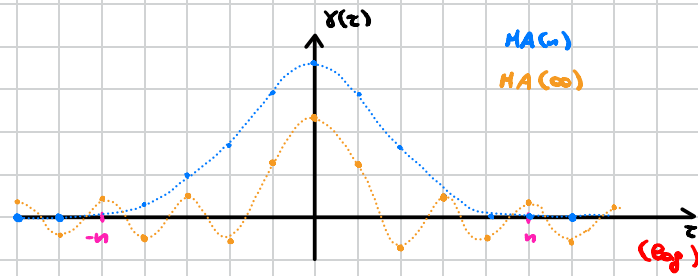


24/02 - Autoregressive Models

The main weak point of MA is related to the choice of τ .
 $MA(\tau)$ is practical but limited modeling power; $MA(\infty)$ can model any SSP, but not usable in practice (∞ coefficient) due to its heavy computation.



There exist a class of SSP that can shape $y(t)$ $\forall t$ with a finite set of coefficient: **Autoregressive Models**.

DEF: Let $e(t) \sim WN(0, \sigma^2)$ and consider $y(t) = a_1 y(t-1) + a_2 y(t-2) + \dots + a_m y(t-m) + e(t)$. Then $y(t)$ is said **AUTOREGRESSIVE MODEL** of order m ($AR(m)$), with m be the number of coefficient.

$y(t)$ depends on time and on its previous outcome ($y(t-1), y(t-2), \dots$)

AR $\Leftrightarrow$ steady-state solution of difference equation. We don't care about the initial condition, we only consider the relationship with the input

example: Consider the process $y(t) = a y(t-1) + e(t)$ with $e(t) \sim WN(0, \sigma^2)$

Steady-state solution: $y(t) = a y(t-1) + e(t)$

write $y(t-1) = a y(t-2) + e(t-1)$

$$= a(a y(t-2) + e(t-1)) + e(t)$$

$$= a^2 y(t-2) + e(t) + a e(t-1)$$

write $y(t-2) = a y(t-3) + e(t-2)$

$$= a^2(a y(t-3) + e(t-2)) + e(t) + a e(t-1)$$

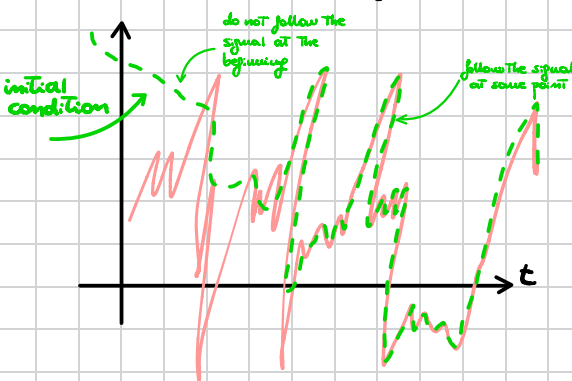
$\vdots$

$$= e(t) + a e(t-1) + a^2 e(t-2) + \dots + a^{t-t_0} y(t_0) \quad \text{with } t_0 \rightarrow -\infty$$

external excitation

initial condition (do not consider)

I can continue forever, until...



For Autoregressive Model (of SSP) with CANNOT consider the initial condition component in the solution $\Rightarrow$ **The initial part is not SSP**

The external excitation is a linear combination that is a $MA(\infty)$ (even with a single coefficient)

So, $AR(1) \cong MA(\infty)$ with $C_1 = 1, C_2 = a, \dots$. This is why we shall obtain $y(t) \neq 0$ also for $t \rightarrow +\infty$

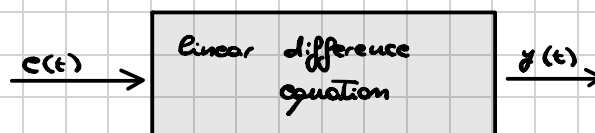
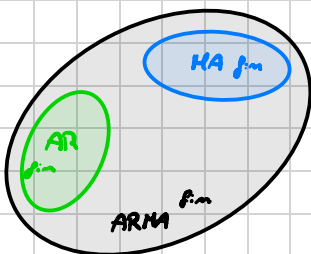
Remark: The modeling power of $MA(\infty)$ is still higher than that of $AR(1)$, as the coefficient are constrained.

ARMA models (Autoregressive + Moving Average models)

DEF: Let $e(t) \sim WN(0, \sigma^2)$ and consider a process $y(t)$ made by an $AR(m)$ and a $MA(n)$ parts:

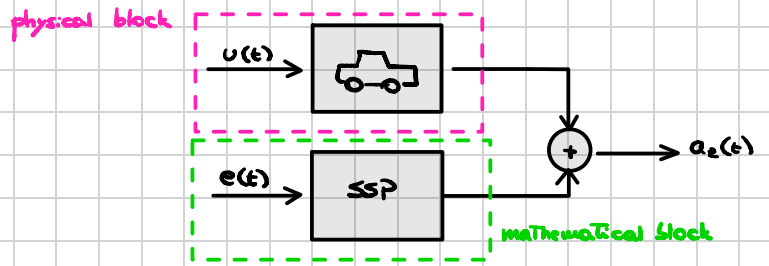
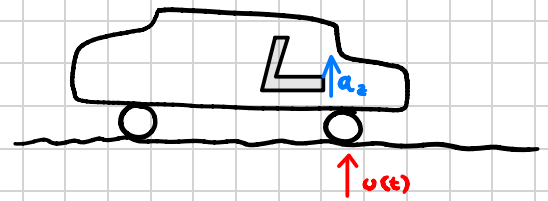
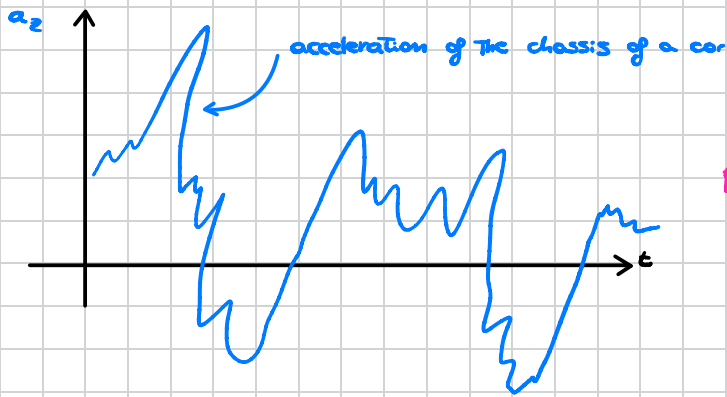
$$y(t) = \underbrace{a_1 y(t-1) + \dots + a_m y(t-m)}_{AR(m)} + \underbrace{c_0 e(t) + \dots + c_n e(t-n)}_{MA(n)}$$

$y(t)$ is said **ARMA(m, n)**, with m be the number of coefficient of the $AR(m)$ part, and n the same for $MA(n)$.



ARMA are powerful for modeling Time series

In practice, consider for example The acceleration of a car...



Combination of a physical phenomena and a mathematical block, makes $a_z(t)$ a SSP?

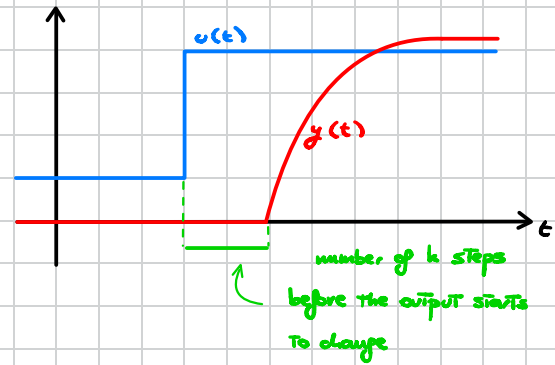
ARMAX models (ARMA + Exogenous part)

An ARMAX model adds to the classic ARMA model an **exogenous component** that represents all the external input of the process. So an ARMAX model is defined as:

$$y(t) = a_1 y(t-1) + \dots + a_m y(t-m) + \text{AR}(m) \\ + c_0 e(t) + \dots + c_n e(t-n) + \text{MA}(n) \\ + b_0 u(t-k) + \dots + b_p u(t-k-p) \quad \text{X}(k,p)$$

where

- k: pure input-output delay
- p: order of exogenous part



N-ARMAX model (nonlinear)

$$y(t) = f(y(t-1), \dots, y(t-m), e(t), \dots, e(t-n), u(t-k), \dots, u(t-k-p))$$

where the function f could be:

polynomial spline wavelets neural networks

Is the AR model stationary? We need additional tools to study the stationarity of models including AR parts

Operational Representation

DEF: The backward-shift operator z^{-1} is defined as $z^{-1} x(t) = x(t-1)$

The forward-shift operator z is defined as $z x(t) = x(t+1)$

PROPERTIES:

- **Linearity**: $z^{-1}(a x(t) + b y(t)) = z^{-1} a x(t) + z^{-1} b y(t)$
- **Recursive application**: $z^{-1}(z^{-1}(z^{-1}(x(t)))) = z^{-1}(z^{-1}(x(t-1))) = \dots = z^{-3} x(t) = x(t-3)$
- **Linear composition**: $(a z^{-1} + b z + c z^{-3} + d z^2) x(t) = a x(t-1) + b x(t+1) + c x(t-3) + d x(t+2)$

Given an ARMA(m,n) model:

$$y(t) = a_1 y(t-1) + a_2 y(t-2) + \dots + c_0 e(t) + \dots + c_n e(t-n)$$

we can apply z^{-1} (backward-shift operator):

$$y(t) = a_1 z^{-1} y(t) + a_2 z^{-2} y(t) + \dots + c_0 e(t) + \dots + c_n z^{-n} e(t) \\ \Rightarrow (1 - a_1 z^{-1} - a_2 z^{-2} - \dots - a_m z^{-m}) y(t) = (c_0 + c_1 z^{-1} + \dots + c_n z^{-n}) e(t)$$

$$y(t) = \frac{c_0 + c_1 z^{-1} + \dots + c_n z^{-n}}{1 - a_1 z^{-1} - \dots - a_m z^{-m}} e(t) = \frac{C(z)}{A(z)} e(t) = W(z) e(t)$$

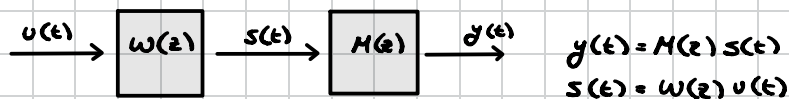
Transfer function

discrete-time Transfer function

Operations with Transfer function

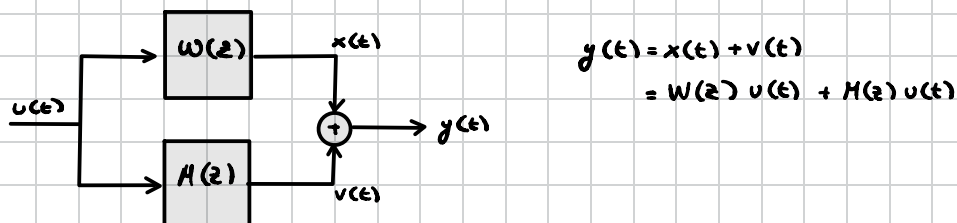
Let $W(z)$ and $H(z)$ be Transfer function of linear digital filters

Series



$$y(t) = \frac{H(z)W(z)}{\text{product}} u(t)$$

Parallel



$$y(t) = \frac{(W(z) + H(z))}{\text{Sum}} u(t)$$

Consider: up an ARMAX model now

$$y(t) = a_1 y(t-1) + \dots + a_m y(t-m) + c_0 e(t) + \dots + c_n e(t-n) + b_0 u(t-k) + \dots + b_p u(t-k-p)$$

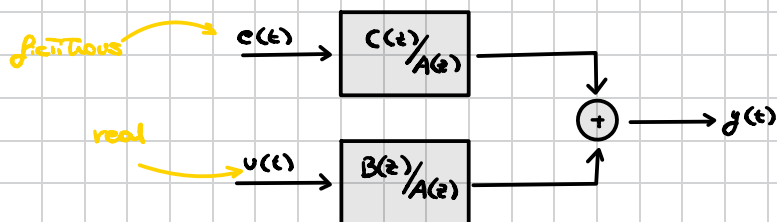
$$\Rightarrow a_1 z^{-1} y(t) + \dots + a_m z^{-m} y(t)$$

$$\Rightarrow c_0 e(t) + \dots + c_n z^{-n} e(t)$$

$$\Rightarrow b_0 z^{-k} u(t) + b_1 z^{-k} z^{-1} u(t) + \dots + b_p z^{-k} z^{-p} u(t)$$

$$\frac{(1 - a_1 z^{-1} - \dots - a_m z^{-m})}{A(z)} y(t) = \frac{(c_0 + c_1 z^{-1} + \dots + c_n z^{-n})}{C(z)} e(t) + \frac{(b_0 + b_1 z^{-1} + \dots + b_p z^{-p})}{B(z)} z^{-k} u(t)$$

$$\Rightarrow y(t) = \frac{B(z)}{A(z)} z^{-k} u(t) + \frac{C(z)}{A(z)} e(t) \quad e(t) \sim WN(0, \lambda^2)$$



$u(t)$ is "real", whereas $e(t)$ is fictitious

! $\frac{c_0 + c_1 z^{-1}}{1 - a_1 z^{-1}} = \frac{c_0 z + c_1}{z - a_1}$ both the negative / positive power of z will be used but please don't mix them!

Poles/zeros

$$W(z) = \frac{C(z)}{A(z)}$$

zeros: roots of NUM

poles: roots of DEN (in case of no cancellation)

THEOREM: A linear digital filter with Transfer function $W(z)$ is asymptotically stable if and only if all its poles are strictly inside the unit circle (in the complex plane)

THEOREM: The steady-state output $y(t)$ is stationary if and only if

- $e(t)$ is SSP ($e(t) \sim WN(0, \lambda^2)$ in our scenario, so it's always true)
- $W(z)$ is asymptotically stable

