ECE276B: Planning & Learning in Robotics
Lecture 16: Linear Quadratic Control

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Globally Optimal Closed-Loop Control

- **Deterministic finite-horizon continuous-time optimal control**:

$$
\begin{aligned}
\min_{\pi} \quad & V^{\pi}(0, \mathbf{x}_0) := \int_0^T \ell(\mathbf{x}(t), \pi(t, \mathbf{x}(t)))dt + \mathfrak{q}(\mathbf{x}(T)) \\
\text{s.t.} \quad & \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)), \;\; \mathbf{x}(0) = \mathbf{x}_0 \\
& \mathbf{x}(t) \in \mathcal{X}, \;\; \pi(t, \mathbf{x}(t)) \in PC^0([0, T], \mathcal{U})
\end{aligned}
$$

- **Hamiltonian**: $H(\mathbf{x}, \mathbf{u}, \mathbf{p}) := \ell(\mathbf{x}, \mathbf{u}) + \mathbf{p}^\top \mathbf{f}(\mathbf{x}, \mathbf{u})$

HJB PDE: Sufficient Conditions for Optimality

If $V(t, \mathbf{x})$ satisfies the HJB PDE:

$$
\begin{aligned}
V(T, \mathbf{x}) &= \mathfrak{q}(\mathbf{x}), && \forall \mathbf{x} \in \mathcal{X} \\
-\frac{\partial}{\partial t} V(t, \mathbf{x}) &= \min_{\mathbf{u} \in \mathcal{U}} H(\mathbf{x}(t), \mathbf{u}, \nabla_x V(t, \cdot)), && \forall \mathbf{x} \in \mathcal{X}, t \in [0, T]
\end{aligned}
$$

then it is the optimal value function and the policy $\pi(t, \mathbf{x})$ that attains the minimum is an optimal policy.

Locally Optimal Open-Loop Control

- **Deterministic finite-horizon continuous-time optimal control**:

$$\begin{aligned}
\min_{\pi} \quad & V^{\pi}(0, \mathbf{x}_0) := \int_0^T \ell(\mathbf{x}(t), \pi(t, \mathbf{x}(t)))dt + \mathfrak{q}(\mathbf{x}(T)) \\
\text{s.t.} \quad & \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)), \;\; \mathbf{x}(0) = \mathbf{x}_0 \\
& \mathbf{x}(t) \in \mathcal{X}, \; \pi(t, \mathbf{x}(t)) \in PC^0([0, T], \mathcal{U})
\end{aligned}$$

- **Hamiltonian**: $H(\mathbf{x}, \mathbf{u}, \mathbf{p}) := \ell(\mathbf{x}, \mathbf{u}) + \mathbf{p}^\top \mathbf{f}(\mathbf{x}, \mathbf{u})$

PMP ODE: Necessary Conditions for Optimality

If $(\mathbf{x}^*(t), \mathbf{u}^*(t))$ for $t \in [0, T]$ is a trajectory from an optimal policy $\pi^*(t, x)$, then it satisfies:

$$\begin{aligned}
&\dot{\mathbf{x}}^*(t) = \mathbf{f}(\mathbf{x}^*(t), \mathbf{u}^*(t)), && \mathbf{x}^*(0) = \mathbf{x}_0 \\
&\dot{\mathbf{p}}^*(t) = -\nabla_{\mathbf{x}}\ell(\mathbf{x}^*(t), \mathbf{u}^*(t)) - [\nabla_{\mathbf{x}}\mathbf{f}(\mathbf{x}^*(t), \mathbf{u}^*(t))]^\top \mathbf{p}^*(t), && \mathbf{p}^*(T) = \nabla_x \mathfrak{q}(\mathbf{x}^*(T)) \\
&\mathbf{u}^*(t) = \arg\min_{\mathbf{u} \in \mathcal{U}} H(\mathbf{x}^*(t), \mathbf{u}, \mathbf{p}^*(t)), && \forall t \in [0, T] \\
&H(\mathbf{x}^*(t), \mathbf{u}^*(t), \mathbf{p}^*(t)) = \textit{constant}, && \forall t \in [0, T]
\end{aligned}$$

Tractable Problems

- Control-affine dynamics and quadratic-in-control cost:

$$\dot{\mathbf{x}} = \mathbf{a}(\mathbf{x}) + B(\mathbf{x})\mathbf{u} \qquad \ell(\mathbf{x},\mathbf{u}) = q(\mathbf{x}) + \frac{1}{2}\mathbf{u}^\top R(\mathbf{x})\mathbf{u} \qquad R(\mathbf{x}) \succ 0$$

- **Hamiltonian**:

$$H(\mathbf{x},\mathbf{u},\mathbf{p}) = q + \frac{1}{2}\mathbf{u}^\top R\mathbf{u} + \mathbf{p}^\top(\mathbf{a} + B\mathbf{u})$$

$$\nabla_{\mathbf{u}} H(\mathbf{x},\mathbf{u},\mathbf{p}) = R\mathbf{u} + B^\top\mathbf{p} \qquad \nabla^2_{\mathbf{u}} H(\mathbf{x},\mathbf{u},\mathbf{p}) = R$$

- **HJB PDE**: obtains the globally optimal value function and policy:

$$\begin{aligned}
\pi^*(t,\mathbf{x}) &= \arg\min_{\mathbf{u}} H(\mathbf{x},\mathbf{u},V_x(t,\mathbf{x})) = -R^{-1}B^\top V_x(t,\mathbf{x}), && t \in [0,T], \mathbf{x} \in \mathcal{X}\\
V(T,\mathbf{x}) &= \mathfrak{q}(\mathbf{x}), && x \in \mathcal{X}\\
-V_t(t,\mathbf{x}) &= q + \mathbf{a}^\top V_x(t,\mathbf{x}) - \frac{1}{2}V_x(t,\mathbf{x})^\top BR^{-1}B^\top V_x(t,\mathbf{x}), && t \in [0,T], x \in \mathcal{X}
\end{aligned}$$

- **PMP**: both necessary and sufficient for a local minimum:

$$\begin{aligned}
\mathbf{u}(t) &= \arg\min_{\mathbf{u}} H(\mathbf{x},\mathbf{u},\mathbf{p}) = -R^{-1}B^\top\mathbf{p}(t), && t \in [0,T]\\
\dot{\mathbf{x}} &= \mathbf{a}(\mathbf{x}) - B(\mathbf{x})R^{-1}(\mathbf{x})B^\top(\mathbf{x})\mathbf{p}, && \mathbf{x}(0) = \mathbf{x}_0\\
\dot{\mathbf{p}} &= -q_x(\mathbf{x}) - a_x(\mathbf{x})^\top\mathbf{p}, && \mathbf{p}(T) = \nabla_x\mathfrak{q}(\mathbf{x}(T))
\end{aligned}$$

Example: Pendulum

$$\dot{\mathbf{x}} = \begin{bmatrix} x_2 \\ k\sin(x_1) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u, \quad \mathbf{x}(0) = \mathbf{x}_0$$

$$a_x(\mathbf{x}) = \begin{bmatrix} 0 & 1 \\ k\cos(x_1) & 0 \end{bmatrix}$$

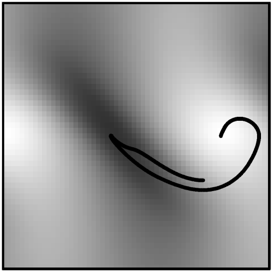
- Cost:

$$\ell(\mathbf{x}, u) = 1 - e^{-2x_1^2} + \frac{r}{2}u^2 \text{ and } \mathfrak{q}(x) = 0$$

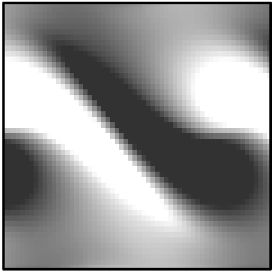
- PMP locally optimal trajectories:

$$\begin{aligned} u(t) &= -r^{-1}p_2(t), && t \in [0, T] \\ \dot{x}_1 &= x_2, && x_1(0) = 0 \\ \dot{x}_2 &= k\sin(x_1) - r^{-1}p_2, && x_2(0) = 0 \\ \dot{p}_1 &= -4e^{-2x_1^2}x_1 - p_2, && p_1(T) = 0 \\ \dot{p}_2 &= -k\cos(x_1)p_1, && p_2(T) = 0 \end{aligned}$$

- Optimal value from HJB:



- Optimal policy from HJB:



Linear Quadratic Regulator

- Key assumptions that allowed minimizing the Hamiltonian analytically:
  - The system dynamics are linear in the control u
  - The stage-cost is quadratic in the control u
- **Linear Quadratic Regulator** (LQR): a deterministic time-invariant linear system needs to minimize a quadratic cost over a finite horizon:

$$\min_{\pi} V^{\pi}(0, \mathbf{x}_0) := \int_0^T \underbrace{\frac{1}{2}\mathbf{x}(t)^\top Q \mathbf{x}(t) + \frac{1}{2}\mathbf{u}(t)^\top R \mathbf{u}(t)}_{\ell(\mathbf{x}(t), \mathbf{u}(t))} dt + \underbrace{\frac{1}{2}\mathbf{x}(T)^\top Q_T \mathbf{x}(T)}_{\mathfrak{q}(\mathbf{x}(T))}$$

$$\text{s.t.} \quad \dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}, \;\; \mathbf{x}(0) = \mathbf{x}_0$$

$$\mathbf{x}(t) \in \mathbb{R}^n, \; \mathbf{u}(t) = \pi(t, x(t)) \in \mathbb{R}^m$$

where $Q = Q^T \succeq 0$, $Q_T = Q_T^T \succeq 0$, and $R = R^T \succ 0$

LQR via the PMP

- Hamiltonian: $H(\mathbf{x}, \mathbf{u}, \mathbf{p}) = \frac{1}{2}\mathbf{x}^\top Q\mathbf{x} + \frac{1}{2}\mathbf{u}^\top R\mathbf{u} + \mathbf{p}^\top A\mathbf{x} + \mathbf{p}^\top B\mathbf{u}$
- Canonical equations with boundary conditions:

$$\begin{aligned}
\dot{\mathbf{x}} &= \nabla_p H(\mathbf{x}, \mathbf{u}, \mathbf{p}) = A\mathbf{x} + B\mathbf{u}, & \mathbf{x}(0) &= \mathbf{x}_0 \\
\dot{\mathbf{p}} &= -\nabla_x H(\mathbf{x}, \mathbf{u}, \mathbf{p}) = -Q\mathbf{x} - A^\top\mathbf{p}, & \mathbf{p}(T) &= \nabla_x \mathfrak{q}(\mathbf{x}(T)) = Q_T\mathbf{x}(T)
\end{aligned}$$

- Minimum principle:

$$\begin{aligned}
\nabla_u H(\mathbf{x}, \mathbf{u}, \mathbf{p}) &= R\mathbf{u} + B^\top\mathbf{p} = 0 & \Rightarrow \quad & \mathbf{u}^*(t) = -R^{-1}B^\top\mathbf{p}(t) \\
\nabla_u^2 H(\mathbf{x}, \mathbf{u}, \mathbf{p}) &= R \succ 0 & \Rightarrow \quad & \mathbf{u}^*(t) \text{ is a minimum}
\end{aligned}$$

- **Hamiltonian matrix**: the canonical equations can now be simplified to a linear time-invariant (LTI) system with two-point boundary conditions:

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\mathbf{p}} \end{bmatrix} = \begin{bmatrix} A & -BR^{-1}B^\top \\ -Q & -A^\top \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{p} \end{bmatrix}, \qquad \begin{aligned} \mathbf{x}(0) &= \mathbf{x}_0 \\ \mathbf{p}(T) &= Q_T\mathbf{x}(T) \end{aligned}$$

LQR via the PMP

- **Claim**: There exists a matrix $M(t) = M(t)^T \succeq 0$ such that $\mathbf{p}(t) = M(t)\mathbf{x}(t)$ for all $t \in [0, T]$
- We can solve the LTI system described by the Hamiltonian matrix backwards in time:

$$\begin{bmatrix} \mathbf{x}(t) \\ \mathbf{p}(t) \end{bmatrix} = \underbrace{e^{\begin{bmatrix} A & -BR^{-1}B^\top \\ -Q & -A^\top \end{bmatrix}(t-T)}}_{\Phi(t,T)} \begin{bmatrix} \mathbf{x}(T) \\ Q_T\mathbf{x}(T) \end{bmatrix}$$

$$\mathbf{x}(t) = (\Phi_{11}(t, T) + \Phi_{12}(t, T)Q_T)\mathbf{x}(T)$$

$$\mathbf{p}(t) = (\Phi_{21}(t, T) + \Phi_{22}(t, T)Q_T)\mathbf{x}(T)$$

- It turns out that $D(t, T) := \Phi_{11}(t, T) + \Phi_{12}(t, T)Q_T$ is invertible for $t \in [0, T]$ and thus:

$$\mathbf{p}(t) = \underbrace{(\Phi_{21}(t, T) + \Phi_{22}(t, T)Q_T)D^{-1}(t, T)}_{=:M(t)}\mathbf{x}(t), \quad \forall t \in [0, T]$$

LQR via the PMP

- From $\mathbf{x}(0) = D(0, T)\mathbf{x}(T)$, we obtain an **open-loop control policy**:

$$\mathbf{u}(t) = -R^{-1}B^\top(\Phi_{21}(t, T) + \Phi_{22}(t, T)Q_T)D(0, T)^{-1}\mathbf{x}_0$$

- From the claim that $\mathbf{p}(t) = M(t)\mathbf{x}(t)$, however, we can also obtain a **linear state feedback** control policy:

$$\mathbf{u}(t) = -R^{-1}B^\top M(t)\mathbf{x}(t)$$

- We can obtain a better description of $M(t)$ by differentiating $\mathbf{p}(t) = M(t)\mathbf{x}(t)$ and using the canonical equations:

$$\begin{aligned}
\dot{\mathbf{p}}(t) &= \dot{M}(t)\mathbf{x}(t) + M(t)\dot{\mathbf{x}}(t) \\
-Q\mathbf{x}(t) - A^\top\mathbf{p}(t) &= \dot{M}(t)\mathbf{x}(t) + M(t)A\mathbf{x}(t) - M(t)BR^{-1}B^\top\mathbf{p}(t) \\
-\dot{M}(t)\mathbf{x}(t) &= Q\mathbf{x}(t) + A^\top M(t)\mathbf{x}(t) + M(t)A\mathbf{x}(t) - M(t)BR^{-1}B^\top M(t)\mathbf{x}(t)
\end{aligned}$$

  which needs to hold for all $\mathbf{x}(t)$ and $t \in [0, T]$ and satisfy the boundary condition $\mathbf{p}(T) = M(T)\mathbf{x}(T) = Q_T\mathbf{x}(T)$

LQR via the PMP (Summary)

- A unique candidate $\mathbf{u}(t) = -R^{-1}B^\top M(t)\mathbf{x}(t)$ satsifies the necessary conditions of the PMP for optimality
- The candidate policy is linear in the state and the matrix $M(t)$ satisfies a quadratic **Riccati differential equation** (RDE):

$$-\dot{M}(t) = Q + A^\top M(t) + M(t)A - M(t)BR^{-1}B^\top M(t), \quad M(T) = Q_T$$

- The HJB PDE is needed to decide whether $\mathbf{u}(t)$ is globally optimal

LQR via the HJB PDE

- Hamiltonian: $H(\mathbf{x}, \mathbf{u}, \mathbf{p}) = \frac{1}{2}\mathbf{x}^\top Q\mathbf{x} + \frac{1}{2}\mathbf{u}^\top R\mathbf{u} + \mathbf{p}^\top A\mathbf{x} + \mathbf{p}^\top B\mathbf{u}$
- HJB PDE:

$$\begin{aligned}
\pi^*(t, \mathbf{x}) &= \operatorname*{arg\,min}_{\mathbf{u}\in\mathcal{U}} H(\mathbf{x}, \mathbf{u}, V_x(t, \mathbf{x})) = -R^{-1}B^\top V_x(t, \mathbf{x}), && t \in [0, T], \mathbf{x} \in \mathcal{X} \\
-V_t(t, \mathbf{x}) &= \frac{1}{2}\mathbf{x}^\top Q\mathbf{x} + \mathbf{x}^\top A^\top V_x(t, \mathbf{x}) - \frac{1}{2}V_x(t, \mathbf{x})^\top BR^{-1}B^\top V_x(t, \mathbf{x}), && t \in [0, T], \mathbf{x} \in \mathcal{X} \\
V(T, \mathbf{x}) &= \frac{1}{2}\mathbf{x}^\top Q_T\mathbf{x}
\end{aligned}$$

- Guess a solution to the HJB PDE based on the intuition from the PMP:

$$\begin{aligned}
\pi(t, \mathbf{x}) &= -R^{-1}B^\top M(t)\mathbf{x} \\
V(t, \mathbf{x}) &= \frac{1}{2}\mathbf{x}^\top M(t)\mathbf{x} \\
V_t(t, \mathbf{x}) &= \frac{1}{2}\mathbf{x}^\top \dot{M}(t)\mathbf{x} \\
V_x(t, \mathbf{x}) &= M(t)\mathbf{x}
\end{aligned}$$

LQR via the HJB PDE

- Substituting the candidate $V(t, \mathbf{x})$ into the HJB PDE leads to the same **RDE** as before and we know that $M(t)$ satisfies it!

$$\frac{1}{2}\mathbf{x}^\top M(T)\mathbf{x} = \frac{1}{2}\mathbf{x}^\top Q_T \mathbf{x}$$
$$-\frac{1}{2}\mathbf{x}^\top \dot{M}(t)\mathbf{x} = \frac{1}{2}\mathbf{x}^\top Q\mathbf{x} + \mathbf{x}^\top A^\top M(t)\mathbf{x} - \frac{1}{2}\mathbf{x}^\top M(t)BR^{-1}B^\top M(t)\mathbf{x},\ t \in [0, T], \mathbf{x} \in \mathcal{X}$$

- **Conclusion**: Since $M(t)$ satisfies the RDE, $V(t, \mathbf{x}) = \mathbf{x}^\top M(t)\mathbf{x}$ is the unique solution to the HJB PDE and is the optimal value function for the linear quadratic problem with an associated optimal policy $\pi(t, \mathbf{x}) = -R^{-1}B^\top M(t)\mathbf{x}$.

- General strategy for continuous-time optimal control problems:
  1. Identify a candidate policy using the PMP
  2. Use intuition from 1. to guess a candidate value function
  3. Verify that the candidate policy and value function satisfy the HJB PDE

Continuous-time Finite-horizon LQG

- **Linear Quadratic Gaussian** (LQG) regulation problem:

$$\min_{\pi} \quad V^{\pi}(0,\mathbf{x}_0) := \frac{1}{2}\mathbb{E}\left\{\int_0^T e^{-\frac{t}{\gamma}} \begin{bmatrix}\mathbf{x}^\top(t) & \mathbf{u}^\top(t)\end{bmatrix} \begin{bmatrix} Q & P^\top \\ P & R\end{bmatrix} \begin{bmatrix}\mathbf{x}(t) \\ \mathbf{u}(t)\end{bmatrix} dt + e^{-\frac{T}{\gamma}}\mathbf{x}(T)^\top Q_T \mathbf{x}(T)\right\}$$

$$\text{s.t.} \quad \dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u} + C\boldsymbol{\omega}, \;\; \mathbf{x}(0) = \mathbf{x}_0$$

$$\mathbf{x}(t) \in \mathbb{R}^n, \; \mathbf{u}(t) = \pi(t,\mathbf{x}(t)) \in \mathbb{R}^m$$

- **Discount factor**: $\gamma \in [0,\infty]$
- **Optimal value**: $V^*(t,\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top M(t)\mathbf{x} + m(t)$
- **Optimal policy**: $\pi^*(t,\mathbf{x}) = -R^{-1}(P + B^\top M(t))\mathbf{x}$
- **Riccati Equation**:

$$-\dot{M}(t) = Q + A^\top M(t) + M(t)A - (P + B^\top M(t))^\top R^{-1}(P + B^\top M(t)) - \frac{1}{\gamma}M(t), \qquad M(T) = Q_T$$

$$-\dot{m} = \frac{1}{2}\operatorname{tr}(CC^\top M(t)) - \frac{1}{\gamma}m(t), \qquad m(T) = 0$$

- $M(t)$ is independent of the noise amplitude C, which implies that the optimal policy $\pi^*(t,\mathbf{x})$ is **the same for the stochastic (LQG) and deterministic (LQR) problems**!

Continuous-time Infinite-horizon LQG

- **Linear Quadratic Gaussian** (LQG) regulation problem:

$$\begin{aligned}\min_{\pi} \quad & V^{\pi}(\mathbf{x}_0) := \frac{1}{2}\mathbb{E}\left\{\int_0^{\infty} e^{-\frac{t}{\gamma}} \begin{bmatrix}\mathbf{x}^\top(t) & \mathbf{u}^\top(t)\end{bmatrix} \begin{bmatrix} Q & P^\top \\ P & R\end{bmatrix} \begin{bmatrix}\mathbf{x}(t) \\ \mathbf{u}(t)\end{bmatrix} dt\right\} \\ \text{s.t.} \quad & \dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u} + C\boldsymbol{\omega}, \;\; \mathbf{x}(0) = \mathbf{x}_0 \\ & \mathbf{x}(t) \in \mathbb{R}^n, \; \mathbf{u}(t) = \pi(\mathbf{x}(t)) \in \mathbb{R}^m\end{aligned}$$

- **Discount factor**: $\gamma \in [0, \infty)$
- **Optimal value**: $V^*(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top M\mathbf{x} + m$
- **Optimal policy**: $\pi^*(\mathbf{x}) = -R^{-1}(P + B^\top M)\mathbf{x}$
- **Riccati Equation** ('care' in Matlab):

$$\begin{aligned}\frac{1}{\gamma}M &= Q + A^\top M + MA - (P + B^\top M)^T R^{-1}(P + B^\top M) \\ m &= \frac{\gamma}{2}\operatorname{tr}(CC^\top M)\end{aligned}$$

- M is independent of the noise amplitude C, which implies that the optimal policy $\pi^*(\mathbf{x})$ is **the same for LQG and LQR**!

Discrete-time Linear Quadratic Control

Discrete-time Finite-horizon Linear Quadratic Regulator

- **Linear Quadratic Regulator** (LQR) problem:

$$
\begin{aligned}
\min_{\pi_{0:T-1}} \quad & V_0^{\pi}(\mathbf{x}) := \frac{1}{2}\left\{\sum_{t=0}^{T-1}\left(\mathbf{x}_t^\top Q\mathbf{x}_t + \mathbf{u}_t^\top R\mathbf{u}_t\right) + \mathbf{x}_T^\top Q_T\mathbf{x}_T\right\} \\
\text{s.t.} \quad & \mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{u}_t, \;\; \mathbf{x}_0 = \mathbf{x} \\
& \mathbf{x}(t) \in \mathbb{R}^n, \; \mathbf{u}_t = \pi_t(\mathbf{x}_t) \in \mathbb{R}^m
\end{aligned}
$$

- Since this is a discrete-time finite-horizon problem, we can use Dynamic Programming

- At $t = T$, there are no control choices and the value function is quadratic in $\mathbf{x}$:

$$
V_T^*(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top M_T\mathbf{x} := \frac{1}{2}\mathbf{x}^\top Q_T\mathbf{x}, \qquad \forall \mathbf{x} \in \mathbb{R}^n
$$

- Iterate backwards in time $t = T-1, \ldots, 0$:

$$
V_t^*(\mathbf{x}) = \min_{\mathbf{u}}\left\{\frac{1}{2}\left(\mathbf{x}^\top Q\mathbf{x} + \mathbf{u}^\top R\mathbf{u}\right) + V_{t+1}^*(A\mathbf{x} + B\mathbf{u})\right\}
$$

Discrete-time Finite-horizon Linear Quadratic Regulator

- At $t = T - 1$:

$$V^*_{T-1}(\mathbf{x}) = \min_{\mathbf{u}} \frac{1}{2} \left\{ \mathbf{x}^\top Q \mathbf{x} + \mathbf{u}^\top R \mathbf{u} + (A\mathbf{x} + B\mathbf{u})^\top M_T (A\mathbf{x} + B\mathbf{u}) \right\}$$

- $V^*_{T-1}(\mathbf{x})$ is a positive-definite quadratic function of $\mathbf{u}$ since $R \succ 0$
- Taking the gradient and setting it equal to 0:

$$\begin{aligned}
\pi^*_{T-1}(\mathbf{x}) &= -\left(B^\top Q_T B + R\right)^{-1} B^\top Q_T A\mathbf{x} \\
V^*_{T-1}(\mathbf{x}) &= \frac{1}{2}\mathbf{x}^\top M_{T-1}\mathbf{x} \\
M_{T-1} &= A^\top M_T A + Q - A^\top M_T B \left(B^\top M_T B + R\right)^{-1} B^\top M_T A
\end{aligned}$$

Discrete-time Finite-horizon Linear Quadratic Regulator

- At $t = T - 2$:

$$V^*_{T-2}(\mathbf{x}) = \min_{\mathbf{u}} \frac{1}{2} \left\{ \mathbf{x}^\top Q \mathbf{x} + \mathbf{u}^\top R \mathbf{u} + (A\mathbf{x} + B\mathbf{u})^\top M_{T-1} (A\mathbf{x} + B\mathbf{u}) \right\}$$

- $V^*_{T-2}(\mathbf{x})$ is a positive-definite quadratic function of $\mathbf{u}$ since $R \succ 0$

- Taking the gradient and setting it equal to 0:

$$\pi^*_{T-2}(\mathbf{x}) = -\left(B^\top M_{T-1} B + R \right)^{-1} B^\top M_{T-1} A \mathbf{x}$$

$$V^*_{T-2}(\mathbf{x}) = \frac{1}{2} \mathbf{x}^\top M_{T-2} \mathbf{x}$$

$$M_{T-2} = A^\top M_{T-1} A + Q - A^\top M_{T-1} B \left(B^\top M_{T-1} B + R \right)^{-1} B^\top M_{T-1} A$$

Discrete-time Finite-horizon Linear Quadratic Regulator

- **Batch Approach**: instead of using the DP algorithm, express the system evolution as a large matrix system

$$\underbrace{\begin{bmatrix} \mathbf{x}_0 \\ \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_T \end{bmatrix}}_{\mathbf{s}} = \underbrace{\begin{bmatrix} I \\ A \\ \vdots \\ A^T \end{bmatrix}}_{\mathcal{A}} \mathbf{x}_0 + \underbrace{\begin{bmatrix} 0 & \cdots & \cdots & 0 \\ B & 0 & \cdots & 0 \\ AB & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ A^{T-1}B & \cdots & \cdots & B \end{bmatrix}}_{\mathcal{B}} \underbrace{\begin{bmatrix} \mathbf{u}_0 \\ \mathbf{u}_1 \\ \vdots \\ \mathbf{u}_{T-1} \end{bmatrix}}_{\mathbf{v}}$$

- Write the objective function in terms of $\mathbf{s}$ and $\mathbf{v}$:

$$V_0^\pi(\mathbf{x}_0) = \frac{1}{2}\left(\mathbf{s}^T \mathcal{Q} \mathbf{s} + \mathbf{v}^T \mathcal{R} \mathbf{v}\right) \qquad \begin{aligned} \mathcal{Q} &:= \mathbf{diag}(Q, \ldots, Q, Q_T) \succeq 0 \\ \mathcal{R} &:= \mathbf{diag}(R, \ldots, R) \succ 0 \end{aligned}$$

Discrete-time Finite-horizon Linear Quadratic Regulator

- Express $V_0^\pi(\mathbf{x}_0)$ only in terms of the initial condition $\mathbf{x}_0$ and the control sequence $\mathbf{v}$ by using the batch dynamics $\mathbf{s} = \mathcal{A}\mathbf{x}_0 + \mathcal{B}\mathbf{v}$:

$$V_0^\pi(\mathbf{x}_0) = \frac{1}{2}\left(\mathbf{v}^\top\left(\mathcal{B}^\top\mathcal{Q}\mathcal{B} + \mathcal{R}\right)\mathbf{v} + 2\mathbf{x}_0^\top\left(\mathcal{A}^\top\mathcal{Q}\mathcal{A}\right)\mathbf{v} + \mathbf{x}_0^\top\mathcal{A}^\top\mathcal{Q}\mathcal{A}\mathbf{x}_0\right)$$

- $V_0^\pi(\mathbf{x}_0)$ is a positive-definite quadratic function of $\mathbf{v}$ since $\mathcal{R} \succ 0$

- Taking the gradient wrt $\mathbf{v}$ and setting it equal to 0:

$$\begin{aligned}
\mathbf{v}^* &= -\left(\mathcal{B}^\top\mathcal{Q}\mathcal{B} + \mathcal{R}\right)^{-1}\mathcal{B}^\top\mathcal{Q}\mathcal{A}\mathbf{x}_0 \\
V_0^*(\mathbf{x}_0) &= \frac{1}{2}\mathbf{x}_0^\top\left(\mathcal{A}^\top\mathcal{Q}\mathcal{A} - \mathcal{A}^\top\mathcal{Q}\mathcal{B}\left(\mathcal{B}^\top\mathcal{Q}\mathcal{B} + \mathcal{R}\right)^{-1}\mathcal{B}^\top\mathcal{Q}\mathcal{A}\right)\mathbf{x}_0
\end{aligned}$$

- The optimal sequence of control inputs $\mathbf{u}_{0:T-1}^*$ is a linear function of $\mathbf{x}_0$

- The optimal value function $V_0^*(\mathbf{x}_0)$ is a quadratic function of $\mathbf{x}_0$

Discrete-time Finite-horizon LQG

- **Linear Quadratic Gaussian** (LQG) regulation problem:

$$\min_{\pi_{0:T-1}} \quad V_0^{\pi}(\mathbf{x}) := \frac{1}{2}\mathbb{E}\left\{\sum_{t=0}^{T-1}\gamma^t\left(\mathbf{x}_t^\top Q\mathbf{x}_t + 2\mathbf{u}_t^\top P\mathbf{x}_t + \mathbf{u}_t^\top R\mathbf{u}_t\right) + \gamma^T\mathbf{x}_T^\top Q_T\mathbf{x}_T\right\}$$

$$\text{s.t.} \quad \mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{u}_t + C\mathbf{w}_t, \;\; \mathbf{x}_0 = \mathbf{x}, \; \mathbf{w}_t \sim \mathcal{N}(0, I)$$

$$\mathbf{x}_t \in \mathbb{R}^n, \; \mathbf{u}_t = \pi_t(\mathbf{x}_t) \in \mathbb{R}^m$$

- **Discount factor**: $\gamma \in [0, 1]$
- **Optimal value**: $V_t^*(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top M_t\mathbf{x} + m_t$
- **Optimal policy**: $\pi_t^*(\mathbf{x}) = -(R + \gamma B^\top M_{t+1}B)^{-1}(P + \gamma B^\top M_{t+1}A)\mathbf{x}$
- **Riccati Equation**:

$$M_t = Q + \gamma A^\top M_{t+1}A - (P + \gamma B^\top M_{t+1}A)^\top(R + \gamma B^\top M_{t+1}B)^{-1}(P + \gamma B^\top M_{t+1}A), \quad M_T = Q_T$$

$$m_t = \gamma m_{t+1} + \gamma\frac{1}{2}\text{tr}(CC^\top M_{t+1}), \qquad m_T = 0$$

- M_t is independent of the noise amplitude C, which implies that the optimal policy $\pi_t^*(\mathbf{x})$ is **the same for LQG and LQR**!

Discrete-time Infinite-horizon LQG

- **Linear Quadratic Gaussian** (LQG) regulation problem:

$$\min_{\pi} \; V^{\pi}(\mathbf{x}) := \frac{1}{2}\mathbb{E}\left\{\sum_{t=0}^{\infty}\gamma^{t}\left(\mathbf{x}_t^\top Q\mathbf{x}_t + 2\mathbf{u}_t^\top P\mathbf{x}_t + \mathbf{u}_t^\top R\mathbf{u}_t\right)\right\}$$

$$\text{s.t.} \quad \mathbf{x}_{t+1} = A\mathbf{x}_t + B\mathbf{u}_t + C\mathbf{w}_t, \;\; \mathbf{x}_{t_0} = \mathbf{x}_0, \;\; \mathbf{w}_t \sim \mathcal{N}(0, I)$$

$$\mathbf{x}_t \in \mathbb{R}^n, \; \mathbf{u}_t = \pi(\mathbf{x}_t) \in \mathbb{R}^m$$

- **Discount factor**: $\gamma \in [0, 1)$
- **Optimal value**: $V^*(\mathbf{x}) = \frac{1}{2}\mathbf{x}^\top M\mathbf{x} + m$
- **Optimal policy**: $\pi^*(\mathbf{x}) = -(R + \gamma B^\top MB)^{-1}(P + \gamma B^\top MA)\mathbf{x}$
- **Riccati Equation** ('dare' in Matlab):

$$M = Q + \gamma A^\top MA - (P + \gamma B^\top MA)^\top(R + \gamma B^\top MB)^{-1}(P + \gamma B^\top MA)$$

$$m = \frac{\gamma}{2(1-\gamma)}\operatorname{tr}(CC^\top M)$$

- M is independent of the noise amplitude C, which implies that the optimal policy $\pi^*(\mathbf{x})$ is **the same for LQG and LQR**!

Relation between Continuous- and Discrete-time LQR

- The continuous-time system:

$$\dot{\mathbf{x}} = A\mathbf{x} + B\mathbf{u}$$
$$\ell(\mathbf{x}, \mathbf{u}) = \frac{1}{2}\mathbf{x}^\top Q\mathbf{x} + \frac{1}{2}\mathbf{u}^\top R\mathbf{u}$$

  can be discretized with time step τ:

$$\mathbf{x}_{t+1} = (I + \tau A)\mathbf{x}_t + \tau B\mathbf{u}_t$$
$$\tau\ell(\mathbf{x}, \mathbf{u}) = \frac{\tau}{2}\mathbf{x}^\top Q\mathbf{x} + \frac{\tau}{2}\mathbf{u}^\top R\mathbf{u}$$

- In the limit as $\tau \to 0$, the discrete-time Riccati equation reduces to the continuous one:

$$\begin{aligned}
M &= \tau Q + (I + \tau A)^\top M(I + \tau A) \\
&\qquad - (I + \tau A)^\top M\tau B(\tau R + \tau B^\top M\tau B)^{-1}\tau B^\top M(I + \tau A) \\
M &= \tau Q + M + \tau A^\top M + \tau MA - \tau MB(R + \tau B^\top MB)^{-1}B^\top M + o(\tau^2) \\
0 &= Q + A^\top M + MA - MB(R + \tau B^\top MB)^{-1}B^\top M + \frac{1}{\tau}o(\tau^2)
\end{aligned}$$

Encoding Goals as Quadratic Costs

- In the finite-horizon case, the matrices A, B, Q, R can be time-varying which is useful for specifying reference trajectories $\mathbf{x}_t^*$ and for approximating non-LQG problems
- The cost $\|\mathbf{x}_t - \mathbf{x}_t^*\|^2$ can be captured in the LQG formulation by modifying the state and cost as follows:

$$\tilde{\mathbf{x}} = \begin{bmatrix} \mathbf{x} \\ 1 \end{bmatrix} \qquad \tilde{A} = \begin{bmatrix} A & 0 \\ 0 & 1 \end{bmatrix}, \text{etc.}$$

$$\frac{1}{2}\tilde{\mathbf{x}}^\top \tilde{Q}_t \tilde{\mathbf{x}} = \frac{1}{2}\tilde{\mathbf{x}}^\top (D_t^T D_t)\tilde{\mathbf{x}} \qquad D_t \tilde{\mathbf{x}}_t := \begin{bmatrix} I & -\mathbf{x}_t^* \end{bmatrix} \tilde{\mathbf{x}}_t = \mathbf{x}_t - \mathbf{x}_t^*$$

- If the target/goal is stationary, we can instead include it in the state $\tilde{\mathbf{x}}$ and use $D := \begin{bmatrix} I & -I \end{bmatrix}$. This has the advantage that the resulting policy is independent of $\mathbf{x}^*$ and can be used for any target $\mathbf{x}^*$.