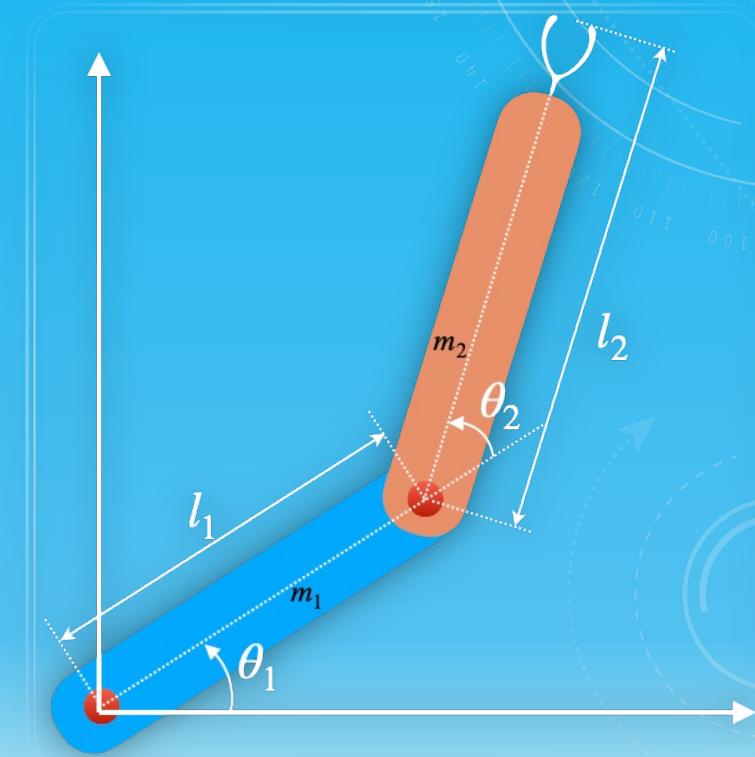
The background features a complex, abstract design composed of several concentric circles and arrows. The outermost circle is a solid light blue ring with a white arrow pointing clockwise. Inside it is a larger, semi-transparent grey circle with a white arrow pointing counter-clockwise. This pattern repeats multiple times, creating a sense of depth and motion. The numbers 140, 150, 160, 170, 180, 190, 200, 210, 220, 230, 240, and 250 are visible along the inner edges of the circles.

# ROBOTICS (OPTIMAL CONTROL)

SUNEESH JACOB A.

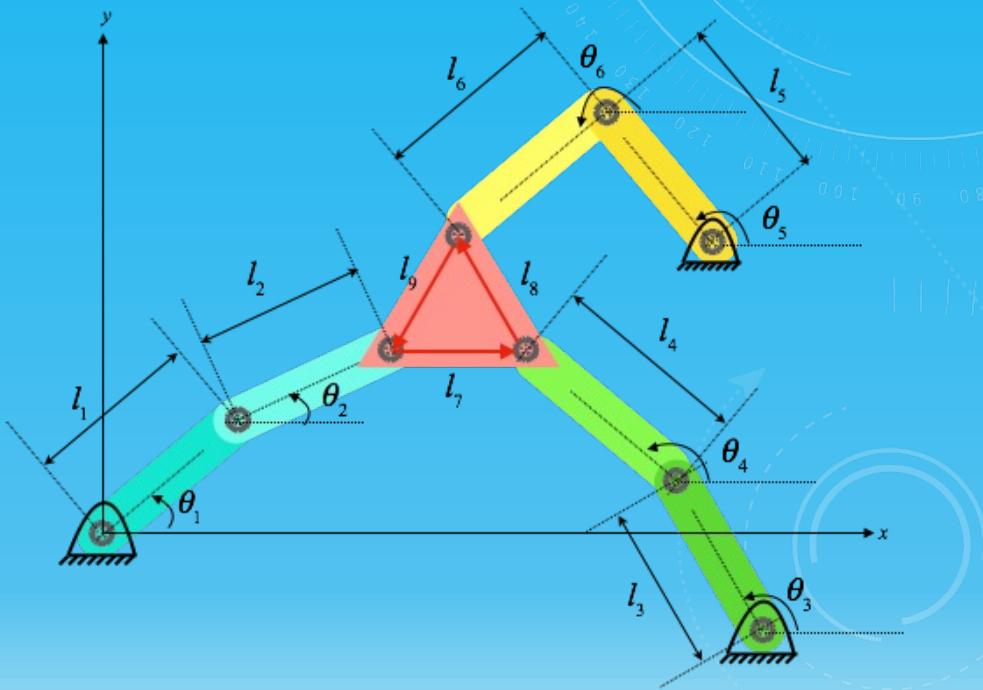
# TWO-LINK ROBOT KINEMATICS

- $\vec{p} = \begin{cases} l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2) \\ l_1 \sin(\theta_1) + l_2 \sin(\theta_1 + \theta_2) \end{cases}$



# EIGHT-LINK PARALLEL ROBOT KINEMATICS

- $\vec{p}_1 = \begin{cases} l_1 \cos(\theta_1) + l_2 \cos(\theta_2) \\ l_1 \sin(\theta_1) + l_2 \sin(\theta_2) \end{cases}$
- $\vec{p}_2 = \begin{cases} l_3 \cos(\theta_3) + l_4 \cos(\theta_4) \\ l_3 \sin(\theta_3) + l_4 \sin(\theta_4) \end{cases}$
- $\vec{p}_3 = \begin{cases} l_5 \cos(\theta_5) + l_6 \cos(\theta_6) \\ l_5 \sin(\theta_5) + l_6 \sin(\theta_6) \end{cases}$
- $\vec{o}_2 = \vec{o}_1 + \begin{cases} l_1 \cos(\theta_1) + l_2 \cos(\theta_2) + l_7 \cos(\theta_7) - l_4 \cos(\theta_4) - l_3 \cos(\theta_3) \\ l_1 \sin(\theta_1) + l_2 \sin(\theta_2) + l_7 \sin(\theta_7) - l_4 \sin(\theta_4) - l_3 \sin(\theta_3) \end{cases}$
- $\vec{o}_3 = \vec{o}_2 + \begin{cases} l_3 \cos(\theta_3) + l_4 \cos(\theta_4) + l_8 \cos(\theta_8) - l_6 \cos(\theta_6) - l_5 \cos(\theta_5) \\ l_3 \sin(\theta_3) + l_4 \sin(\theta_4) + l_8 \sin(\theta_8) - l_6 \sin(\theta_6) - l_5 \sin(\theta_5) \end{cases}$
- $\vec{o}_1 = \vec{o}_3 + \begin{cases} l_5 \cos(\theta_5) + l_6 \cos(\theta_6) + l_9 \cos(\theta_9) - l_2 \cos(\theta_2) - l_1 \cos(\theta_1) \\ l_5 \sin(\theta_5) + l_6 \sin(\theta_6) + l_9 \sin(\theta_9) - l_2 \sin(\theta_2) - l_1 \sin(\theta_1) \end{cases}$



# WHAT IS MOTOR CONTROL

Control: Computing appropriate torque to bring the robot's actuating joint from one state to another state

Drive: Converting the small current/voltage signals to real-time (large) signals that can be fed to motor

# WHY DO WE NEED MOTOR CONTROL

- Input → force
- Output → state (position and velocity)

# DYNAMICS

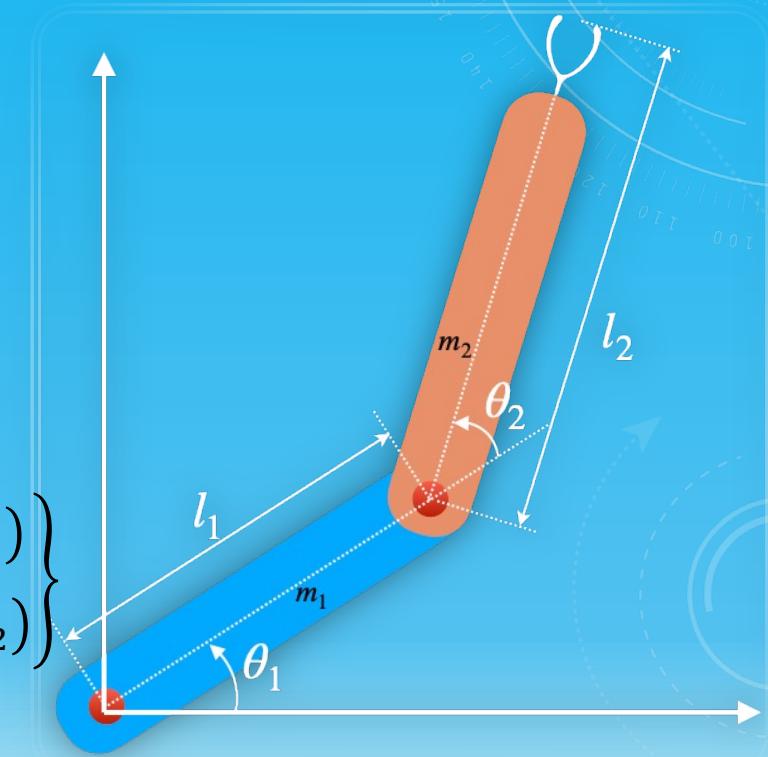
- Dynamic equations

# TWO-LINK ROBOT DYNAMICS

$$\bullet \quad \vec{p}_1 = \begin{cases} \frac{l_1}{2} \cos(\theta_1) \\ \frac{l_1}{2} \sin(\theta_1) \end{cases} \quad \bullet \quad \vec{p}_2 = \begin{cases} l_1 \cos(\theta_1) + \frac{l_2}{2} \cos(\theta_1 + \theta_2) \\ l_1 \sin(\theta_1) + \frac{l_2}{2} \sin(\theta_1 + \theta_2) \end{cases}$$

$$\bullet \quad \vec{v}_1 = \begin{cases} -\frac{l_1}{2} \sin(\theta_1) \dot{\theta}_1 \\ \frac{l_1}{2} \cos(\theta_1) \dot{\theta}_1 \end{cases} \quad \bullet \quad \vec{v}_2 = \begin{cases} -l_1 \sin(\theta_1) \dot{\theta}_1 - \frac{l_2}{2} \sin(\theta_1 + \theta_2) (\dot{\theta}_1 + \dot{\theta}_2) \\ -l_1 \cos(\theta_1) \dot{\theta}_1 + \frac{l_2}{2} \cos(\theta_1 + \theta_2) (\dot{\theta}_1 + \dot{\theta}_2) \end{cases}$$

$$\bullet \quad \omega_1 = \dot{\theta}_1 \quad \bullet \quad \omega_2 = \dot{\theta}_1 + \dot{\theta}_2$$

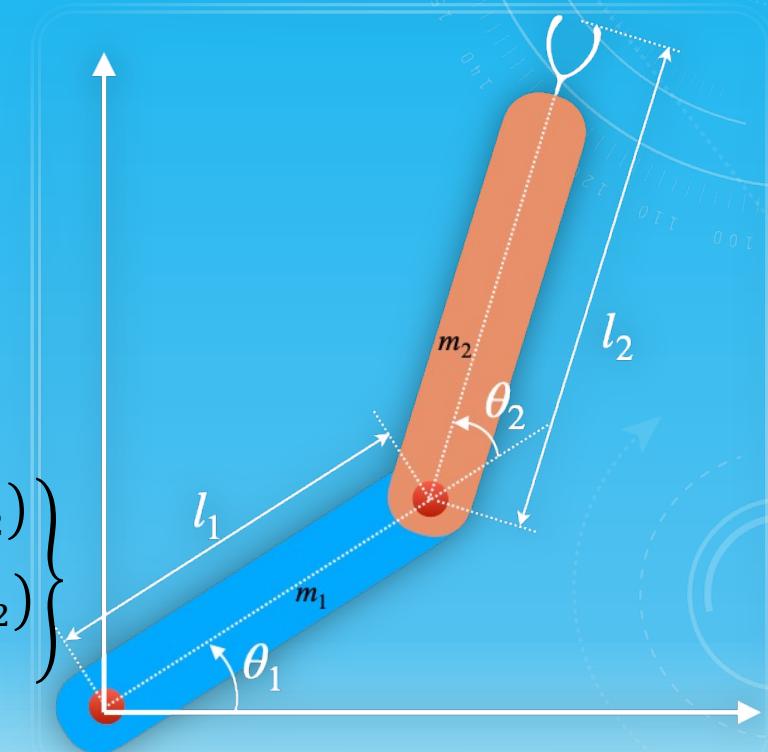


# TWO-LINK ROBOT DYNAMICS

- $\vec{p}_1 = \begin{Bmatrix} \frac{l_1}{2} \cos(\theta_1) \\ \frac{l_1}{2} \sin(\theta_1) \\ 0 \end{Bmatrix}$
- $\vec{p}_2 = \begin{Bmatrix} l_1 \cos(\theta_1) + \frac{l_2}{2} \cos(\theta_1 + \theta_2) \\ l_1 \sin(\theta_1) + \frac{l_2}{2} \sin(\theta_1 + \theta_2) \\ 0 \end{Bmatrix}$

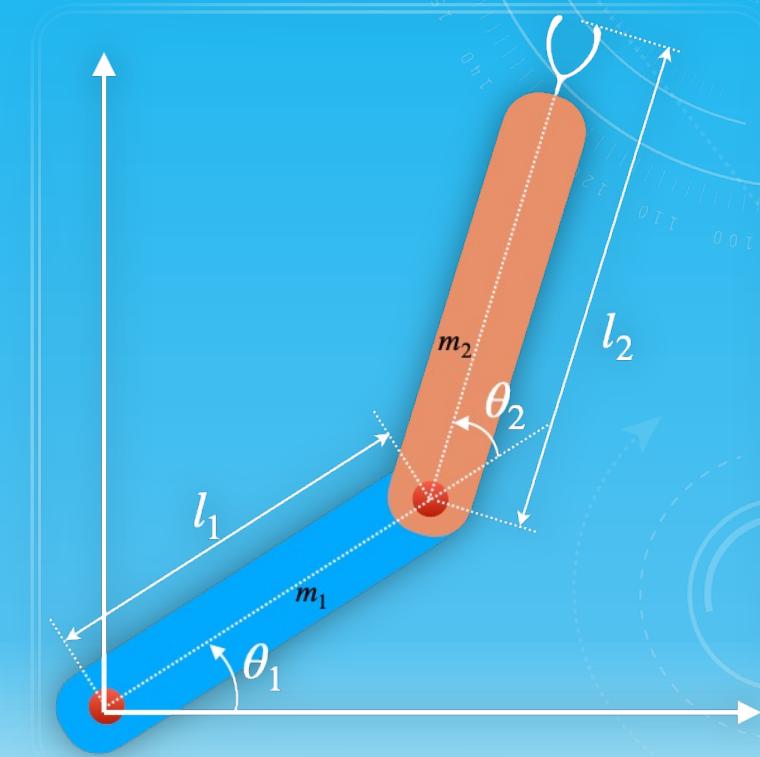
- $\vec{v}_1 = \begin{Bmatrix} -\frac{l_1}{2} \sin(\theta_1) \dot{\theta}_1 \\ \frac{l_1}{2} \cos(\theta_1) \dot{\theta}_1 \\ 0 \end{Bmatrix}$
- $\vec{v}_2 = \begin{Bmatrix} -l_1 \sin(\theta_1) \dot{\theta}_1 - \frac{l_2}{2} \sin(\theta_1 + \theta_2) (\dot{\theta}_1 + \dot{\theta}_2) \\ -l_1 \cos(\theta_1) \dot{\theta}_1 + \frac{l_2}{2} \cos(\theta_1 + \theta_2) (\dot{\theta}_1 + \dot{\theta}_2) \\ 0 \end{Bmatrix}$

- $\vec{\omega}_1 = \begin{Bmatrix} 0 \\ 0 \\ \dot{\theta}_1 \end{Bmatrix}$
- $\vec{\omega}_2 = \begin{Bmatrix} 0 \\ 0 \\ \dot{\theta}_1 + \dot{\theta}_2 \end{Bmatrix}$



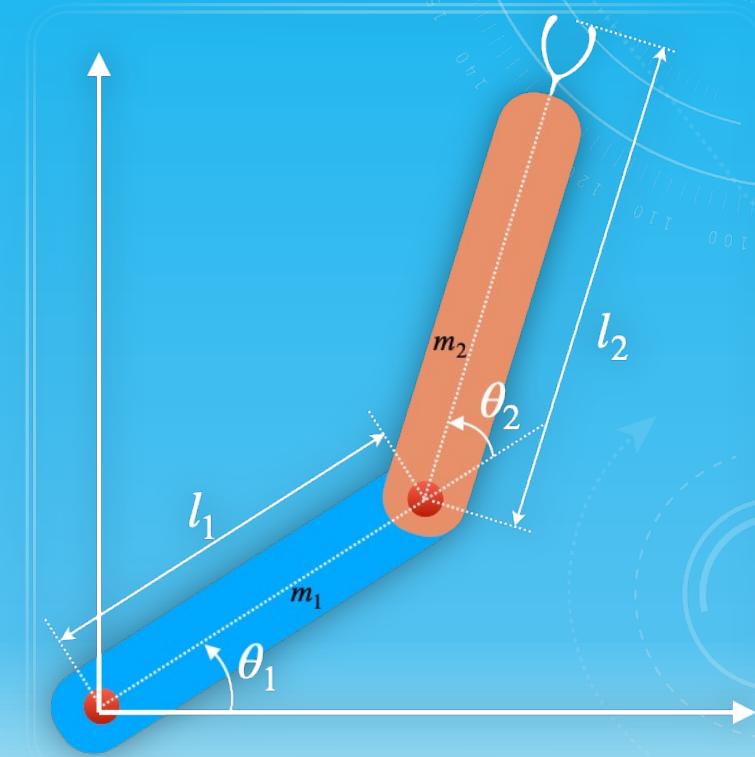
# TWO-LINK ROBOT DYNAMICS

- $T = \frac{1}{2}m_1(\vec{v}_1 \cdot \vec{v}_1) + \frac{1}{2}m_2(\vec{v}_2 \cdot \vec{v}_2) + \frac{1}{2}I_1(\vec{\omega}_1 \cdot \vec{\omega}_1) + \frac{1}{2}I_2(\vec{\omega}_2 \cdot \vec{\omega}_2)$
- $V = 0$
- $L = T - V$
- $\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}_1}\right) - \frac{\partial L}{\partial \theta_1} = \tau_1$
- $\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{\theta}_2}\right) - \frac{\partial L}{\partial \theta_2} = \tau_2$



# TWO-LINK ROBOT DYNAMICS

- $\tau_1 = \left( \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_2 - m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$
- $\tau_2 = m_2 \left( \frac{1}{3}l_2^2 + \frac{1}{2}l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 \right) \ddot{\theta}_2 + \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$



# TWO-LINK ROBOT DYNAMICS

- $\tau_1 = \left( \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_2 - m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$
- $\tau_2 = m_2 \left( \frac{1}{3}l_2^2 + \frac{1}{2}l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 \right) \ddot{\theta}_2 + \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$

$$\begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{Bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{Bmatrix} + \begin{Bmatrix} E \\ F \end{Bmatrix} = \begin{Bmatrix} \tau_1 \\ \tau_2 \end{Bmatrix}$$

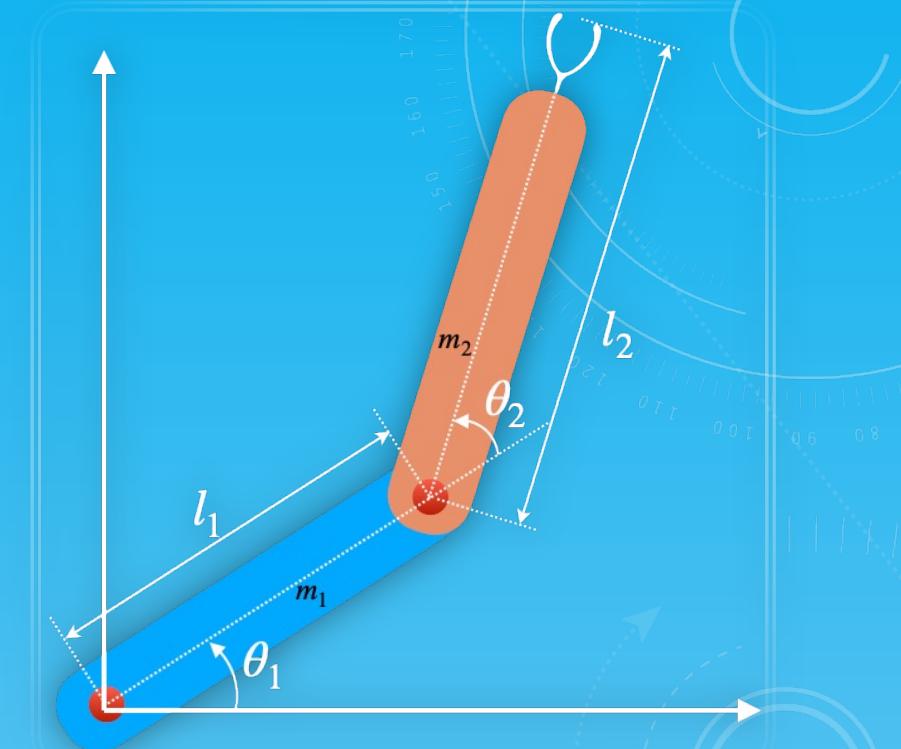
$$\Rightarrow \begin{Bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{Bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix}^{-1} \left( \begin{Bmatrix} \tau_1 \\ \tau_2 \end{Bmatrix} - \begin{Bmatrix} E \\ F \end{Bmatrix} \right)$$

$$\ddot{\theta}_1 = \frac{D\tau_1 - B\tau_2 + BF - DE}{AD - BC}$$

$$\ddot{\theta}_2 = \frac{-C\tau_1 + A\tau_2 + EC - AF}{AD - BC}$$

$$\ddot{\theta}_1 = f_1(\theta_1, \dot{\theta}_1, \theta_2, \dot{\theta}_2, \tau_1, \tau_2)$$

$$\ddot{\theta}_2 = f_2(\theta_1, \dot{\theta}_1, \theta_2, \dot{\theta}_2, \tau_1, \tau_2)$$



$$A = \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right)$$

$$B = C = \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2)$$

$$D = \frac{1}{3}m_2l_2^2$$

$$E = -m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$$

$$F = \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$$

# TWO-LINK ROBOT DYNAMICS

- $\tau_1 = \left( \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_2 - m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$
- $\tau_2 = m_2 \left( \frac{1}{3}l_2^2 + \frac{1}{2}l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 \right) \ddot{\theta}_2 + \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$

$$\ddot{\theta}_1 = \frac{D\tau_1 - B\tau_2 + BF - DE}{AD - BC}$$

$$\ddot{\theta}_2 = \frac{-C\tau_1 + A\tau_2 + EC - AF}{AD - BC}$$

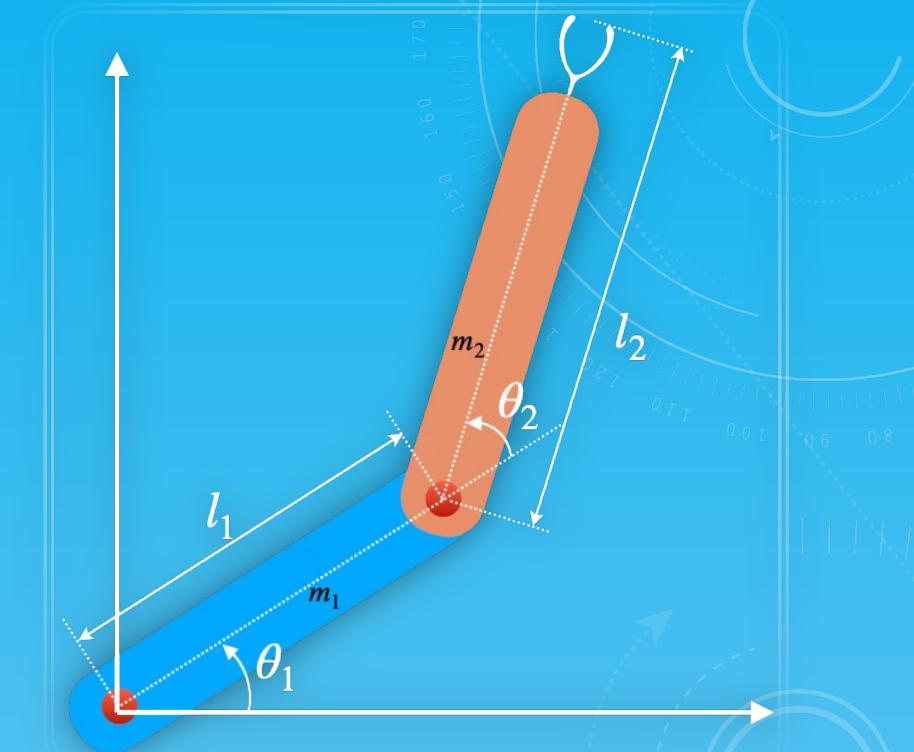
$$z_1 = \theta_1, z_2 = \theta_2, z_3 = \dot{\theta}_1, z_4 = \dot{\theta}_2$$

$$\dot{z}_1 = \dot{\theta}_1 = z_2$$

$$\dot{z}_2 = \dot{\theta}_2 = z_4$$

$$\dot{z}_3 = \ddot{\theta}_1 = \frac{D\tau_1 - B\tau_2 + BF - DE}{AD - BC}$$

$$\dot{z}_4 = \ddot{\theta}_2 = \frac{-C\tau_1 + A\tau_2 + EC - AF}{AD - BC}$$



$$A = \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right)$$

$$B = C = \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2)$$

$$D = \frac{1}{3}m_2l_2^2$$

$$E = -m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$$

$$F = \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$$

# TWO-LINK ROBOT DYNAMICS

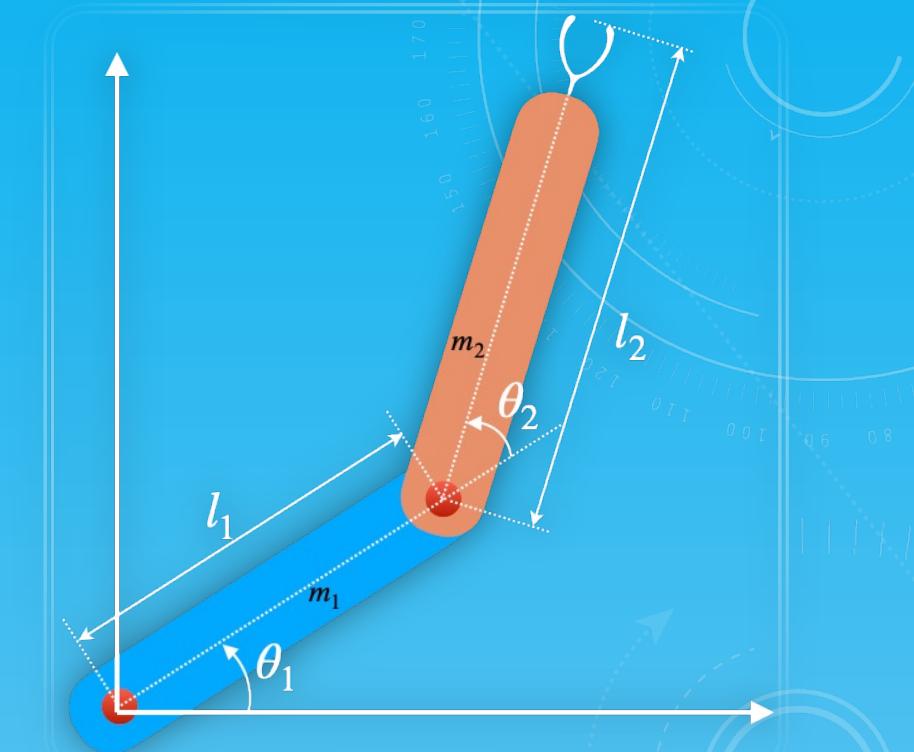
- $\tau_1 = \left( \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_2 - m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$
- $\tau_2 = m_2 \left( \frac{1}{3}l_2^2 + \frac{1}{2}l_1l_2 \cos(\theta_2) \right) \ddot{\theta}_1 + \left( \frac{1}{3}m_2l_2^2 \right) \ddot{\theta}_2 + \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$

$$\ddot{\theta}_1 = \frac{D\tau_1 - B\tau_2 + BF - DE}{AD - BC}$$

$$\ddot{\theta}_2 = \frac{-C\tau_1 + A\tau_2 + EC - AF}{AD - BC}$$

$$z_1 = \theta_1, z_2 = \theta_2, z_3 = \dot{\theta}_1, z_4 = \dot{\theta}_2$$

$$\begin{Bmatrix} \dot{z}_1 \\ \dot{z}_2 \\ \dot{z}_3 \\ \dot{z}_4 \end{Bmatrix} = \begin{Bmatrix} z_2 \\ z_4 \\ \frac{D\tau_1 - B\tau_2 + BF - DE}{AD - BC} \\ \frac{-C\tau_1 + A\tau_2 + EC - AF}{AD - BC} \end{Bmatrix} = f(t, \mathbf{z}, \boldsymbol{\tau})$$



$$A = \frac{1}{3}m_1l_1^2 + m_2 \left( l_1^2 + \frac{1}{3}l_2^2 + l_1l_2 \cos(\theta_2) \right)$$

$$B = C = \frac{1}{3}m_2l_2^2 + \frac{1}{2}m_2l_1l_2 \cos(\theta_2)$$

$$D = \frac{1}{3}m_2l_2^2$$

$$E = -m_2l_1l_2 \sin(\theta_2) \left( \dot{\theta}_1\dot{\theta}_2 + \frac{1}{2}\dot{\theta}_2^2 \right)$$

$$F = \left( \frac{1}{2}m_2l_1l_2 \sin(\theta_2) \right) \dot{\theta}_1^2$$

# SOLUTION

- Euler's method

- $\frac{dz}{dt} = f(t, z)$
- $\frac{z_{t+\Delta t} - z_t}{\Delta t} = f(t, z_t)$
- $z_{t+\Delta t} = z_t + \Delta t f(t, z_t)$

# SOLUTION

- Runge–Kutta method

- $\frac{dz}{dt} = f(t, z)$

- $z_{t+\Delta t} = z_t + \frac{\Delta t}{6} (k_1 + 2k_2 + 2k_3 + k_4)$

- $k_1 = f(t, z_t)$

- $k_2 = f\left(t + \frac{\Delta t}{2}, z_t + \Delta t \frac{k_1}{2}\right)$

- $k_3 = f\left(t + \frac{\Delta t}{2}, z_t + \Delta t \frac{k_2}{2}\right)$

- $k_4 = f(t + \Delta t, z_t + \Delta t k_3)$

# CONTROL STRATEGIES

- Open-loop controllers
- Closed-loop controllers
- Fuzzy logic controllers
- ML-based controllers
- ...

# CLOSED-LOOP CONTROLLERS

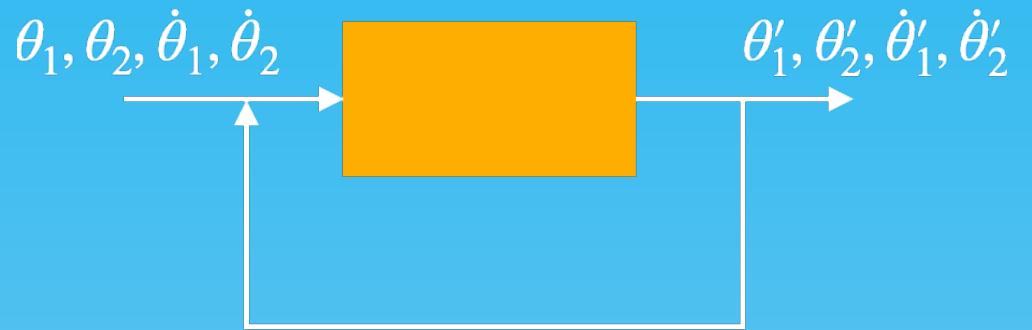
- PID controller

# SOLUTION

- Open loop control

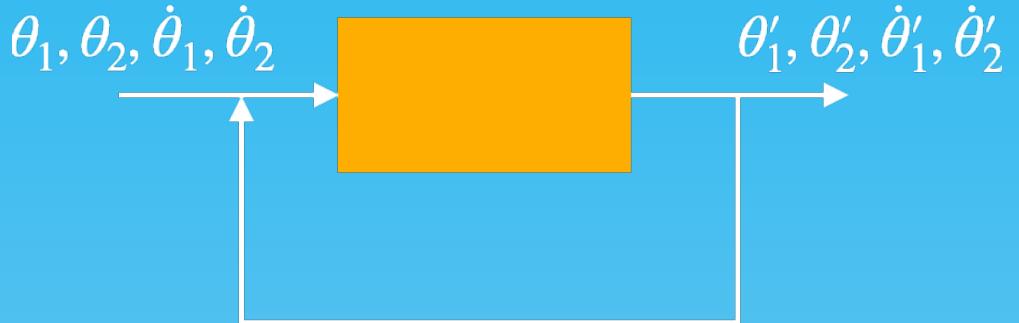


# ERROR

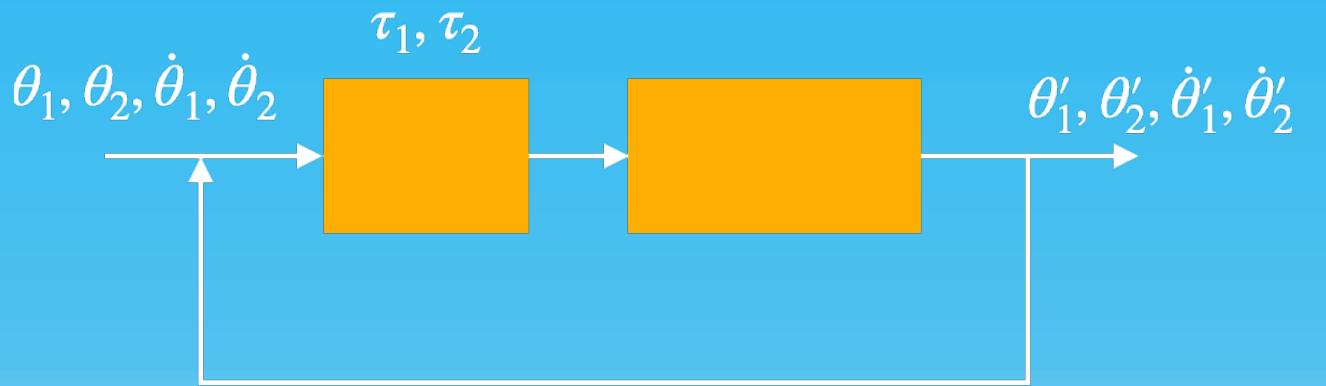


# ERROR

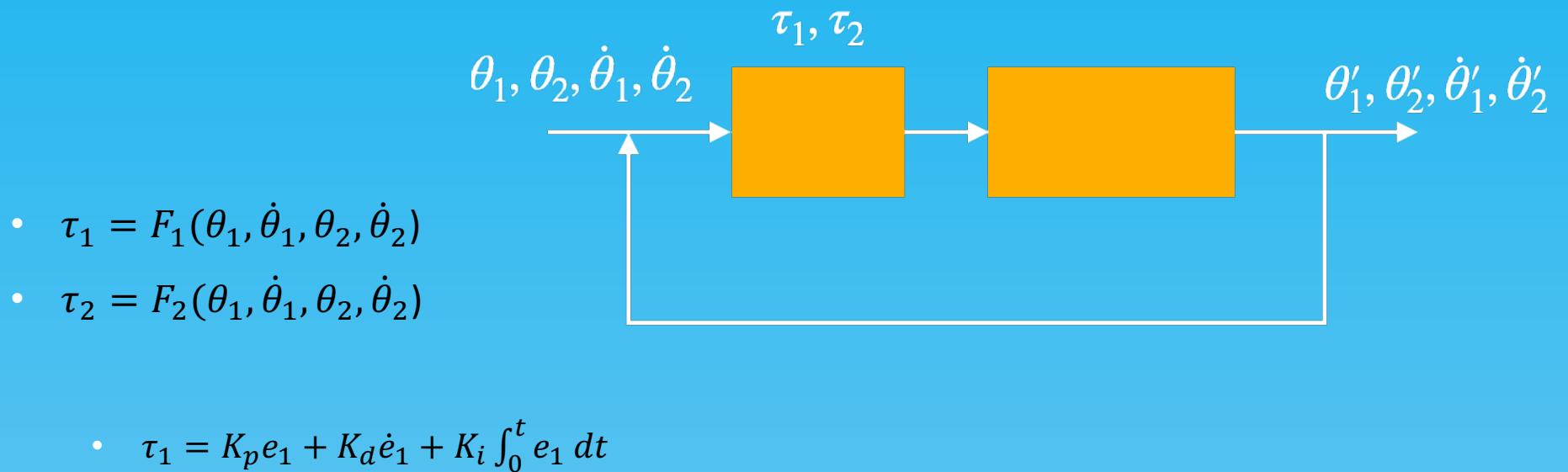
- $e_1 = \theta_1 - \theta'_1$
- $e_2 = \theta_2 - \theta'_2$
- $\dot{e}_1 = \dot{\theta}_1 - \dot{\theta}'_1$
- $\dot{e}_2 = \dot{\theta}_2 - \dot{\theta}'_2$



# ERROR



# ERROR



# CONTROL STRATEGIES

- Open-loop controllers
- Closed-loop controllers
- Fuzzy logic controllers
- ML-based controllers
- ...

# OPEN-LOOP CONTROLLERS

## STEPPER-MOTOR

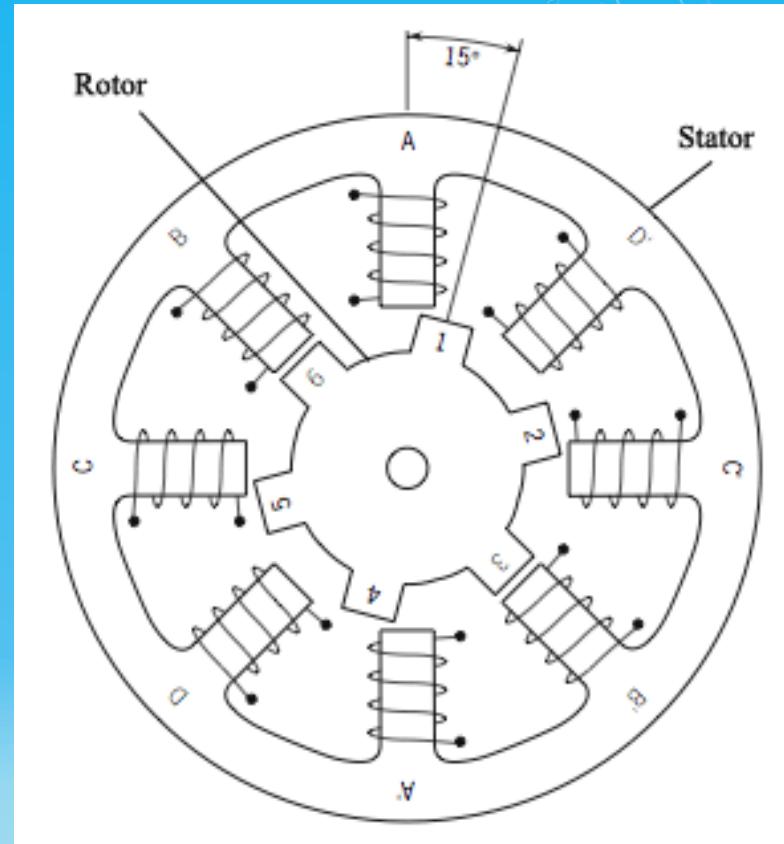


Image source:  
<https://circuitdigest.com/sites/default/files/inlineimages/u/Stepper-Motor-Internal-Structure.png>

# FUZZY LOGIC CONTROL

- Rules-based

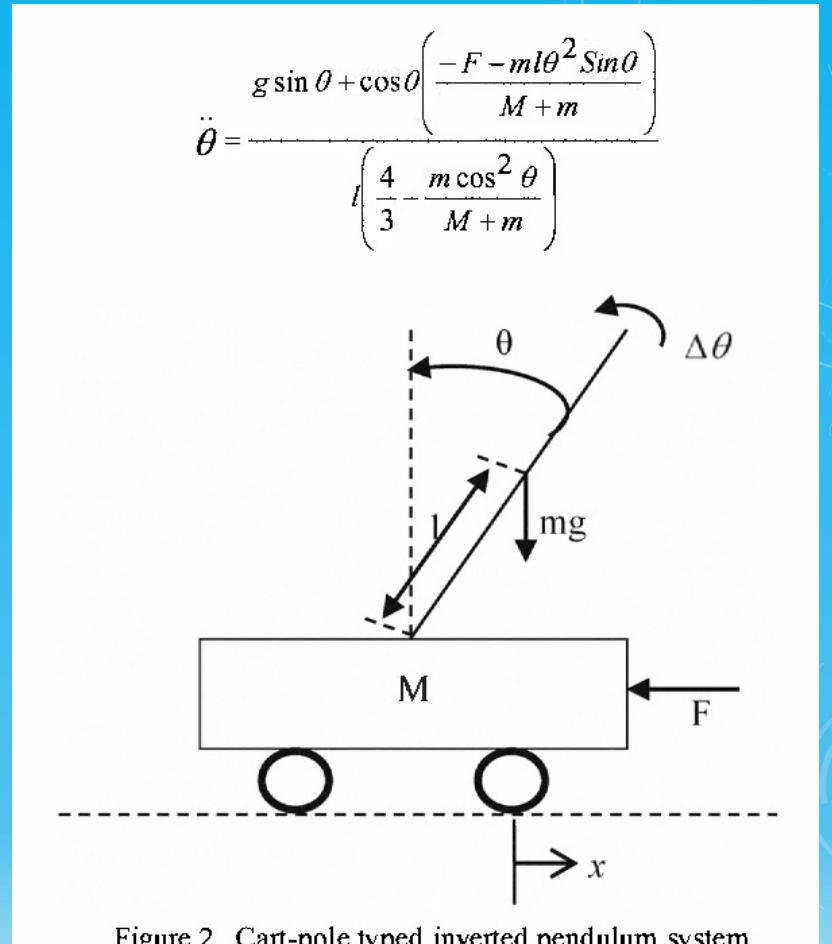


Figure 2. Cart-pole type inverted pendulum system

Image source:

<https://www.semanticscholar.org/paper/Fuzzy-logic-controller-for-an-inverted-pendulum-Shill-Akhand/e6cf50180f74be11ffd7d9d520b36dd1650aae6c/figure/1>

# FUZZY LOGIC CONTROL

- Rules-based

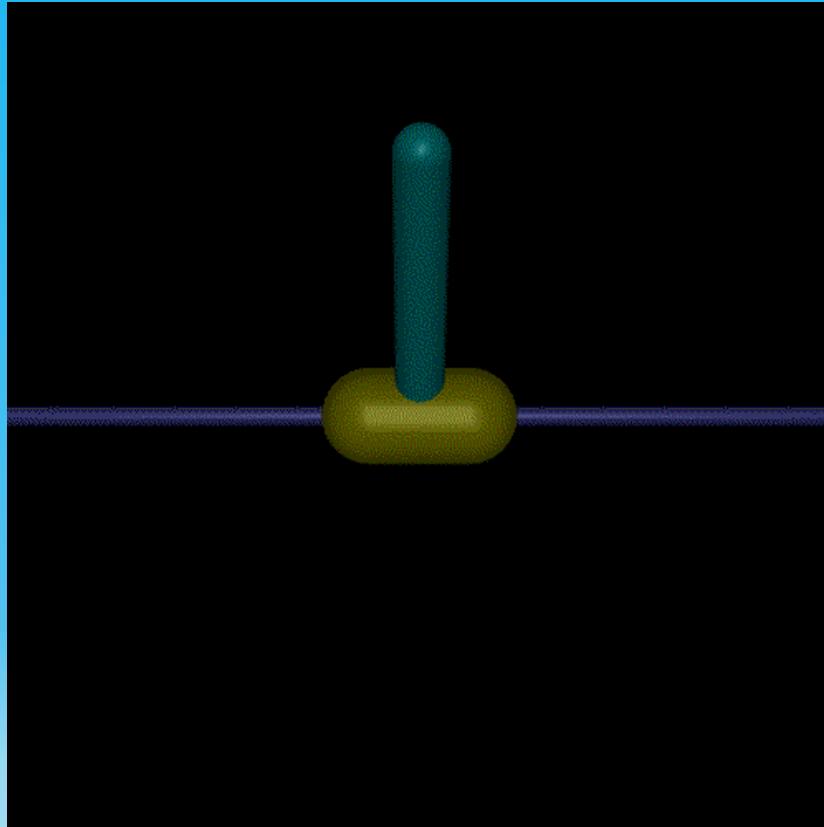


Image source: [https://mgoulao.github.io/gym-docs/\\_images/inverted\\_pendulum.gif](https://mgoulao.github.io/gym-docs/_images/inverted_pendulum.gif)

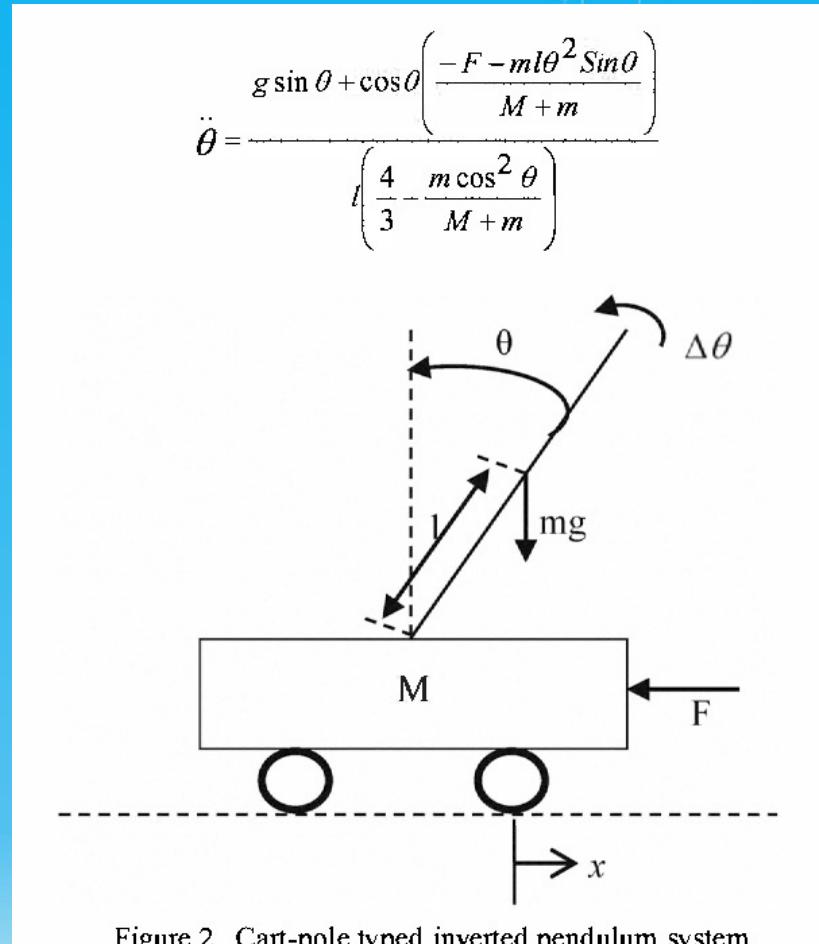


Figure 2. Cart-pole type inverted pendulum system

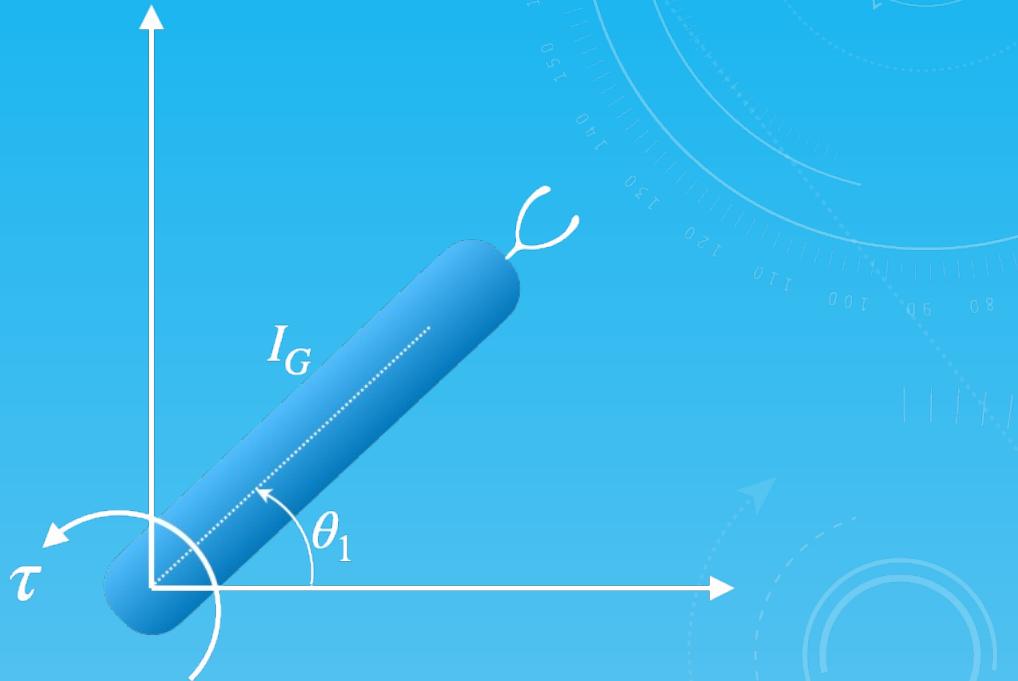
Image source:  
<https://www.semanticscholar.org/paper/Fuzzy-logic-controller-for-an-inverted-pendulum-Shill-Akhand/e6cf50180f74be11ffd7d9d520b36dd1650aae6c/figure/1>

# MACHINE LEARNING

- Data-driven controlling

# MACHINE LEARNING

- Data-driven controlling
  - Joint flexibility
  - Link flexibility
  - Base flexibility



# MACHINE LEARNING

- Data-driven controlling
  - Joint flexibility
  - Link flexibility
  - Base flexibility

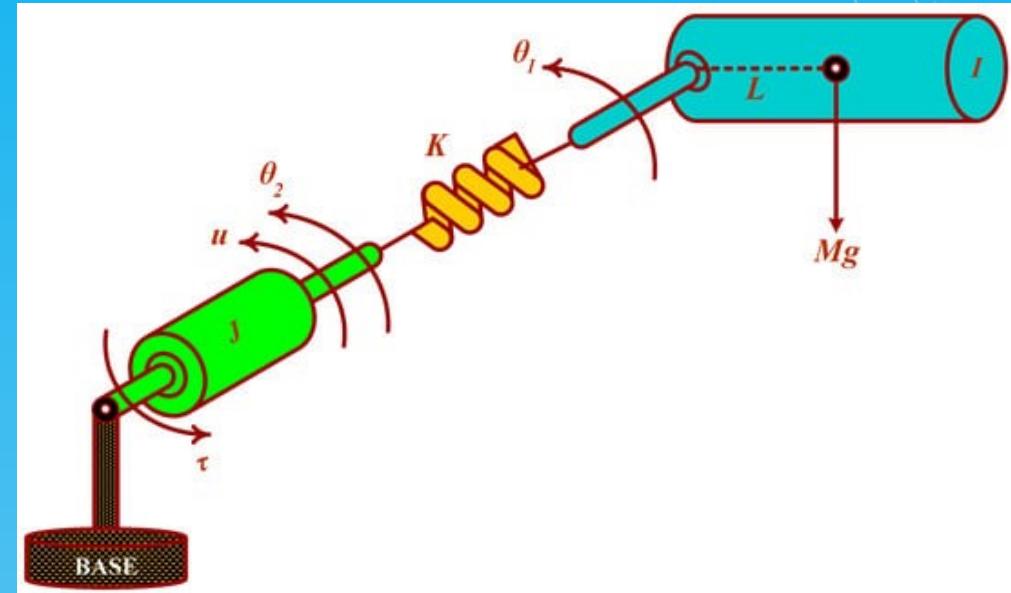


Image source: [https://www.mdpi.com/sensors/sensors-21-03252/article\\_deploy/html/images/sensors-21-03252-g001-550.jpg](https://www.mdpi.com/sensors/sensors-21-03252/article_deploy/html/images/sensors-21-03252-g001-550.jpg)

# MACHINE LEARNING

- Data-driven controlling
  - Joint flexibility
  - Link flexibility
  - Base flexibility

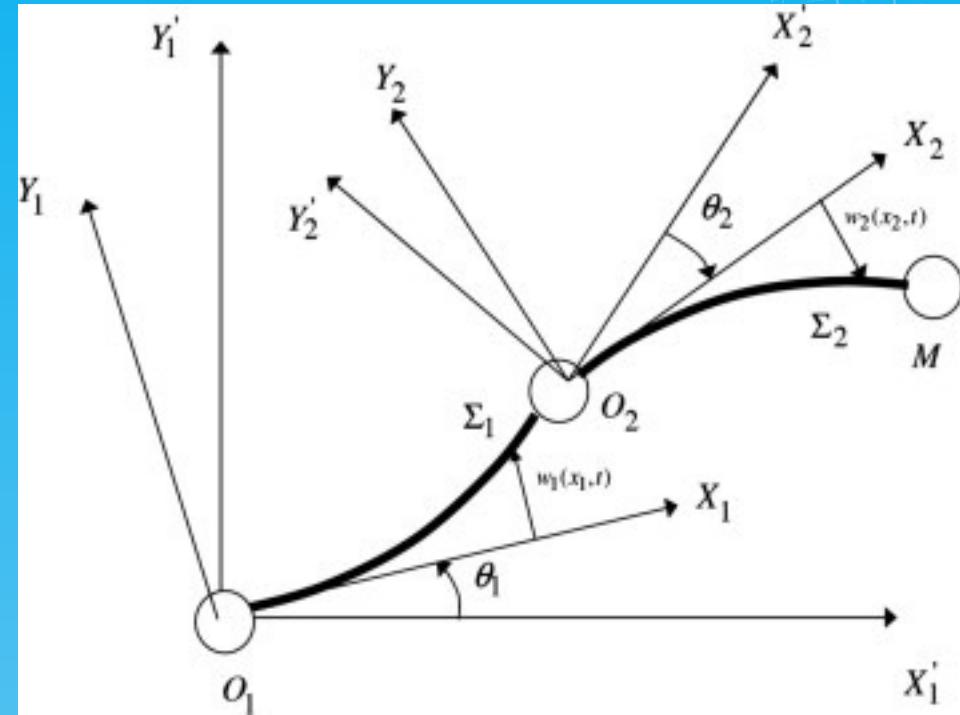


Image source: <https://ars.els-cdn.com/content/image/1-s2.0-S0307904X09000183-gr2.jpg>

# MODEL PREDICTIVE CONTROL

## Optimal Control

- Minimise

$$J = \mathbf{e}_1^2 + \mathbf{e}_2^2 + \cdots + \mathbf{e}_N^2 + \boldsymbol{\tau}_0^2 + \boldsymbol{\tau}_1^2 + \cdots + \boldsymbol{\tau}_{N-1}^2$$

- subject to

$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta t \mathbf{f}(t, \mathbf{z}_k, \boldsymbol{\tau}_k) \quad \text{for } k = 0, 1, 2, \dots, N - 1$$

- where

$$\mathbf{e}_i = \mathbf{z}_i - \mathbf{z}_d$$

$$\boldsymbol{\tau}_i = \begin{cases} \boldsymbol{\tau}_1 \\ \boldsymbol{\tau}_2 \end{cases} \text{ at } i^{\text{th}} \text{ step}$$

# MODEL PREDICTIVE CONTROL

## Optimal Control

- Minimise

$$J = (\mathbf{z}_1 - \mathbf{z}_d)^2 + (\mathbf{z}_2 - \mathbf{z}_d)^2 + \cdots + (\mathbf{z}_N - \mathbf{z}_d)^2 + \boldsymbol{\tau}_0^2 + \boldsymbol{\tau}_1^2 + \cdots + \boldsymbol{\tau}_{N-1}^2$$

- subject to

$$\mathbf{z}_1 = \mathbf{z}_0 + \Delta t \mathbf{f}(t, \mathbf{z}_0, \boldsymbol{\tau}_0)$$

$$\mathbf{z}_2 = \mathbf{z}_1 + \Delta t \mathbf{f}(t, \mathbf{z}_1, \boldsymbol{\tau}_1)$$

$$\mathbf{z}_3 = \mathbf{z}_2 + \Delta t \mathbf{f}(t, \mathbf{z}_2, \boldsymbol{\tau}_2)$$

$$\vdots$$

$$\mathbf{z}_N = \mathbf{z}_{N-1} + \Delta t \mathbf{f}(t, \mathbf{z}_{N-1}, \boldsymbol{\tau}_{N-1})$$

# MODEL PREDICTIVE CONTROL

## Optimal Control

- Minimise

$$(\mathbf{z}_1 - \mathbf{z}_d)^T(\mathbf{z}_1 - \mathbf{z}_d) + (\mathbf{z}_2 - \mathbf{z}_d)^T(\mathbf{z}_2 - \mathbf{z}_d) + \cdots + (\mathbf{z}_N - \mathbf{z}_d)^T(\mathbf{z}_N - \mathbf{z}_d) + \\ \boldsymbol{\tau}_0^T \boldsymbol{\tau}_0 + \boldsymbol{\tau}_1^T \boldsymbol{\tau}_1 + \cdots + \boldsymbol{\tau}_{N-1}^T \boldsymbol{\tau}_{N-1}$$

- subject to

$$\mathbf{z}_1 = \mathbf{z}_0 + \Delta t \mathbf{f}(t, \mathbf{z}_0, \boldsymbol{\tau}_0)$$

$$\mathbf{z}_2 = \mathbf{z}_1 + \Delta t \mathbf{f}(t, \mathbf{z}_1, \boldsymbol{\tau}_1)$$

$$\mathbf{z}_3 = \mathbf{z}_2 + \Delta t \mathbf{f}(t, \mathbf{z}_2, \boldsymbol{\tau}_2)$$

$$\vdots$$

$$\mathbf{z}_N = \mathbf{z}_{N-1} + \Delta t \mathbf{f}(t, \mathbf{z}_{N-1}, \boldsymbol{\tau}_{N-1})$$

# MODEL PREDICTIVE CONTROL

## Optimal Control

- Minimise

$$(\mathbf{z}_1 - \mathbf{z}_d)^T \mathbf{Q} (\mathbf{z}_1 - \mathbf{z}_d) + (\mathbf{z}_2 - \mathbf{z}_d)^T \mathbf{Q} (\mathbf{z}_2 - \mathbf{z}_d) + \cdots + (\mathbf{z}_N - \mathbf{z}_d)^T \mathbf{Q} (\mathbf{z}_N - \mathbf{z}_d) + \\ \boldsymbol{\tau}_0^T \mathbf{R} \boldsymbol{\tau}_0 + \boldsymbol{\tau}_1^T \mathbf{R} \boldsymbol{\tau}_1 + \cdots + \boldsymbol{\tau}_{N-1}^T \mathbf{R} \boldsymbol{\tau}_{N-1}$$

- subject to

$$\mathbf{z}_1 = \mathbf{z}_0 + \Delta t \mathbf{f}(t, \mathbf{z}_0, \boldsymbol{\tau}_0)$$

$$\mathbf{z}_2 = \mathbf{z}_1 + \Delta t \mathbf{f}(t, \mathbf{z}_1, \boldsymbol{\tau}_1)$$

$$\mathbf{z}_3 = \mathbf{z}_2 + \Delta t \mathbf{f}(t, \mathbf{z}_2, \boldsymbol{\tau}_2)$$

$$\vdots$$

$$\mathbf{z}_N = \mathbf{z}_{N-1} + \Delta t \mathbf{f}(t, \mathbf{z}_{N-1}, \boldsymbol{\tau}_{N-1})$$

# MODEL PREDICTIVE CONTROL

## Optimal Control

- Minimise

$$J = \sum_{i=0}^{N-1} (\mathbf{z}_{i+1} - \mathbf{z}_d)^T \mathbf{Q} (\mathbf{z}_{i+1} - \mathbf{z}_d) + \boldsymbol{\tau}_i^T \mathbf{R} \boldsymbol{\tau}_i$$

- subject to

$$\mathbf{z}_{k+1} = \mathbf{z}_k + \Delta t \mathbf{f}(t, \mathbf{z}_k, \boldsymbol{\tau}_k) \quad \text{for } k = 0, 1, 2, \dots, N-1$$

Decision variables:  $\boldsymbol{\tau}_i$

# REINFORCEMENT-BASED CONTROL

DDPG

- Bellman's equation

$$Q(\mathbf{s}, \mathbf{a}) = R(\mathbf{s}, \mathbf{a}) + \gamma \max_{\mathbf{s}'} Q(\mathbf{s}', \mathbf{a}')$$

- Reward function

$$R(\mathbf{s}, \mathbf{a}) = -(\mathbf{s} - \mathbf{s}_d)^T (\mathbf{s} - \mathbf{s}_d) - \lambda_{\text{torque}} \mathbf{a}^T \mathbf{a}$$

# REINFORCEMENT-BASED CONTROL

DDPG

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$$\mathbf{s} = \begin{Bmatrix} \mathbf{z} \\ \mathbf{z}_d \end{Bmatrix}, \mathbf{a} = \boldsymbol{\tau}$$

# REINFORCEMENT-BASED CONTROL

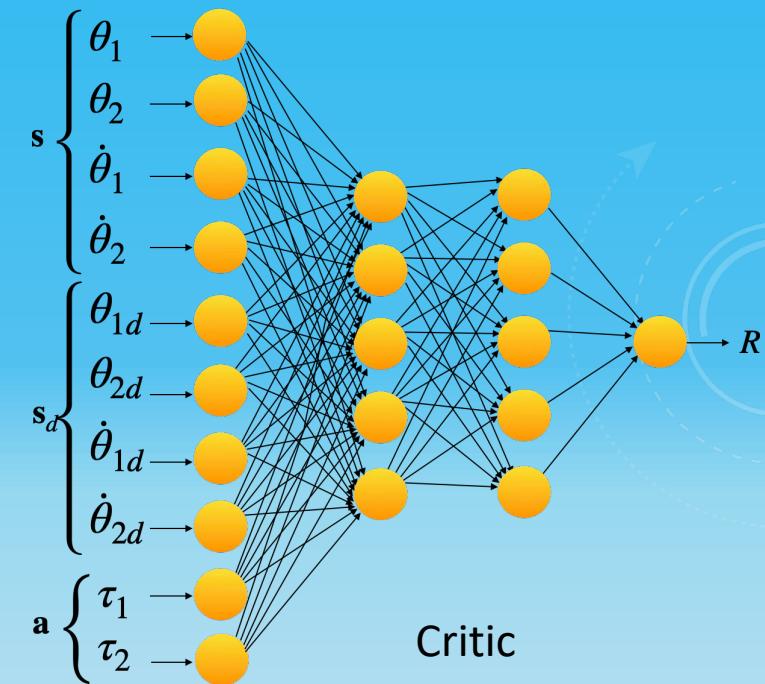
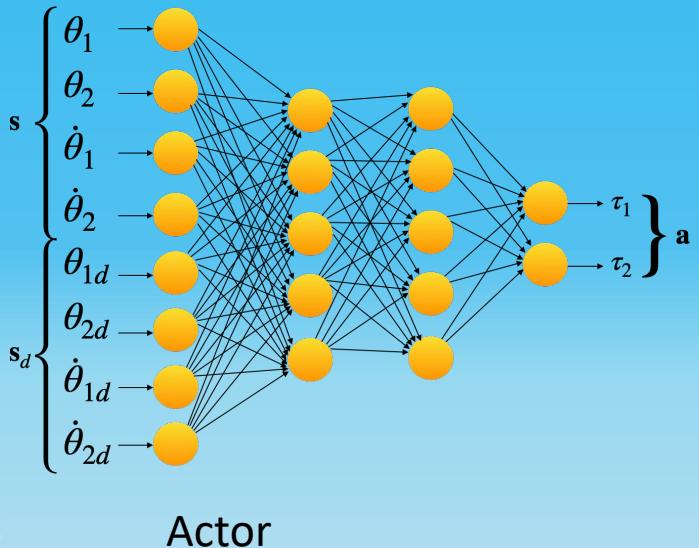
DDPG

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$$Q(\mathbf{s}, \mathbf{a}) = R(\mathbf{s}, \mathbf{a}) + \gamma \max_{\mathbf{s}'} Q(\mathbf{s}', \mathbf{a}')$$

- Reward function

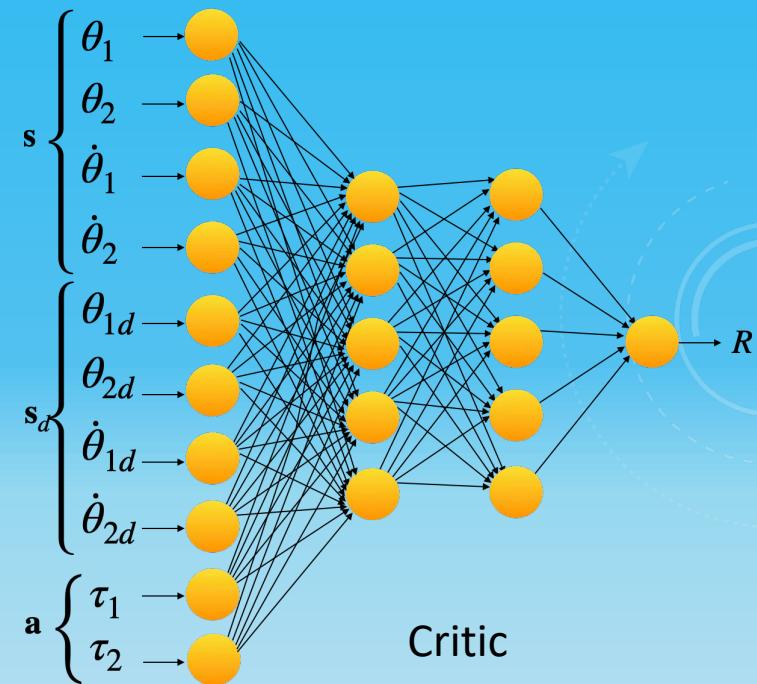
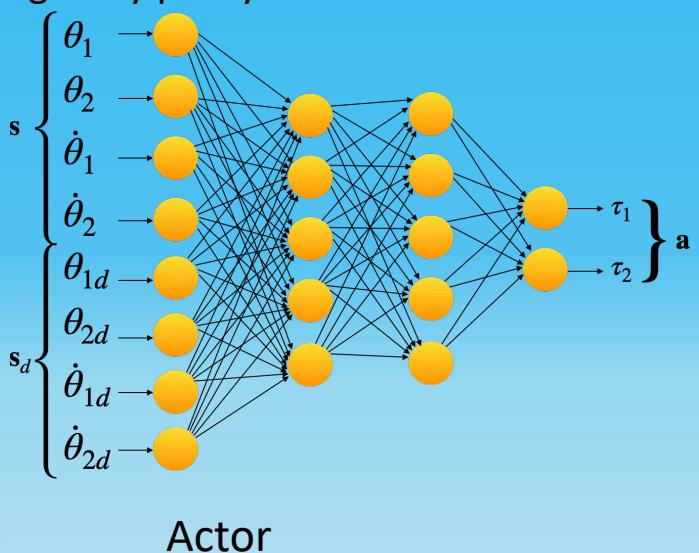
$$R(\mathbf{s}, \mathbf{a}) = -(\mathbf{s} - \mathbf{s}_d)^T (\mathbf{s} - \mathbf{s}_d) - \lambda_{\text{torque}} \mathbf{a}^T \mathbf{a}$$



# REINFORCEMENT-BASED CONTROL

## DDPG

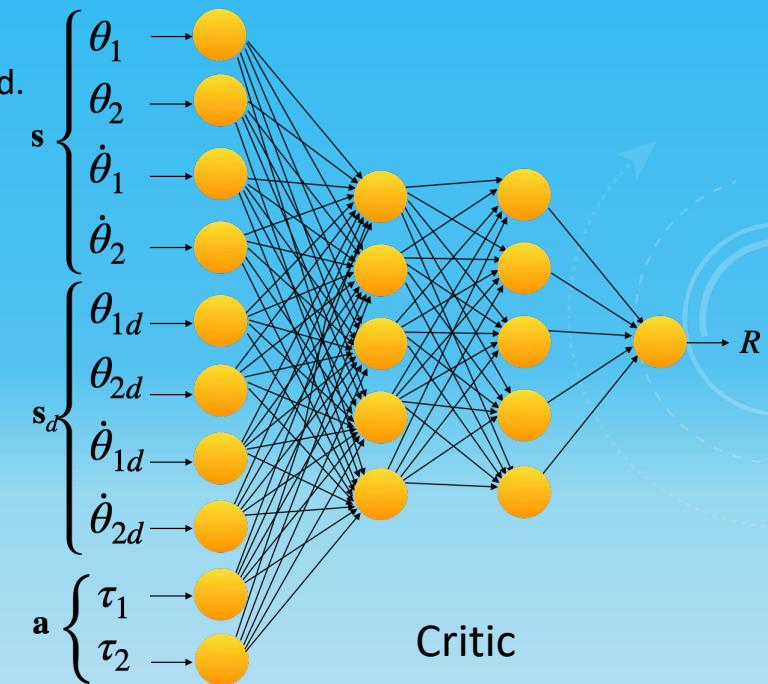
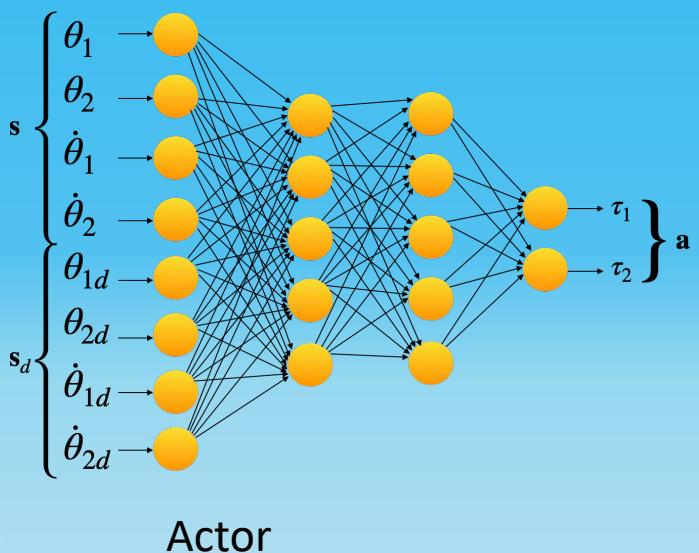
- Actor loss function:  $-Q(s, s_d, a)$
- Critic loss function:  $R(s, a) + \gamma \max_{s'} Q(s', a') - Q(s, a)$
- Replay buffer row:  $[s \quad a \quad s' \quad R \quad \text{done}]$
- $\epsilon$ -greedy policy for actor network actions vs randomised actions



# REINFORCEMENT-BASED CONTROL

## DDPG

- Generation of actions
  - After training, use the actor network with the initial state and the desired state to generate actions for the next step.
  - Find the next state using differential equation and use this as the new input state.
  - Again find the actions using the first step, and repeat until the goal state is reached.



# Queries?

**Thank you!**