

$$\Delta J = \frac{\partial J}{\partial u} \Delta u$$

$$\Rightarrow \Delta J = \frac{\partial J}{\partial x_{T+1}} \frac{\partial x_{T+1}}{\partial u} \Delta u$$

$$\left[\begin{array}{c|c|c|c|c} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_m} & \dots & \frac{\partial f}{\partial x_{T+1}} \\ \hline A_{11} & \dots & A_{1m} & \dots & A_{1,T+1} \\ \vdots & & \vdots & & \vdots \\ A_{T+1,1} & \dots & A_{T+1,m} & \dots & A_{T+1,T+1} \end{array} \right] \left[\begin{array}{c} \Delta u[0] \\ \vdots \\ \Delta u[T] \end{array} \right] = \left[\begin{array}{c} \lambda[1] B_0 \\ \lambda[2] B_1 \\ \vdots \\ \lambda[T+1] B_{T+1} \end{array} \right] \Delta u$$

$$\frac{\partial J}{\partial u[t]} = \left(\frac{\partial f}{\partial x_1} \Big|_{t+1} \dots A_{T+1,T+1} \right) \left(\begin{array}{c} \Delta u[0] \\ \vdots \\ \Delta u[T] \end{array} \right)$$

n: # states
m: # inputs

$$\left[\begin{array}{c|c|c} \frac{\partial f}{\partial u[0]} & \dots & \frac{\partial f}{\partial u[T]} \end{array} \right]$$

$$\left[\begin{array}{c|c|c} \frac{\partial f}{\partial x_1} & \dots & 0 \\ \hline 0 & \dots & 0 \\ \vdots & & \vdots \\ 0 & \dots & 0 \end{array} \right] \left[\begin{array}{c} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_{T+1}} \end{array} \right] \dots \xrightarrow{\text{compute these terms recursively}}$$

$$\left[\begin{array}{c|c|c} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_{T+1}} \\ \hline \frac{\partial f}{\partial x_1} & \dots & 0 \\ \vdots & & \vdots \\ \frac{\partial f}{\partial x_{T+1}} & \dots & 0 \end{array} \right] \xrightarrow{\lambda^T[T-2]}$$

$$\left[\begin{array}{c|c|c} \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_{T+1}} \\ \hline \frac{\partial f}{\partial x_1} & \dots & \frac{\partial f}{\partial x_{T+1}} + \frac{\partial f}{\partial x_{T+2}} \\ \vdots & & \vdots \\ \frac{\partial f}{\partial x_{T+1}} & \dots & \frac{\partial f}{\partial x_{T+2}} \end{array} \right] \xrightarrow{\lambda^T[T-1]}$$

$$\lambda^T[T-1] = \lambda^T[T] \frac{\partial f}{\partial x_{T+1}} + \frac{\partial l}{\partial x_{T+1}}, \quad \lambda^T[T] = \frac{\partial l}{\partial x_{T+1}}$$

unaugmented sys.

$$\text{from } \lambda^T[T+1]: \quad \frac{\partial J}{\partial u[T+1]} = \lambda^T[T+1] \frac{\partial f}{\partial u[T+1]} + \frac{\partial l}{\partial u[T+1]}$$

$$\text{Solve: } \lambda^T[T+1] = \lambda^T[T] \frac{\partial f}{\partial x_{T+1}} + \frac{\partial l}{\partial x_{T+1}} \quad \lambda^T[T] = \frac{\partial l}{\partial x_{T+1}}$$

$$\frac{\partial J}{\partial u[T]} = \lambda^T[T+1] \frac{\partial f}{\partial u[T]} + \frac{\partial l}{\partial u[T]}$$

Computer function for $\frac{\partial J}{\partial u}$:

function [out] = dJdu(u, x0)
 full control vector...
 (open loop) solver
 → compute $x(t)$ by plugging $u(t)$ into $x[T+1] = f(x, u, t)$, $x[0] = x_0$
 → linearize around $x(t)$, $u(t)$
 → solve for costate: $\lambda^T[T-1] = \lambda^T[T] \frac{\partial f}{\partial x_{T+1}} + \frac{\partial l}{\partial x_{T+1}}$, $\lambda^T[T] = \frac{\partial l}{\partial x_{T+1}}$ backwards
 → solve for gradient: $\frac{\partial J}{\partial u[T]} = \lambda^T[T] \frac{\partial f}{\partial u[T]} + \frac{\partial l}{\partial u[T]}$

$$\text{out} = \left[\frac{\partial J}{\partial u[0]} \dots \frac{\partial J}{\partial u[T]} \right]$$

Gradient Descent Code
 $u = \underbrace{\dots}_{\text{initial control guess}}$ \leftrightarrow initial control guess

for $k = 1 : K$
 $\text{for } t = 0 : T$

$$x[T+1] = f(x, u, t) \quad x[0] = x_0$$

for $t = T-1 : 1$

$$\lambda^T[t-1] = \lambda^T[t] \frac{\partial f}{\partial x_{t+1}} + \frac{\partial l}{\partial x_{t+1}} \quad \lambda^T[T] = \frac{\partial l}{\partial x_T}$$

$$\frac{\partial J}{\partial u[T]} = \lambda^T[T] \frac{\partial f}{\partial u[T]} + \frac{\partial l}{\partial u[T]}$$

$$u = u - \alpha \frac{\partial J}{\partial u}$$

$$\overset{\uparrow}{\gamma} \quad 1 - \alpha \overset{\downarrow}{\gamma} \quad 1$$

repeat

$$J(u) = \sum_{t=0}^{T-1} (l(x, u, t)) + l(x[T])$$

need $x(t)$ from $u(t)$

pseudo code $J(u) \dots$

$$u[0] \rightarrow x(t) \quad x[T+1] = f(x, u, t) \quad x[0] = x_0$$

$$J = \sum_{t=0}^{T-1} (l(x, u, t)) + l(x[T])$$

numerical time iteration: costate propagation

solver
terrible
pseudo
ode

functions:
 $f(x, u, t)$
 $l(x, u, t)$

$$\frac{\partial f}{\partial x}$$

$$\frac{\partial f}{\partial x}$$

$$\frac{\partial f}{\partial u}$$

$$\frac{\partial l}{\partial u}$$

$l(x, u, t)$ in LQR is

$$x(t)^T Q(t) x(t) + u(t)^T R(t) u(t)$$

pick

for dynamics

$t=0$

continuous time version: costate propagation

$$-\dot{\lambda}(t) = \lambda^T \frac{\partial f}{\partial x}|_t + \frac{\partial l}{\partial x}|_t \quad \lambda(t) = \frac{\partial l}{\partial x}|_T$$

$$\text{LQR} \cdot -\dot{\lambda} = \lambda^T A + x^T Q \quad \lambda(T) = \lambda^T Q_T$$



$$\frac{\partial J}{\partial u} = \lambda(t) \frac{\partial f}{\partial u}|_t + \frac{\partial l}{\partial u}|_t$$

for dynamics

$$\dot{x} = f(x, u, t)$$

$$J = \int_0^T l(x, u, t) dt + l(x(0))$$

$$\lambda^T B + u^T R = 0 \quad \text{not doing anymore}$$

$$u = R^{-1} B^T \lambda$$

Examples:

in time interval $[0, T]$

make a ball roll as far as possible

reduced to Brachistochrone

$$\max_{u(t)} x(T) - (y(T) - \bar{y})^2$$

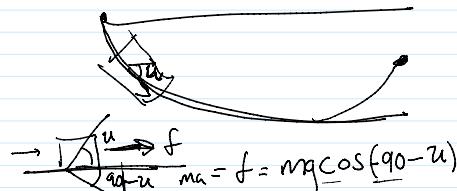
$$\text{s.t. } \dot{x} = v \cos(u) \quad x(0) = 0$$

$$\dot{y} = v \sin(u) \quad y(0) = 0$$

$$\ddot{v} = -g \sin(u) \quad v(0) = 0$$

$$\text{target } y(T) = \bar{y}$$

$$u(t) = 0$$



$$\rightarrow F = ma = mg \cos(\theta) = m g \cos(-90^\circ - u)$$

$$a = g \cos(-90^\circ - u)$$

$$= g \cos(90^\circ + u) / \sin(u)$$

Example:

$$\min (\bar{\theta} - \theta(T))^2 + \dot{\theta}(T)^2$$

$\bar{\theta}$ = pendulum upright

s.t. inverted pendulum

$\dot{\theta}$

H₂ & H_∞ control

G(s) : matrix of transfer functions

$$\text{TF: } V(s) \rightarrow [G(s)] \rightarrow Z(s)$$

ways to measure the "size" or energy gain of system

H₂ norm:

$$\|G(s)\|_2 = \left(\frac{1}{2\pi} \int_{-\infty}^{\infty} \text{Tr} \left(G(j\omega)^* G(j\omega) \right) d\omega \right)^{1/2}$$

integral $|G(j\omega)|^2_F$

vectorizing $G(j\omega)$, and then taking the ℓ^2 norm

$$\|G(j\omega)\|_F^2 = \left(\sum_{ij} |G_{ij}(j\omega)|^2 \right)$$

H_∞ norm:

$$\|G(s)\|_\infty = \max_{\omega} \overline{\sigma}(G(j\omega))$$

$$\max_{\omega} \max_{V \neq 0} \frac{\|G(j\omega)V\|_2}{\|V\|_2}$$

$$\sqrt{V^T G^* G V} / \sqrt{V^T V}$$

$$\max_{\omega} \max_{V \neq 0} \frac{\|G V\|_2}{\|V\|_2} \quad \begin{cases} \text{worst case energy gain} \\ \text{of output} \end{cases}$$

$$\sum_{\omega} \sum_{ij} (G_{ij})^2 \quad \begin{cases} \text{average} \\ \text{total} \\ \text{energy gain} \\ \text{of output} \end{cases}$$

RMS energy at $t=1$ the input

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(t) g(t) dt = \int_{-\infty}^{\infty} f(t) \bar{g}(t) dt$$

From
energy
of
the output
when

the input
white noise
of mag 1
Pascals
Then

energy loss
output
for
of mag 1.

$$\int_{-\infty}^{\infty} f(t) \bar{g}(t) dt$$

$\bar{f}(j\omega)$ is Fourier
transform
of $f(t)$

Time Domain:

$$|G(s)|_2 = \left(\int_0^\infty \text{Tr}(g(t)^T g(t)) dt \right)^{1/2}$$

$g(t)$: matrix of impulse
responses

$g_{ij}(t)$: impulse
response of $G_{ij}(s)$

min $|G(s)|_2$ easy...

but average performance

$$|G(s)|_\infty = \max_w \max_{V(t)} \frac{\int_0^\infty z(t)^T z(t) dt}{\int_0^\infty V(t)^T V(t) dt}$$

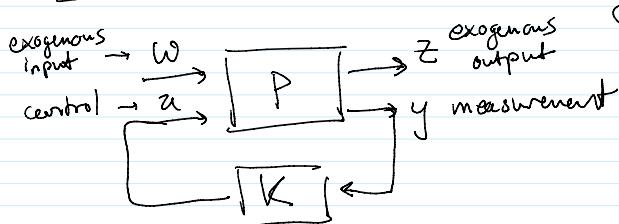
where $V(t)$ is a sinusoid
with freq. w

$\frac{|Gv|_2}{|V|_2}$ hard
to solve

$$\min |G(s)|_\infty = \min_w \max_{V(t)} \frac{\int_0^\infty z(t)^T z(t) dt}{\int_0^\infty V(t)^T V(t) dt}$$

other... worst case \rightarrow robustness

General Control Formulation:



goal: $z = \boxed{G_{zw}(P, K)} w$

$$\min_K |G_{zw}(P, K)|_2 \text{ or } \min_K |G_{zw}(P, K)|_\infty$$

pick w & z to define performance
of your system...

state space model: $\begin{cases} \dot{x} = Ax + B_1 w + B_2 u \\ z = C_1 x + D_{11} w + D_{12} u \\ y = C_2 x + D_{21} w + D_{22} u \end{cases} \rightarrow$

Special Case of

H_2 optimization: LQG

noise model
white noise

$$\dot{x} = Ax + Bu + wd$$

$$y = Cx + w_n$$

$$E \left(\begin{bmatrix} w_d(t) \\ w_n(t) \end{bmatrix} \left[\begin{bmatrix} w_d(t) & w_n(t) \end{bmatrix} \right] \right) = \begin{bmatrix} w_d & 0 \\ 0 & w_n \end{bmatrix} S(t - \tau)$$

Find $u = K(s)y$

$$r - \sqrt{\tau} - \tau - 1.1 - u - \tau$$

Find $u = K(s)y$

$$J = E \left[\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T [x^T Q x + u^T R u] dt \right] \text{ with } Q = Q^T \geq 0 \\ R = R^T \geq 0$$

$$z = \begin{bmatrix} Q^{1/2} & 0 \\ 0 & R^{1/2} \end{bmatrix} \begin{bmatrix} x \\ w \end{bmatrix} \quad \begin{pmatrix} w_d \\ w_n \end{pmatrix} = \begin{bmatrix} W_d^{1/2} & 0 \\ 0 & W_n^{1/2} \end{bmatrix} \underline{w} \quad \begin{array}{l} \text{white noise} \\ \text{w unit norm} \end{array}$$

$$J = E \left| \lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T z(t)^T z(t) dt \right| = \| G_{zw}(P, K) \|_2$$

with

$$\dot{x} = Ax + \begin{bmatrix} W_d^{1/2} & 0 \end{bmatrix} \underline{w} + Bu \\ z = \begin{bmatrix} Q^{1/2} \\ 0 \end{bmatrix} \dot{x} + \begin{bmatrix} 0 \\ R^{1/2} \end{bmatrix} u \\ y = Cx + \begin{bmatrix} 0 & W_n^{1/2} \end{bmatrix} \underline{w}$$

state space model
s.t. LQG
is $\| G_{zw}(P, K) \|_2$

$$z = x^T Q^{1/2} x + w^T R^{1/2} w$$

Solving $\min_K \| G_{zw}(P, K) \|_\infty$ hard

look for controllers $\| G_{zw}(P, K) \|_\infty < \gamma$, search over γ

$$\min_K \max_w \int_0^\infty \underbrace{z(t)^T z(t)}_{\text{magnitude of output}} - \underbrace{\gamma^2 w(t)^T w(t)}_{\text{mag. input}} dt$$

Controller and input.

Competition between

searching for a small enough gamma where the controller can win.

$$[\gamma_-, \gamma_+] \leftarrow [0, \bar{\gamma}]$$

- set. $\gamma = \frac{\gamma_+ + \gamma_-}{2}$

- try to find a controller

- try to find a controller
 - ↳ if you can find one, set $\gamma_+ = \gamma$
 - ↳ if not set $\gamma_- = \gamma$
- repeat to find smallest γ .