

CSE 478 Robot Autonomy

Linear Quadratic Regulator

Abhishek Gupta (abhgupta@cs)
Siddhartha Srinivasa (siddh@cs)

TAs:

Carolina Higuera (chiguera@cs)
Rishabh Jain (jrishabh@cs)
Entong Su (ensu@cs)



Control as an Optimization Problem

- For a sequence of H control actions
 1. Use model to predict consequence of actions (i.e., H future states)
 2. Evaluate the cost function
- Compute optimal sequence of H control actions (minimizes cost)

Linear Quadratic Regulator

- **Linear** system (model)
- **Quadratic** cost function to minimize

$$\begin{aligned}x_{t+1} &= Ax_t + Bu_t \\ \sum_t x_t^\top Q x_t + u_t^\top R u_t\end{aligned}$$

Linear System

- **Linear** system (model)
- **Quadratic** cost function to minimize

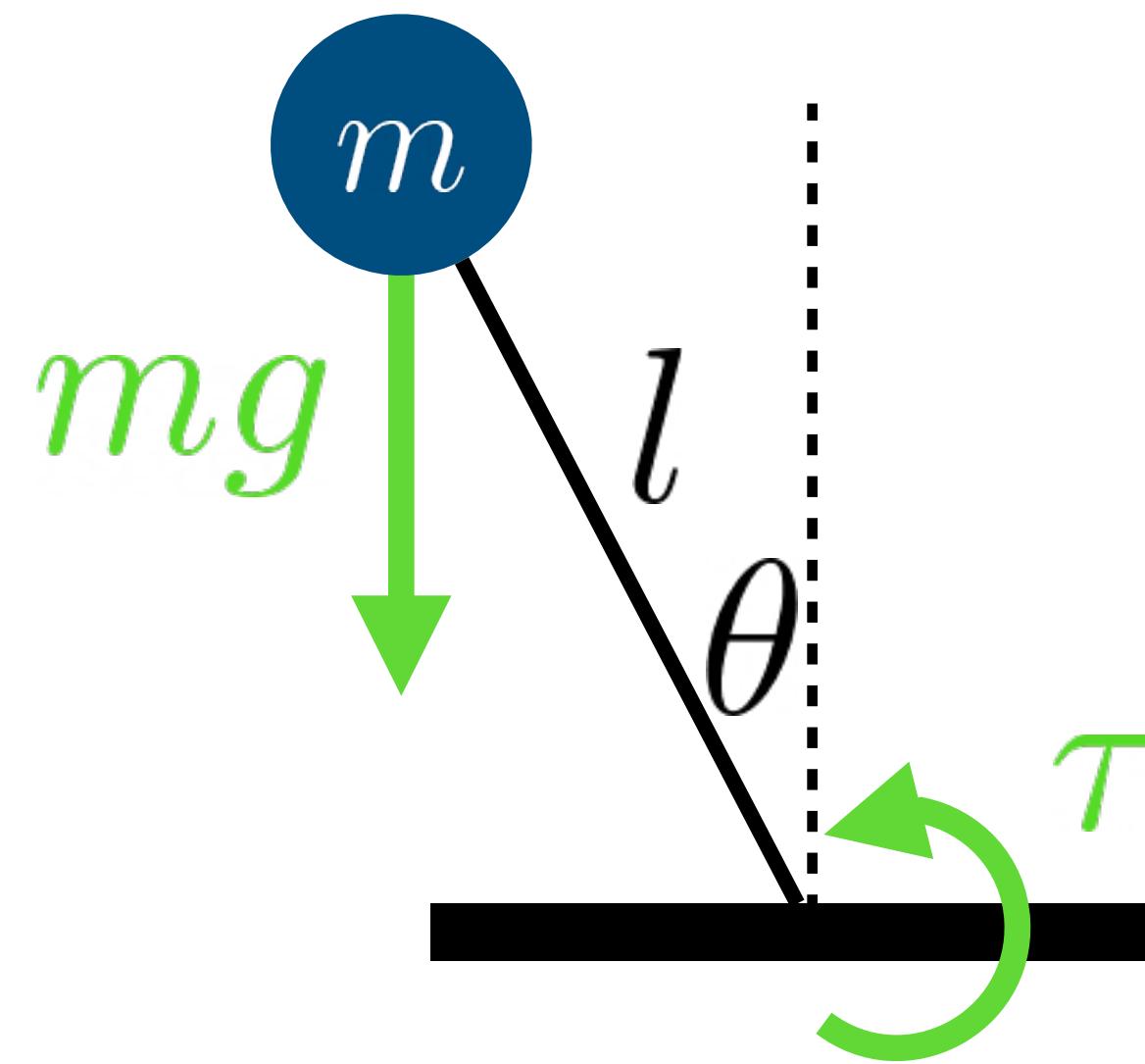
$$x_{t+1} = Ax_t + Bu_t$$
$$\sum_t x_t^\top Q x_t + u_t^\top R u_t$$

$$x_{t+1} = A x_t + B u_t$$
$$(N \times 1) \quad (N \times N) (N \times 1) \quad (N \times M) (M \times 1)$$

STATE → NEXT
STATE

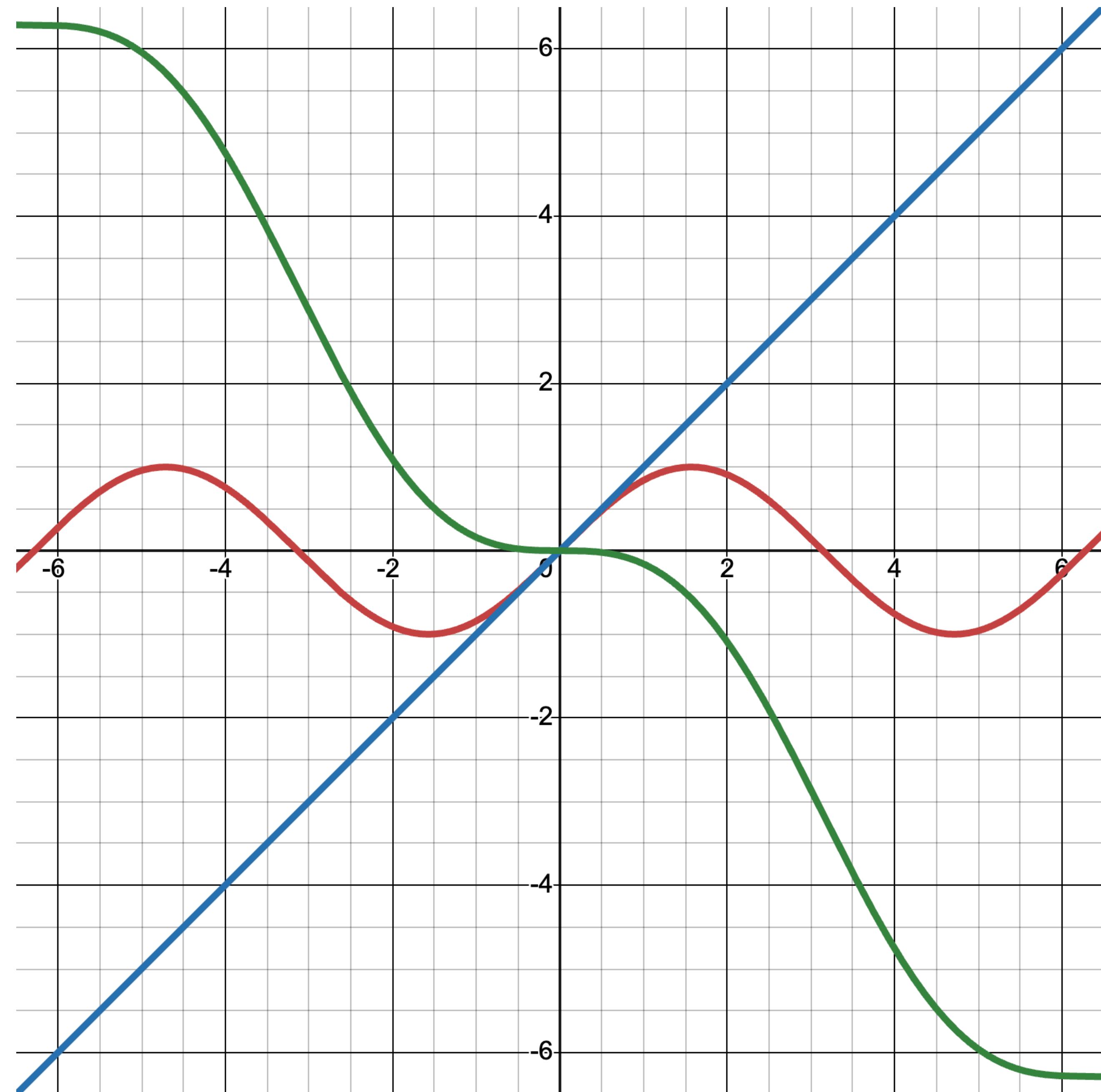
CONTROL → NEXT
STATE

Example: Inverted Pendulum (Linear System)



$$mgl \sin \theta + \tau = ml^2 \ddot{\theta}$$
$$\ddot{\theta} = \frac{g}{l} \sin \theta + \frac{\tau}{ml^2} \approx \frac{g}{l} \theta + \frac{\tau}{ml^2}$$

Small angle assumption

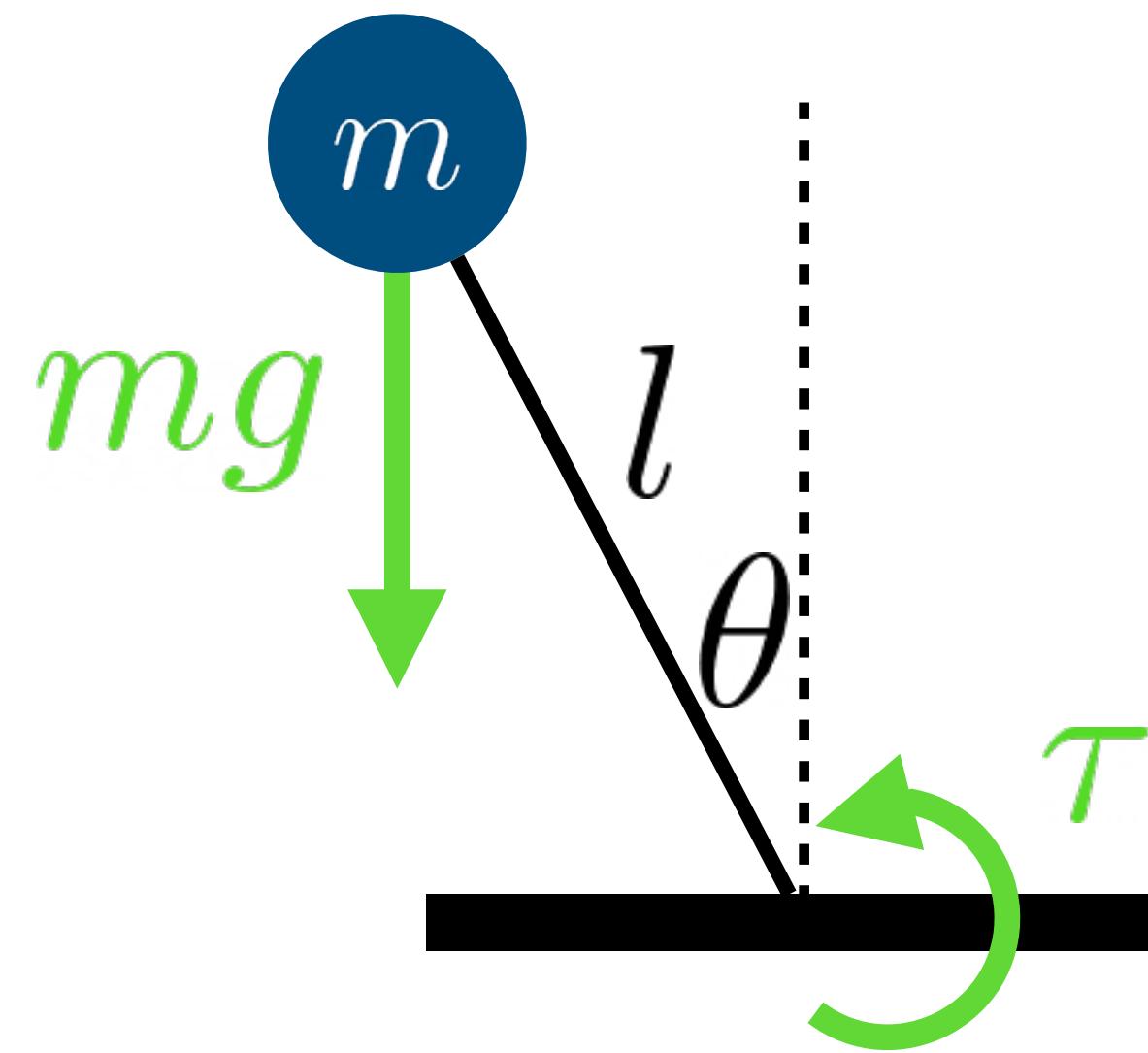


$$y = x$$

$$y = \sin(x)$$

$$y = x - \sin(x)$$

Example: Inverted Pendulum (Linear System)



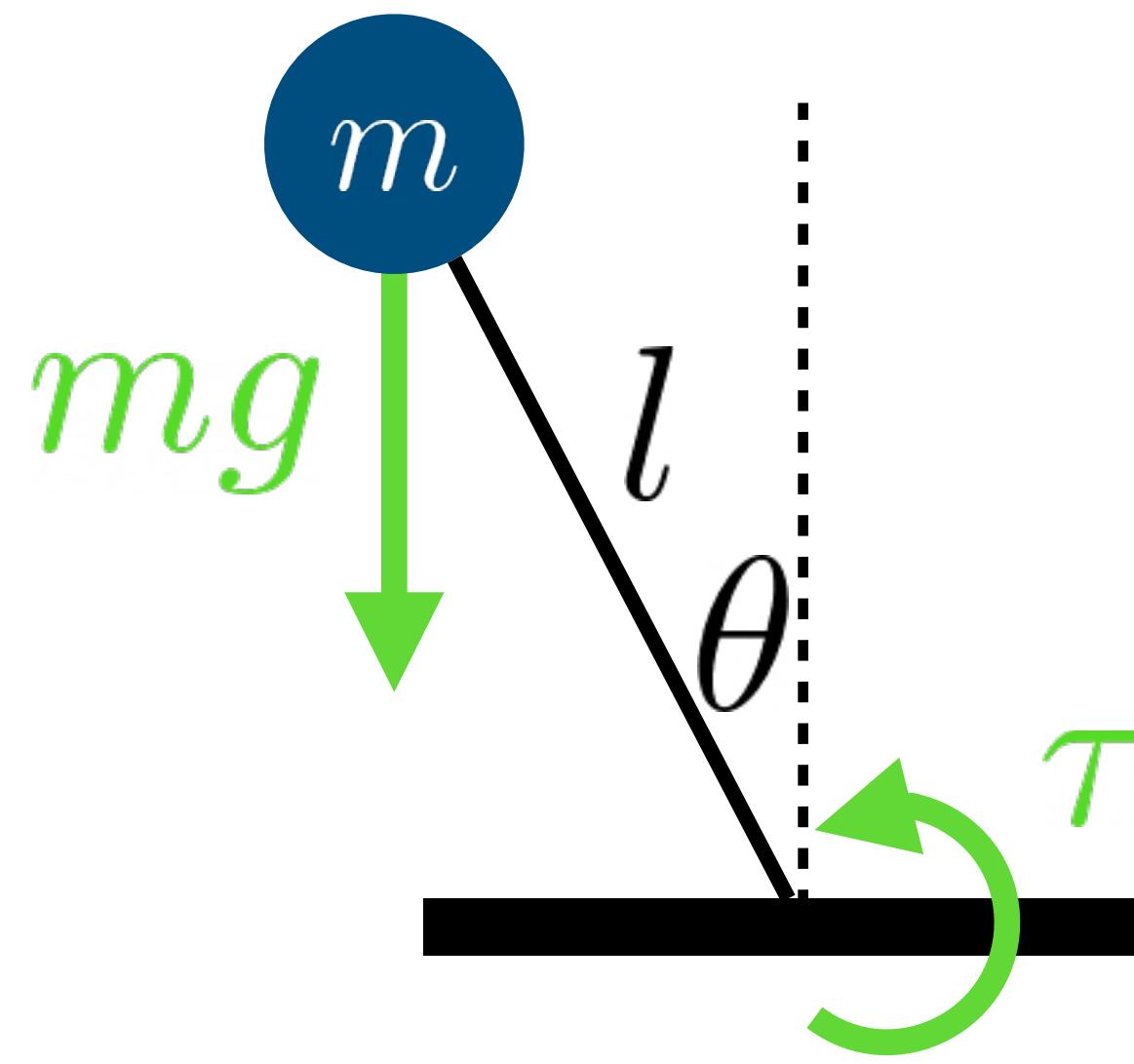
$$mgl \sin \theta + \tau = ml^2 \ddot{\theta}$$
$$\ddot{\theta} = \frac{g}{l} \sin \theta + \frac{\tau}{ml^2} \approx \frac{g}{l} \theta + \frac{\tau}{ml^2}$$

$$\dot{\theta}_{t+1} = \frac{\theta_{t+1} - \theta_t}{\Delta t}$$

$$\ddot{\theta}_{t+1} = \frac{\dot{\theta}_{t+1} - \dot{\theta}_t}{\Delta t}$$

Finite Differences

Example: Inverted Pendulum (Linear System)



$$mgl \sin \theta + \tau = ml^2 \ddot{\theta}$$
$$\ddot{\theta} = \frac{g}{l} \sin \theta + \frac{\tau}{ml^2} \approx \frac{g}{l} \theta + \frac{\tau}{ml^2}$$

$$\begin{bmatrix} \theta_{t+1} \\ \dot{\theta}_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ \frac{g}{l} \Delta t & 1 \end{bmatrix} \begin{bmatrix} \theta_t \\ \dot{\theta}_t \end{bmatrix} + \begin{bmatrix} 0 \\ \Delta t \end{bmatrix} \frac{\tau}{ml^2}$$

 x_{t+1} A x_t B u_t

Quadratic Cost Function

- **Linear** system (model)
- **Quadratic** cost function to minimize

**What state errors
do we care about?**

$$x_t^\top Q x_t$$

$(1 \times N)(N \times N)(N \times 1)$

STATE COST

$$x_{t+1} = Ax_t + Bu_t$$
$$\sum_t x_t^\top Q x_t + u_t^\top R u_t$$

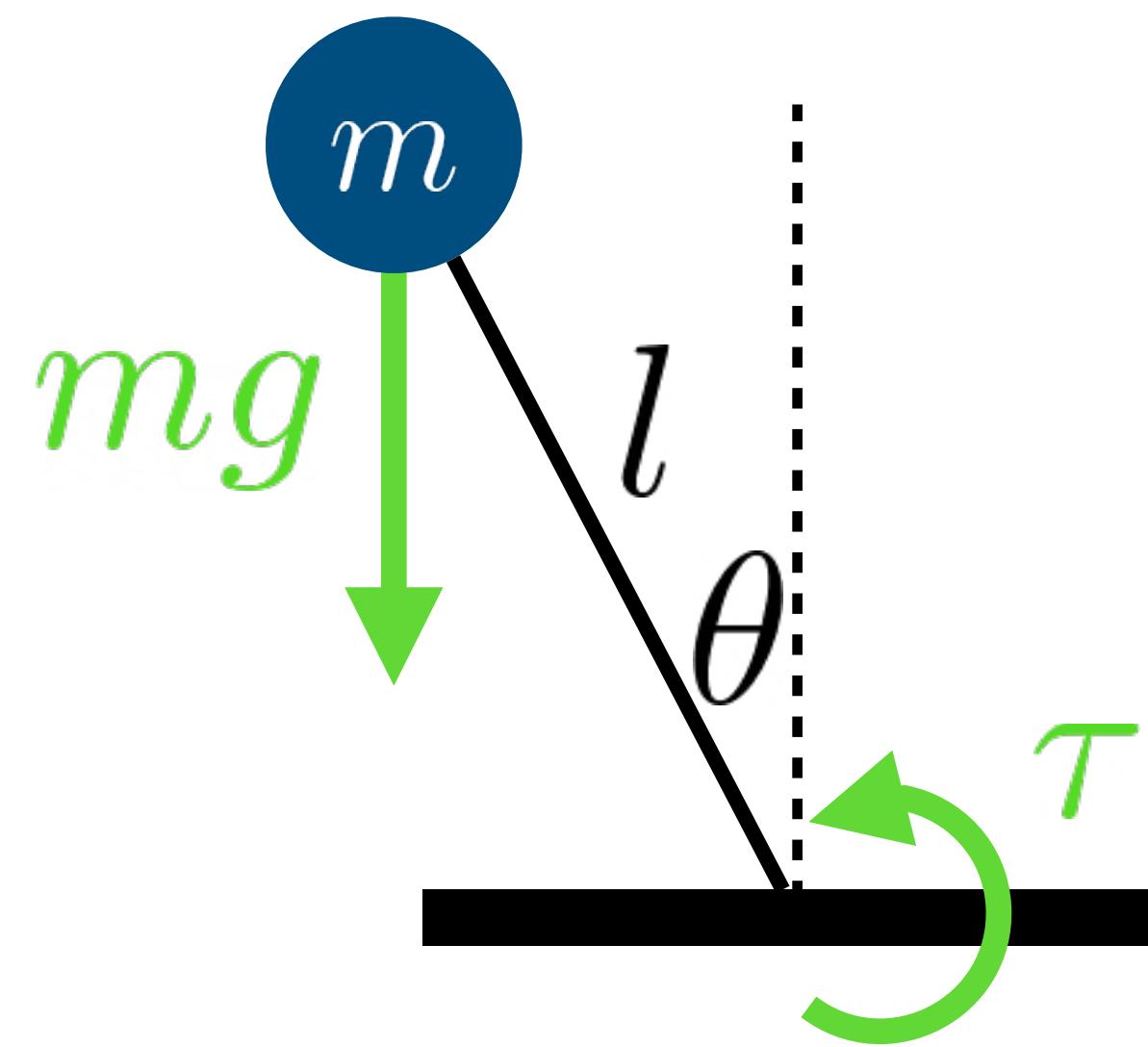
**How much does
the effort hurt?**

$$u_t^\top R u_t$$

$(1 \times M)(M \times M)(M \times 1)$

CONTROL COST

Example: Inverted Pendulum (State Cost)

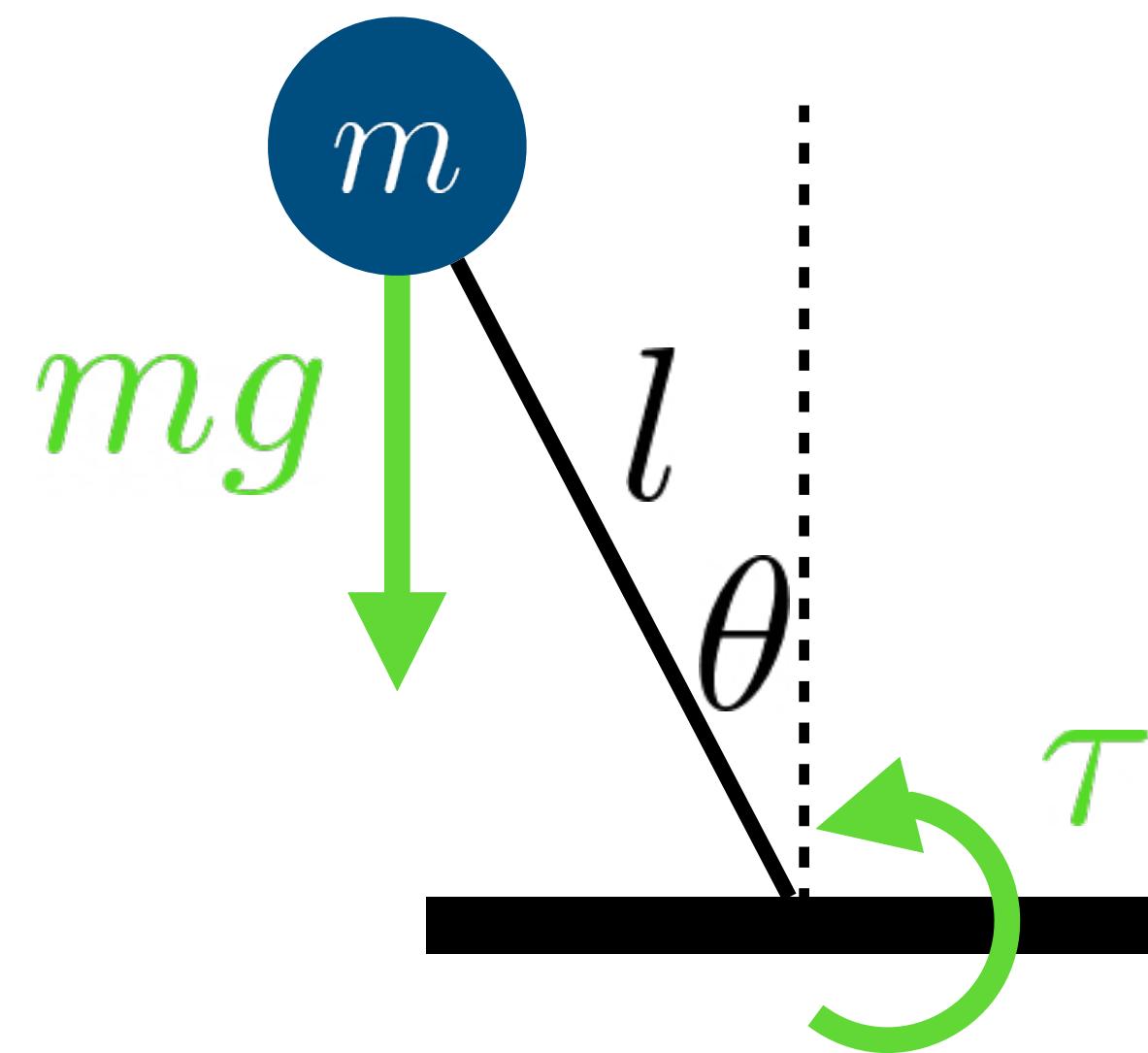


$$x_t^\top Q x_t \quad (\text{QUADRATIC FORM})$$
$$= \begin{bmatrix} \theta_t \\ \dot{\theta}_t \end{bmatrix}^\top \begin{bmatrix} Q_{\theta\theta} & Q_{\theta\dot{\theta}} \\ Q_{\dot{\theta}\theta} & Q_{\dot{\theta}\dot{\theta}} \end{bmatrix} \begin{bmatrix} \theta_t \\ \dot{\theta}_t \end{bmatrix}$$

$$= Q_{\theta\theta} \theta_t^2 + 2Q_{\theta\dot{\theta}} \theta_t \dot{\theta}_t + Q_{\dot{\theta}\dot{\theta}} \dot{\theta}_t^2$$

$$Q \succ 0 \leftrightarrow z^\top Q z > 0, \forall z \neq 0$$

Example: Inverted Pendulum (Control Cost)



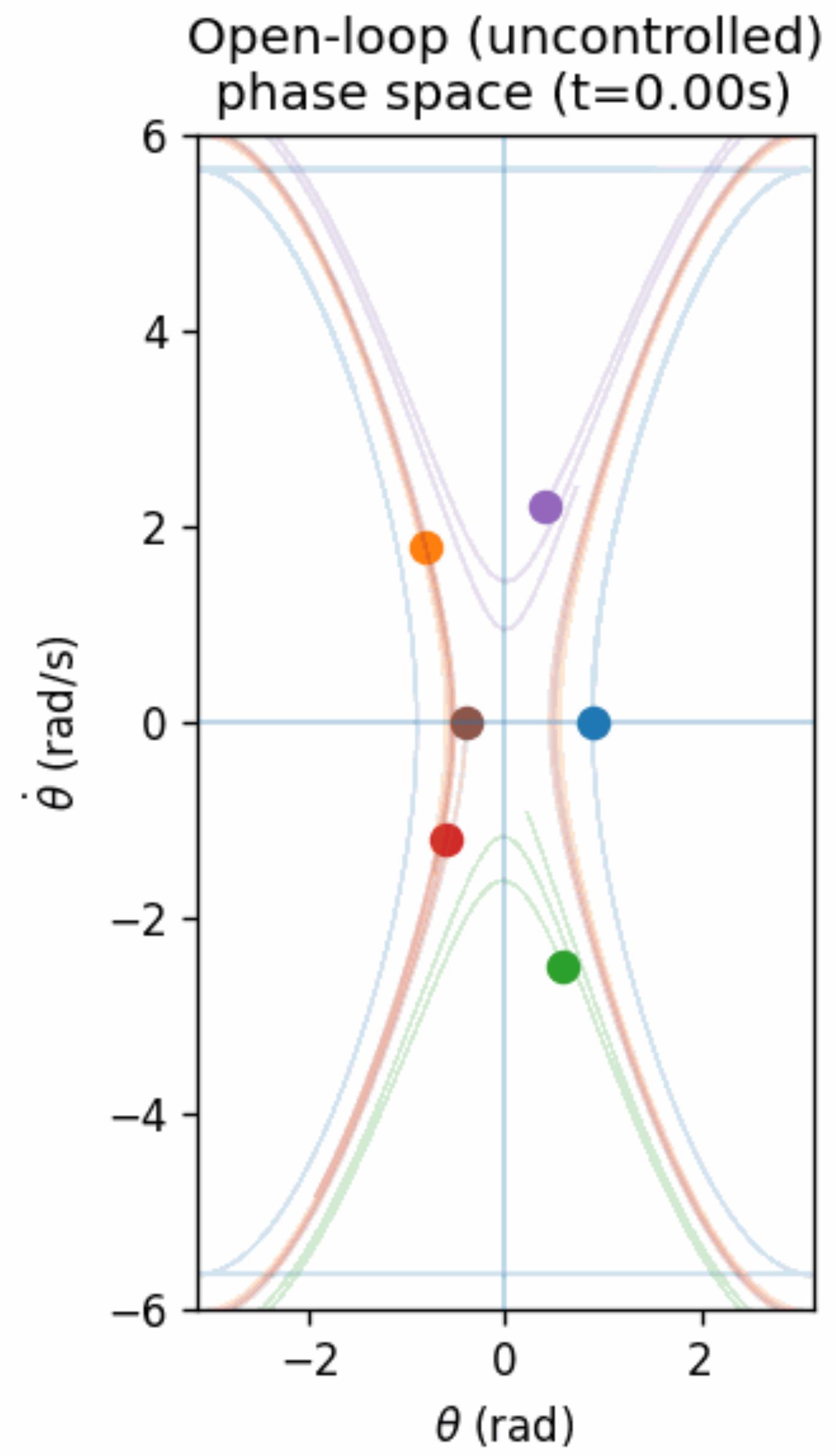
$$u_t^\top R u_t$$

(QUADRATIC
FORM)

$$= \frac{\tau_t}{ml^2} [R_{\tau\tau}] \frac{\tau_t}{ml^2}$$

$$= R_{\tau\tau} \left(\frac{\tau_t}{ml^2} \right)^2$$

$$R \succ 0 \leftrightarrow z^\top R z > 0, \forall z \neq 0$$



traj 1



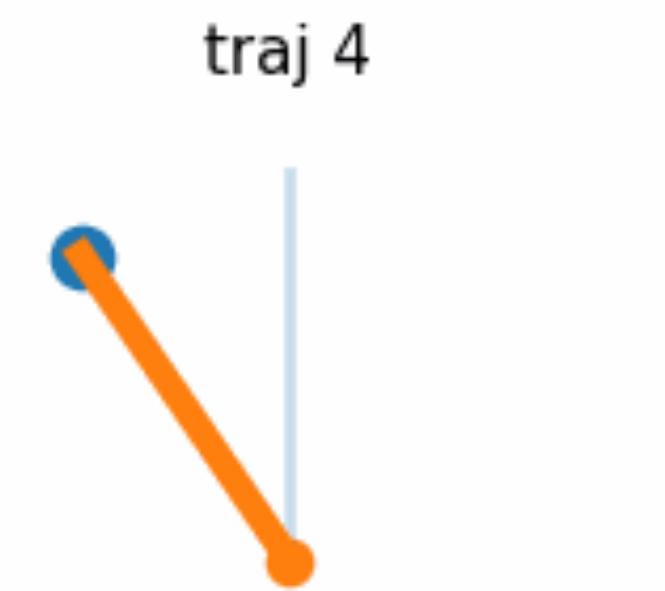
traj 2



traj 3



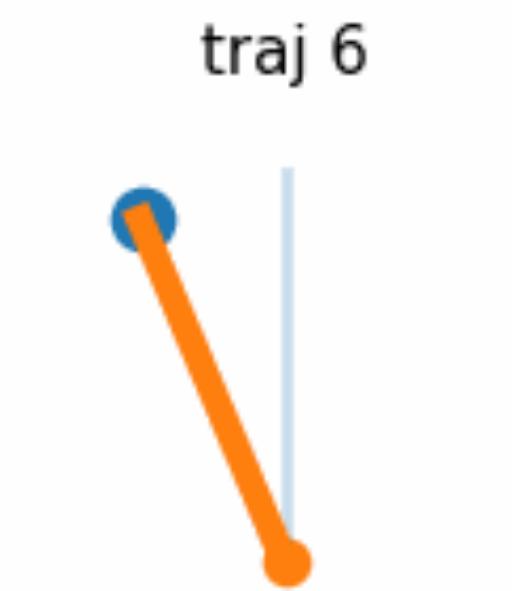
traj 4



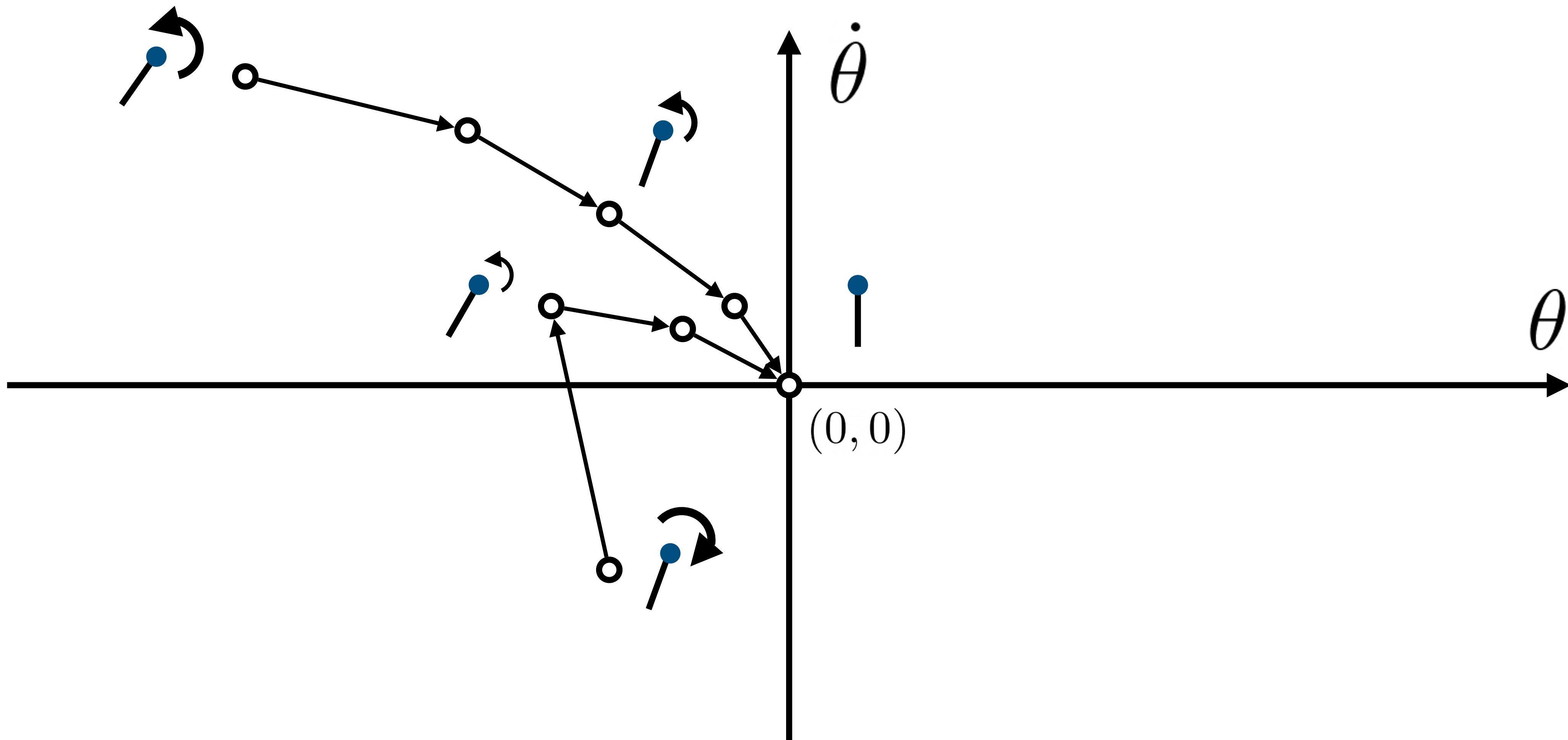
traj 5



traj 6



Example: Inverted Pendulum



Bellman Equation for Dynamic Programming

- **Linear** system (model)
- **Quadratic** cost function to minimize

$$\begin{aligned}x_{t+1} &= Ax_t + Bu_t \\ \sum_t x_t^\top Q x_t + u_t^\top R u_t\end{aligned}$$

**Whatever you do now, you must finish optimally
from wherever you end up.**

$$J^*(x_t) = \min_{u_t} x_t^\top Q x_t + u_t^\top R u_t + J^*(x_{t+1})$$

**MINIMUM COST,
STARTING FROM**

x_t

IMMEDIATE COST

**MINIMUM FUTURE
COST, STARTING**

FROM x_{t+1}

Value Iteration (Horizon = 0)

$$J_0(x) = \min_u x^\top Q x + u^\top R u = x^\top Q x = x^\top P_0 x$$

Value Iteration (Horizon = 1)

$$J_0(x) = \min_u x^\top Qx + u^\top Ru = x^\top Qx = x^\top P_0x$$

$$J_1(x) = \min_u x^\top Qx + u^\top Ru + J_0(Ax + Bu)$$

Value Iteration (Horizon = 1)

$$J_1(x) = \min_u [x^\top Qx + u^\top Ru + (Ax + Bu)^\top P_0(Ax + Bu)]$$

$$\nabla_u [\cdot] = 2Ru + 2B^\top P_0(Ax + Bu) = 0$$

$$u = -(R + B^\top P_0 B)^{-1} B^\top P_0 A x$$

$$J_1(x) = x^\top P_1 x$$

$$P_1 = Q + K_1^\top R K_1 + (A + B K_1)^\top P_0 (A + B K_1)$$

$$K_1 = -(R + B^\top P_0 B)^{-1} B^\top P_0 A$$

Value Iteration (Horizon = i)

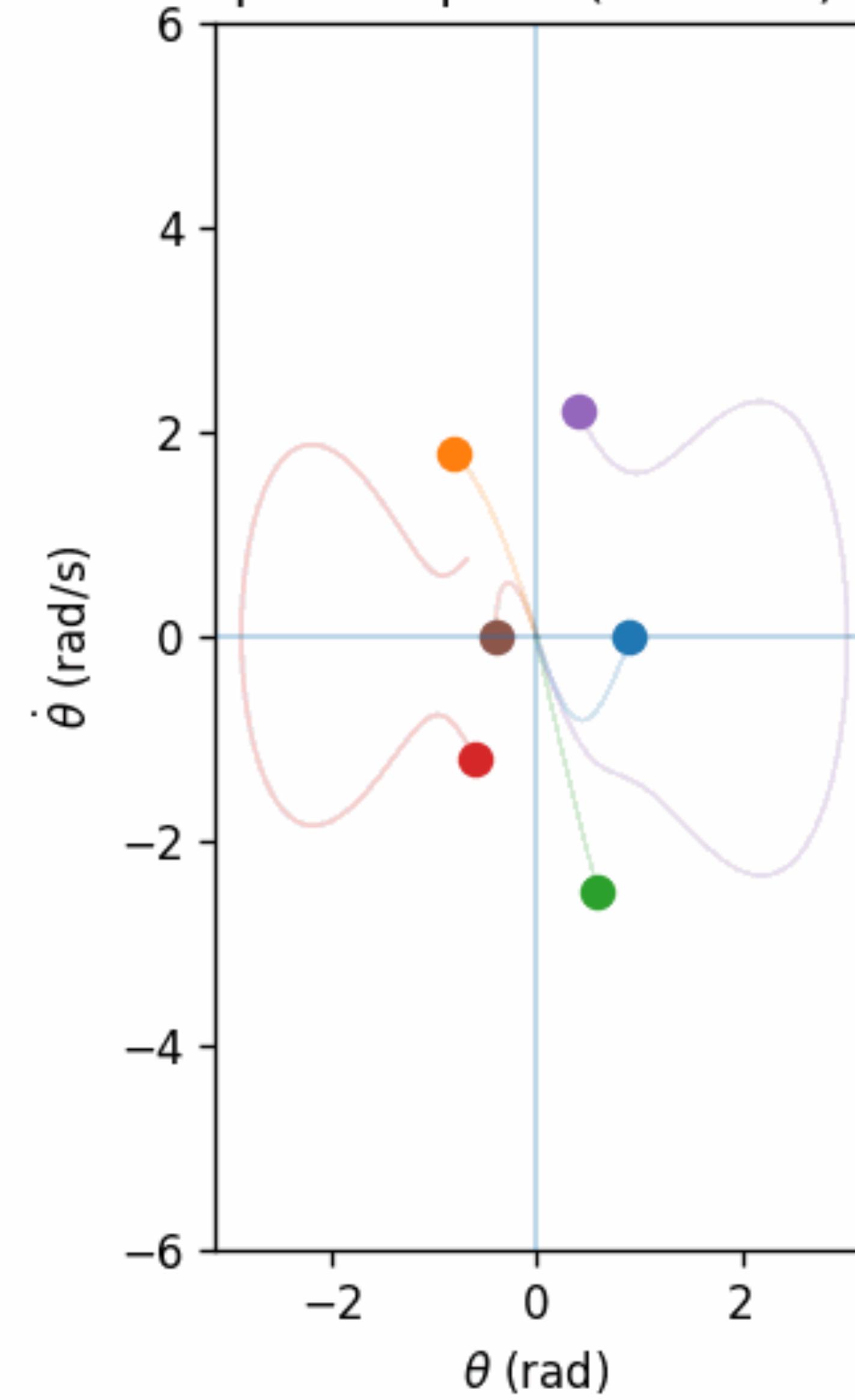
$$K_i = -(R + B^\top P_{i-1} B)^{-1} B^\top P_{i-1} A$$

$$P_i = Q + K_i^\top R K_i + (A + B K_i)^\top P_{i-1} (A + B K_i)$$

$$u = K_i x, \quad J_i(x) = x^\top P_i x$$

RUNTIME: $O(H(n^3 + m^3))$

Closed-loop (LQR feedback)
phase space ($t=0.00s$)



traj 1



traj 2



traj 3



traj 4



traj 5



traj 6



LQR in Action: Stanford Helicopter



Linear Quadratic Regulator

- For **linear** systems with **quadratic** costs, we can write down very efficient algorithms that return the optimal sequence of actions!
 - Special case where dynamic programming can be applied to continuous states and actions (typically only discrete states and actions)
- Many LQR extensions: non-linear systems, linear time-varying systems, trajectory following for non-linear systems, arbitrary costs, etc.

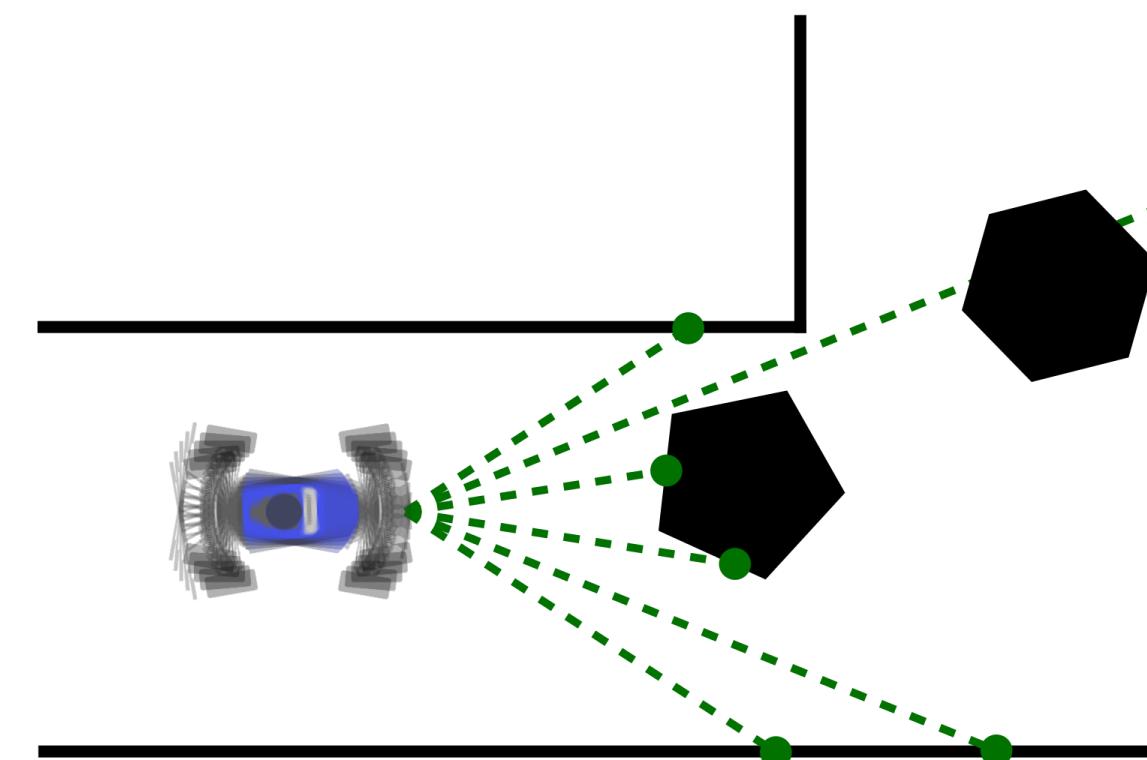
Control as an Optimization Problem

- For a sequence of H control actions
 1. Use model to predict consequence of actions (i.e., H future states)
 2. Evaluate the cost function
- Compute optimal sequence of H control actions (minimizes cost)

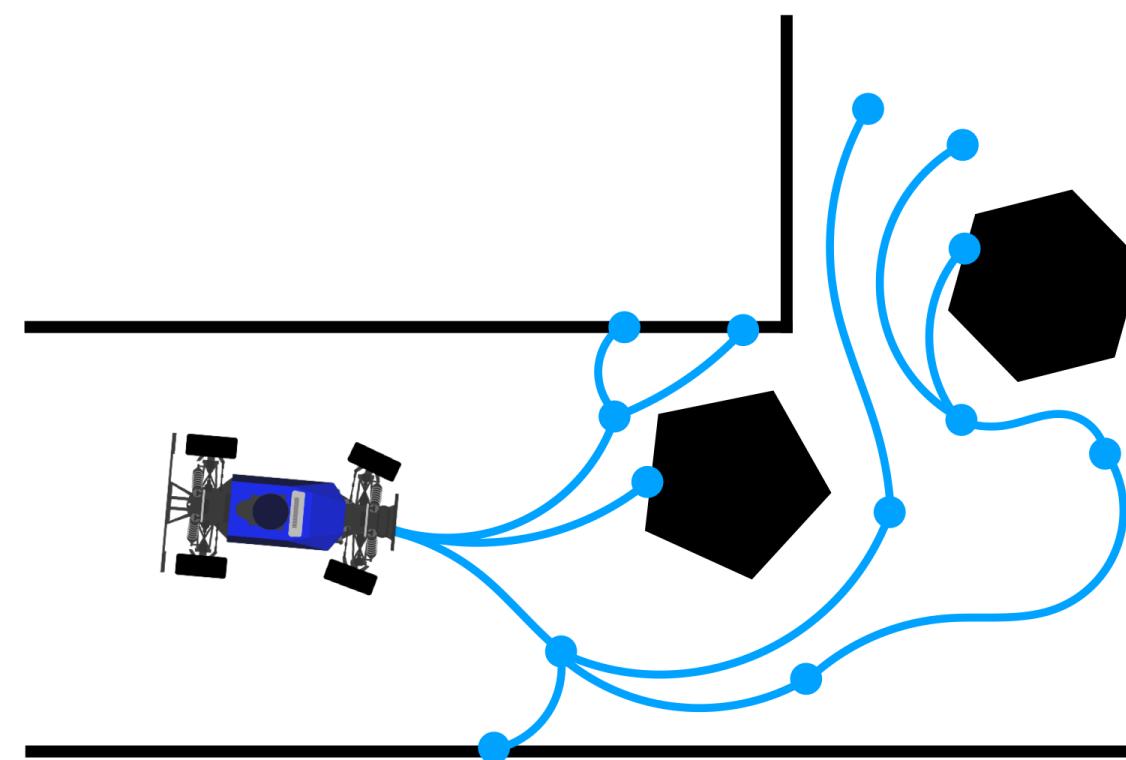
Different Control Laws

- Proportional-integral-derivative (PID) control
- Pure-pursuit control
- Model-predictive control (MPC)
- Linear-quadratic regulator (LQR)
- And many many more!

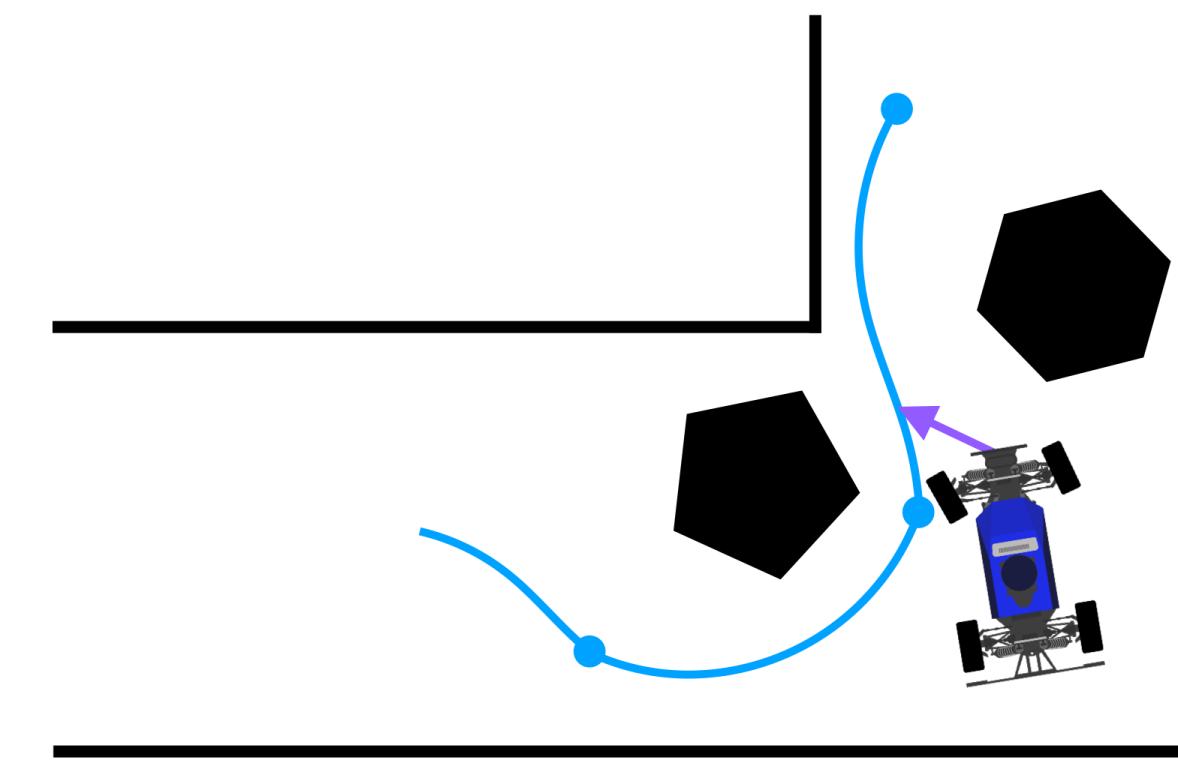
The Sense-Plan-Act Paradigm



Estimate
robot state



Plan sequence of
motions



Control robot to
follow plan

CSE 478 Robot Autonomy

Linear Quadratic Regulator

Abhishek Gupta (abhgupta@cs)
Siddhartha Srinivasa (siddh@cs)

TAs:

Carolina Higuera (chiguera@cs)
Rishabh Jain (jrishabh@cs)
Entong Su (ensu@cs)

