} \Big\{ (x_1 - x_1^*)^2 + u_1^2 + J_2 \big( x_1 + u_1 + w_1 \big) \Big\},\$$

gives

$$J_1(2) = 2 \quad \text{with} \quad \mu_1^*(2) = 0 \text{ or } -1,$$
  

$$J_1(1) = 2 \quad \text{with} \quad \mu_1^*(1) = 0,$$
  

$$J_1(0) = 6 \quad \text{with} \quad \mu_1^*(0) = 0 \text{ or } 1,$$
  

$$J_1(-1) = 12 \quad \text{with} \quad \mu_1^*(-1) = 1,$$
  

$$J_1(-2) = 22 \quad \text{with} \quad \mu_1^*(-2) = 1.$$

Similarly, using the the Dynamic Programming Algorithm for k = 0,

$$J_0(x_0) = \min_{u_0 \in \{-1,0,1\}} E_{w_0} \Big\{ u_0^2 + J_1 \big( x_0 + u_0 + w_0 \big) \Big\},$$

gives

$$J_0(0) = 5$$
 with  $\mu_0^*(2) = 1$ .

- iii) Effect of adding  $(x_0 x_0^*)^2$ : There won't be any effect on the optimal policy since it is a fixed constant value.
- **b)** Continuous input case where  $u_k \in [-1, 1]$  for k = 0, 1:
  - i) Optimal cost-to-go and the optimal policy for  $x_1 = 2, 1, \text{and} 2$ Terminal cost:  $(x_2 - x_2^*)^2 = J_2(x_2)$ Now, using the the Dynamic Programming Algorithm for k = 1 gives

$$J_{1}(x_{1}) = \min_{u_{1} \in [-1,1]} \mathbb{E}_{w_{1}} \{ (x_{1} - x_{1}^{*})^{2} + u_{1}^{2} + J_{2}(x_{1} + u_{1} + w_{1}) \}$$
  
$$= \min_{u_{1} \in [-1,1]} \{ (x_{1} - x_{1}^{*})^{2} + u_{1}^{2} + 0.5(x_{1} + u_{1} + 1 - x_{2}^{*})^{2} + 0.5(x_{1} + u_{1} - 1 - x_{2}^{*})^{2} \}$$
  
$$+ 0.5(x_{1} + u_{1} - 1 - x_{2}^{*})^{2} \}.$$
(1)

Since  $u_1^2$  in (1) has a positive coefficient, the minimization can be done by setting the derivative with respect to  $u_1$  to zero.

$$0 = 4u_1 + 2x_1 - 2x_2^*.$$

This implies,

$$\mu_1(x_1) = \frac{x_2^* - x_1}{2}.$$
(2)

Now, for  $x_1 = 2$  and 1 a straight forward substitution yields,

$$\mu_1^*(x_1 = 2) = -0.5 \qquad J_1(x_1 = 2) = 1.5$$
  
$$\mu_1^*(x_1 = 1) = 0 \qquad J_1(x_1 = 1) = 2$$

For  $x_1 = -2$  an additional step is required since  $\mu_1(x_1 = -2) = 1.5$  is not a feasible input. Since the function to be minimized in (1) is monotonically decreasing in  $u_1$ 's feasible range [-1, 1],  $\mu_1(x_1 = -2) = 1$  is the feasible minimizer. Finally,

$$\mu_1^*(x_1 = -2) = 1 \implies J_1(x_1 = -2) = 22.$$