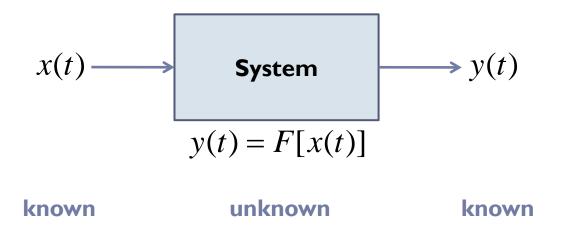


#### What is a system?

Black-box description of characteristic behaviour



#### Superposition principle (SPP)

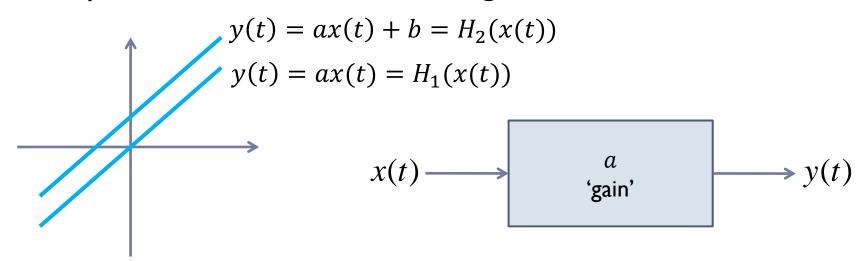
- ► If input  $x_1(t)$   $\rightarrow$  output  $y_1(t)$ ► If input  $x_2(t)$   $\rightarrow$  output  $y_2(t)$
- Then:  $\alpha x_1(t) + \beta x_2(t) \rightarrow \alpha y_1(t) + \beta y_2(t)$

$$x(t) \longrightarrow \mathbf{System} \longrightarrow y(t)$$
$$y(t) = F[x(t)]$$

In general:  $\sum_{n=1}^{N} \alpha_n x_n(t) \rightarrow \sum_{n=1}^{N} \alpha_n y_n(t)$ 

▶ This is true for all t !!!

Surprise I: what looks linear might not be linear



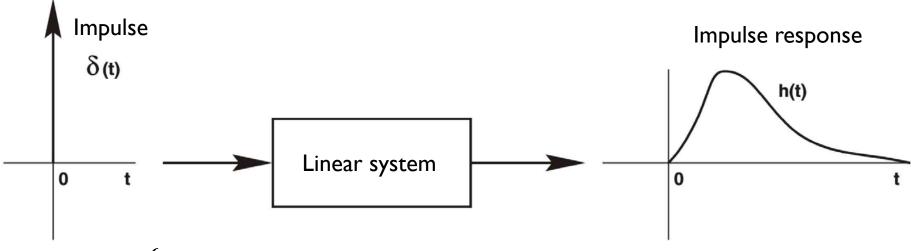
$$H_1(x_1 + x_2) = ax_1 + ax_2$$

$$H_2(x_1 + x_2) = ax_1 + ax_2 + b \neq H(x_1) + H(x_2) = ax_1 + ax_2 + 2b$$



#### Central concept: Impulse response of a Linear System

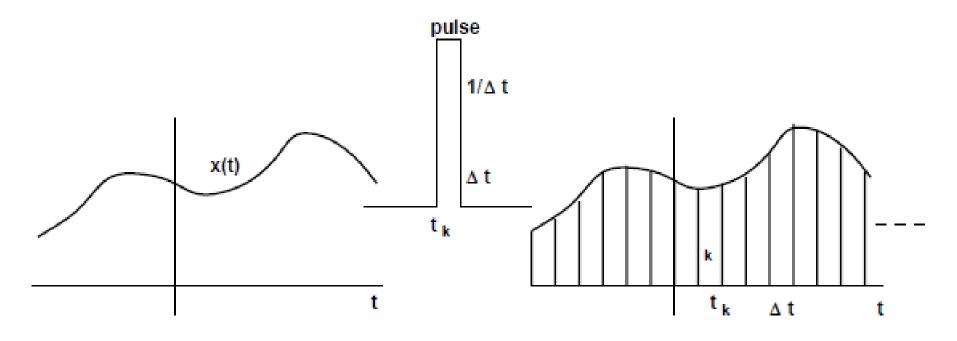
Surprise 2: a linear system can completely change the shape of the input signal!!!



$$\delta(t) = \begin{cases} \infty \text{ for } t = 0 \\ 0 \text{ elsewhere} \end{cases} \text{ such that } \int_{-\infty}^{\infty} \delta(t) dt = 1 \text{ and } f(t_0) = \int_{-\infty}^{\infty} \delta(t - t_0) f(t) dt$$

As a result of the SPP the response of the Linear System to an arbitrary input can be computed from the system's impulse response!

#### Any signal can be decomposed into a series of pulses



$$\delta(t) = \begin{cases} \infty \text{ for } t = 0 \\ 0 \text{ elsewhere} \end{cases} \text{ such that } \int_{-\infty}^{\infty} \delta(t) dt = 1 \text{ and } f(t_0) = \int_{-\infty}^{\infty} \delta(t - t_0) f(t) dt$$

#### Central concept: Impulse response of a Linear System

- How is this useful?
  - Precise description of signal x(t) by Dirac impulses

$$x(t) = \int_{-\infty}^{+\infty} x(\tau) \cdot \delta(t - \tau) \cdot d\tau$$

Precise description of response y(t) from the impulse response

$$y(t) = \int_{0}^{+\infty} x(\tau) \cdot h(t-\tau) \cdot d\tau$$

▶ Considering only causal systems, i.e.  $h(t-\tau) = 0$  for  $\tau \ge t$ 

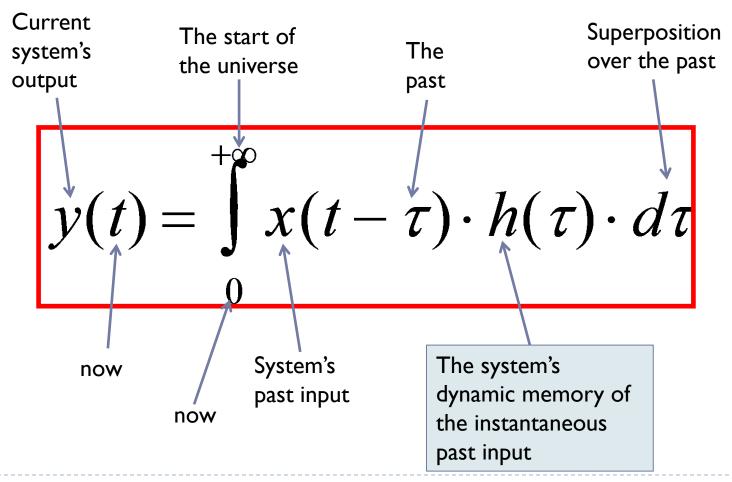
$$y(t) = \int_{-\infty}^{t} x(\tau) \cdot h(t-\tau) \cdot d\tau$$

$$y(t) = \int_{-\infty}^{t} x(\tau) \cdot h(t - \tau) \cdot d\tau$$

$$\Rightarrow \text{ Change of variables: } y(t) = \int_{0}^{+\infty} x(t - \tau) \cdot h(\tau) \cdot d\tau$$

**Convolution** Integral

#### What does the convolution integral mean?



#### Exercise

- Suppose you have  $x(t) = \sin(\omega t)$  and assume impulse response h(t). What is the system's output?
  - We need:  $\sin(t \tau) = \sin(t)\cos(\tau) \cos(t)\sin(\tau)$
- Answer:  $y(t) = G(\omega) \cdot \sin(\omega t + \varphi(\omega))$
- Thus the output is a harmonic function again!
  - Amplitude and phase depend on frequency of input
  - But output frequency has not changed!
  - ▶ Harmonic functions are Eigenfunctions of linear systems!!!

- Alternative characterization of linear systems
  - Amplitude characteristic  $G(\omega)$
  - Phase characteristic  $\varphi(\omega)$

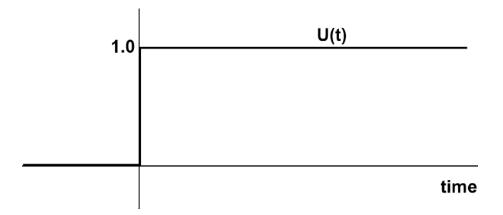
$$y(t) = G(\omega) \cdot \sin(\omega t + \varphi(\omega))$$

- Together, they provide the transfer characteristic!
  - H(ω)
  - Fourier analysis:  $H(\omega)$  is the Fourier transform of  $h(\tau)!$

$$X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t}dt$$

$$Y(\omega) = H(\omega) \cdot X(\omega)$$

- Problem: the Fourier transform of many often used functions is not defined!
  - E.g. step function



$$U(\omega) = \int_{-\infty}^{\infty} U(t)e^{-i\omega t}dt = \int_{0}^{\infty} e^{-i\omega t}dt = -\frac{1}{i\omega}e^{-i\omega t}\Big|_{0}^{\infty}$$

#### Solution: Laplace transform!

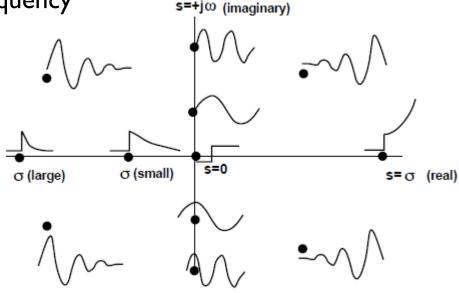
- Integral transform
- Resolves a function or signal into its moments
  - e.g. statistical moments (mean, variance, etc...)
  - Modes of vibration (frequencies)
  - Transform between time and frequency
- Compact systems description
- Definition:

$$F(s) = \mathcal{L}\{f(t)\} = \int_{0}^{\infty} e^{-st} \cdot f(t) dt$$

s: complex number

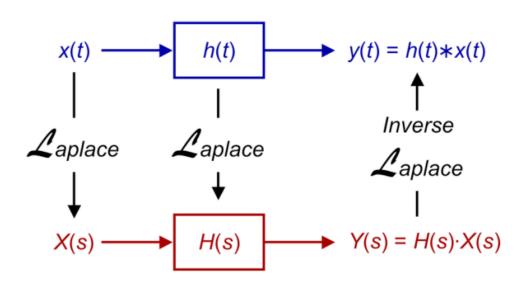
$$s = \sigma + i\omega$$

The Complex s-plane



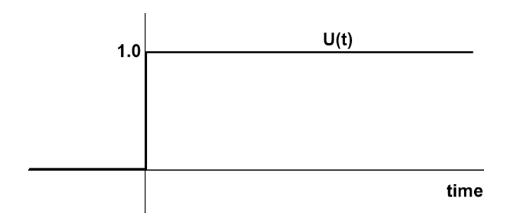
#### Laplace transform





Frequency domain

- We can now solve our problem...
  - Step function has a solution in Laplace space!



$$\mathcal{L}[U(t)] = \int_0^\infty U(t)e^{-st}dt = -\frac{1}{s}e^{-st}\bigg|_0^\infty = \frac{1}{s}$$

#### Laplace transform

		Time domain	's' domain	Comment
<b>→</b>	Linearity	af(t) + bg(t)	aF(s) + bG(s)	Can be proved using basic rules of integration.
	Frequency differentiation	tf(t)	-F'(s)	$F^\prime$ is the first derivative of $F$ .
	Frequency differentiation	$t^n f(t)$	$(-1)^n F^{(n)}(s)$	More general form, (n)th derivative of F(s).
<b>→</b>	Differentiation	f'(t)	sF(s) - f(0)	f is assumed to be a differentiable function, and its derivative is assumed to be of exponential type. This can then be obtained by integration by parts
	Second Differentiation	f''(t)	$s^2 F(s) - sf(0) - f'(0)$	f is assumed twice differentiable and the second derivative to be of exponential type. Follows by applying the Differentiation property to $f'(t)$ .
	General Differentiation	$f^{(n)}(t)$	$s^n F(s) - s^{n-1} f(0) - \dots - f^{(n-1)}(0)$	$f$ is assumed to be $n$ -times differentiable, with $n^{\rm th}$ derivative of exponential type. Follow by mathematical induction.
	Frequency integration	$\frac{f(t)}{t}$	$\int_{s}^{\infty} F(\sigma)  d\sigma$	
<b>→</b>	Integration	$\int_0^t f(\tau) d\tau = (u * f)(t)$	$\frac{1}{s}F(s)$	u(t) is the Heaviside step function. Note $(u * f)(t)$ is the convolution of $u(t)$ and $f(t)$ .
<b>&gt;</b>	Scaling	f(at)	$\frac{1}{ a }F\left(\frac{s}{a}\right)$	
	Frequency shifting	$e^{at}f(t)$	F(s-a)	
$\longrightarrow$	Time shifting	f(t-a)u(t-a)	$e^{-as}F(s)$	u(t) is the Heaviside step function
	Convolution	(f*g)(t)	$F(s) \cdot G(s)$	f(t) and $g(t)$ are extended by zero for $t < 0$ in the definition of the convolution.
Wikipedia	Periodic Function	f(t)	$\frac{1}{1 - e^{-Ts}} \int_0^T e^{-st} f(t) dt$	$f(t)$ is a periodic function of period $T$ so that $f(t)=f(t+T),\ \forall t\geq 0$ . This is the result of the time shifting property and the geometric series.

Laplace transform

	ID	Function	Time domain $f(t) = \mathcal{L}^{-1}\left\{F(s) ight\}$	Laplace s-domain $F(s) = \mathcal{L}\left\{f(t) ight\}$	Region of convergence
	1	ideal delay	$\delta(t- au)$	$e^{-\tau s}$	
	1a	unit impulse	$\delta(t)$	1	all $s$
	2	delayed <i>n</i> th power with frequency shift	$\frac{(t-\tau)^n}{n!}e^{-\alpha(t-\tau)}\cdot u(t-\tau)$	$\frac{e^{-\tau s}}{(s+\alpha)^{n+1}}$	$\operatorname{Re}\{s\} > -\alpha$
	2a	nth power (for integer n)	$\frac{t^n}{n!} \cdot u(t)$	$\frac{1}{s^{n+1}}$	$ \operatorname{Re}\{s\} > 0 \\ (n > -1) $
2	a.1	qth power (for complex q)	$\frac{t^q}{\Gamma(q+1)} \cdot u(t)$	$\frac{1}{s^{q+1}}$	$ \operatorname{Re}\{s\} > 0 \\ (\operatorname{Re}\{q\} > -1) $
2	a.2	unit step	u(t)	$\frac{1}{s}$	$\operatorname{Re}\{s\} > 0$
	2b	delayed unit step	u(t- au)	$ \frac{\frac{1}{s}}{\frac{e^{-\tau s}}{s}} $	$\operatorname{Re}\{s\} > 0$
	2c	ramp	$t \cdot u(t)$	$\frac{1}{s^2}$	$\operatorname{Re}\{s\} > 0$
	2d	nth power with frequency shift	$\frac{t^n}{n!}e^{-\alpha t}\cdot u(t)$	$\frac{1}{(s+\alpha)^{n+1}}$	$\operatorname{Re}\{s\} > -\alpha$
2	d.1	exponential decay	$e^{-\alpha t} \cdot u(t)$	$\frac{1}{s+\alpha}$	$\operatorname{Re}\{s\} > -\alpha$
	3	exponential approach	$(1 - e^{-\alpha t}) \cdot u(t)$	$\frac{\frac{\alpha}{s(s+\alpha)}}{\frac{\omega}{s(s+\alpha)}}$	$Re\{s\} > 0$
	4	sine	$\sin(\omega t) \cdot u(t)$	$\frac{\omega}{s^2 + \omega^2}$	$\operatorname{Re}\{s\} > 0$
	5	cosine	$\cos(\omega t) \cdot u(t)$	$s^2 + \omega^2$	$\operatorname{Re}\{s\} > 0$
	6	hyperbolic sine	$\sinh(\alpha t) \cdot u(t)$	$\frac{\alpha}{s^2 - \alpha^2}$	$\operatorname{Re}\{s\} >  \alpha $
	7	hyperbolic cosine	$\cosh(\alpha t) \cdot u(t)$	$\frac{s}{s^2 - \alpha^2}$	$\operatorname{Re}\{s\} >  \alpha $
	8	Exponentially-decaying sine wave	$e^{-\alpha t}\sin(\omega t)\cdot u(t)$	$(s+\alpha)^2 + \omega^2$	$\operatorname{Re}\{s\} > \alpha$
	9	Exponentially-decaying cosine wave	$e^{-\alpha t}\cos(\omega t)\cdot u(t)$	$\frac{s+\alpha}{(s+\alpha)^2+\omega^2}$	$\operatorname{Re}\{s\} > \alpha$
	10	nth root	$\sqrt[n]{t} \cdot u(t)$	$s^{-(n+1)/n} \cdot \Gamma\left(1 + \frac{1}{n}\right)$	$\operatorname{Re}\{s\} > 0$

#### Laplace transform

Example: solving 
$$\frac{dn(t)}{dt} = -\lambda n(t)$$

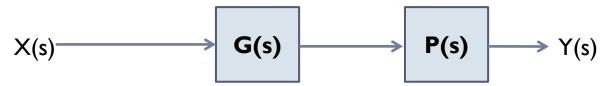
▶ Laplace transform:  $(sN(s)-n(0))+\lambda N(s)=0$ 

$$\Leftrightarrow N(s) = \frac{n(0)}{s+\lambda}$$

Inverse Laplace transform:  $n(t) = \mathcal{L}^{-1}(N(s)) = n(0) \cdot e^{-\lambda t}$ 

The role of feedback

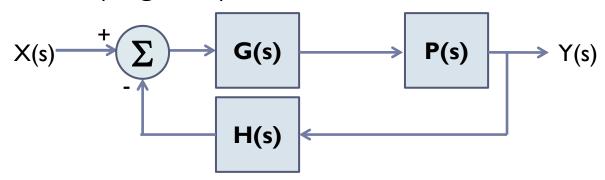
If we have a system G controlling a plant P



- Cascade of 2 linear systems
- Transfer function  $\frac{Y(s)}{X(s)} = G(s) \cdot P(s)$
- Example
  - ▶ P is an elastic band (exponential decay)
  - $P(s) = \frac{1}{Ts+1} \text{ with time constant T}$
  - If G(s) = constant = K, then

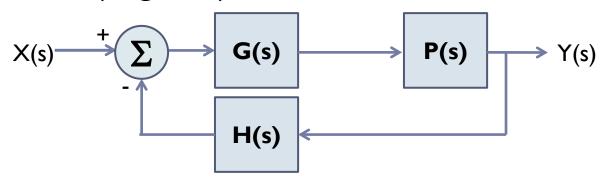
$$\frac{Y(s)}{X(s)} = \frac{K}{Ts+1}$$

Now let's add (negative) feedback…!



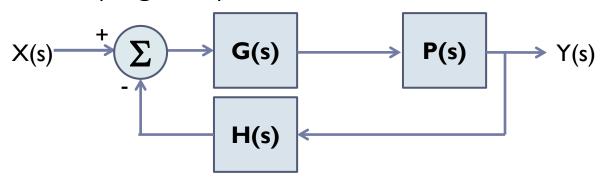
- Transfer function  $\frac{Y(s)}{X(s)} = \frac{G(s) \cdot P(s)}{1 + H(s) \cdot G(s) \cdot P(s)}$
- Example
  - If H(s) = I, then  $\frac{Y(s)}{X(s)} = \frac{G_{fb}}{T_{fb}s+1}$
  - With  $G_{fb} = \frac{K}{(1+K)}$  and  $T_{fb} = \frac{T}{(1+K)}$
  - Result: smaller time constant = faster response!!!

Now let's add (negative) feedback…!



- Transfer function  $\frac{Y(s)}{X(s)} = \frac{G(s) \cdot P(s)}{1 + H(s) \cdot G(s) \cdot P(s)}$
- Example
  - If  $H(s) \cdot G(s) \cdot P(s) \gg 1$ , then  $\frac{Y(s)}{X(s)} = \frac{1}{H(s)}!!!$
  - Result: system is independent of feed-forward path!!!
  - I.e. feedback ensures that the total system is still highly reliable! (even for vulnerable systems, e.g. fatigue, large gain changes...)

▶ Now let's add (negative) feedback…!



Transfer function 
$$\frac{Y(s)}{X(s)} = \frac{G(s) \cdot P(s)}{1 + H(s) \cdot G(s) \cdot P(s)}$$

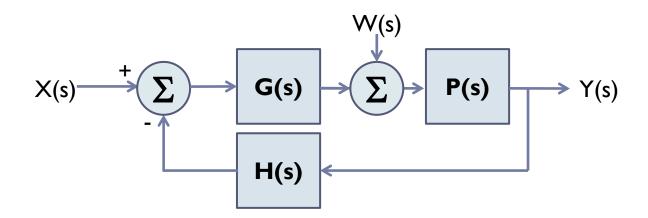
Example

H total system

Integrator	$\Leftrightarrow$	Differentiator	
Differentiator	$\Leftrightarrow$	Integrator	
Low-pass filter	$\Leftrightarrow$	High pass filter	
High-pass filter	$\Leftrightarrow$	Low pass filter	

External perturbations? Y(s)  $X(s) \xrightarrow{+} \sum \qquad G(s) \qquad \sum \qquad P(s)$  H(s)

- Without feedback:  $\frac{Y(s)}{W(s)} = P(s) = \frac{1}{Ts+1}$
- With feedback:  $\frac{Y(s)}{W(s)} = \frac{P(s)}{1 + KP(s)} = \frac{G_{pert}}{T_{fb}s + 1}$
- With  $G_{pert} = \frac{1}{(1+K)}$
- Nesult: gain to external perturbation is reduced by  $\approx 1/K$  for K>>I



- Other advantages of feedback:
  - Reduced sensitivity of a system to parameter variations
  - Potential to stabilize unstable systems...

Stability, zeros & poles

#### **Definitions**

- Poles: values of complex variable s for which the transfer function becomes infinite
- **Zeros**: values of complex variable s for which the transfer function becomes zero

Example: 
$$G(s) = \frac{10(s+2)}{s(s+1)(s+3)}$$

G(s) has once zero at s=-2 and three poles at s=0, s=-1 and s=-3

#### **Definitions**

- Stability: A system is stable if the output is bounded for any bounded input
  - Criterion for stability: The real portion of all poles must be negative!

Example: 
$$G(s) = \frac{P(s)}{(s+a_1)(s+a_2)....(s+a_n)} = \frac{K_1}{(s+a_1)} + \frac{K_2}{(s+a_2)} + ... + \frac{K_n}{(s+a_n)}$$

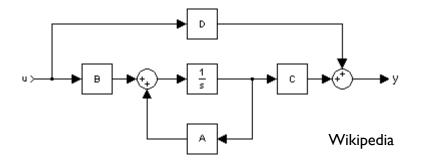
- ▶ This corresponds to  $\mathcal{L}^{-1}[G(s)] = K_1 e^{-a_1 t} + K_2 e^{-a_2 t} + ... K_n e^{-a_n t}$ 
  - ☐ For ai>0, poles are negative, reflecting **decaying** exponentials = STABLE
  - ☐ For ai<0, poles are positive, reflecting **rising** exponentials = UNSTABLE

# More on linear systems

Linear systems theory

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

- System with p inputs, q outputs and n state variables
  - **x**: state vector  $\in \Re^n$
  - **y**: output vector ∈  $\Re^q$
  - ▶ **u**: input (control) vector  $\in \Re^p$
  - ► A: state matrix (n x n)
  - **B**: input matrix  $(n \times p)$
  - $\triangleright$  **C**: output matrix (q x n)
  - ▶ D: feed-through matrix (q x p)
- In continuous time-invariant models, all matrices are constant



#### Transfer functions

- Back to our linear system...  $\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t)$  $\mathbf{y}(t) = \mathbf{C}(t)\mathbf{x}(t) + \mathbf{D}(t)\mathbf{u}(t)$
- Laplace transform of x yields: sX(s) = AX(s) + BU(s)
- Solving for X:  $\mathbf{X}(s) = \frac{\mathbf{BU}(s)}{s\mathbf{I} \mathbf{A}}$
- Similarly for Y:  $Y(s) = C \frac{BU(s)}{sI A} + DU(s)$  Wikipedia

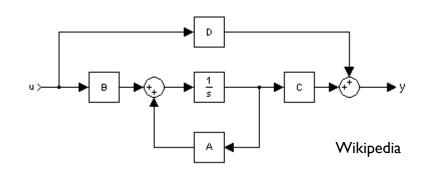
Transfer function G: (ratio of output to input of system)

$$\mathbf{G}(s) \equiv \frac{\mathbf{Y}(s)}{\mathbf{U}(s)} = \mathbf{C} \frac{\mathbf{B}}{s\mathbf{I} - \mathbf{A}} + \mathbf{D}$$

#### Transfer functions

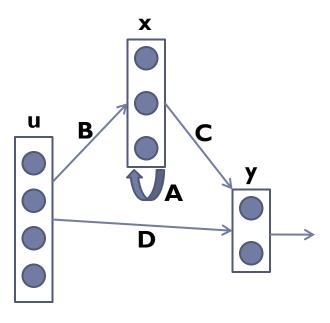
Transfer function **G**: 
$$\mathbf{G}(s) \equiv \frac{\mathbf{Y}(s)}{\mathbf{U}(s)} = \mathbf{C} \frac{\mathbf{B}}{s\mathbf{I} - \mathbf{A}} + \mathbf{D}$$

- ightharpoonup G is  $(q \times p)$  matrix
- For every input, there are q transfer functions, i.e. one for each output
- Simple representation of input-output mapping
- Examples
  - y = integral of u
  - If  $\mathbf{A} = \mathbf{I}$ , then exponential



Linear systems theory 
$$\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t)$$
  
 $\mathbf{y}(t) = \mathbf{C}(t)\mathbf{x}(t) + \mathbf{D}(t)\mathbf{u}(t)$ 

Link to neural networks (linear time-invariant models)



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

$$\mathbf{y}(t) = \mathbf{C}(t)\mathbf{x}(t) + \mathbf{D}(t)\mathbf{u}(t)$$

- Controllability
  - It is possible (by admissible inputs) to steer the states from any initial value to any final value within some finite time window.
  - Continuous time-invariant models are controllable if

$$rank \begin{bmatrix} \mathbf{B} & \mathbf{A}\mathbf{B} & \mathbf{A}^2\mathbf{B} & \dots & \mathbf{A}^{n-1}\mathbf{B} \end{bmatrix} = n$$

(rank = number of linearly independent rows in the matrix)

# state variables

Linear systems theory 
$$\dot{\mathbf{x}}(t) = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t)$$
  
 $\mathbf{y}(t) = \mathbf{C}(t)\mathbf{x}(t) + \mathbf{D}(t)\mathbf{u}(t)$ 

- **Observability** 
  - A measure of how well internal states of a system can be inferred by knowledge of its external outputs.
  - Continuous time-invariant models are observable if

$$\begin{bmatrix} \mathbf{C} \\ \mathbf{C}\mathbf{A} \\ \dots \\ \mathbf{C}\mathbf{A}^{n-1} \end{bmatrix} = n$$

# Next up: Saccades