

# 114-1 Robot Perception and Learning

## CartPole Optimal Control: A Case Study

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# Important Reminder

The withdrawal deadline for this course is **Friday, October 17**. Requests submitted after this date will **not be accepted**.

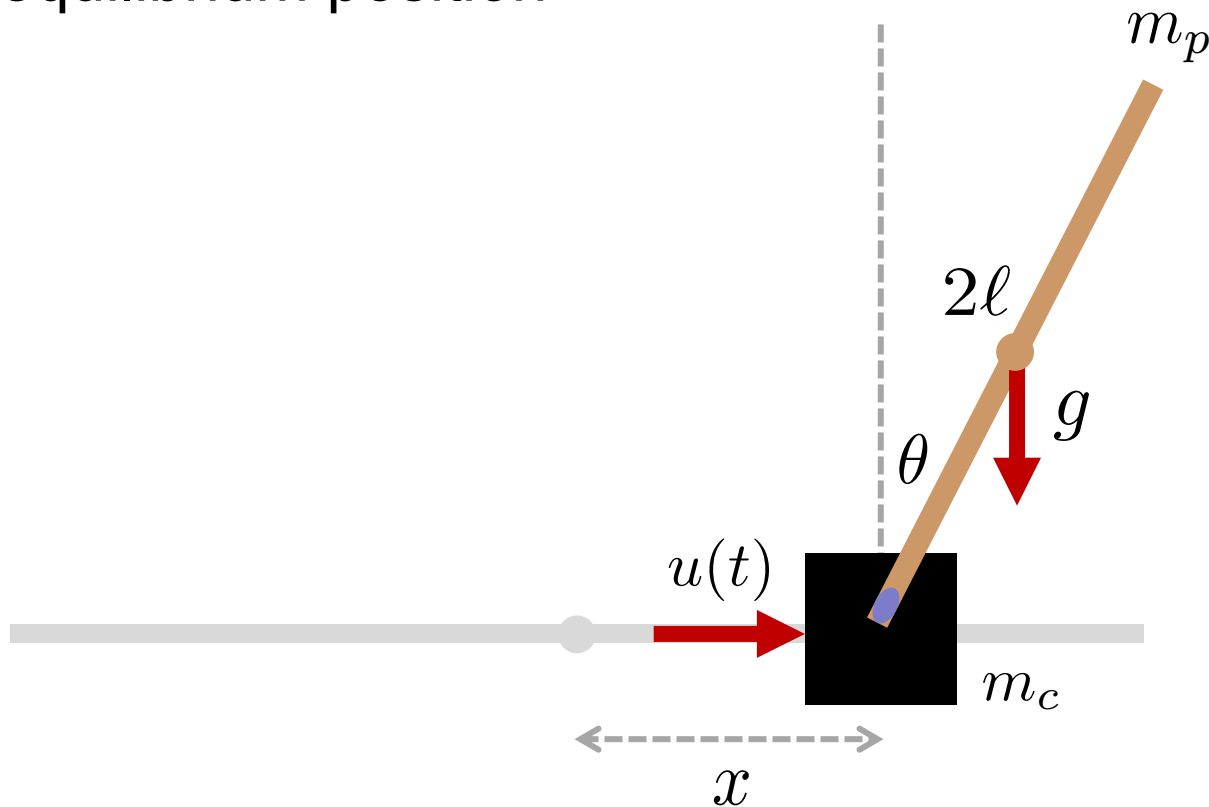


# Outline

- CartPole Problem
- Discrete-time LQR
- Steady-state Regulator
- Iterative LQR

# CartPole Problem

We aim to control the cart by applying a horizontal force  $u(t)$  such that the inverted pendulum mounted on top of the cart remains stabilized near the upright equilibrium position



- Cart mass  $m_c$
- Pole mass  $m_p$
- Pole length  $2\ell$
- Total mass  $M = m_c + m_p$
- Cart displacement  $x$
- Pole angle  $\theta$
- Gravity  $g$

# Continuous-time Dynamical System

**Nonlinear**

$$\ddot{\theta} = \frac{g \sin \theta - \cos \theta \frac{u + m_p \ell \dot{\theta}^2 \sin \theta}{M}}{\ell \left( \frac{4}{3} - \frac{m_p}{M} \cos^2 \theta \right)}$$
$$\ddot{x} = \frac{u + m_p \ell \dot{\theta}^2 \sin \theta}{M} - \frac{m_p \ell \cos \theta}{M} \ddot{\theta}$$

$$\theta \approx 0, \dot{\theta} \approx 0$$



$$\sin \theta \approx \theta$$

$$\cos \theta \approx 1$$

**Linear**

$$\ddot{\theta} \approx \frac{g}{D} \theta - \frac{1}{DM} u$$
$$\ddot{x} \approx -\alpha g \theta + \frac{1 + \alpha}{M} u$$

$$D = \ell \left( \frac{4}{3} - \frac{m_p}{M} \right)$$

$$\alpha = \frac{3m_p}{4M - 3m_p}$$

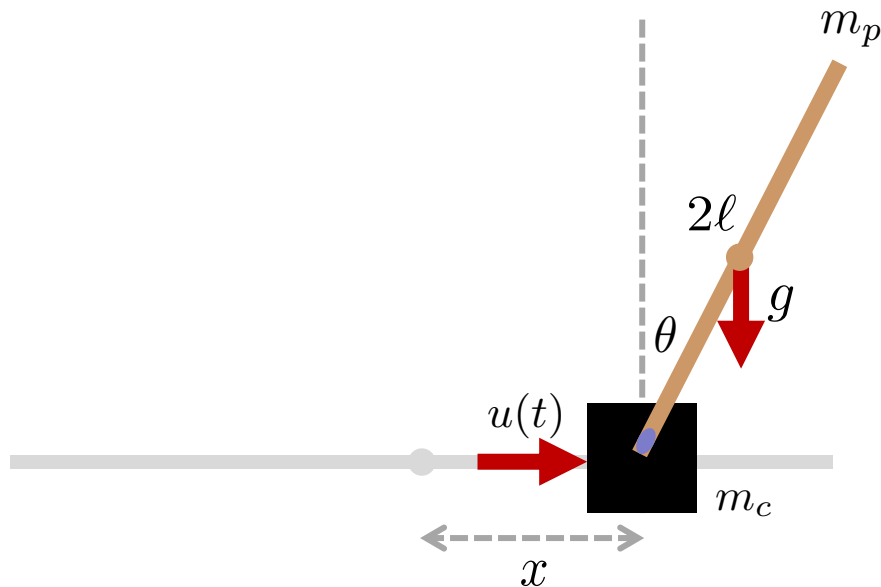


# Continuous-time Dynamical System

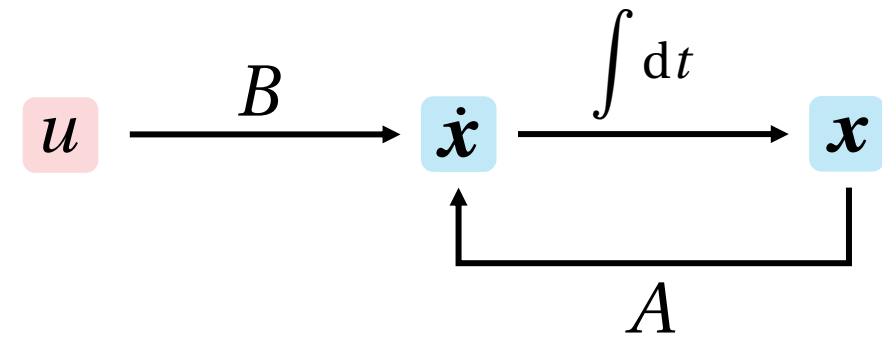
$$\begin{aligned}\ddot{\theta} &\approx \frac{g}{D}\theta - \frac{1}{DM}u \\ \ddot{x} &\approx -\alpha g\theta + \frac{1+\alpha}{M}u\end{aligned}$$



$$\begin{bmatrix} \dot{x} \\ \ddot{x} \\ \dot{\theta} \\ \ddot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & -\alpha g & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & \frac{g}{D} & 0 \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \\ \theta \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1+\alpha}{M} \\ 0 \\ -\frac{1}{DM} \end{bmatrix} u(t)$$



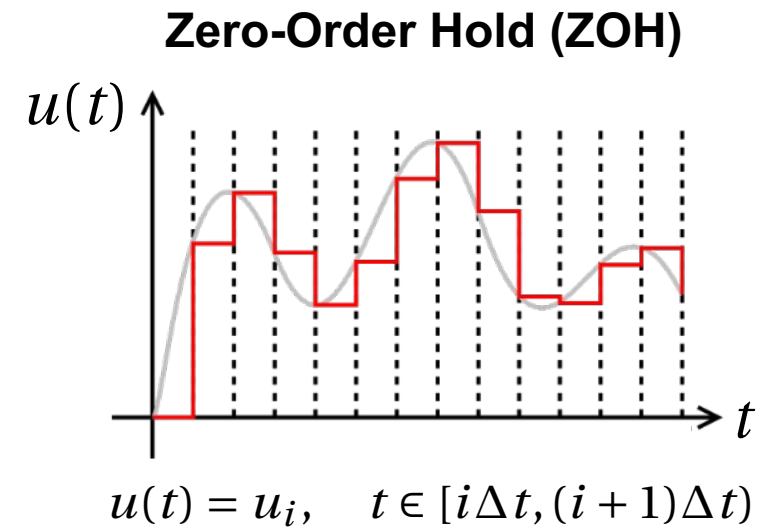
$$\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B u(t)$$



# Discretization

Consider the continuous-time linear dynamical system  $\dot{\mathbf{x}}(t) = A\mathbf{x}(t) + B u(t)$ . By integrating the dynamics from  $i\Delta t$  to  $(i+1)\Delta t$ , we obtain

$$\begin{aligned}\mathbf{x}_{i+1} &= e^{A\Delta t} \mathbf{x}_i + \int_{i\Delta t}^{(i+1)\Delta t} e^{A((i+1)\Delta t - \tau)} B u_i d\tau \\ &= e^{A\Delta t} \mathbf{x}_i + \left( \int_0^{\Delta t} e^{A\sigma} d\sigma \right) B u_i \\ &= A_d \mathbf{x}_i + B_d u_i\end{aligned}$$



# Discrete-time Linear Quadratic Regulator

Consider the discrete-time linear dynamical system  $\mathbf{x}_{i+1} = A_d \mathbf{x}_i + B_d u_i$  and the finite-horizon quadratic cost

$$J = \sum_{i=0}^{T-1} \left( \underbrace{\frac{1}{2} \mathbf{x}_i^\top Q \mathbf{x}_i}_{\text{Error term}} + \underbrace{\frac{1}{2} R u_i^2}_{\text{Control term}} \right) + \underbrace{\frac{1}{2} \mathbf{x}_T^\top Q_f \mathbf{x}_T}_{\text{Terminal error term}}$$

where  $Q, Q_f$  are positive definite and  $R > 0$ .

The objective is to find the sequence  $\{(\mathbf{x}_i, u_i)\}_{i=0}^T$  to minimize  $J$  subject to the system dynamics.



# Solution of Discrete-time LQR

Consider the discrete-time linear dynamical system  $\mathbf{x}_{i+1} = A_d \mathbf{x}_i + B_d u_i$ . The problem can be solved using *dynamic programming (DP)* with the terminal condition  $P_T = Q_f$ :

$$\begin{cases} P_i = Q + A_d^\top P_{i+1} A_d - A_d^\top P_{i+1} B_d (R + B_d^\top P_{i+1} B_d)^{-1} B_d^\top P_{i+1} A_d \\ K_i = (R + B_d^\top P_{i+1} B_d)^{-1} B_d^\top P_{i+1} A_d \\ u_i = -K_i \mathbf{x}_i \end{cases}$$

# Steady-state Regulator

If the system satisfies the following conditions:

- (i)  $A_d, B_d$  are fixed
- (ii)  $(A_d, B_d)$  is controllable
- (iii)  $(A_d, Q^{1/2})$  is observable
- (iv)  $Q$  is positive definite and  $R > 0$ .

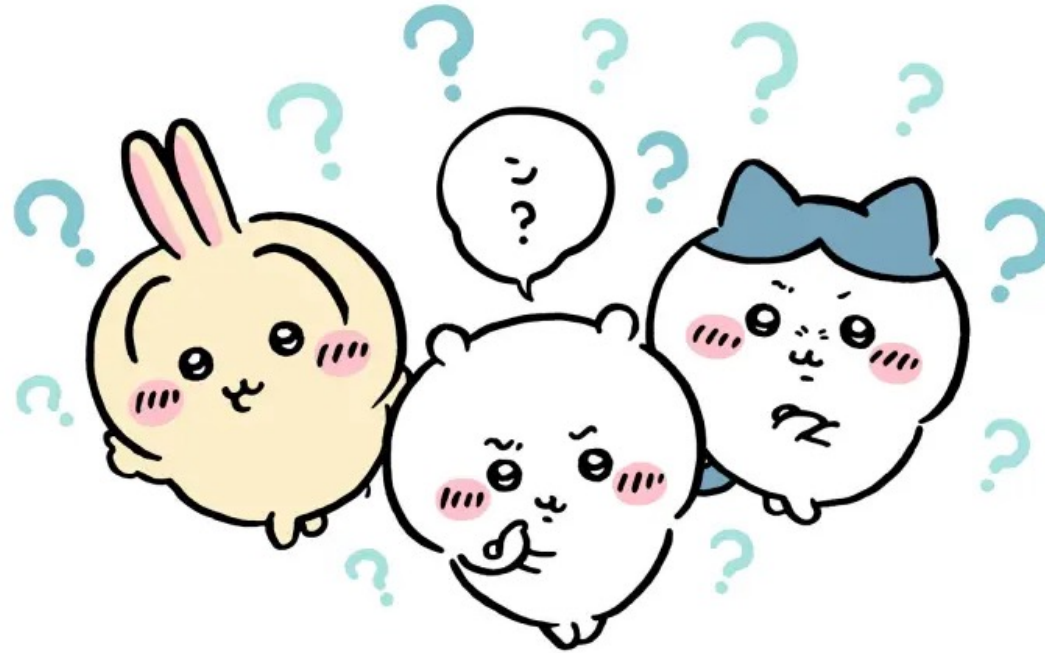
Then the sequence  $\{P_i\}$  converges to a steady-state matrix  $P_\infty$ , which satisfies the *discrete algebraic Riccati equation (DARE)*:

$$P_\infty = Q + A_d^\top P_\infty A_d - A_d^\top P_\infty B_d (R + B_d^\top P_\infty B_d)^{-1} B_d^\top P_\infty A_d$$

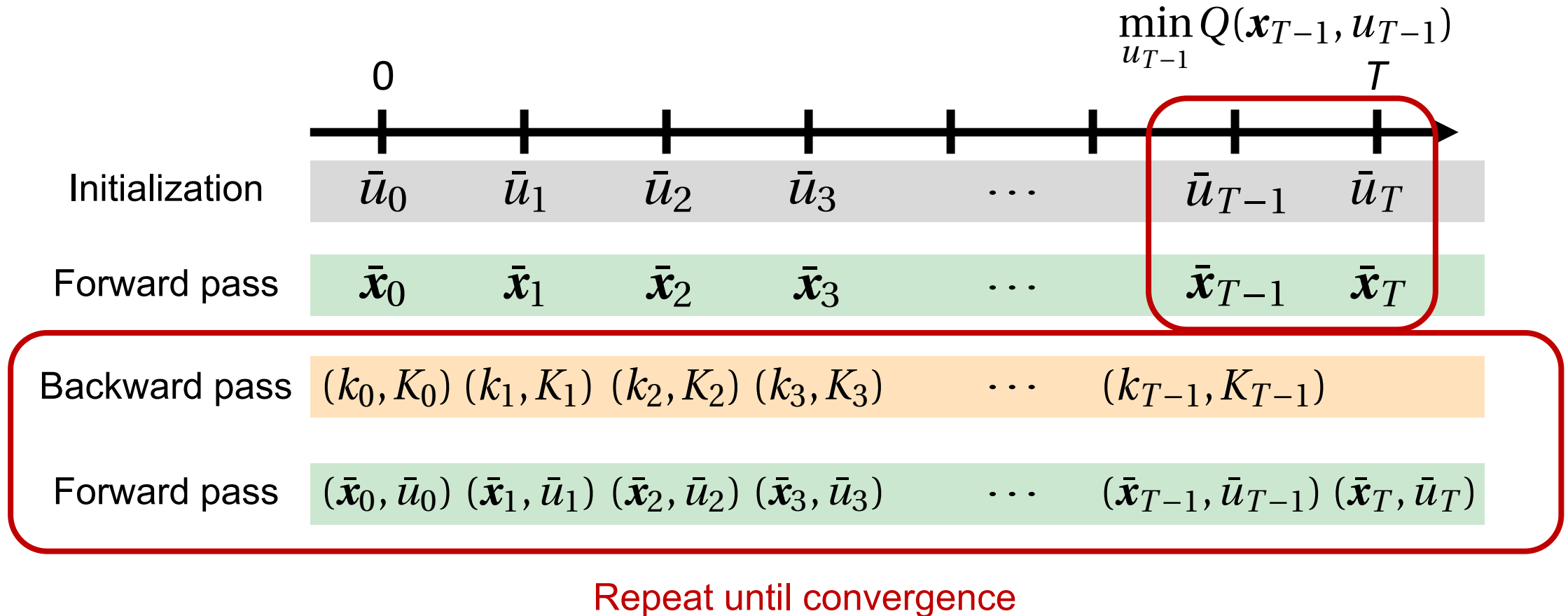
The steady-state control gain is  $K_\infty = (R + B_d^\top P_\infty B_d)^{-1} B_d^\top P_\infty A_d$  and the corresponding feedback law is

$$u_i = -K_\infty \mathbf{x}_i$$

*LQR makes life easy, but robots don't always follow linear scripts.  
So what's next?*



# Iterative LQR (iLQR)



# Iterative LQR (iLQR)

$$\boxed{\mathbf{x}_{i+1} = f(\mathbf{x}_i, u_i)} \xrightarrow{\text{Linearization}} \boxed{\mathbf{x}_{i+1} \approx \frac{\partial f}{\partial \mathbf{x}}(\mathbf{x}_i, u_i) \mathbf{x}_i + \frac{\partial f}{\partial u}(\mathbf{x}_i, u_i) u_i}$$

Let  $\{(\bar{\mathbf{x}}_i, \bar{u}_i)\}_{i=1}^T$  be the nominal trajectory. We denote deviations by

$$\delta \mathbf{x}_i = \mathbf{x}_i - \bar{\mathbf{x}}_i, \quad \delta u_i = u_i - \bar{u}_i.$$

Then we obtain

$$\delta \mathbf{x}_{i+1} = A_i \delta \mathbf{x}_i + B_i \delta u_i$$

where  $A_i = \frac{\partial f}{\partial \mathbf{x}}(\mathbf{x}_i, u_i)$  and  $B_i = \frac{\partial f}{\partial u}(\mathbf{x}_i, u_i)$ .

# Iterative LQR (iLQR)

Consider the discrete-time linear dynamical system  $\mathbf{x}_{i+1} = A_i \mathbf{x}_i + B_i u_i$  and the finite-horizon quadratic cost

$$J = \sum_{i=0}^{T-1} \underbrace{c(\mathbf{x}_i, u_i)}_{\text{Running cost}} + \underbrace{\phi(\mathbf{x}_T)}_{\text{Terminal cost}}$$

The objective is to find the sequence  $\{(\mathbf{x}_i, u_i)\}_{i=0}^T$  to minimize  $J$  subject to the system dynamics.

# Iterative LQR (iLQR)

Let the *value function* be

$$V(\mathbf{x}_t, t) := \min_{\{u_k\}_{k=t}^{T-1}} \sum_{k=t}^{T-1} c(\mathbf{x}_k, u_k) + \phi(\mathbf{x}_T)$$

The recursion has the form (Bellman equation):

$$\begin{aligned} V(\mathbf{x}_t, t) &= \min_{\{u_k\}_{k=t}^{T-1}} \left[ c(\mathbf{x}_t, u_t) + \sum_{k=t+1}^{T-1} c(\mathbf{x}_k, u_k) + \phi(\mathbf{x}_T) \right] \\ &= \min_{u_t} [c(\mathbf{x}_t, u_t) + V(\mathbf{x}_{t+1}, t+1)] \end{aligned}$$

# Iterative LQR (iLQR)

Define the *Q-function* as

$$Q(\mathbf{x}_t, u_t) = c(\mathbf{x}_t, u_t) + V(\mathbf{x}_{t+1}, t + 1)$$

The value function can be written as

$$V(\mathbf{x}_t, t) = \min_{u_t} Q(\mathbf{x}_t, u_t).$$



# Backward Pass

Comparing coefficients of  $Q(\mathbf{x}_t, u_t) = c(\mathbf{x}_t, u_t) + V(\mathbf{x}_{t+1}, t+1)$

$$Q(\mathbf{x}_t, u_t) \approx Q(\bar{\mathbf{x}}_t, \bar{u}_t) + Q_{\mathbf{x}_t}^\top \delta \mathbf{x}_t + Q_{u_t}^\top \delta u_t \\ + \frac{1}{2} \delta \mathbf{x}_t^\top Q_{\mathbf{x}_t \mathbf{x}_t} \delta \mathbf{x}_t + \frac{1}{2} \delta u_t^\top Q_{u_t u_t} \delta u_t + \delta u_t^\top Q_{\mathbf{x}_t u_t} \delta \mathbf{x}_t$$

$$c(\mathbf{x}_t, u_t) \approx c(\bar{\mathbf{x}}_t, \bar{u}_t) + c_{\mathbf{x}_t}^\top \delta \mathbf{x}_t + c_{u_t}^\top \delta u_t \\ + \frac{1}{2} \delta \mathbf{x}_t^\top c_{\mathbf{x}_t \mathbf{x}_t} \delta \mathbf{x}_t + \frac{1}{2} \delta u_t^\top c_{u_t u_t} \delta u_t + \delta u_t^\top c_{\mathbf{x}_t u_t} \delta \mathbf{x}_t$$

$$V(\mathbf{x}_{t+1}, t+1) = V(\bar{\mathbf{x}}_{t+1}, t+1) + V_{\mathbf{x}_{t+1}}^\top A_t \delta \mathbf{x}_t + V_{\mathbf{x}_{t+1}}^\top B_t \delta u_t \\ + \frac{1}{2} \delta \mathbf{x}_t^\top A_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} A_t \delta \mathbf{x}_t + \frac{1}{2} \delta u_t^\top B_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} B_t \delta u_t \\ + \delta u_t^\top B_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} A_t \delta \mathbf{x}_t$$

$$Q_{\mathbf{x}_t} = c_{\mathbf{x}_t} + A_t^\top V_{\mathbf{x}_{t+1}}$$

$$Q_{u_t} = c_{u_t} + B_t^\top V_{\mathbf{x}_{t+1}}$$

$$Q_{\mathbf{x}_t \mathbf{x}_t} = c_{\mathbf{x}_t \mathbf{x}_t} + A_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} A_t$$

$$Q_{u_t u_t} = c_{u_t u_t} + B_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} B_t$$

$$Q_{u_t \mathbf{x}_t} = c_{\mathbf{x}_t u_t} + B_t^\top V_{\mathbf{x}_{t+1} \mathbf{x}_{t+1}} A_t$$

# Backward Pass

$$V(\mathbf{x}_t, t) = \min_{u_t} Q(\mathbf{x}_t, u_t)$$

$$\begin{aligned} Q(\mathbf{x}_t, u_t) \approx & Q(\bar{\mathbf{x}}_t, \bar{u}_t) + Q_{\mathbf{x}_t}^\top \delta \mathbf{x}_t + Q_{u_t}^\top \delta u_t \\ & + \frac{1}{2} \delta \mathbf{x}_t^\top Q_{\mathbf{x}_t \mathbf{x}_t} \delta \mathbf{x}_t + \frac{1}{2} \delta u_t^\top Q_{u_t u_t} \delta u_t + \delta u_t^\top Q_{\mathbf{x}_t u_t} \delta \mathbf{x}_t \end{aligned}$$

To minimize  $Q$ , we set its first-order condition to zero:

$$0 = \frac{\partial Q}{\partial u_t} = Q_{u_t} + Q_{u_t u_t} \delta u_t + Q_{u_t \mathbf{x}_t} \delta \mathbf{x}_t$$

Then we have

$$u_t = \bar{u}_t + k_t + K_t \delta \mathbf{x}_t$$

where  $k_t = -Q_{u_t u_t}^{-1} Q_{u_t}$  and  $K_t = -Q_{u_t u_t}^{-1} Q_{u_t \mathbf{x}_t}$ .

# Forward Pass

Given the feedback gains  $\{(k_t, K_t)\}_{t=1}^T$ , define the updated control around the nominal as

$$u'_t = \bar{u}_t + k_t + K_t \delta \mathbf{x}_t$$

$$\mathbf{x}'_{t+1} = f(\mathbf{x}'_t, u'_t)$$

# iLQR Algorithm

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## Algorithm 1 Iterative Linear Quadratic Regulator (iLQR)

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- 1: **Input:** dynamics function  $f$ , cost function  $l$ , terminal cost  $\phi$ , initial state  $\bar{x}_0$ , initial control sequence  $\{\bar{u}_t\}_{t=0}^{T-1}$ , horizon  $T$
- 2: Compute initial nominal trajectory  $\{\bar{x}_t\}_{t=0}^T$  by forward rollout:  $\bar{x}_{t+1} = f(\bar{x}_t, \bar{u}_t)$
- 3: Compute cost:  $J \leftarrow \phi(\bar{x}_T) + \sum_{t=0}^{T-1} l(\bar{x}_t, \bar{u}_t)$
- 4: **while**  $J$  does not converge **do**
- 5:   Linearize dynamics around nominal trajectory:

$$\delta x_t = x_t - \bar{x}_t, \quad \delta u_t = u_t - \bar{u}_t$$

$$A_t = \left. \frac{\partial f}{\partial x} \right|_{(\bar{x}_t, \bar{u}_t)}, \quad B_t = \left. \frac{\partial f}{\partial u} \right|_{(\bar{x}_t, \bar{u}_t)}$$

### Backward Pass

- 6: Initialize terminal value function derivatives:  $V_{x_T} = \phi_{x_T}(\bar{x}_T)$ ,  $V_{x_T x_T} = \phi_{x_T x_T}(\bar{x}_T)$
- 7: **for**  $t = T - 1$  to  $0$  **do**
- 8:   Compute  $Q$ -function coefficients:
 
$$Q_{x_t} \leftarrow c_{x_t} + A_t^\top V_{x_{t+1}}$$

$$Q_{u_t} \leftarrow c_{u_t} + B_t^\top V_{x_{t+1}}$$

$$Q_{x_t x_t} \leftarrow c_{x_t x_t} + A_t^\top V_{x_{t+1} x_{t+1}} A_t$$

$$Q_{u_t u_t} \leftarrow c_{u_t u_t} + B_t^\top V_{x_{t+1} x_{t+1}} B_t$$

$$Q_{u_t x_t} \leftarrow c_{u_t x_t} + B_t^\top V_{x_{t+1} x_{t+1}} A_t$$
- 9:   Compute local optimal feedback gains:
 
$$k_t \leftarrow -Q_{u_t u_t}^{-1} Q_{u_t}$$

$$K_t \leftarrow -Q_{u_t u_t}^{-1} Q_{u_t x_t}$$
- 10:   Update value function derivatives:
 
$$V_{x_t} \leftarrow Q_{x_t} - Q_{u_t x_t}^\top Q_{u_t u_t}^{-1} Q_{u_t}$$

$$V_{x_t x_t} \leftarrow Q_{x_t x_t} - Q_{u_t x_t}^\top Q_{u_t u_t}^{-1} Q_{u_t x_t}$$
- 11: **end for**

### Forward Pass

- 12:  $x'_0 \leftarrow \bar{x}_0$
  - 13: **for**  $t = 0$  to  $T - 1$  **do**
  - 14:   Update control action and state:
 
$$u'_t \leftarrow \bar{u}_t + k_t + K_t(x'_t - \bar{x}_t)$$

$$x'_{t+1} \leftarrow f(x'_t, u'_t)$$
  - 15: **end for**
  - 16:   Compute cost:  $J \leftarrow \phi(x'_T) + \sum_{t=0}^{T-1} c(x'_t, u'_t)$
  - 17:   Update nominal sequence:  $\{(\bar{x}_t, \bar{u}_t)\}_{t=1}^T \leftarrow \{(x'_t, u'_t)\}_{t=1}^T$
  - 18: **end while**
  - 19: **return**  $\{(x'_t, u'_t)\}_{t=1}^T$
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# Takeaway

- LQR offers a mathematically elegant solution to stabilize linearized CartPole dynamics.
- Steady-state LQR simplifies control with constant gain in infinite-horizon settings.
- iLQR generalizes this idea to nonlinear systems, updating nominal trajectories iteratively for locally optimal performance and forming a fundamental concept in modern trajectory optimization in robotics.

# Thank you