

EE365: Linear Quadratic Regulator

Linear quadratic regulator

- ▶ $x_{t+1} = A_t x_t + B_t u_t + w_t$
- ▶ $\mathbf{E} w_t = 0, \mathbf{E} w_t w_t^\top = W_t$
- ▶ stage cost is (convex quadratic)

$$\frac{1}{2}(x_t^\top Q_t x_t + u_t^\top R_t u_t)$$

with $Q_t \geq 0, R_t > 0$

- ▶ terminal cost $\frac{1}{2}x_T^\top Q_T x_T, Q_T \geq 0$
- ▶ variation: terminal constraint $x_T = 0$

Linear quadratic regulator: DP

- ▶ value functions are quadratic plus constant (linear terms are zero):

$$v_t(x) = \frac{1}{2}(x^\top P_t x + r_t)$$

- ▶ $P_T = Q_T$, $r_T = 0$

- ▶ optimal expected tail cost:

$$\begin{aligned} & \mathbf{E} v_{t+1}(f_t(x, u, w_t)) \\ &= \frac{1}{2}(r_{t+1} + \mathbf{E}(A_t x + B_t u + w_t)^\top P_{t+1} (A_t x + B_t u + w_t)) \\ &= \frac{1}{2}(r_{t+1} + (A_t x + B_t u)^\top P_{t+1} (A_t x + B_t u) + \mathbf{Tr}(P_{t+1} W_t)) \end{aligned}$$

using $\mathbf{E} w_t = 0$ and

$$\mathbf{E} w_t^\top P_{t+1} w_t = \mathbf{E} \mathbf{Tr}(P_{t+1} w_t w_t^\top) = \mathbf{Tr}(P_{t+1} W_t)$$

Linear quadratic regulator: DP

- ▶ minimize over u to get optimal policy:

$$\begin{aligned}\mu_t(x) &= \underset{u}{\operatorname{argmin}} \left(u^\top R_t u + u^\top B_t^\top P_{t+1} B_t u + 2(B_t^\top P_{t+1} A_t x)^\top u \right) \\ &= - \left(R_t + B_t^\top P_{t+1} B_t \right)^{-1} B_t^\top P_{t+1} A_t x \\ &= K_t x\end{aligned}$$

- ▶ optimal policy is linear (as opposed to affine)
- ▶ using $u = K_t x$ we then have

$$v_t(x) = \frac{1}{2}(r_{t+1} + \mathbf{Tr}(P_{t+1} W_t)) + x^\top (Q_t + K_t^\top R_t K_t)x + x^\top (A_t + B_t K_t)^\top P_{t+1} (A_t + B_t K_t)x$$

- ▶ so coefficients of v_t are

$$\begin{aligned}P_t &= Q_t + K_t^\top R_t K_t + (A_t + B_t K_t)^\top P_{t+1} (A_t + B_t K_t), \\ r_t &= r_{t+1} + \mathbf{Tr}(P_{t+1} W_t)\end{aligned}$$

Linear quadratic regulator: Riccati recursion

▶ set $P_T = Q_T$

▶ for $t = T - 1, \dots, 0$

$$K_t = -(R_t + B_t^\top P_{t+1} B_t)^{-1} B_t^\top P_{t+1} A_t$$

$$P_t = Q_t + K_t^\top R_t K_t + (A_t + B_t K_t)^\top P_{t+1} (A_t + B_t K_t)$$

▶ called Riccati recursion; gives optimal policies, which are linear functions

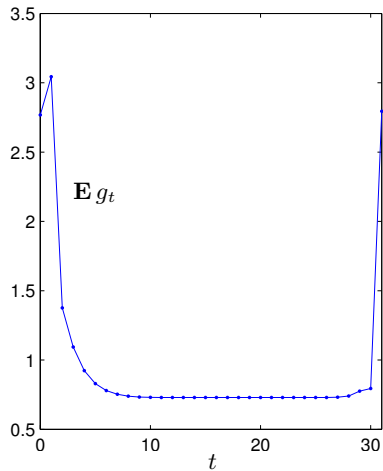
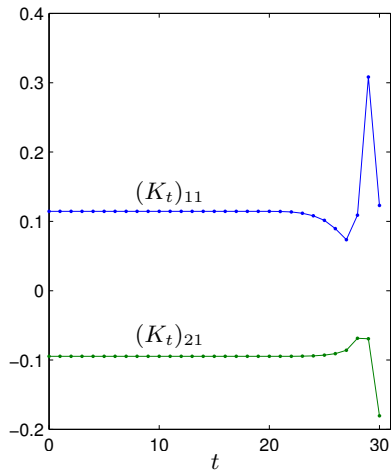
▶ *surprise*: optimal policy does not depend on the disturbance distribution (provided it is zero mean)

▶ $J^* = \frac{1}{2} (\text{Tr}(P_0 X_0) + \sum_{t=0}^{T-1} \text{Tr}(P_{t+1} W_t))$, where $X_0 = \mathbf{E}(x_0 x_0^\top)$

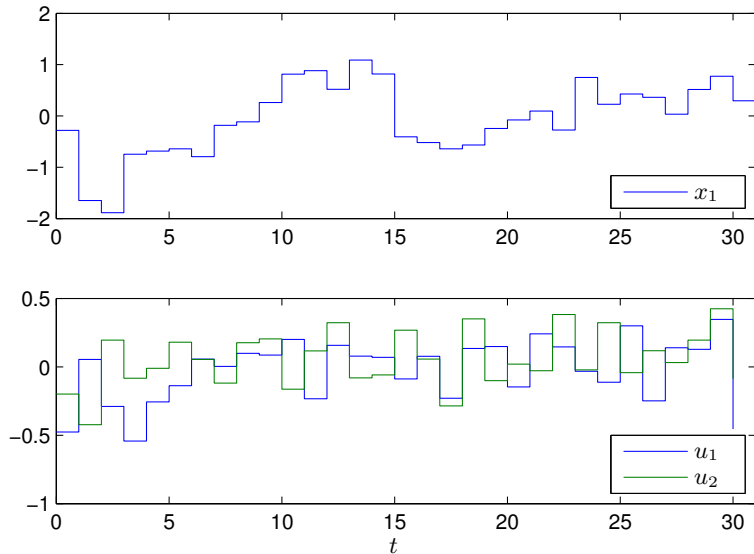
Linear quadratic regulator: Example

- ▶ $n = 5$ states, $m = 2$ inputs, horizon $T = 31$
- ▶ A, B chosen randomly; A scaled so $\max_i |\lambda_i(A)| = 1$
- ▶ $Q_t = I, R_t = I, t = 0, \dots, T - 1, Q_T = 5I$
- ▶ $x_0 \sim \mathcal{N}(0, X_0), X_0 = I$
- ▶ $w_t \sim \mathcal{N}(0, W), W = 0.1I$

Linear quadratic regulator: Example



Linear quadratic regulator: Sample trajectory



Linear quadratic regulator: Cost comparison

compare cost for

- ▶ optimal policy, J^*
- ▶ prescient policy, J^{pre} : w_0, \dots, w_T known in advance
- ▶ open loop policy, J^{ol} : choose u_0, \dots, u_T with knowledge of x_0 only
- ▶ no control (1-step greedy), J^{nc} : $u_0, \dots, u_T = 0$

Linear quadratic regulator: Cost comparison

total stage cost histograms, $N = 5000$ Monte Carlo simulations

