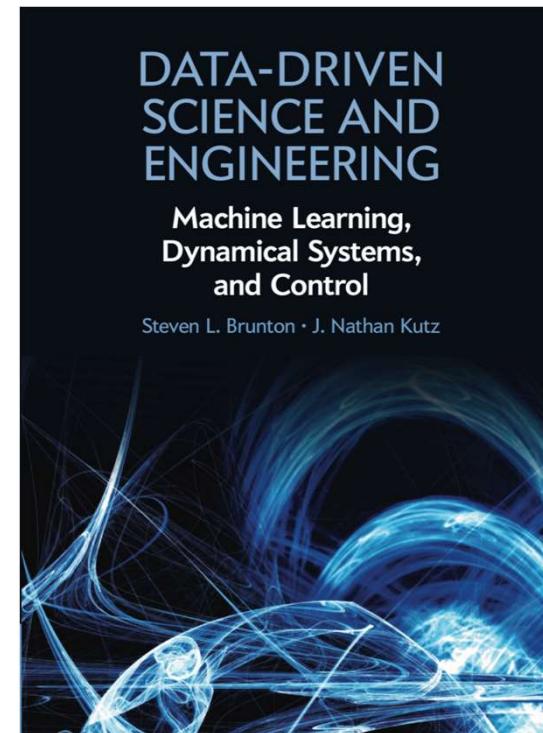
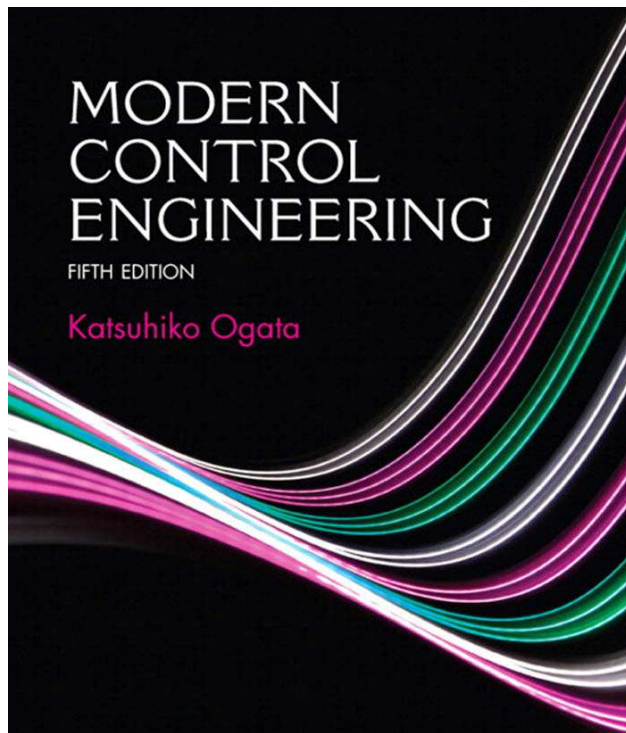


EECE5550 – Mobile Robotics

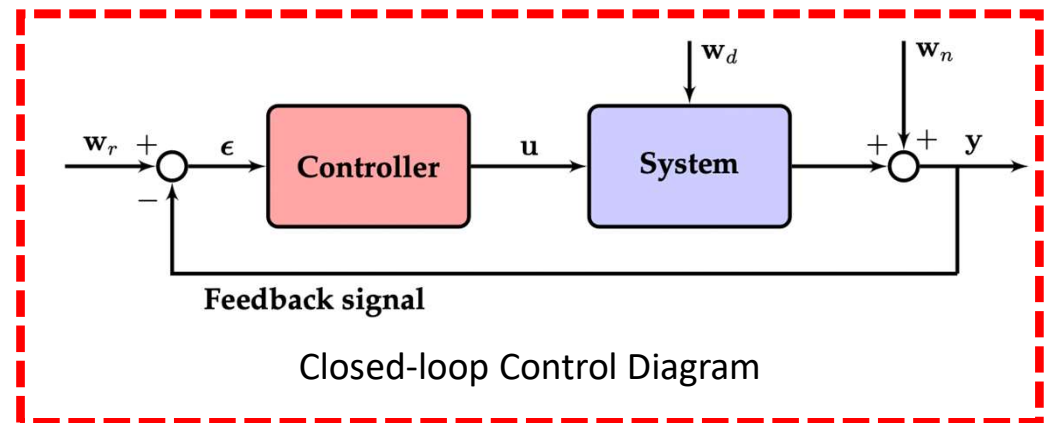
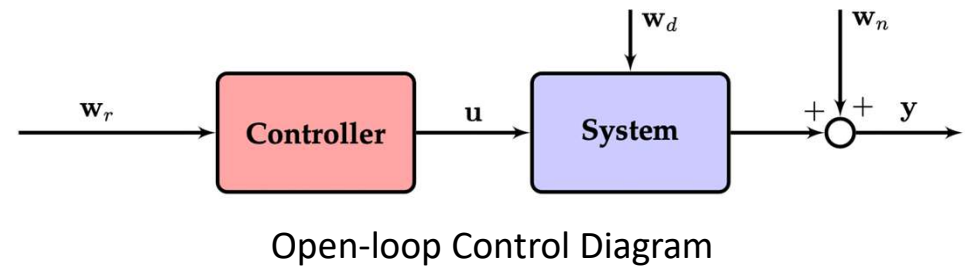
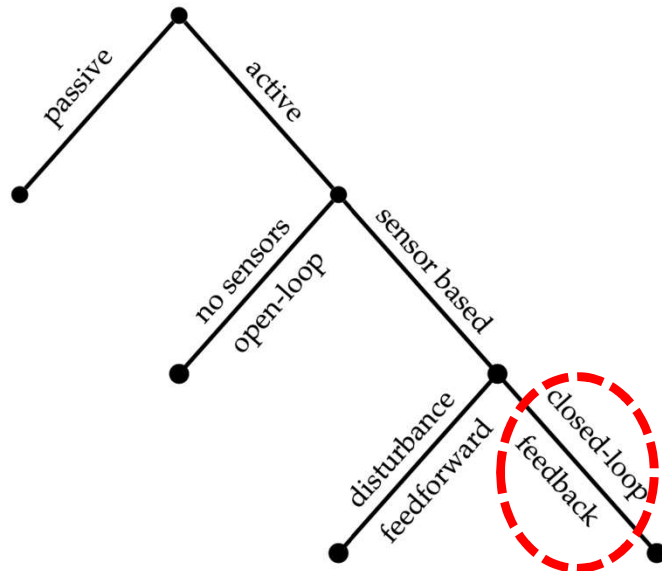
Closed-loop Feedback Control

Reference Books



Why close the loop?

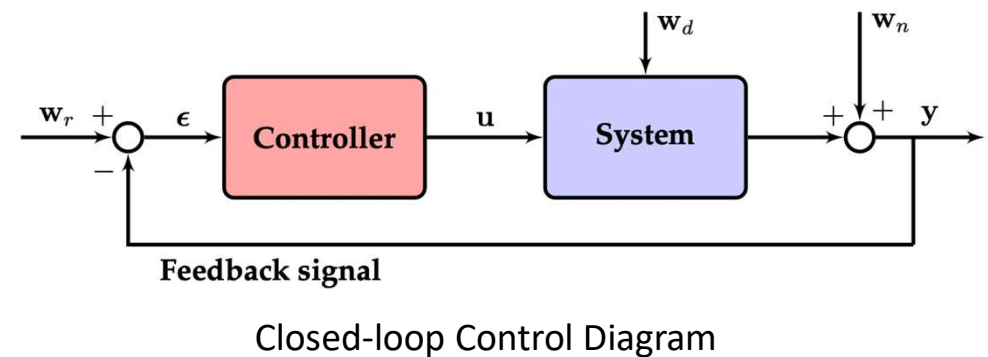
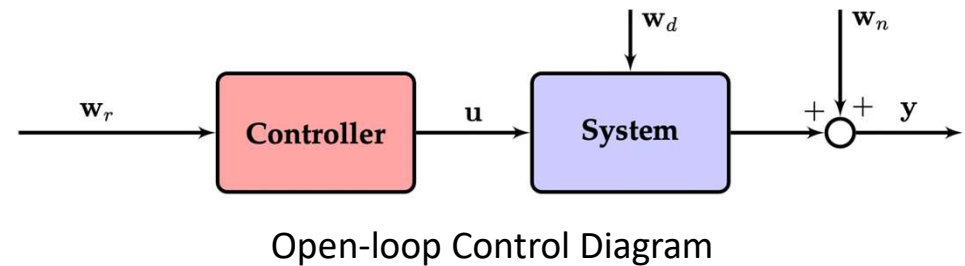
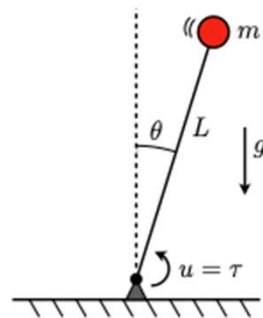
- Types of control



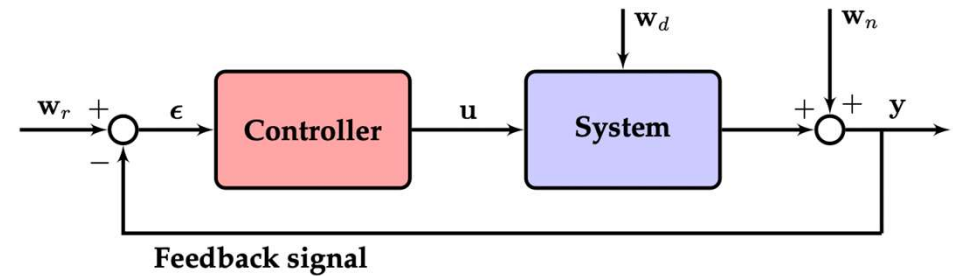
Figures are from Data-Driven Science and Engineering Book by J. Nathan Kutz and Steven L. Brunton

Why close the loop?

- Uncertainty
 - System model inaccuracies
- Instability
 - Stabilizing system dynamics
- Disturbances
 - Unmodelled errors on system
- Efficiency



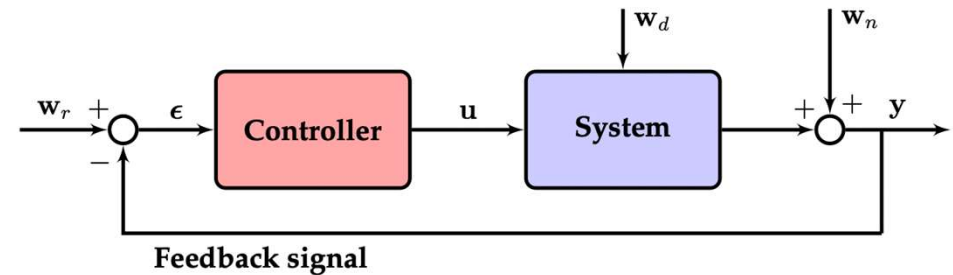
Basic Feedback Control



Closed-loop Control Diagram

- System dynamics and measurements
 - $\dot{x} = f(x, u, w_d)$
 - $y = g(x, u, w_n)$
- Goal is to design a controller $u = k(x, w_r)$ that will hold the system in a desired state
 - $\dot{x} = f(x, k(x, w_r), w_d)$

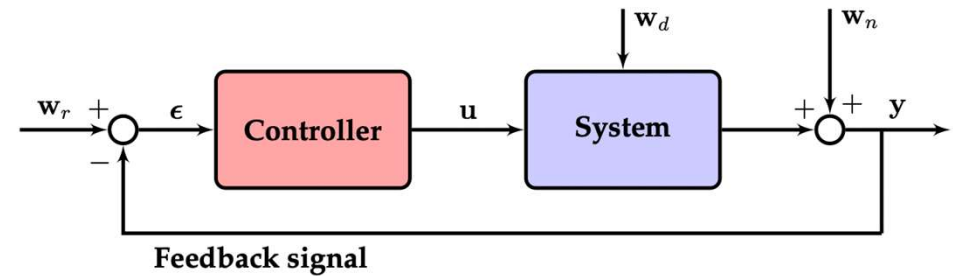
Basic Feedback Control



Closed-loop Control Diagram

- Motivating example: Cruise control
 - Let y be the car's speed and u be the gas fed into the engine
 - A simple model: $y = u$
 - An open-loop controller: $u = w_r$
 - Error is zero: $e = y - w_r$
 - BUT
 - If we have incorrect model i.e., in actuality $y = 2u$
 - What if go from driving flat to up hill? i.e., if $y = u + \sin(t)$
 - Open-loop would not work!
 - In contrast, the closed-loop control would reduce the error:
 - Closed-loop control: $u = K(y - w_r)$
 - For the actual model: $y = 2u$ $y = \frac{2K}{2K+1} w_r$ and $K=50$ then we have 1% steady-state error.

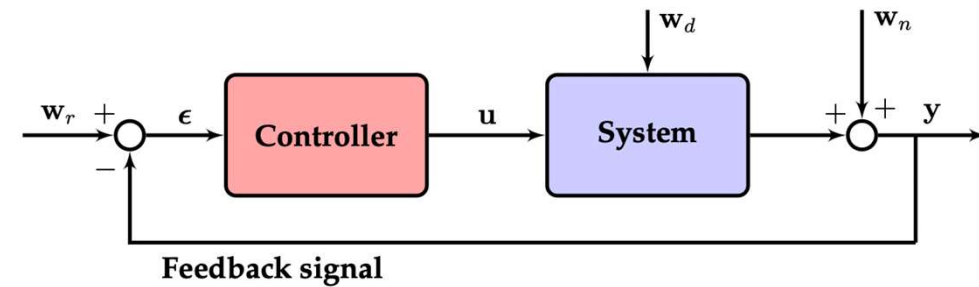
Basic Feedback Control



Closed-loop Control Diagram

- Linear time-invariant systems (LTI)
 - $\dot{\mathbf{x}} = \mathbf{A}\mathbf{x}$
 - Where $\mathbf{x} \in R^n, \mathbf{A} \in R^{n \times n}$ constant
- We know that $\mathbf{x}(t) = e^{\mathbf{A}t}\mathbf{x}(0)$ where $\mathbf{x}(0)$ is the initial state.
- Stability:
 - An LTI system is **asymptotically stable** if and only if all the eigenvalues of \mathbf{A} have **strictly negative real parts**.
- The simplest case: single-input single-output (SISO)
 - $x(t) = e^{at}x(0)$ if $a \geq 0$ the state blows as time goes to infinity.

Basic Feedback Control



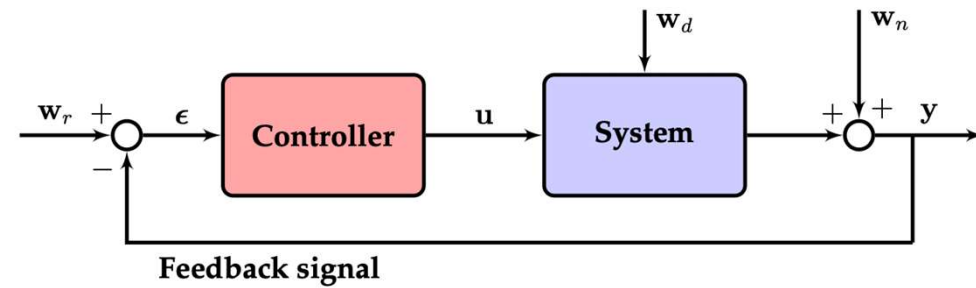
Closed-loop Control Diagram

- Stability:
 - Multi-input multi-output (MIMO)
 - $\mathbf{x}(t) = e^{\mathbf{A}t} \mathbf{x}(0)$
 - Eigen decomposition of \mathbf{A} : $\mathbf{A}\mathbf{T} = \mathbf{T}\mathbf{\Lambda}$ where \mathbf{T} is the eigenvector and $\mathbf{\Lambda}$ is the diagonal matrix of eigenvalues.
 - $\mathbf{e}^{\mathbf{A}t} = \mathbf{e}^{\mathbf{T}\mathbf{\Lambda}\mathbf{T}^{-1}} = \mathbf{T}\mathbf{e}^{\mathbf{\Lambda}t}\mathbf{T}^{-1}$
 - For full derivation -> Section 8.2 of Data Driven Science and Engineering Book
 - Eigenvalues may be complex values:
 - $\lambda = a + ib$
 - If ALL of the eigen values have real negative real part i.e., $Re(\lambda) = a < 0$ then the system is stable.

$$e^{\mathbf{\Lambda}t} = \begin{bmatrix} e^{\lambda_1 t} & 0 & \dots & 0 \\ 0 & e^{\lambda_2 t} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & e^{\lambda_n t} \end{bmatrix}$$

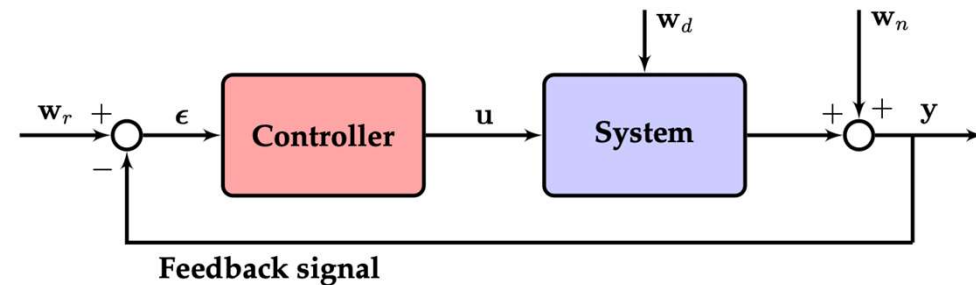
Basic Feedback Control

- Eigenvalues and Linear Phase Portraits
 - Visualization in Wolfram Player



Closed-loop Control Diagram

Basic Feedback Control



Closed-loop Control Diagram

- Controlling LTI systems
 - $\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \rightarrow \dot{\mathbf{x}} = (\mathbf{A} - \mathbf{B}\mathbf{K})\mathbf{x}$
 - $\mathbf{y} = \mathbf{C}\mathbf{x}$
 - The problem is reduced to an **autonomous** system of differential equations.
- Select a \mathbf{K} such that the system is stabilized:
 - Assuming \mathbf{C} is identity
 - No control input $\mathbf{x}(t) = e^{\mathbf{A}t}\mathbf{x}(0)$
 - With control input $\mathbf{x}(t) = e^{(\mathbf{A} - \mathbf{B}\mathbf{K})t}\mathbf{x}(0) = e^{\tilde{\mathbf{A}}t}\mathbf{x}(0)$
 - Analyze $\tilde{\mathbf{A}}$ and select the eigenvalues that would stabilize the system

Linearization

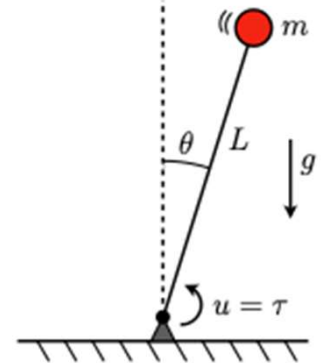
- Majority of the systems are nonlinear
 - $\dot{x} = f(x, u) \quad y = g(x, u)$
- To apply linear control theory, we linearize the system at fixed points:
 - Find fixed points (\hat{x}, \hat{u}) where $f(\hat{x}, \hat{u}) = 0$
 - Expand the input-output functions in a Taylor series for small displacements
 $\Delta x = x - \tilde{x} \quad \Delta u = u - \tilde{u}$

$$f(\bar{x} + \Delta x, \bar{u} + \Delta u) = f(\bar{x}, \bar{u}) + \underbrace{\left. \frac{df}{dx} \right|_{(\bar{x}, \bar{u})}}_A \cdot \Delta x + \underbrace{\left. \frac{df}{du} \right|_{(\bar{x}, \bar{u})}}_B \cdot \Delta u + \dots \quad g(\bar{x} + \Delta x, \bar{u} + \Delta u) = g(\bar{x}, \bar{u}) + \underbrace{\left. \frac{dg}{dx} \right|_{(\bar{x}, \bar{u})}}_C \cdot \Delta x + \underbrace{\left. \frac{dg}{du} \right|_{(\bar{x}, \bar{u})}}_D \cdot \Delta u + \dots$$

- Drop the higher order terms as they are negligible:
 - $\dot{x} = Ax + Bu \quad y = Cx + Du$

Example: Inverted pendulum

- System dynamics: $\ddot{\theta} = -\frac{g}{L} \sin(\theta) + u$.
- State: angular position and velocity. Control input: torque.



$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \theta \\ \dot{\theta} \end{bmatrix} \quad \Rightarrow \quad \frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ -\frac{g}{L} \sin(x_1) + u \end{bmatrix}$$

- Take the derivative: $\frac{d\mathbf{f}}{d\mathbf{x}} = \begin{bmatrix} 0 & 1 \\ -\frac{g}{L} \cos(x_1) & 0 \end{bmatrix}, \quad \frac{d\mathbf{f}}{d\mathbf{u}} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$

- Linearize at fixed points: up ($x_1 = \pi, x_2 = 0$) down ($x_1 = 0, x_2 = 0$)

- $\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{g}{L} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{Pendulum up, } \lambda = \pm \sqrt{g/L}} \quad \underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{g}{L} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{Pendulum down, } \lambda = \pm i \sqrt{g/L}} \quad \text{Is the system stable?}$
 (Assume $\sqrt{g}/L=1$)

Example: Inverted pendulum

- Is the system stable?

- Yes, if pendulum down

- No, if pendulum up because positive eigen value

- $\lambda = \pm 1$

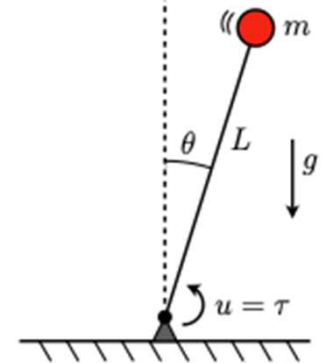
- Let's apply closed-loop control $\dot{x} = (A - BK)x$

- Can you find a K that will stabilize the pendulum when it is up?

- Assume $\sqrt{g}/L=1$

$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{g}{L} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{Pendulum up, } \lambda = \pm \sqrt{g/L}}$$

$$\underbrace{\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -\frac{g}{L} & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u}_{\text{Pendulum down, } \lambda = \pm i\sqrt{g/L}}$$



Example: Inverted pendulum

- Is the system stable?

- Yes, if pendulum down
- No, if pendulum up because positive eigen value
 - $\lambda = \pm 1$

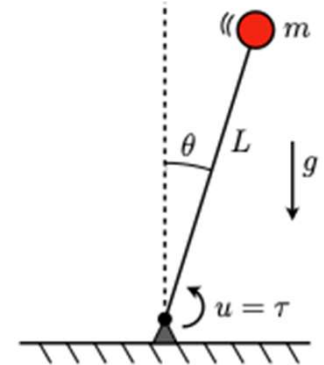
- Let's apply closed-loop control $\dot{x} = (A - BK)x$

- Select $K = [4, 4]$ and analyze eigenvalues ->

- The new eigenvalues are -1, -7
- The system is stabilized for the up position for small displacements of control input

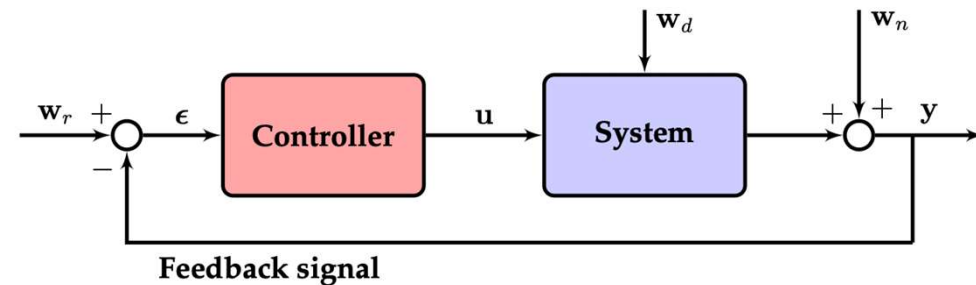
$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ \frac{g}{L} & 0 \end{bmatrix}}_{\text{Pendulum up, } \lambda = \pm \sqrt{g/L}} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{\text{Pendulum down, } \lambda = \pm i \sqrt{g/L}} u$$

$$\frac{d}{dt} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ -\frac{g}{L} & 0 \end{bmatrix}}_{\text{Pendulum down, } \lambda = \pm i \sqrt{g/L}} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \underbrace{\begin{bmatrix} 0 \\ 1 \end{bmatrix}}_{\text{Pendulum up, } \lambda = \pm \sqrt{g/L}} u$$



```
In [10]: A = np.array([[0, 1], [1, 0]])
In [11]: B = np.array([0, 1])
In [12]: K = np.array([4, 4])
In [13]: A_ = A - np.dot(B, K)
In [14]: np.linalg.eig(A_)
Out[14]:
(array([-1., -7.]),
 array([[ 0.70710678,  0.70710678],
        [-0.70710678,  0.70710678]]))
```

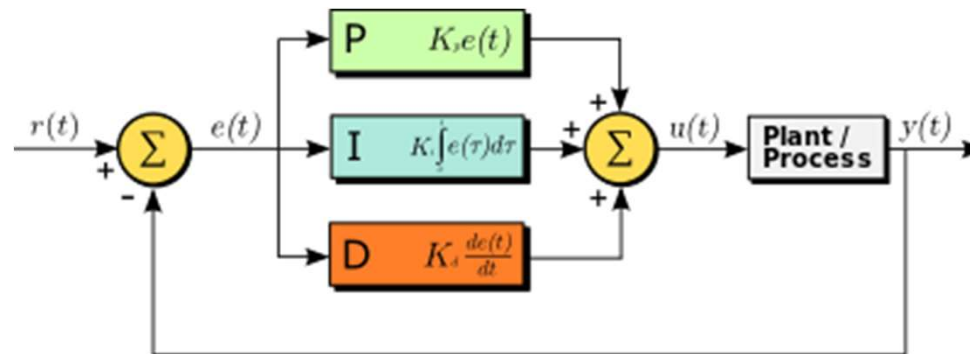
Basic Feedback Control



Closed-loop Control Diagram

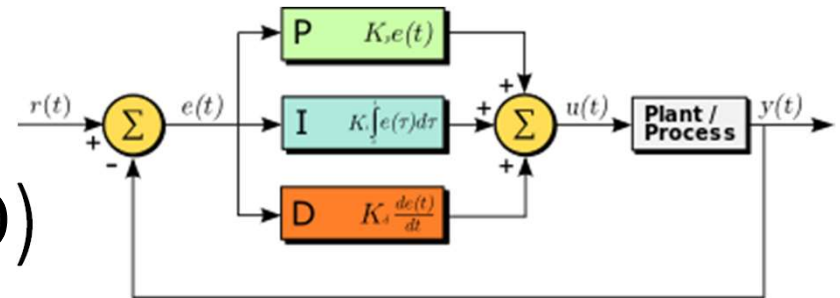
- Is selecting K naively a good strategy?
 - System might be stabilized but it might not be *optimal*
 - Overly stable eigenvalues might use large control inputs
 - The controller can overreact to disturbances and noise
- Solution: Optimal Control
 - Formulate the selection of K as an optimization problem
 - Find a balance between the controller stability and and aggressiveness of control
 - E.g., Linear-Quadratic Controller (LQR)

Proportional-Integral-Derivative Controller (PID)

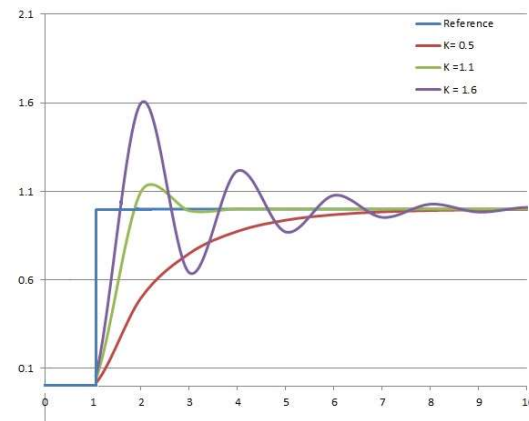


- Goal is to minimize the error term: $e(t) = r(t) - y(t)$
 - $\lim_{t \rightarrow \infty} e(t) = 0$
- PID control law: $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$

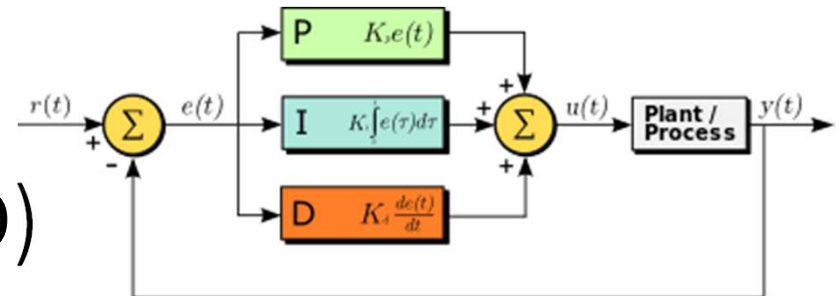
Proportional-Integral-Derivative Controller (PID)



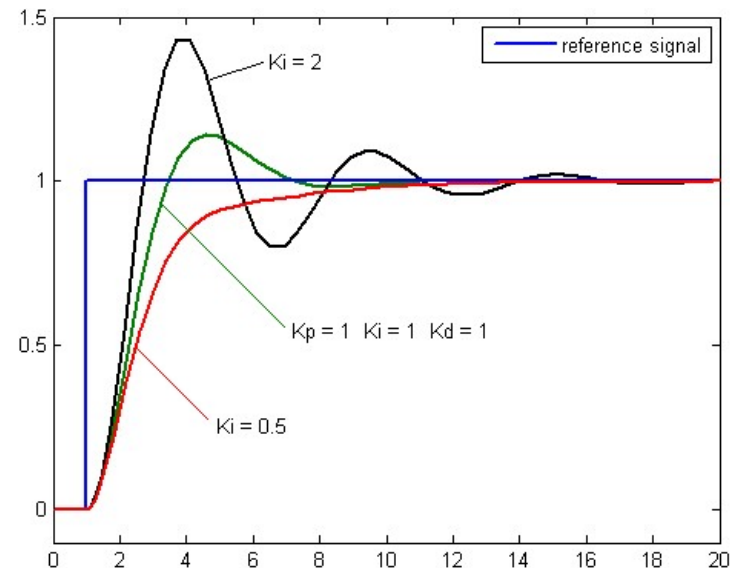
- PID control law: $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$
 - **P term**: proportional gain $u(t) = K_p e(t)$
 - The control input is proportional to the error.
 - Steady-state error: As the error gets close to 0, small P would not reach the desired state and large P would overshoot.
 - The control input would be 0 at the system at the desired state. Thus, the system would oscillate



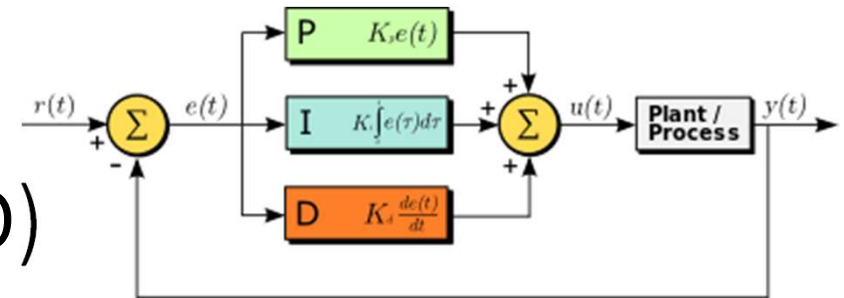
Proportional-Integral-Derivative Controller (PID)



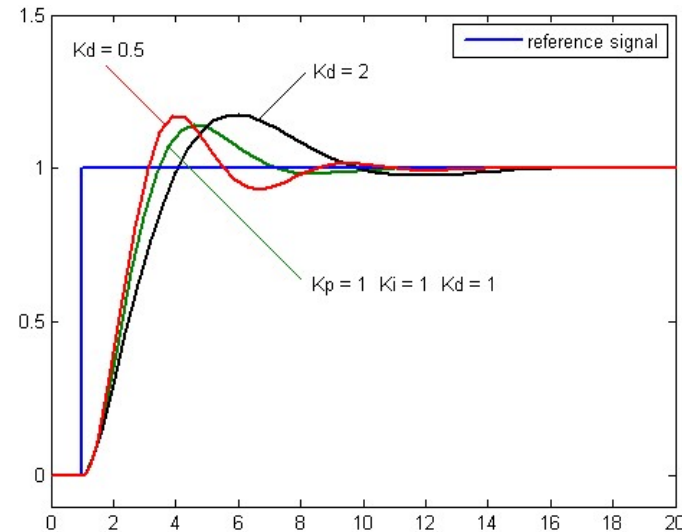
- PID control law: $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$
 - **I term:** integrator gain $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau$
 - Uses the history of error accumulation
 - Can overcome the steady-state error



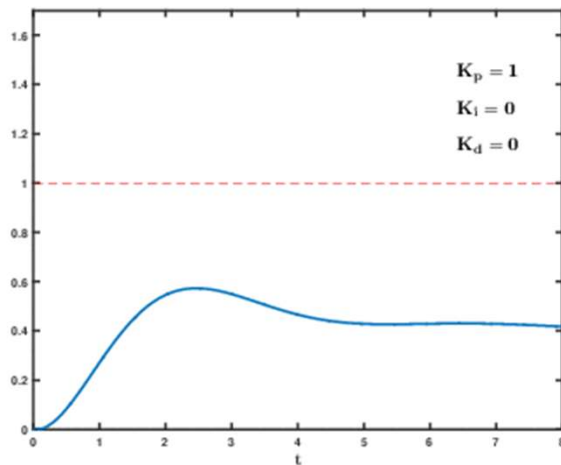
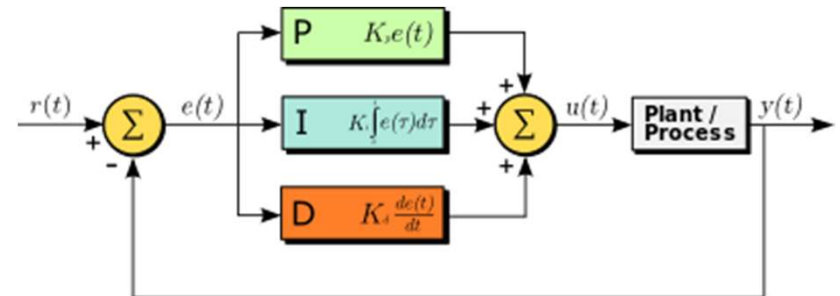
Proportional-Integral-Derivative Controller (PID)



- PID control law: $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$
 - **D term:** derivative gain $u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt}$
 - Measures the rate of error change
 - Looks at the future



Effects of PID Gains



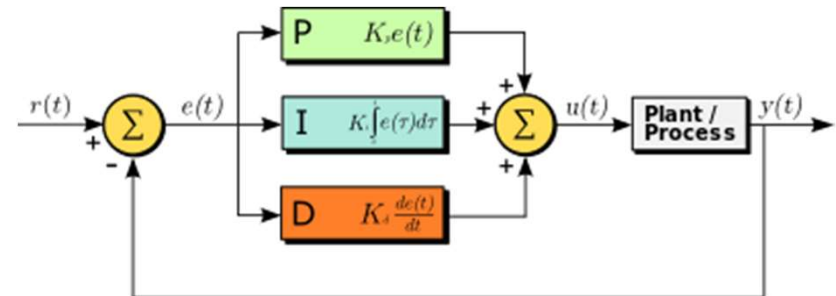
Effects of different PID gains

Effects of *increasing* a parameter independently^{[22][23]}

Parameter	Rise time	Overshoot	Settling time	Steady-state error	Stability
K_p	Decrease	Increase	Small change	Decrease	Degrade
K_i	Decrease	Increase	Increase	Eliminate	Degrade
K_d	Minor change	Decrease	Decrease	No effect in theory	Improve if K_d small

Figures are from Wikipedia: https://en.wikipedia.org/wiki/PID_controller

Tuning PID Gains



Effects of increasing a parameter independently^{[22][23]}

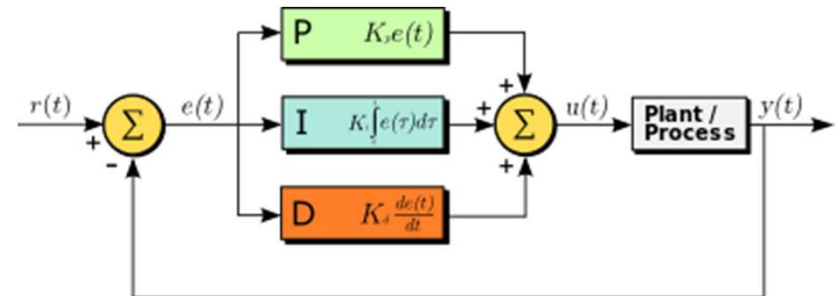
Parameter	Rise time	Overshoot	Settling time	Steady-state error	Stability
K_p	Decrease	Increase	Small change	Decrease	Degrade
K_i	Decrease	Increase	Increase	Eliminate	Degrade
K_d	Minor change	Decrease	Decrease	No effect in theory	Improve if K_d small

- Manual tuning:
 - Set K_i and K_d to 0
 - Increase K_p until the system oscillates
 - Set K_p to half the oscillated value
 - Increase K_i until the steady-state error disappears (if exists)
 - Large K_i can contribute to overshooting
 - If needed, increase K_d until the the system is acceptably quick to reach to desired state

Tuning PID Gains

- Ziegler-Nichols method:

- Set K_i and K_d to 0
- Increase K_p until the system oscillates K_u
- Measure the oscillation rate T_u
- Use the following values to set the gains using T_u and K_u



Effects of increasing a parameter independently^{[22][23]}

Parameter	Rise time	Overshoot	Settling time	Steady-state error	Stability
K_p	Decrease	Increase	Small change	Decrease	Degrade
K_i	Decrease	Increase	Increase	Eliminate	Degrade
K_d	Minor change	Decrease	Decrease	No effect in theory	Improve if K_d small

Ziegler-Nichols method

Control Type	K_p	K_i	K_d
P	$0.50K_u$	—	—
PI	$0.45K_u$	$0.54K_u/T_u$	—
PID	$0.60K_u$	$1.2K_u/T_u$	$3K_uT_u/40$

Tuning PID gains

