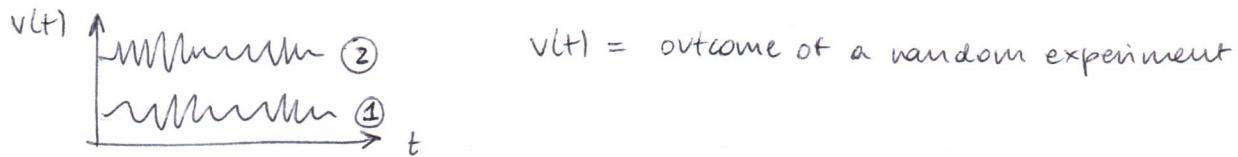
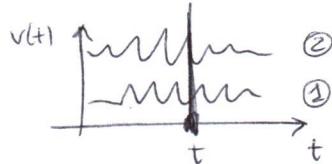


STOCHASTIC PROCESS = sequence of random variables in indexed order (indexed by time) :

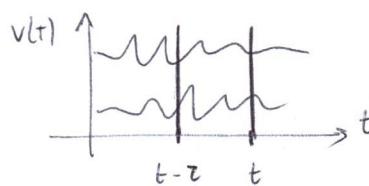


We can have ① or ② (:= realizations of the process)

- Expected value = $\mathbb{E}[v(t)]$ describes the average behaviour of the process ~~at a f~~ for each time t



- Covariance function = $\mathbb{E}[(v(t) - \mathbb{E}[v(t)])(v(t-\tau) - \mathbb{E}[v(t-\tau)])]$



If $\tau=0 \Rightarrow \mathbb{E}[(v(t) - \mathbb{E}[v(t)])^2] := \text{variance of the process}$

(express how the process $v(t)$ is spread from the average value)

If $\tau \neq 0 \Rightarrow \gamma_v(t, \tau)$ express the correlation of the process for different time instants

STATIONARY (STOCHASTIC) PROCESS

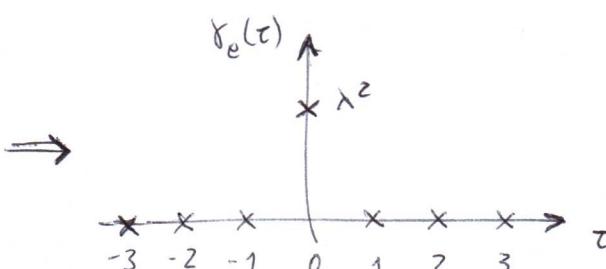
$$1. \mathbb{E}[v(t)] = m \quad \forall t$$

$$2. \gamma_v(t, \tau) = \gamma_v(\tau) \quad (\perp t)$$

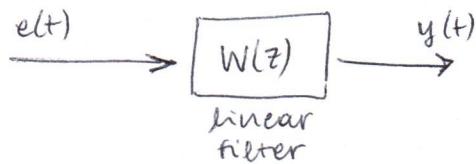
WHITE NOISE

$$e(t) \sim WN(\mu, \lambda^2) : 1. \mathbb{E}[e(t)] = \mu \quad \forall t$$

$$2. \gamma_e(\tau) = \begin{cases} \lambda^2 & \tau = 0 \\ 0 & \tau \neq 0 \end{cases} \Rightarrow \text{it's a signal completely uncorrelated}$$



Why is important? Because we use it for obtaining a stochastic process.



$$\text{For example: } y(t) = e(t) + \frac{1}{2}e(t-1) - e(t-2) \quad e(t) \sim WN(0,1)$$

These type of processes are called **MOVING AVERAGE PROCESSES**, in this case we have a **MA(2)**.

We use on it the delay operator:

$$\begin{aligned} y(t) &= e(t) + \frac{1}{2}z^{-1}e(t) - z^{-2}e(t) \\ &= \boxed{\left(1 + \frac{1}{2}z^{-1} - z^{-2}\right)} e(t) \\ &\quad := W(z) \\ &\quad \text{transfer function} \end{aligned}$$

- Expected value of the process:

$$\mathbb{E}[y(t)] = \mathbb{E}\left[e(t) + \frac{1}{2}e(t-1) - e(t-2)\right] = \cancel{\mathbb{E}[e(t)]} + \frac{1}{2}\cancel{\mathbb{E}[e(t-1)]} - \cancel{\mathbb{E}[e(t-2)]} = 0$$

- Covariance function:

$$\begin{aligned} \gamma(\tau=0) &= \mathbb{E}[y^2(t)] = \mathbb{E}\left[\left(e(t) + \frac{1}{2}e(t-1) - e(t-2)\right)^2\right] \\ &= \mathbb{E}\left[e^2(t) + \frac{1}{4}e^2(t-1) + e^2(t-2) + e(t)e(t-1) - 2e(t)e(t-2) - e(t-1)e(t-2)\right] \\ &= \cancel{\mathbb{E}[e^2(t)]} + \frac{1}{4}\cancel{\mathbb{E}[e^2(t-1)]} + \cancel{\mathbb{E}[e^2(t-2)]} + \cancel{\mathbb{E}[e(t)e(t-1)]} - 2\cancel{\mathbb{E}[e(t)e(t-2)]} - \cancel{\mathbb{E}[e(t-1)e(t-2)]} \\ &= 1 + \frac{1}{4} \cdot 1 + 1 \\ &= \frac{9}{4} \end{aligned}$$

$$\begin{aligned} \gamma_y(\tau=1) &= \mathbb{E}[y(t)y(t-1)] = \mathbb{E}\left[\left(e(t) + \frac{1}{2}e(t-1) - e(t-2)\right) y(t-1)\right] \\ &= \mathbb{E}[e(t)y(t-1)] + \frac{1}{2}\mathbb{E}[e(t-1)y(t-1)] - \mathbb{E}[e(t-2)y(t-1)] \\ &= \mathbb{E}\left[e(t)\left(e(t-1) + \frac{1}{2}e(t-2) - e(t-3)\right)\right] + \\ &+ \frac{1}{2}\mathbb{E}\left[e(t-1)\left(e(t-1) + \frac{1}{2}e(t-2) - e(t-3)\right)\right] + \\ &- \mathbb{E}\left[e(t-2)\left(e(t-1) + \frac{1}{2}e(t-2) - e(t-3)\right)\right] \\ &= \frac{1}{2}\mathbb{E}[e^2(t-1)] - \frac{1}{2}\mathbb{E}[e^2(t-2)] = \frac{1}{2} \cdot 1 - \frac{1}{2} \cdot 1 = 0 \end{aligned}$$

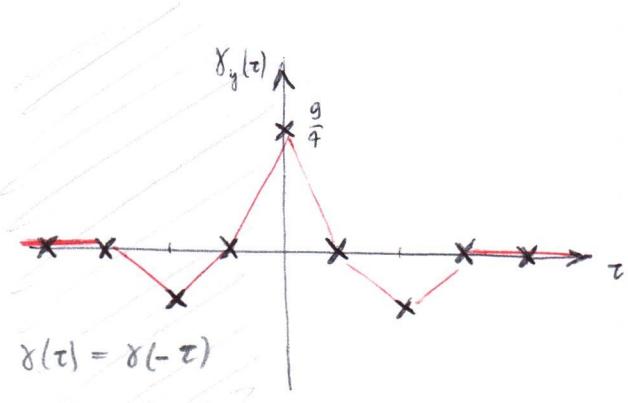
only the $e(\cdot)$ with the same time instant have mean $\neq 0$

$$\gamma_y(\tau=2) = \mathbb{E}[y(t)y(t-2)] = \mathbb{E}[(e(t) + \frac{1}{2}e(t-1) - e(t-2))(e(t-2) + \frac{1}{2}e(t-3) - e(t-4))] \\ = \mathbb{E}[e^2(t-2)](-\frac{1}{2}) = -1$$

$$\gamma_y(\tau=3) = \mathbb{E}[y(t)y(t-3)] = \mathbb{E}[(e(t) + \frac{1}{2}e(t-1) - e(t-2))(e(t-3) + \frac{1}{2}e(t-4) - e(t-5))] \\ = 0 \quad (\text{no terms with the same time})$$

$$\gamma_y(\tau>2) = 0$$

$$\Rightarrow \gamma(\tau) = \begin{cases} 9/4 & \tau=0 \\ 0 & \tau=1 \\ -1 & \tau=2 \\ 0 & \tau>2 \end{cases}$$



Remark: Given MA(n) process : $y(t) = c_0 e(t) + c_1 e(t-1) + \dots + c_n e(t-n)$ with $e(t) \sim WN(\mu, \lambda^2)$ we know that $y(t)$ is a stationary stochastic process $\forall \{c_0, c_1, \dots, c_n\}$ with :

$$\gamma_y(\tau) = \begin{cases} (c_0^2 + c_1^2 + \dots + c_n^2) \lambda^2 & \tau=0 \\ (c_0 c_1 + c_1 c_2 + \dots + c_{n-1} c_n) \lambda^2 & \tau=\pm 1 \\ \dots & \tau=\pm n \\ 0 & |\tau|>n \end{cases}$$

Consider now the process :

$$y(t) = \frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t) \quad e(t) \sim WN(0, 1)$$

$y(t)$ is an AUTOREGRESSIVE PROCESS : AR(2)

using the delay operator :

$$\begin{aligned} y(t) &= \frac{1}{2}z^{-1}y(t) - \frac{1}{4}z^{-2}y(t) + e(t) \\ &\stackrel{\downarrow}{=} \left(\frac{1}{2}z^{-1} - \frac{1}{4}z^{-2} \right) y(t) + e(t) \\ \Rightarrow y(t) &= \boxed{\frac{1}{1 - \frac{1}{2}z^{-1} + \frac{1}{4}z^{-2}}} e(t) \\ &:= w(z) \end{aligned}$$

• Expected value :

$$\mathbb{E}[y(t)] = \mathbb{E}\left[\frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t)\right] = \frac{1}{2}\mathbb{E}[y(t-1)] - \frac{1}{4}\mathbb{E}[y(t-2)] + \mathbb{E}[e(t)]$$

We assume that $y(t)$ is stationary $\Rightarrow \mathbb{E}[y(t)] = \mathbb{E}[y(t-1)] = \mathbb{E}[y(t-2)] = m$

$$\Rightarrow \mathbb{E}[y(t)] = \frac{1}{2}m - \frac{1}{4}m + 0 = m \quad \Rightarrow m=0$$

THEOREM: $y(t) = W(z) u(t)$

$u(t)$ stationary process	}	\Rightarrow	$y(t)$ is a stationary stochastic process
$W(z)$ stable system			

\Rightarrow we have to compute the poles of $W(z)$:

$$W(z) = \frac{1}{1 - \frac{1}{2}z^{-1} + \frac{1}{4}z^{-2}} \cdot \frac{z^2}{z^2} = \frac{z^2}{z^2 - \frac{1}{2}z + \frac{1}{4}}$$

$$\text{For the poles: } z^2 - \frac{1}{2}z + \frac{1}{4} = 0 \Rightarrow z_{1,2} = \frac{1}{4} \pm j\sqrt{\frac{3}{4}}$$

$$|z_{1,2}| = \sqrt{\frac{1}{16} + \frac{3}{16}} = \frac{1}{2} \Rightarrow |z_{1,2}| < 1 \Rightarrow W(z) \text{ is stable}$$

$\Rightarrow y(t)$ is stationary \Rightarrow our H.p. of $y(t)$ stationary is good
 $\Rightarrow \mathbb{E}[y(t)] = 0$

• Covariance function:

$$\begin{aligned} \gamma_y(0) &= \mathbb{E}[(y(t) - 0)^2] = \mathbb{E}[y^2(t)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t)\right)^2\right] \\ &\stackrel{1}{=} \mathbb{E}\left[\frac{1}{4}y^2(t-1) + \frac{1}{16}y^2(t-2) + e^2(t) - \frac{1}{4}y(t-1)y(t-2) + y(t-1)e(t) - \frac{1}{2}y(t-2)e(t)\right] \\ &\stackrel{2}{=} \frac{1}{4}\mathbb{E}[y^2(t-1)] + \frac{1}{16}\mathbb{E}[y^2(t-2)] + \mathbb{E}[e^2(t)] - \frac{1}{4}\mathbb{E}[y(t-1)y(t-2)] + \mathbb{E}[y(t-1)e(t)] - \frac{1}{2}\mathbb{E}[y(t-2)e(t)] \\ &\quad y(t) \text{ stationary} \Rightarrow \mathbb{E}[y(t-1)^2] = \mathbb{E}[y(t-2)^2] = \gamma_y(0) \\ &= \frac{1}{4}\gamma_y(0) + \frac{1}{16}\gamma_y(0) + 1 + \underbrace{\mathbb{E}[y(t-1)e(t)]}_{\text{is a function of } e(t-1), e(t-2), \dots} - \frac{1}{2}\underbrace{\mathbb{E}[y(t-2)e(t)]}_{\text{un-correlated}} - \frac{1}{4}\underbrace{\mathbb{E}[y(t-1)y(t-2)]}_{\text{un-correlated}} \\ &\quad \text{y}(t-1) \text{ is a process s.t.} \\ &\quad \text{is a function of } e(t-1), e(t-2), \dots \\ &\quad \Rightarrow y(t-1) \text{ and } e(t) \text{ are uncorrelated} \\ &\quad \Rightarrow \mathbb{E}[y(t-1)e(t)] = \mathbb{E}[y(t-1)] \mathbb{E}[e(t)] = 0 \end{aligned}$$

we have to compute
 $\gamma_y(1)$ to find $\gamma_y(0)$

$$\Rightarrow \frac{11}{16}\gamma_y(0) + \frac{1}{4}\gamma_y(1) = 1 \quad (1)$$

$$-\frac{1}{4}\gamma_y(1) =$$

$$\begin{aligned} \gamma_y(1) &= \mathbb{E}[y(t)y(t-1)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t)\right)y(t-1)\right] \\ &\stackrel{1}{=} \mathbb{E}\left[\frac{1}{2}y^2(t-1)\right] - \frac{1}{4}\mathbb{E}[y(t-2)y(t-1)] + \mathbb{E}[e(t)y(t-1)] \\ &\stackrel{2}{=} \frac{1}{2}\gamma_y(0) - \frac{1}{4}\gamma_y(1) \quad (2) \end{aligned}$$

$$(1) + (2) \Rightarrow \begin{cases} \gamma_y(0) = \frac{80}{63} \\ \gamma_y(1) = \frac{32}{63} \end{cases}$$

$$\begin{aligned} \gamma_y(2) &= \mathbb{E}[y(t)y(t+2)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t)\right)y(t+2)\right] \\ &= \frac{1}{2}\mathbb{E}[y(t-1)y(t+2)] - \frac{1}{4}\mathbb{E}[y^2(t-2)] + \mathbb{E}[e(t)y(t+2)] \\ &= \frac{1}{2}\gamma_y(1) - \frac{1}{4}\gamma_y(0) = -\frac{4}{63} \end{aligned}$$

$$f_y(\tau) = \frac{1}{2} f_y(\tau-1) - \frac{1}{4} f_y(\tau-2) \quad \tau \geq 2$$

MA(∞) REPRESENTATION

1. SUBSTITUTION :

$$\begin{aligned}
 y(t) &= \frac{1}{2}y(t-1) - \frac{1}{4}y(t-2) + e(t) \\
 &\stackrel{1}{=} \frac{1}{2} \left[\frac{1}{2}y(t-2) - \frac{1}{4}y(t-3) + e(t-1) \right] - \frac{1}{4}y(t-2) + e(t) \\
 &\stackrel{2}{=} e(t) + \frac{1}{2}e(t-1) + \cancel{\frac{1}{4}y(t-2)} - \cancel{\frac{1}{8}y(t-3)} - \cancel{\frac{1}{4}y(t-2)} \\
 &\stackrel{3}{=} e(t) + \frac{1}{2}e(t-1) - \frac{1}{8} \left(\frac{1}{2}y(t-4) - \frac{1}{4}y(t-5) + e(t-3) \right) \\
 &\stackrel{4}{=} \textcircled{e(t)} + \textcircled{\frac{1}{2}e(t-1)} - \textcircled{-\frac{1}{8}e(t-3)} - \textcircled{-\frac{1}{16}y(t-4)} + \textcircled{\frac{1}{32}y(t-5)} \\
 &\stackrel{5}{=} f(e(t), e(t-1), e(t-2), \dots)
 \end{aligned}$$

2. LONG DIVISION

$$\begin{array}{c}
 \begin{array}{r}
 1 - \frac{1}{2}z^{-1} + \frac{1}{4}z^{-2} \\
 \hline
 1 - \frac{1}{2}z^{-1} - \frac{1}{4}z^{-2} \\
 \hline
 \frac{1}{2}z^{-1} - \frac{1}{4}z^{-2} + \frac{1}{8}z^{-3} \\
 \hline
 1 \quad 1 \quad -\frac{1}{8}z^{-3} \\
 \quad \quad \quad -\frac{1}{8}z^{-3} + \frac{1}{16}z^{-4} - \frac{1}{32}z^{-5} \\
 \quad \quad \quad \dots
 \end{array}
 \end{array}$$

These are the same coefficients that we found in the previous representation.

These are the Coefficients of MA(0) representation of $y(t)$

(EX. 1)

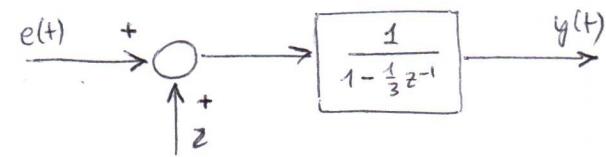
11/03

$$\text{AR(1)}: \quad y(t) = \frac{1}{3}y(t-1) + e(t) + 2 \quad e(t) \sim \text{WN}(0, 1)$$

constant signal

$$y(t) = \frac{1}{3}z^{-1}y(t) + e(t) + 2$$

$$(1 - \frac{1}{3}z^{-1})y(t) = e(t) + 2$$



$$W(z) = \frac{1}{1 - \frac{1}{3}z^{-1}} = \frac{z}{z - \frac{1}{3}} : \begin{array}{l} \text{zero: } z=0 \\ \text{pole: } z=\frac{1}{3} \end{array} \left\{ \begin{array}{l} \Rightarrow \text{(for the theorem)} \\ y(t) \text{ is stationary} \end{array} \right.$$

• Expected value:

$$\begin{aligned} \mathbb{E}[y(t)] &= \mathbb{E}\left[\frac{1}{3}y(t-1) + e(t) + 2\right] = \frac{1}{3}(\mathbb{E}[y(t-1)] + \mathbb{E}[e(t)]) + 2 \\ &\stackrel{\downarrow}{=} \frac{1}{3}\mathbb{E}[y(t)] + 1 + 2 \end{aligned}$$

= $\mathbb{E}[y(t)]$
since it's a stationary process

$$(1 - \frac{1}{3})\mathbb{E}[y(t)] = 3 \implies \mathbb{E}[y(t)] = \frac{9}{2}$$

• Covariance function:

$$\text{Note: } \mathbb{E}[e(t)e(t-1)] \neq 0$$

What is null in this case?

$$\mathbb{E}[(e(t)-1)(e(t-1)-1)] = 0$$

! DETREND or DEBIAS PROCESS

$$\tilde{e}(t) = e(t) - 1 \implies \mathbb{E}[\tilde{e}(t)] = 0 \quad \tilde{e}(t) \sim \text{WN}(0, 1)$$

$$\tilde{y}(t) = y(t) - \frac{9}{2} \implies \mathbb{E}[\tilde{y}(t)] = 0$$

$$\gamma_y(\tau) = \mathbb{E}\left[\left(y(t) - \frac{9}{2}\right)\left(y(t-\tau) - \frac{9}{2}\right)\right] = \mathbb{E}[\tilde{y}(t)\tilde{y}(t-\tau)] = \gamma_{\tilde{y}}(\tau) \quad (*)$$

$$\begin{cases} y(t) = \tilde{y}(t) + \frac{9}{2} \\ e(t) = \tilde{e}(t) + 1 \end{cases}$$

$$\implies \tilde{y}(t) + \frac{9}{2} = \frac{1}{3}\left[\tilde{y}(t-1) + \frac{9}{2}\right] + \tilde{e}(t) + 1 + 2$$

$$\implies \boxed{\tilde{y}(t) = \frac{1}{3}\tilde{y}(t-1) + \tilde{e}(t)}$$

$$\gamma_{\tilde{y}}(0) = \mathbb{E}[\tilde{y}^2(t)] = \mathbb{E}\left[\left(\frac{1}{3}\tilde{y}(t-1) + \tilde{e}(t)\right)^2\right]$$

$$\stackrel{\downarrow}{=} \underbrace{\frac{1}{9}\mathbb{E}[\tilde{y}^2(t-1)]}_{\text{since it's stationary}} + \mathbb{E}[\tilde{e}^2(t)] + \frac{2}{3}\mathbb{E}[\tilde{y}(t-1)\tilde{e}(t)]$$

$$\stackrel{\downarrow}{=} \frac{1}{9}\gamma_{\tilde{y}}(0) + 1$$

$f(\tilde{e}(t-1), \tilde{e}(t-2), \dots) \perp\!\!\!\perp \tilde{e}(t)$

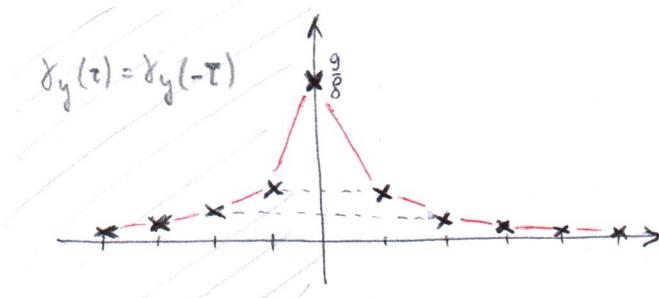
$$\Rightarrow \gamma_{\tilde{y}}(0) = \frac{9}{8}$$

$$\begin{aligned}\gamma_{\tilde{y}}(1) &= \mathbb{E}[\tilde{y}(t)\tilde{y}(t-1)] = \mathbb{E}\left[\left(\frac{1}{3}\tilde{y}(t-1) + \tilde{e}(t)\right)\tilde{y}(t-1)\right] \\ &\stackrel{\mathbb{E}[\tilde{e}(t)\tilde{y}(t-1)]}{=} \frac{1}{3}\mathbb{E}[\tilde{y}^2(t-1)] + \mathbb{E}[\tilde{e}(t)\tilde{y}(t-1)] \\ &\stackrel{\mathbb{E}[\tilde{e}(t)\tilde{y}(t-1)]}{=} \frac{1}{3}\gamma_{\tilde{y}}(0) = \frac{3}{8}\end{aligned}$$

$$\begin{aligned}\gamma_{\tilde{y}}(2) &= \mathbb{E}[\tilde{y}(t)\tilde{y}(t-2)] = \mathbb{E}\left[\left(\frac{1}{3}\tilde{y}(t-1) + \tilde{e}(t)\right)\tilde{y}(t-2)\right] \\ &\stackrel{\mathbb{E}[\tilde{e}(t)\tilde{y}(t-2)]}{=} \frac{1}{3}\mathbb{E}[\tilde{y}(t-1)\tilde{y}(t-2)] + \mathbb{E}[\tilde{e}(t)\tilde{y}(t-2)] \\ &\stackrel{\mathbb{E}[\tilde{e}(t)\tilde{y}(t-2)]}{=} \frac{1}{3}\gamma_{\tilde{y}}(1) = \frac{1}{8}\end{aligned}$$

$$\gamma_y(\tau) = \frac{1}{3}\gamma_{\tilde{y}}(\tau-1) \quad \Rightarrow \quad \gamma_y(\tau) = \begin{cases} \frac{9}{8} & \tau=0 \\ \frac{1}{3}\gamma_{\tilde{y}}(\tau-1) & \tau>0 \end{cases}$$

(*) $\gamma_y(\tau) = \gamma_{\tilde{y}}(\tau)$:



Remark: EULER-WALKER FORMULA
(for the covariance function)

$$y(t) = ay(t-1) + e(t) \quad e(t) \sim WN(0, \lambda^2)$$

$$\Rightarrow \gamma_y(\tau) = \begin{cases} \frac{1}{1-a^2} \lambda^2 & \tau=0 \\ a\gamma_y(\tau-1) & \tau \geq 1 \end{cases}$$

Moreover: $\gamma(\tau) = \gamma(-\tau)$

(EX. 2)

$$y(t) = \underbrace{\frac{1}{2}y(t-1)}_{AR(1)} + \underbrace{\eta(t)}_{MA(1)} \quad \eta(t) \sim WN(1, 9)$$

$\Rightarrow y(t)$ is an AR MA (1, 1)

$$y(t) = \frac{1}{2}z^{-1}y(t) + \eta(t) \quad z^{-1}\eta(t)$$

$$\Rightarrow y(t) = \frac{1-z^{-1}}{1-\frac{1}{2}z^{-1}} \eta(t) = \frac{z-1}{z-\frac{1}{2}} \eta(t) \Rightarrow \begin{array}{l} \text{zero: } z=0 \\ \text{pole: } z=\frac{1}{2} \end{array}$$

\Rightarrow (for the theorem) : $y(t)$ is stationary

• Expected value:

$$\begin{aligned}\mathbb{E}[y(t)] &= \mathbb{E}\left[\frac{1}{2}y(t-1) + \eta(t) - \eta(t-1)\right] = \frac{1}{2}\mathbb{E}[y(t)] + \mathbb{E}[\eta(t)] - \mathbb{E}[\eta(t-1)] \\ &= \frac{1}{2}\mathbb{E}[y(t)] + 1 - 1 \\ \implies \mathbb{E}[y(t)] &= 0\end{aligned}$$

• Covariance function:

$$e(t) = \eta(t) - 1$$

$$\mathbb{E}[e(t)] = \mathbb{E}[\eta(t)] - 1 = 0$$

$$\mathbb{E}[e^2(t)] = \mathbb{E}[(\eta(t) - 1)^2] = \mathbb{E}[\eta^2(t)] + 1 - 2\mathbb{E}[\eta(t)] = g$$

$$\implies e(t) \sim WN(0, g)$$

$$\begin{aligned}\mathbb{E}[y(t)] &= \frac{1}{2}\mathbb{E}[y(t-1)] + \mathbb{E}[e(t)] + 1 - \mathbb{E}[e(t-1)] \\ y(t) &\stackrel{\text{def}}{=} \frac{1}{2}y(t-1) + e(t) - e(t-1)\end{aligned}$$

$$\begin{aligned}\gamma_y(0) &= \mathbb{E}[y^2(t)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) + e(t) - e(t-1)\right)^2\right] \\ &= \frac{1}{4}\underbrace{\mathbb{E}[y^2(t-1)]}_{\gamma_y(0) \text{ since the process is stationary}} + \underbrace{\mathbb{E}[e^2(t)]}_g + \underbrace{\mathbb{E}[e^2(t-1)]}_{g = \text{Var}(e)} + \underbrace{\mathbb{E}[y(t-1)e(t)]}_{y(t-1) \perp\!\!\!\perp e(t) \text{ and } \mathbb{E}[e(t)] = 0, \mathbb{E}[y(t)] = 0} - \underbrace{\mathbb{E}[y(t-1)e(t-1)]}_{?} - 2\underbrace{\mathbb{E}[e(t)e(t-1)]}_{\mathbb{E}[e(t)] \perp\!\!\!\perp e(t-1) \text{ and } \mathbb{E}[e(t)] = \mathbb{E}[e(t-1)] = 0}\end{aligned}$$

$$\begin{aligned}\mathbb{E}[y(t-1)e(t-1)] &= \mathbb{E}\left[\left(\frac{1}{2}y(t-2) + e(t-1) - e(t-2)\right)e(t-1)\right] \\ &= \frac{1}{2}\underbrace{\mathbb{E}[y(t-2)e(t-1)]}_{\text{Var}(e(t)) = g} + \underbrace{\mathbb{E}[e^2(t-1)]}_g - \underbrace{\mathbb{E}[e(t-1)e(t-2)]}_{\mathbb{E}[e(t-1)] = 0}\end{aligned}$$

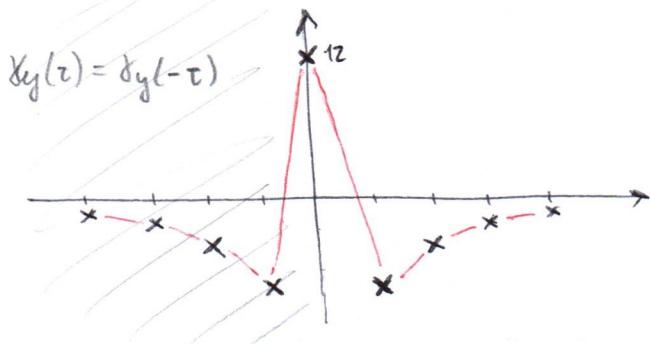
$$\stackrel{?}{=} \frac{1}{4}\gamma_y(0) + g + g - g$$

$$\implies \gamma_y(0) = 12$$

$$\begin{aligned}\gamma_y(1) &= \mathbb{E}[y(t)y(t-1)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) + e(t) - e(t-1)\right)y(t-1)\right] \\ &= \frac{1}{2}\underbrace{\mathbb{E}[y^2(t-1)]}_{\gamma_y(0) \text{ (stationary)}} + \underbrace{\mathbb{E}[e(t)y(t-1)]}_{e(t) \perp\!\!\!\perp y(t-1) \text{ and } \mathbb{E}[e(t)] = 0} - \underbrace{\mathbb{E}[e(t-1)y(t-1)]}_g \text{ (previously)} \\ &= \frac{1}{2}\gamma_y(0) - g = -3\end{aligned}$$

$$\begin{aligned}\gamma_y(2) &= \mathbb{E}[y(t)y(t-2)] = \mathbb{E}\left[\left(\frac{1}{2}y(t-1) + e(t) - e(t-1)\right)y(t-2)\right] \\ &= \frac{1}{2}\underbrace{\mathbb{E}[y(t-1)y(t-2)]}_{\gamma_y(1)} + \underbrace{\mathbb{E}[e(t)y(t-2)]}_{\mathbb{E}[e(t)] = 0} - \underbrace{\mathbb{E}[e(t-1)y(t-2)]}_{\mathbb{E}[e(t-1)] = 0} \\ &\stackrel{?}{=} \frac{1}{2}\gamma_y(1) = -\frac{3}{2}\end{aligned}$$

$$\Rightarrow \gamma_y(\tau) = \begin{cases} 12 & \tau = 0 \\ -3 & \tau = 1 \\ \frac{1}{2} \gamma_y(\tau-1) & \tau \geq 2 \end{cases}$$

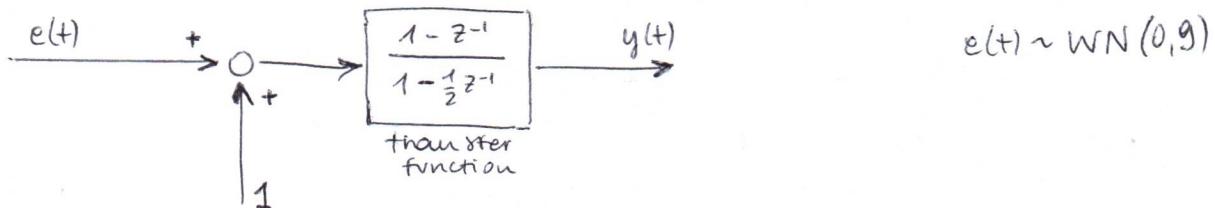


Property of covariance function

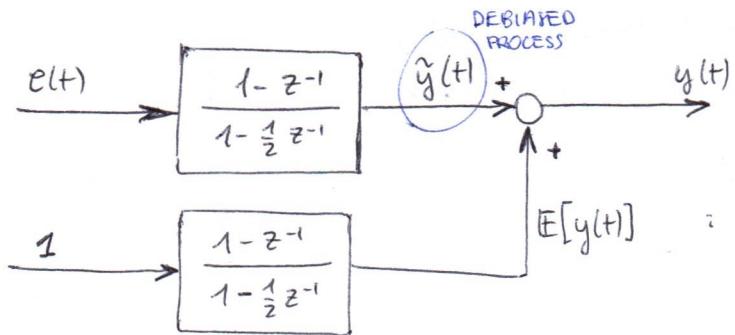
1. $\gamma_y(0) \geq 0$
2. $|\gamma_y(\tau)| \leq \gamma(0)$
3. $\gamma_y(\tau) = \gamma_y(-\tau)$

Useful to recognize if a plot is a covariance function or not

(another way to do the DETREND or DEBIAS PROCESS)



Since the transfer function is linear:



$$E[y(t)] = \left. \frac{1-z^{-1}}{1-\frac{1}{2}z^{-1}} \right|_{z=1} \cdot 1 = 0$$

(Spectrum = Covariance in the frequency domain)

Remarks:

- THEOREM OF THE GAIN

\Rightarrow FINAL VALUE THEOREM

$$y(t) = W(z) u(t)$$

$$y(t \rightarrow \infty) = \lim_{z \rightarrow 1} W(z) U(z) \cdot (z-1)$$

We considered $u(t)$ constant, so: $u(t) = \bar{u}$

$$\Rightarrow U(z) = \frac{z}{z-1} \bar{u}$$

$$\Rightarrow y(t) = \lim_{z \rightarrow 1} W(z) \frac{z}{z-1} \bar{u} (z-1) = W(z=1) \cdot \bar{u}$$

- OPERATOR DELAY z^{-1}

$$y(t-k) \rightarrow z^{-k} Y(z) = z^{-k} y(t)$$

- Linearity: $z [\alpha f(t) + \beta g(t)] = \alpha F(z) + \beta G(z)$

- Convolution: $F(z) G(z) \xrightarrow{z^{-1}} f(t) * g(t) = \sum_k f(k) g(t-k)$

$$= \sum_k f(t-k) g(k)$$

\Rightarrow When we considered:

$$u(t) \rightarrow [W(z)] \rightarrow y(t) ; Y(z) = W(z) U(z)$$

$$\Rightarrow y(t) = \sum_{\tau=-\infty}^{+\infty} h(t-\tau) u(\tau) \quad \left(\textcircled{h(t)} \xrightarrow{z^{-1}} W(z) \right)$$

impulsive response of the system

time domain \rightarrow frequency domain
(covariance function) (spectrum = discrete fourier's transform of the cov. fun)

SPECTRUM of the stochastic process:

$$\Gamma_y(\omega) := \sum_{\tau=-\infty}^{+\infty} X_y(\tau) e^{-j\omega\tau} := \text{discrete fourier's transform of the covariance function}$$

Properties:

- $\Gamma_y(\omega)$ is real
- $\Gamma_y(\omega) \geq 0$
- $\Gamma_y(\omega) = \Gamma_y(-\omega)$
- $\Gamma_y(\omega) = \Gamma_y(\omega + 2k\pi)$

$\frac{T}{\text{period}} = 2\pi \Rightarrow$ we represent the spectrum in $[-\pi, \pi]$

$$5. \quad y(t) = W(z) u(t) \implies Y(w) = |W(z)|_{z=e^{jw}}^2 U(w) \quad \text{Fundamental thm.}$$

$$u(t) \sim WN(0, \lambda^2) \implies \Gamma_y(w) = |N(z)|_{z=e^{jw}}|^2 \lambda^2 \\ (\Gamma_u(w) = \lambda^2 \quad \forall w)$$

$$6. \quad Y_y(0) = \frac{1}{2\pi} \int_{-\pi}^{\pi} \Gamma_y(w) dw \quad \left(\begin{array}{l} \text{this can be a check} \\ \text{for } \Gamma_y(w) \end{array} \right)$$

(EX. 1)

$$y(t) = \frac{1}{2} y(t-1) + e(t) - e(t-1) \quad e(t) \sim WN(0,9)$$

$$\gamma(\tau) = \begin{cases} 12 & \tau = 0 \\ -3 & |\tau| = 1 \\ \frac{1}{2}\gamma_y(|\tau|-1) & |\tau| \geq 2 \end{cases}$$

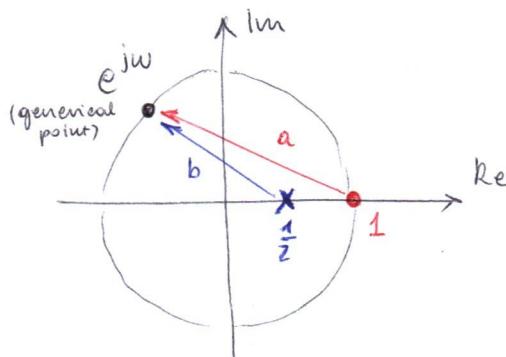
Compute the spectrum.

$$(2) \text{ THM. } W(z) = \frac{z-1}{z-\frac{1}{2}}, \quad \Gamma_e(w) = 9 \quad (e \sim WN(0,9))$$

The system is stable ($z = \frac{1}{2}$) \Rightarrow we use the theorem:

$$\begin{aligned} H_y(w) &= \left| \frac{e^{jw} - 1}{e^{jw} - \frac{1}{2}} \right|^2 \cdot g = \frac{(e^{jw} - 1)(e^{-jw} - 1)}{(e^{jw} - \frac{1}{2})(e^{-jw} - \frac{1}{2})} \cdot g \\ &= \frac{(1 - e^{jw} - e^{-jw} + 1)}{(1 - \frac{1}{2}e^{jw} - \frac{1}{2}e^{-jw} + \frac{1}{4})} \cdot g \\ &= \frac{2 - \frac{2}{2}(e^{jw} + e^{-jw})}{\frac{5}{4} - \frac{1}{2}(e^{jw} + e^{-jw})} \cdot g = \frac{18 - 18 \cos(w)}{\frac{5}{4} - \cos(w)} \end{aligned}$$

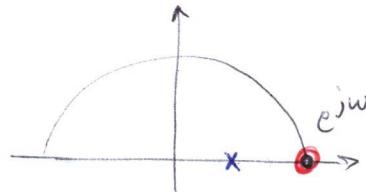
(3)
GRAPHICAL
(qualitative)



$$\Gamma_y(w) = \frac{\|a\|^2}{\|b\|^2} \cdot g$$

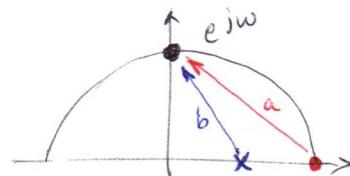
We need to check a phen w:

$w = 0$:



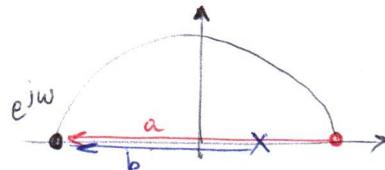
$$\|a\| = 0 \Rightarrow \Gamma_y(0) = 0$$

$w = \frac{\pi}{2}$:



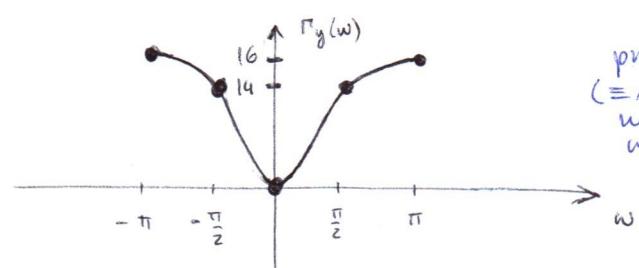
$$\begin{cases} \|a\| = \sqrt{2} \\ \|b\| = \sqrt{1 + \frac{1}{4}} \end{cases} \Rightarrow \Gamma_y\left(\frac{\pi}{2}\right) = \frac{72}{5} \approx 14$$

$w = \pi$:



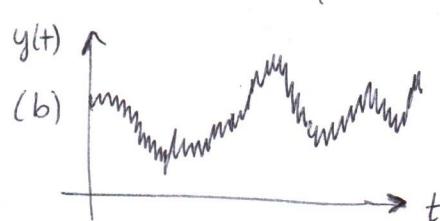
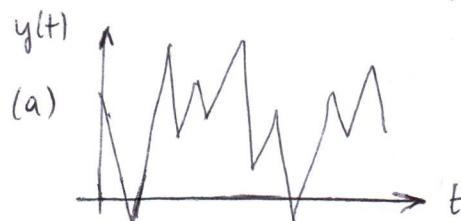
$$\begin{cases} \|a\| = 2 \\ \|b\| = \frac{3}{2} \end{cases} \Rightarrow \Gamma_y(\pi) = 16$$

\Rightarrow



predominanza di ALTE frequenze
(= regolare che varia molto rapidamente nel dominio del tempo)

Which realization of this process is more likely?



Lo spettro favorisce alte frequenze. Il grafico (a) contiene variazioni molto veloci come moduli $y(t)$, quindi cambiamenti "ad alta frequenza". (RICORDIAMO che i segnali sono a tempo discreto)

The high frequency are predominant. In (a) the signal is very fast, (b) is slow (has low frequencies) \Rightarrow (a) is more likely.

(EX. 2)

$$y(t) = \left[(1 - z^{-1} + z^{-2}) \left(1 + \frac{3}{2} z^{-1} \right) \right] e(t), \quad e(t) \sim WN(0, 1)$$

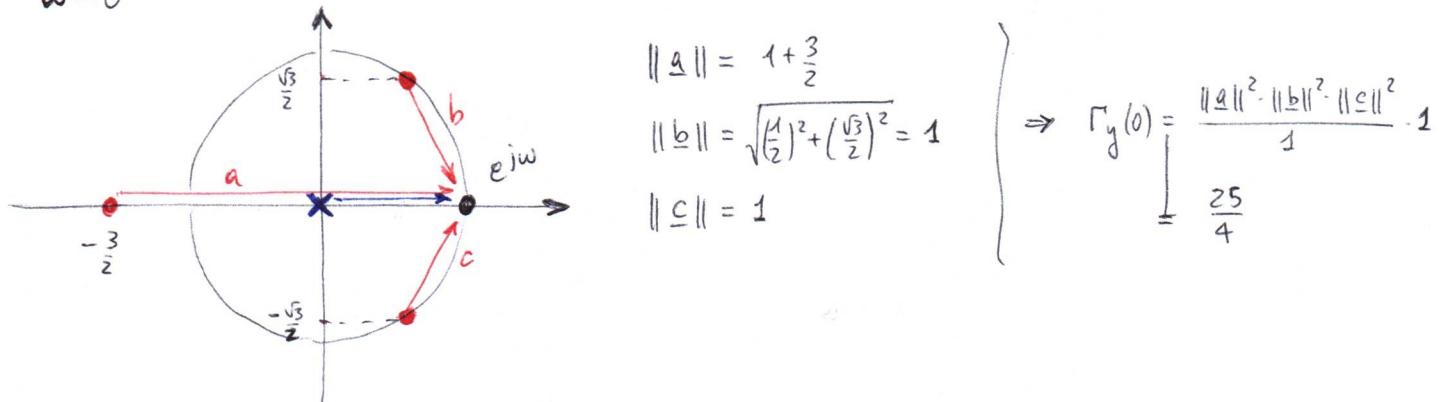
Compute the spectrum.

$$y(t) = \left(\frac{z^2 - z + 1}{z^2} \right) \left(\frac{z+3}{2z} \right) e(t) = \frac{(z^2 - z + 1)(z+1)}{z^3} e(t) :$$

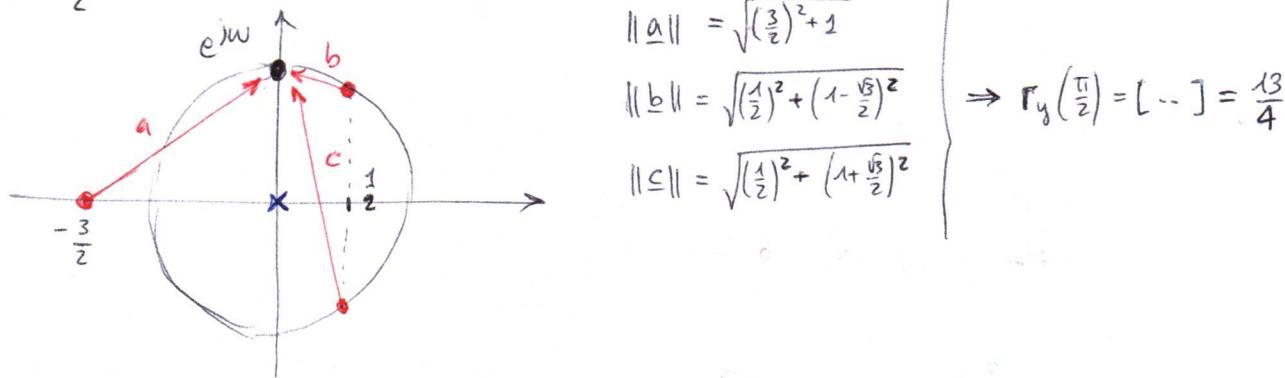
- poles: $z=0$ (3)
- zeros: $z = -\frac{3}{2}$, $z = \frac{1}{2} \pm j \frac{\sqrt{3}}{2}$

$$\Rightarrow \Gamma_y(\omega) = \frac{|e^{j\omega} + \frac{3}{2}|^2 |e^{j\omega} - \frac{1}{2} - j \frac{\sqrt{3}}{2}|^2 |e^{j\omega} - \frac{1}{2} + j \frac{\sqrt{3}}{2}|^2}{(|e^{j\omega}|^2)^3} \cdot 1$$

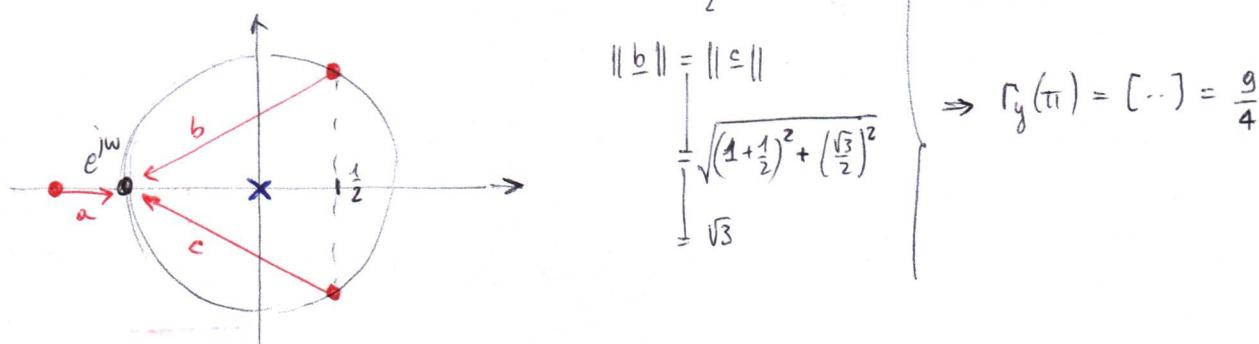
$$\omega = 0$$

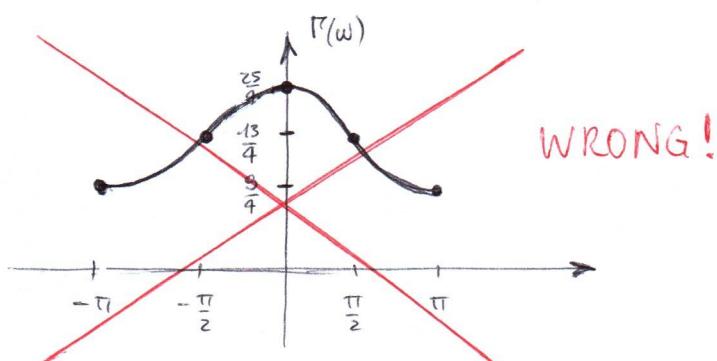


$$\omega = \frac{\pi}{2}$$



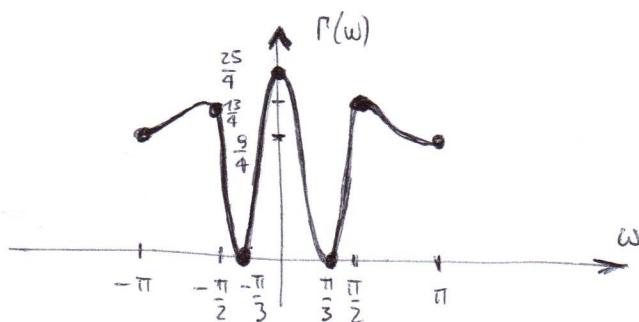
$$\omega = \pi$$

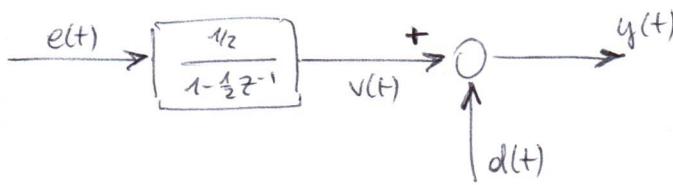




! We lost the zeros on the unit disk!
 (If we had a pole the system wouldn't be asymptotically stable, with a zero we have that the spectrum is 0 in that point)

$$r_y \left(w = \frac{\pi}{3} \right) = 0$$





$$e(t) \sim WN(0,1)$$

$$1. d(t) \sim WN(0, 4)$$

$e(t) \perp d(t)$ = completely uncorrelated

$$2. d(t) = -\frac{1}{3} e(t)$$

$$\Gamma_y(\omega) ?$$

$$1. y(t) = v(t) + d(t)$$

$$\mathbb{E}[y(t)] = \mathbb{E}[v(t)] + \mathbb{E}[d(t)]$$

$$v(t) = \frac{1/2}{1 - \frac{1}{2}z^{-1}} e(t) \Rightarrow v(t) = \frac{1}{2} v(t-1) + \frac{1}{2} e(t)$$

$$\mathbb{E}[v(t)] = \frac{1}{2} \mathbb{E}[v(t-1)] + \frac{1}{2} \mathbb{E}[e(t)]$$

$$W(z) = \frac{\frac{1}{2}z}{z - \frac{1}{2}}$$

→ stable → stationary

$$\Rightarrow \mathbb{E}[v(t)] = \frac{1}{2} \mathbb{E}[v(t)] + 0 \Rightarrow \mathbb{E}[v(t)] = 0$$

$$= 0$$

$$\gamma_y(\tau) = \mathbb{E}[y(t)y(t-\tau)] = \mathbb{E}[(v(t)+d(t))(v(t-\tau) + d(t-\tau))]$$

$$= \mathbb{E}[v(t)v(t-\tau) + d(t)v(t-\tau) + v(t)d(t-\tau) + d(t)d(t-\tau)]$$

$$= \underbrace{\mathbb{E}[v(t)v(t-\tau)]}_{\gamma_v(\tau)} + \underbrace{\mathbb{E}[d(t)v(t-\tau)]}_{\text{because they're uncorrelated}} + \underbrace{\mathbb{E}[v(t)d(t-\tau)]}_{\gamma_v(\tau)} + \underbrace{\mathbb{E}[d(t)d(t-\tau)]}_{\gamma_d(\tau)}$$

$$= \gamma_v(\tau) + \gamma_d(\tau)$$

$$\Gamma_y(\omega) = \sum_{\tau=-\infty}^{+\infty} \gamma_y(\tau) e^{-j\omega\tau} = \sum_{\tau=-\infty}^{+\infty} \gamma_v(\tau) e^{-j\omega\tau} + \sum_{\tau=-\infty}^{+\infty} \gamma_d(\tau) e^{-j\omega\tau}$$

$$\Gamma_v(\omega) = \left| \frac{\frac{1}{2}}{1 - \frac{1}{2}z^{-1}} \right|_{z=e^{j\omega}}^2 \quad \Gamma_e(\omega) = \frac{|1/2|^2}{|1 - \frac{1}{2}e^{-j\omega}|^2}$$

$$4/4$$

$$\frac{4}{(1 - \frac{1}{2}e^{j\omega})(1 - \frac{1}{2}e^{-j\omega})}$$

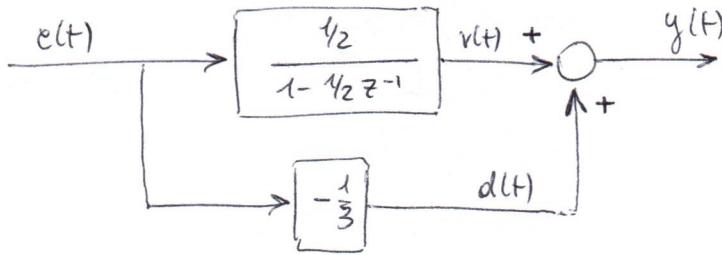
$$\frac{1/4}{1 - \frac{1}{2}(e^{j\omega} + e^{-j\omega}) + \frac{1}{4}}$$

$$\frac{1/4}{\frac{5}{4} - \cos(\omega)}$$

$$\Gamma_d(\omega) = 1 \quad \forall \omega$$

$$\Rightarrow \Gamma_y(\omega) = \frac{1/4}{\frac{5}{4} - \cos(\omega)} + 1$$

2. $d(t) = -\frac{1}{3} e(t)$:
 (FOR VS)



$$y(t) = \left(\frac{1/2}{1 - \frac{1}{2}z^{-1}} - \frac{1}{3} \right) e(t) = \frac{1}{6} \frac{z+1}{z-\frac{1}{2}} e(t) \rightarrow \Gamma_y(w) \text{ with}$$

- 1. Fundamental theorem
- 2. graphical method

ESTIMATION OF PROCESS CHARACTERISTICS

$$\hat{\gamma}_y(\tau) := \frac{1}{N-\tau} \sum_{t=1}^{N-\tau} y(t) y(t-\tau)$$

unbiased
and consistent

N s.t. $\tau < \frac{N}{4}$, $N \geq 50$

$$\hat{\gamma}_y(\tau) = \frac{1}{N-|\tau|} \sum_{t=1}^{N-|\tau|} y(t) y(t+|\tau|)$$

$$\hat{\delta}'_y(\tau) = \frac{1}{N} \sum_{t=1}^{N-|\tau|} y(t) y(t+|\tau|) \quad (|\tau| \leq N-1)$$

Not correct, but for $N \rightarrow \infty$ is asymptotically correct,
it also work for N large and τ small

$$\hat{\Pi}_y(w) := \sum_{\tau=-N+1}^{N-1} \hat{\delta}'_y(\tau) e^{-jw\tau}$$

$$\hat{\Gamma}'_y(w) := \sum_{\tau=-N+1}^{N-1} \hat{\delta}'_y(\tau) e^{-jw\tau}$$

we prefer this
because $\hat{\Pi}_y(w)$ can
be negative

$$\hat{\Pi}'_y(w) = \frac{1}{N} \left(\sum_{t=1}^N y(t) e^{-jwt} \right)^2$$

Fourier's
discrete transform
of $y(t)$

- not unbiased
- not consistent

$$\bar{\Pi}(w) = \frac{1}{r} \sum_{i=1}^r \hat{\Pi}'_i(w)$$

PREDICTION

$$\left. \begin{array}{l} y(t), y(t-1), y(t-2) \\ \text{process data} \end{array} \right\} \rightarrow \hat{y}(t+k|t) \quad (k = \text{prediction horizon})$$

(EX.)

$$y(t) = \frac{1}{2} y(t-2) + \eta(t) + 4\eta(t-1) \quad \eta(t) \sim WN(0,1)$$

$$\hat{y}(t+1|t) ?$$

$$y(t) - \frac{1}{2} z^{-2} y(t) = \eta(t) + 4z^{-1} \eta(t) \Rightarrow y(t) = \frac{1 + 4z^{-1}}{1 - \frac{1}{2} z^{-2}} \eta(t)$$

$$\Rightarrow y(t) = \frac{z(z+4)}{z^2 - \frac{1}{2}} \eta(t) : \begin{aligned} &\bullet \text{zeros: } z=0, z=-4 \\ &\bullet \text{poles: } z = \frac{1}{\sqrt{2}}, z = -\frac{1}{\sqrt{2}} \end{aligned}$$

$\Rightarrow y(t)$ is stationary

1. Check the canonical representation:

$$y(t) = W(z) u(t)$$

$$\begin{aligned} W(z) &= \frac{N(z)}{D(z)} = \frac{(1+4z^{-1})}{(1-\frac{1}{2}z^{-2})} : \\ &= \frac{z(z+4)}{z^2 - \frac{1}{2}} \end{aligned}$$

\Rightarrow 4. is not verified

(zeros: $z =$

CANONICAL REPRESENTATION

1. $N(z)$ and $D(z)$ must have the same degree
2. $N(z)$ and $D(z)$ must be monic (the coefficient of the highest power of z must be = 1)
3. $N(z)$ and $D(z)$ must be coprime (no common factor to simplify)
4. zeros and poles must be inside the unit circle

How can we remove this zero?

$$\begin{aligned} y(t) &= \frac{1+4z^{-1}}{1-\frac{1}{2}z^{-2}} \cdot \frac{1+\frac{1}{4}z^{-1}}{1+\frac{1}{4}z^{-1}} \eta(t) \\ &= \frac{1+\frac{1}{4}z^{-1}}{1-\frac{1}{2}z^{-2}} \cdot \boxed{\frac{1+4z^{-1}}{1+\frac{1}{4}z^{-1}} \eta(t)} := e(t) \end{aligned}$$

GAIN THEOREM

$$\begin{aligned} e(t) &= \frac{1+4z^{-1}}{1+\frac{1}{4}z^{-1}} \eta(t) : \quad \bullet E[e(t)] = \frac{1+4}{1+\frac{1}{4}} E[\eta(t)] = 0 \\ &\bullet R_e(w) = \frac{|1+4e^{jw}|^2}{|1+\frac{1}{4}e^{-jw}|^2} \cdot 1 \\ &\quad \boxed{\frac{(1+4e^{-jw})(1+4e^{+jw})}{(1+\frac{1}{4}e^{-jw})(1+\frac{1}{4}e^{+jw})}} \\ &\quad \boxed{\frac{1+4e^{jw}+4e^{-jw}+16}{1+\frac{1}{4}e^{jw}+\frac{1}{4}e^{-jw}+\frac{1}{16}}} = 16 \quad \forall w \end{aligned}$$

$$(1.) \Rightarrow e(t) \sim WN(0, 16)$$

$$\Rightarrow \text{CANONICAL REPRESENTATION: } y(t) = \frac{(1 + \frac{1}{4}z^{-1})}{(1 - \frac{1}{2}z^{-2})} e(t) \quad e(t) \sim WN(0, 16)$$

\Rightarrow ARMA (2,1)

Z. Prediction computation

Z.1. LONG DIVISION :

$$\begin{array}{c|cc} 1 + \frac{1}{4}z^{-1} & & 1 - \frac{1}{2}z^{-2} \\ \hline 1 & - \frac{1}{2}z^{-2} \\ \hline 1 & \left(\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2} \right) F(z) & E(z) \end{array}$$

$$y(t) = \frac{C(z)}{A(z)} e(t) = \left(E(z) + \frac{F(z)}{A(z)} \right) e(t) = 1 + \left(\frac{\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2}}{1 - \frac{1}{2}z^{-2}} \right) e(t)$$

$$= e(t) + \frac{\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2}}{1 - \frac{1}{2}z^{-2}} e(t-1)$$

unpredictable
at time $t-1$

predictable
at time $t-1$:
 $f(e(t-1), e(t-2), \dots)$
MA(∞)

$$\hat{y}(t|t-1) = \frac{\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2}}{1 - \frac{1}{2}z^{-2}} e(t-1)$$

predictable
part of the process

PREDICTION FROM THE NOISE

but we have $y(\cdot)$, not $e(\cdot)$

$$\underline{Z.2.} \quad y(t) = \frac{C(z)}{A(z)} e(t) \xrightarrow[\text{thanks to the canonical repr.}]{} e(t) = \frac{A(z)}{C(z)} y(t)$$

$$\begin{aligned} \hat{y}(t|t-1) &= \frac{\left(\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2} \right)}{1 - \frac{1}{2}z^{-2}} e(t) \\ &= \frac{\left(\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2} \right)}{\left(1 - \frac{1}{2}z^{-2} \right)} \frac{\left(1 - \frac{1}{2}z^{-2} \right)}{\left(1 + \frac{1}{4}z^{-1} \right)} y(t) \\ &= \frac{\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2}}{1 + \frac{1}{4}z^{-1}} y(t-1) \end{aligned}$$

PREDICTOR FROM
THE DATA

$$\Rightarrow \hat{y}(t+1|t) = \frac{\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2}}{1 + \frac{1}{4}z^{-1}} y(t)$$

$$\Rightarrow \left(1 + \frac{1}{4}z^{-1} \right) \hat{y}(t+1|t) = \left(\frac{1}{4}z^{-1} + \frac{1}{2}z^{-2} \right) y(t)$$

$$\Rightarrow \hat{y}(t+1|t) = -\frac{1}{4} \hat{y}(t|t-1) + \frac{1}{4} y(t) + \frac{1}{2} y(t-1)$$

PREDICTOR FROM
THE DATA IN TIME DOMAIN

t	$y(t)$	$\hat{y}(t+1 t)$
0	0	$\hat{y}(1 0)$
1	1	$\hat{y}(2 1)$
2	0	$\hat{y}(3 2)$
3	$-\frac{1}{2}$	$\hat{y}(4 3)$

We use the predictor from the data in time domain:

$$\hat{y}(t+1|t) = -\frac{1}{4} \hat{y}(t|t-1) + \frac{1}{4} y(t) + \frac{1}{2} y(t-1)$$

- $\hat{y}(1|0) = 0$
- $\hat{y}(2|1) = -\frac{1}{4} \hat{y}(1|0) + \frac{1}{4} y(1) + \frac{1}{2} y(0) = \frac{1}{4}$
- $\hat{y}(3|2) = -\frac{1}{4} \hat{y}(2|1) + \frac{1}{4} y(2) + \frac{1}{2} y(1) = \frac{7}{16}$
- $\hat{y}(4|3) = -\frac{1}{4} \hat{y}(3|2) + \frac{1}{4} y(3) + \frac{1}{2} y(2) = -\frac{15}{64}$

Another way to predict:

$$\hat{y}(t|t-1) = \frac{C(z) - A(z)}{A(z)} \cdot e(t) \quad \text{PREDICTOR FROM NOISE}$$

$$\hat{y}(t|t-1) = \frac{C(z) - A(z)}{C(z)} y(t) \quad \text{PREDICTOR FROM DATA}$$

$$\Rightarrow \hat{y}(t|t-1) = \frac{\left(1 + \frac{1}{4}z^{-1}\right)\left(1 - \frac{1}{2}z^{-2}\right)}{\left(1 - \frac{1}{2}z^{-2}\right)} e(t) = \frac{\left(1 + \frac{1}{4}z^{-1} - \frac{1}{2}z^{-2}\right)}{1 - \frac{1}{2}z^{-2}} e(t)$$

$$= \frac{\frac{1}{4} + \frac{1}{2}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t-1) \quad (\text{from NOISE})$$

For us: check the "from DATA" formula

3. Predictor error

$$\epsilon(t|t-1) = y(t) - \hat{y}(t|t-1)$$

$$y(t) = e(t) + \frac{\frac{1}{4} - \frac{1}{2}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t-1)$$

$$\hat{y}(t|t-1) = \frac{\frac{1}{4} - \frac{1}{2}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t-1)$$

$$\rightarrow \epsilon(t|t-1) = e(t)$$

Unpredictable part
⇒ OPTIMAL PREDICTION

$$\mathbb{E}[\epsilon(t|t-1)^2] = \mathbb{E}[e^2(t)] = 16$$

Variance of the prediction error

$$\hat{y}(t|t-2) ?$$

$$y(t) = \frac{1 + \frac{1}{4}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t), \quad e(t) \sim WN(0, 16)$$

2.1.

long division:

$$\begin{array}{r} 1 + \frac{1}{4}z^{-1} \\ \underline{-} \quad \quad \quad -\frac{1}{2}z^{-2} \\ \hline \frac{1}{4}z^{-1} + \frac{1}{2}z^{-2} \\ \underline{-} \quad \quad \quad -\frac{1}{8}z^{-3} \\ \hline \frac{1}{2}z^{-2} + \frac{1}{8}z^{-3} \end{array} \quad \left| \begin{array}{r} 1 - \frac{1}{2}z^{-2} \\ \hline 1 + \frac{1}{4}z^{-1} \end{array} \right.$$

$$\Rightarrow y(t) = \left(E(z) + \frac{F(z)}{A(z)} \right) e(t) = \left(1 + \frac{1}{4}z^{-1} + \frac{\frac{1}{2}z^{-2} + \frac{1}{8}z^{-3}}{1 - \frac{1}{2}z^{-2}} \right) e(t)$$

$$= e(t) + \frac{1}{4}e(t-1) + \frac{\frac{1}{2} + \frac{1}{8}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t-2)$$

↑ unpredictable at time t-2 ↓ predictable at time t-2

$$\hat{y}(t|t-2) = \frac{\frac{1}{2} + \frac{1}{8}z^{-1}}{1 - \frac{1}{2}z^{-2}} e(t-2)$$

the only predictable part of $y(t)$ ↑

PREDICTOR FROM THE NOISE

2.2.

thanks to the canonical repr.

$$\hat{y}(t|t-2) = \frac{\left(\frac{1}{2}z^{-2} + \frac{1}{8}z^{-3} \right)}{\left(1 - \frac{1}{2}z^{-2} \right)} \cdot \frac{\left(1 - \frac{1}{2}z^{-2} \right)}{\left(1 + \frac{1}{4}z^{-1} \right)} y(t)$$

$$= \frac{\frac{1}{2} + \frac{1}{8}z^{-1}}{1 + \frac{1}{4}z^{-1}} y(t-2)$$

PREDICTION FROM THE DATA

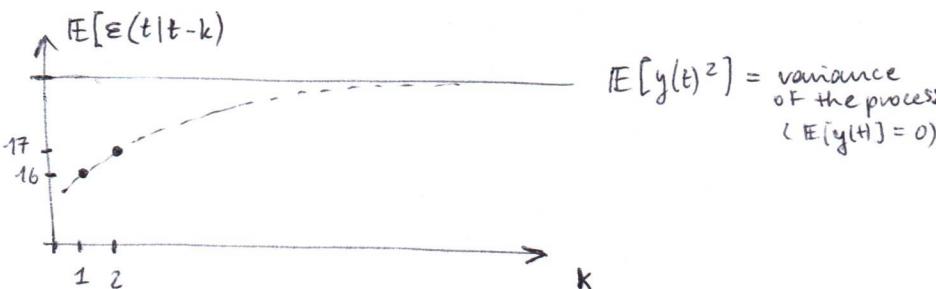
3.

Prediction error:

$$\varepsilon(t|t-2) = y(t) - \hat{y}(t|t-2) = E(z) e(t) \implies MA(2)$$

$$\mathbb{E}[\varepsilon(t|t-2)^2] = \mathbb{E}\left[\left(e(t) + \frac{1}{4}e(t-1)\right)^2\right] = \mathbb{E}[e(t)^2] + \frac{1}{16} \mathbb{E}[e(t-1)^2] = 16 + 1 = 17$$

In general:



$$\mathbb{E}[\varepsilon(t|t-k)^2] = \underbrace{\mathbb{E}[(E(z) e(t))^2]}_{k \rightarrow \infty \text{ MA}(\infty)} = \mathbb{E}[y(t)^2] \implies \hat{y}(t|t-\infty) = 0$$

$$\mathbb{E}[(y(t) - \hat{y}(t|t-\infty))^2] = \mathbb{E}[(y(t) - 0)^2] = \sigma_y^2$$

$$\Rightarrow \hat{y}(t|t-\infty) = 0$$

In general:

$$\mathbb{E}[y(t)] \neq 0 \implies \mathbb{E}[(y(t) - \mathbb{E}[y(t)])^2] = \sigma_y^2$$

$$\Rightarrow \boxed{\hat{y}(t|t-\infty) = \mathbb{E}[y(t)]}$$

with our infinity prediction horizon the only thing we can say about the process is its expected value

PREDICTION

$$y(t) = w(z) e(t) \quad e(t) \sim WN(0, \lambda^2)$$

$$\frac{C(z)}{A(z)} e(t)$$

long division with k steps

$$\left(E(z) + \frac{F(z)}{A(z)} \right) e(t)$$

$$= \boxed{E(z) e(t)} + \boxed{\frac{F(z)}{A(z)} e(t)}$$

unpredictable
(at time) $t-k$

predictable
 $t-k$

$$\Rightarrow \hat{y}(t|t-k) = \frac{F(z)}{A(z)} e(t) \quad \text{PREDICTOR FROM THE NOISE}$$

Since we used the canonical representation:

$$e(t) = \frac{A(z)}{C(z)} y(t) \implies \hat{y}(t|t-k) = \frac{F(z)}{A(z)} \cdot \frac{A(z)}{C(z)} y(t)$$

$$\Rightarrow \hat{y}(t|t-k) = \frac{F(z)}{C(z)} y(t) \quad \text{PREDICTOR FROM THE DATA}$$

We always have the prediction error:

$$\begin{aligned} \varepsilon(t|t-k) &= y(t) - \hat{y}(t|t-k) \\ &= E(z) e(t) + \frac{F(z)}{A(z)} e(t) - \frac{F(z)}{A(z)} e(t) \end{aligned}$$

$$\Rightarrow \varepsilon(t|t-k) = \underbrace{E(z) e(t)}_{\text{unpredictable part of the process}} \quad \text{ERROR}$$

Variance of the predictor error:

$$\mathbb{E}[(E(z) e(t))^2] \implies \text{variance of MA}(k)$$

- $k=1$: $\mathbb{E}[(E(z) e(t))^2] = \mathbb{E}[e(t)^2] = \text{Var}(e(t))$

- $k \rightarrow \infty$: $\varepsilon(t|t-k) = E(z) e(t) = \text{MA}(\infty) = y(t)$

$$\mathbb{E}[(\varepsilon(t|t-k))^2] = \sigma_y^2 \quad (\text{variance of the process})$$

$$\sigma_y^2 = \mathbb{E}[(y(t) - \mathbb{E}[y(t)])^2]$$

$$\sigma_y^2 = \mathbb{E}[(y(t) - \underbrace{\mathbb{E}[y(t)]}_{})^2] = \mathbb{E}[(y(t) - \underbrace{\hat{y}(t|t-k)}_{})^2]$$

$$\Rightarrow \hat{y}(t|t-k) = \mathbb{E}[y(t)] \quad \text{as } k \rightarrow \infty$$

the only thing we can say with an ∞ horizon is the expected value of the process

$$\hat{y}(t|t-2) = \frac{\frac{1}{2} + \frac{1}{8}z^{-1}}{1 + \frac{1}{4}z^{-1}} y(t-2) = \frac{1}{2} \frac{\cancel{1 + \frac{1}{4}z^{-1}}}{\cancel{1 + \frac{1}{4}z^{-1}}} y(t-2) = \frac{1}{2} y(t-2)$$

(yesterday's exercise)

$$y(t) = \underbrace{\frac{1}{2} y(t-2)}_{\text{predictable, in fact this is the predictor } \hat{y}(t|t-2)} + \underbrace{e(t) + \frac{1}{4} e(t-1)}_{\text{unpredictable at time } t-2}$$

$\hat{y}(t|t-3) ?$

$$y(t) = \underbrace{\frac{1}{2} y(t-2) + e(t) + \frac{1}{4} e(t-1)}_{\text{fully unpredictable at time } t-3} \Rightarrow \hat{y}(t|t-3) = 0 \quad \text{WRONG}$$

$y(t-2) \neq y(k) \quad k = t-3, t-4, \dots \Rightarrow y(t-2)$ is predictable, only $e(t)$ and $e(t-1)$ are unpredictable from $t-3$

$$\begin{aligned} y(t-2) &= \frac{1}{2} y(t-4) + e(t-2) + \frac{1}{4} e(t-3) \\ \Rightarrow y(t) &= \frac{1}{4} y(t-4) + \frac{1}{2} e(t-2) + \frac{1}{8} e(t-3) + e(t) + \frac{1}{4} e(t-1) \\ &= \underbrace{\frac{1}{4} y(t-4) + \frac{1}{8} e(t-3)}_{\text{predictable}} + \underbrace{\frac{1}{2} e(t-2) + \frac{1}{4} e(t-1) + e(t)}_{\text{unpredictable}} \end{aligned}$$

$$\Rightarrow \hat{y}(t|t-3) = \frac{1}{4} y(t-4) + \frac{1}{8} e(t-3)$$

depend also on the NOISE
 \Rightarrow to get rid of it we do the LONG DIVISION (ONLY WAY)

(Ex.)

$$y(t) = e(t) + 5e(t-1), \quad e(t) \sim WN(1, 1) \Rightarrow \text{we cannot proceed as before}$$

because:

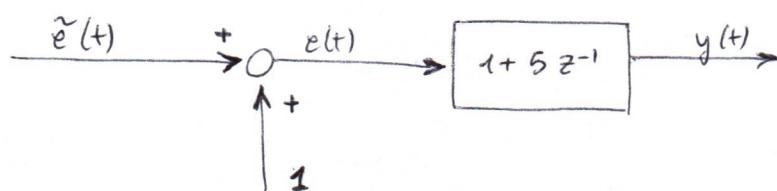
$$\hat{y}(t|t-1) = \underbrace{\mathbb{E}[e(t)]}_{1+5e(t-1)} + 5e(t-1)$$

$\hat{y}(t|t-1) ?$

In order to avoid problems: DEBIAS PROCESS

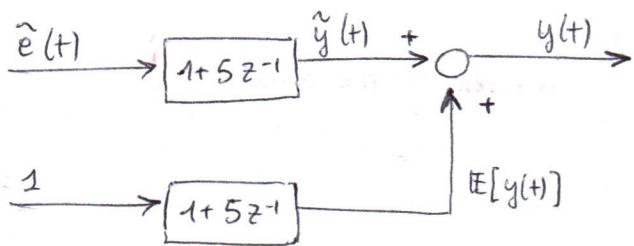
$$\hat{e}(t) := e(t) - \mathbb{E}[e(t)] = e(t) - 1$$

$$\hat{y}(t) := y(t) - \mathbb{E}[y(t)]$$



$$y(t) = f(y(t)) \quad \eta \sim WN(a, b) \quad a \neq 0$$

1. DEBIAS $\rightarrow \hat{y}$
2. \hat{y} from noise
3. \hat{y} from data
4. $\hat{y} \rightarrow \hat{y}$



$$\mathbb{E}[y(t)] = 1 \cdot (1+5) = 6$$

$$\hat{y}(t) = \hat{e}(t) + 5 \hat{e}(t-1) \quad \text{with:} \quad \begin{cases} \hat{y}(t) = y(t) - 6 \\ \hat{e}(t) = e(t) - 1 \end{cases}$$

$\hat{y}(t|t-1)$?

$$\hat{y}(t) = (1 + 5z^{-1}) \hat{e}(t) = \left(\frac{z+5}{z}\right) \hat{e}(t)$$

canonical representation?

- 1. N, D same degree? ✓
- 2. N, D monic? ✓
- 3. N, D coprime? ✓
- 4. zeros and poles in the unit disc? NO.

zero: $z = -5$

pole: $z = 0$

We have to remove this zero:

$$\begin{aligned} \hat{y}(t) &= (1 + 5z^{-1}) \frac{(1 + \frac{1}{5}z^{-1})}{(1 + \frac{1}{5}z^{-1})} \hat{e}(t) \\ &= \left(1 + \frac{1}{5}z^{-1}\right) \left(\frac{1 + 5z^{-1}}{1 + \frac{1}{5}z^{-1}}\right) \hat{e}(t) := \eta(t) \\ &= \left(1 + \frac{1}{5}z^{-1}\right) \eta(t), \quad \eta(t) \sim WN(0, 5^2) = WN(0, 25) \end{aligned}$$

$$\Rightarrow \hat{y}(t) = \underbrace{\eta(t)}_{\text{unpred. at time } t-1} + \underbrace{\frac{1}{5} \eta(t-1)}_{\text{predictable at time } t-1}$$

$$\Rightarrow \hat{y}(t|t-1) = \frac{1}{5} \eta(t-1) \quad \text{PREDICTOR FROM THE NOISE}$$

$$\eta(t) = \frac{1}{1 + \frac{1}{5}z^{-1}} \hat{y}(t) \Rightarrow \hat{y}(t|t-1) = \frac{1}{5} \cdot \frac{z^{-1}}{1 + \frac{1}{5}z^{-1}} \hat{y}(t)$$

PREDICTOR FROM THE DATA

$\Rightarrow \hat{y}(t|t-1)$?

$$\hat{y}(t|t-1) = \hat{y}(t) + 6 = \hat{y}(t|t-1) + 6$$

$$\Rightarrow \hat{y}(t|t-1) = \underbrace{\frac{1/5}{1 + \frac{1}{5}z^{-1}}}_{\frac{1/5}{1 + \frac{1}{5}z^{-1}} (y(t-1) - 6) + 6} \hat{y}(t-1) + 6$$

$$\hat{y}(t|t-1) = \frac{1/5}{1 + \frac{1}{3}z^{-1}} y(t-1) - \frac{6/5}{1 + 1/5} + 6$$

theorem of THE GAIN:

$$\frac{1/5}{1 + \frac{1}{3}z^{-1}} - 6 = \frac{6/5}{1 + 1/5}$$

we consider $z=1$
because we have as
an input a constant
signal

(EX-)

$$\frac{1}{2} y(t) = -\frac{1}{3} y(t-1) - \frac{1}{18} y(t-2) + 3 e(t-2) - 8 e(t-3) - 3 e(t-4), \quad \hat{y}(t|t-1) ?$$

$$\frac{1}{2} y(t) + \frac{1}{3} z^{-1} y(t) + \frac{1}{18} z^{-2} y(t) = 3 z^{-2} e(t) - 8 z^{-3} e(t) - 3 z^{-4} e(t)$$

$$\Rightarrow y(t) = \frac{3 z^{-2} - 8 z^{-3} - 3 z^{-4}}{\frac{1}{2} + \frac{1}{3} z^{-1} + \frac{1}{18} z^{-2}} e(t)$$

canonical? NO.

- no same degree
- no monic

$$y(t) = \frac{\frac{3 z^{-2}}{\frac{1}{2}}}{\frac{(1 - \frac{8}{3}z^{-1} - z^{-2})}{(1 - \frac{2}{3}z^{-1} + \frac{1}{3}z^{-2})}} e(t) := \eta(t) = 6 e(t-1), \quad \eta \sim WN(0, 36)$$

$$\Rightarrow y(t) = \frac{\frac{1 - \frac{8}{3}z^{-1} - z^{-2}}{1 - \frac{2}{3}z^{-1} + \frac{1}{3}z^{-2}}}{\frac{z^2 - \frac{8}{3}z - 1}{z^2 - \frac{2}{3}z + \frac{1}{3}}} \eta(t)$$

- zeros: $z = 3, z = -\frac{1}{3}$
- poles: $z = -\frac{1}{3}, z = -\frac{1}{3}$

$$= \frac{(z-3)(z+\frac{1}{3})}{(z+\frac{1}{3})^2} \eta(t)$$

$$= \frac{z-3}{z+\frac{1}{3}} \eta(t) = \frac{1 - \frac{3}{3}z^{-1}}{1 + \frac{1}{3}z^{-1}} \eta(t)$$

$$= \frac{(1 - \frac{1}{3}z^{-1})}{(1 + \frac{1}{3}z^{-1})} \frac{1 - \frac{3}{3}z^{-1}}{1 - \frac{1}{3}z^{-1}} \eta(t) := w(t), \quad w(t) \sim WN(0, 9 \cdot 36)$$

$$\Rightarrow y(t) = \frac{(1 - \frac{1}{3}z^{-1})}{(1 + \frac{1}{3}z^{-1})} w(t)$$

$$\Rightarrow \hat{y}(t|t-1) = \frac{c(z) - A(z)}{c(z)} y(t)$$

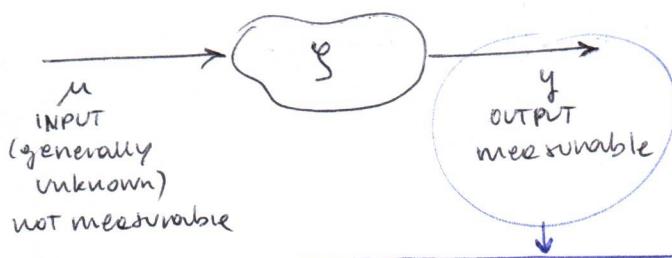
$$= \frac{(1 - \frac{1}{3}z^{-1}) - (1 + \frac{1}{3}z^{-1})}{1 - \frac{1}{3}z^{-1}} y(t)$$

$$= \frac{-\frac{2}{3}z^{-1}}{1 - \frac{1}{3}z^{-1}} y(t)$$

PREDICTOR FROM
THE DATA

IDENTIFICATION

01/04



- Data
- Suppose a family model
- Suppose input $\sim WN$
- \hat{y}
- ε
- $\hat{\theta}_n, \hat{\sigma}^2_n$

Starting from $\{y(1), y(2), \dots, y(N)\}$ we want to deduce the system state generator:

$$y(t) = \frac{c(z)}{A(z)} e(t) \quad e(t) \sim WN(0, \sigma^2)$$

We can only suppose a family models to approximate our system
We focus on a family model: (we suppose a model family)

$$M: y(t) = \frac{C_m(z, \theta)}{A_m(z, \theta)} \xi(t) \quad \xi(t) \sim WN(0, \sigma^2) \quad (\text{we suppose as an input a WN})$$

CANONICAL REPRESENTATION

⇒ AIM: find θ and σ^2 s.t. $y(t)$ (model) describes well the data
We use the PEM method;

PREDICTION ERROR METHOD (P.E.M.)

$$M \rightarrow \hat{M}: \hat{y}(t|t-1, \theta) = \hat{w}(z)y(t)$$

$$\varepsilon(t, \theta) = y(t) - \hat{y}(t|t-1, \theta)$$

prediction error

$$J_N(\theta) = \frac{1}{N} \sum_{t=1}^N \varepsilon(t, \theta)^2 \rightarrow \begin{cases} \hat{\theta}_N = \underset{\theta}{\operatorname{arg\,min}} J_N(\theta) \\ \hat{\sigma}^2_N = J_N(\hat{\theta}_N) \end{cases}$$

What can we expect?

$$\text{If } S \in M \Rightarrow \varepsilon(t, \hat{\theta}_N) = e(t) \quad (e(t) \sim WN) : E[(\varepsilon(t, \hat{\theta}_N))^2] = \lambda^2$$

This method depends on $N \Rightarrow$ is not so good.

We can resolve this having $N \rightarrow \infty$.

What happen if we have $\{y(1), \dots, y(\infty)\}$?

$$J_N(\theta) = \frac{1}{N} \sum_{t=1}^N \varepsilon(t, \theta)^2 \xrightarrow{N \rightarrow \infty} \bar{J}(\theta)$$

$$\hat{\theta}_N = \underset{\theta}{\operatorname{arg\,min}} J_N(\theta) \xrightarrow{N \rightarrow \infty} \underline{\theta^*} = \underset{\theta}{\operatorname{arg\,min}} \bar{J}(\theta)$$

$$\hat{\sigma}^2_N = J_N(\hat{\theta}_N) \xrightarrow{N \rightarrow \infty} \underline{\sigma^2}^* = \bar{J}(\underline{\theta^*})$$

performance indexes

$$\bar{J}(\theta) = E[\varepsilon(t, \theta)^2]$$

$$\underline{\theta^*} = \underset{\theta}{\operatorname{arg\,min}} \bar{J}(\theta)$$

$$\underline{\sigma^2}^* = \bar{J}(\underline{\theta^*})$$

PROBABILISTIC INDEXES

(ASYMPTOTIC ANALYSIS)

$$M: \quad y(t) = \frac{C_m(z, \theta)}{A_m(z, \theta)} \xi(t) \quad \xi(t) \sim WN(0, \sigma^2)$$

$$1. \quad \hat{y}(t|t-1) = \left[\frac{C_m(z, \theta) - A_m(z, \theta)}{C_m(z, \theta)} \right] y(t) \quad (\text{simplified formula})$$

one step predictor

$$2. \quad \varepsilon(t, \theta) = y(t) - \hat{y}(t|t-1) = \left[1 - \frac{C_m(z, \theta) - A_m(z, \theta)}{C_m(z, \theta)} \right] y(t)$$

predictor error

$$\begin{aligned} &= \frac{A_m(z, \theta)}{C_m(z, \theta)} y(t) \\ &= \frac{A_m(z, \theta)}{C_m(z, \theta)} \frac{C(z)}{A(z)} e(t) \end{aligned}$$

$y(t) = \frac{C(z)}{A(z)} e(t)$

$$3. \quad \bar{J}(\theta) = \mathbb{E}[(\varepsilon(t, \theta))^2] \quad \text{variance of predictor error}$$

$$\hat{\theta}^* = \underset{\theta}{\operatorname{arg\,min}} \bar{J}(\theta)$$

$$\sigma^2* = \bar{J}(\hat{\theta}^*)$$

(Ex.)

$$S: \quad y(t) = e(t) + \frac{1}{2} e(t-1) \quad e(t) \sim WN(0, 1) \quad MA(1)$$

$$M: \quad y(t) = a y(t-1) + \xi(t) \quad \xi(t) \sim WN(0, \sigma^2) \quad AR(1)$$

$$\theta^*, \sigma^2* ?$$

$$1. \quad y(t) = \frac{1}{1-a z^{-1}} \xi(t) \quad |a| < 1 \quad (\text{Hyp.})$$

$$\hat{y}(t|t-1) = a y(t-1)$$

$$2. \quad \varepsilon(t, a) = y(t) - \hat{y}(t|t-1) = \frac{(1-a z^{-1}) y(t)}{(1-a z^{-1})(1+\frac{1}{2} z^{-1})} e(t) \quad y(t) = \left(1 + \frac{1}{2} z^{-1}\right) e(t)$$

$$\begin{aligned} &= \frac{(1+\frac{1}{2} z^{-1} - a z^{-1} - \frac{1}{2} a z^{-2}) e(t)}{(1-a z^{-1})(1+\frac{1}{2} z^{-1})} \\ &= e(t) + \left(\frac{1}{2} - a\right) e(t-1) - \frac{1}{2} a e(t-2) \end{aligned}$$

$$3. \quad \bar{J}(a) = \mathbb{E}[\varepsilon(t, a)^2]$$

$$\begin{aligned} &= \mathbb{E}[e(t)^2] + \left(\frac{1}{2} - a\right)^2 \mathbb{E}[e(t-1)^2] + \frac{1}{4} a^2 \mathbb{E}[e(t-2)^2] \quad \text{the double products simplifies} \\ &= 1 + \frac{1}{4} + a^2 - a + \frac{1}{4} a^2 \\ &= \frac{5}{4} - a + \frac{5}{4} a^2 \end{aligned}$$

$$(\bar{J}(a))' = -1 + \frac{5}{4} \cdot 2a = 0 \implies a^* = \frac{2}{5} \quad (< 1 \quad (\text{Hyp. } |a| < 1))$$

$$\Rightarrow \sigma^2* = \bar{J}(a^*) = \frac{5}{4} - \frac{2}{5} + \frac{5}{4} \left(\frac{2}{5}\right)^2 = \frac{21}{20}$$

$$\Rightarrow \varepsilon(t, a^*) = e(t) + \frac{1}{10} e(t-1) - \frac{1}{5} e(t-2)$$

is not a WN as the best result that we could obtain (this is obvious because the system is an MA(1) and we chose AR(1), so $S \neq M$)

\Rightarrow the prediction error is a colored noise, but it's not so bad ($1. \sigma^2 \approx \text{Var}(e(t)) = 1$) 2. the coefficients that make the input not a WN ($\frac{1}{10}$ and $-\frac{1}{5}$) are "small")

(EX+)

$$S: y(t) = e(t) + \frac{1}{2} e(t-1) : e(t) \sim WN(0, 1) \quad MA(1)$$

$$M: y(t) = y(t) + b y(t-1) : y(t) \sim WN(0, \lambda^2) \quad MA(1)$$

$$\theta^* = b^*? \quad \lambda^*=?$$

$$\Rightarrow \text{since they're both MA(1)} : b^* = \frac{1}{2}, \quad \lambda^* = 1$$

How to proceed if we don't notice that?

$$H_p: |b| < 1$$

$$\begin{aligned} 1. \hat{y}(t|t-1) &= \frac{C_m(z) - A_m(z)}{C_m(z)} y(t) \\ &\stackrel{z}{=} \left[\frac{(1+bz^{-1}) - 1}{1+bz^{-1}} \right] y(t) \\ &\stackrel{z}{=} \frac{bz^{-1}}{1+bz^{-1}} y(t) \end{aligned}$$

$$\begin{aligned} 2. \varepsilon(t, b) &= y(t) - \hat{y}(t|t-1) = \left(1 - \frac{bz^{-1}}{1+bz^{-1}} \right) y(t) \\ &\stackrel{z}{=} \frac{1}{1+bz^{-1}} y(t) \\ &\stackrel{z}{=} \frac{1}{1+bz^{-1}} \left(1 + \frac{1}{2} z^{-1} \right) e(t) \\ &\stackrel{z}{=} e(t) \quad \text{if } b = \frac{1}{2} : \quad \mathbb{E}[\varepsilon(t, b)^2] = 1 = \mathbb{E}[e(t)^2] \end{aligned}$$

If we don't notice that is optimal for $b = \frac{1}{2}$?

$$\begin{aligned} 3. \mathbb{E}[\varepsilon(t, b)^2] &= \mathbb{E}\left[(-b\varepsilon(t-1) + e(t) + \frac{1}{2}e(t-1))^2\right] \quad e(t) \sim WN(0, 1) \\ &\stackrel{z}{=} \mathbb{E}[b^2\varepsilon(t-1)^2] + \mathbb{E}[e(t)^2] + \frac{1}{4}\mathbb{E}[e(t-1)^2] - 2b\mathbb{E}[\varepsilon(t-1)e(t)] - \\ &\quad - b\mathbb{E}[\varepsilon(t-1)\varepsilon(t-1)] + \mathbb{E}[e(t)e(t-1)] \\ &\stackrel{\text{stochastic stationary process } (|b| < 1)}{=} b^2 \mathbb{E}[\varepsilon(t, b)^2] + 1 + \frac{1}{4} - b \underbrace{\mathbb{E}[\varepsilon(t-1)\varepsilon(t-1)]}_{\mathbb{E}[(\varepsilon(t-2) + e(t-1) + \frac{1}{2}e(t-2))\varepsilon(t-1)]} = \\ &\quad = \mathbb{E}[-b\mathbb{E}[\varepsilon(t-2)\varepsilon(t-1)] + \mathbb{E}[e(t-1)^2] + \frac{1}{2}\mathbb{E}[e(t-1)e(t-2)]] \\ &\stackrel{z}{=} 1 \end{aligned}$$

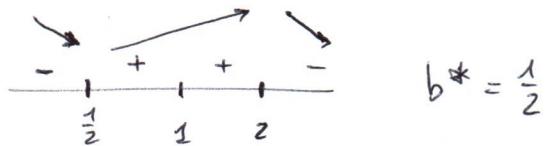
$\varepsilon(t-1) = f(e(t-1), e(t-2), \dots)$
no they're II

$$(3.) \Rightarrow \bar{J}(b) = \frac{\frac{5}{4} - b}{1 - b^2} \quad (|b| < 1)$$

$$(\bar{J}(b))' = \frac{-(1-b^2) + (\frac{5}{4}-b)(2b)}{(1-b^2)^2} = \frac{-b^2 + \frac{5}{2}b - 1}{(1-b^2)^2}$$

$D > 0 \quad \forall b$

$$N \geq 0 : -b^2 + \frac{5}{2}b - 1 \geq 0 \quad : \quad N \geq 0 \quad \frac{1}{2} < b < 2 \quad (|b| < 1)$$



$$\bar{J}(b^*) = \frac{\frac{5}{4} - \frac{1}{2}}{1 - (\frac{1}{2})^2} = 1 \quad (= \text{Var}(e(t)))$$

$$\varepsilon(t) = -\frac{1}{2} \varepsilon(t-1) + e(t) + \frac{1}{2} \varepsilon(t-1)$$

$$\varepsilon(t) + \frac{1}{2} z^{-1} \varepsilon(t) = e(t) + \frac{1}{2} z^{-1} e(t)$$

$$\Rightarrow \varepsilon(t) = \frac{1 + \frac{1}{2} z^{-1}}{1 + \frac{1}{2} z^{-1}} e(t)$$

(EX.)

$$S: y(t) = 3e(t) + 9e(t-1), \quad e(t) \sim WN(0, 1) \quad MA(1)$$

$$M: y(t) = y(t) + b y(t-1), \quad (t) \sim WN(0, \lambda^2) \quad MA(1)$$

$$g^* = b^*? \quad \lambda^{2*}?$$

$$H_p: |b| < 1$$

$S \in M$ but S is not written in the canonical representation!

$$y(t) = (3 + 9z^{-1})e(t) = 3(1 + 3z^{-1})e(t) =$$

$$= \underbrace{3}_{\text{all pass filter}} \underbrace{\frac{1+3z^{-1}}{1+\frac{1}{3}z^{-1}}}_{(1+\frac{1}{3}z^{-1})} (1+\frac{1}{3}z^{-1})e(t) := \xi(t)$$

$$\xi(t) = 3 \frac{(1+3z^{-1})}{(1+\frac{1}{3}z^{-1})} (t) \rightarrow \xi(t) \sim WN(0, 9 \cdot 3^2) = WN(0, 81)$$

$$\Rightarrow y(t) = \left(1 + \frac{1}{3}z^{-1}\right) \xi(t)$$

$$\Rightarrow b^* = \frac{1}{3}, \quad \lambda^{2*} = 81$$

(Ex.)

02/04

$$S: y(t) = e(t) + \frac{1}{2} e(t-1)$$

$$e(t) \sim WN(0, 1)$$

MA(1)

$$M: y(t) = \frac{1}{1+az^{-1}+bz^{-2}} \eta(t)$$

$$\eta(t) \sim WN(0, \lambda^2)$$

AR(2)

$$\theta^* = \begin{bmatrix} a \\ b \end{bmatrix} ? , \quad \lambda^2 = ?$$

Family model ≠ system

$$H_p: z^2 + az + b = 0$$

$$|z_{1,2}| < 1$$

the solution must be
in the unit disc

$$1. y(t) = -ay(t-1) - by(t-2) + \eta(t)$$

only unpredictable term at time t-1

$$\hat{y}(t|t-1) = -ay(t-1) - by(t-2)$$

$$\begin{aligned} 2. \varepsilon(t) &= y(t) - \hat{y}(t|t-1) = y(t) + a y(t-1) + b y(t-2) \\ &\stackrel{(1+az^{-1}+bz^{-2})}{=} y(t) \\ &\stackrel{(1+az^{-1}+bz^{-2})(1+\frac{1}{2}z^{-1})}{=} e(t) \\ &\stackrel{\left(1+\frac{1}{2}z^{-1}+az^{-1}+\frac{1}{2}az^{-2}+bz^{-2}+\frac{1}{2}bz^{-3}\right)}{=} e(t) \\ &\stackrel{\left(1+\left(a+\frac{1}{2}\right)z^{-1}+\left(\frac{1}{2}a+b\right)z^{-2}+\frac{1}{2}bz^{-3}\right)}{=} e(t) \\ &= e(t) + \left(a+\frac{1}{2}\right)e(t-1) + \left(\frac{1}{2}a+b\right)e(t-2) + \frac{1}{2}be(t-3) \end{aligned}$$

$$\begin{aligned} 3. \mathbb{E}[\varepsilon(t)^2] &= \bar{J}(\theta) = \mathbb{E}[e(t)^2] + \left(a+\frac{1}{2}\right)^2 \mathbb{E}[e(t-1)^2] + \left(\frac{1}{2}a+b\right)^2 \mathbb{E}[e(t-2)^2] + \frac{1}{4} \mathbb{E}[e(t-3)^2] \\ &\stackrel{1+(a+\frac{1}{2})^2+(\frac{1}{2}a+b)^2+\frac{1}{4}}{=} 1 + \left(a+\frac{1}{2}\right)^2 + \left(\frac{1}{2}a+b\right)^2 + \frac{1}{4} \\ &\stackrel{\frac{5}{4}+a+ab+\frac{5}{4}a^2+\frac{5}{4}b^2}{=} \frac{5}{4} + a + ab + \frac{5}{4}a^2 + \frac{5}{4}b^2 \end{aligned}$$

$$\nabla \mathbb{E}[\varepsilon(t)^2] = 0$$

$$\begin{cases} \frac{\partial J}{\partial a} = 1 + b + \frac{5}{4} 2a = 0 \\ \frac{\partial J}{\partial b} = a + \frac{5}{4} 2b = 0 \end{cases} \Rightarrow \begin{cases} a^* = -\frac{10}{21} \\ b^* = \frac{4}{21} \end{cases}$$

$$\text{We check the H.p. : } z^2 - \frac{10}{21}z - \frac{4}{21} = 0 \Rightarrow z_{1/2} \begin{cases} 0.735 \\ -0.259 \end{cases}$$

$$\underbrace{\mathbb{E}[\varepsilon(t)^2]}_{=\lambda^2} = \frac{5}{4} - \frac{10}{21} + \left(-\frac{10}{21}\right)\left(\frac{4}{21}\right) + \frac{5}{4}\left(-\frac{10}{21}\right)^2 + \frac{5}{4}\left(\frac{4}{21}\right)^2 = 1,011$$

not so different
from the real
variance of the
process \Rightarrow the model
is quite good

$$\varepsilon(t) = e(t) + \underbrace{\left(\frac{1}{2} - \frac{10}{21}\right)}_{\text{these coeffs. are less than 1}} e(t-1) + \underbrace{\left(\frac{4}{21} - \frac{5}{21}\right)}_{\text{these coeffs. are less than 1}} e(t-2) + \underbrace{\frac{2}{21}}_{\text{these coeffs. are less than 1}} e(t-3)$$

These coeffs. are less than 1 \Rightarrow the error is just slightly colored

Check if the model is good:

- λ^2^* must be similar to $\text{Var}(e(t))$
- $e(t)$ must be as similar as possible to a WN

(EX.)

$$S: y(t) = e(t) + \frac{1}{3} e(t-1) \quad e(t) \sim \text{WN}(0, 1) \quad \text{MA}(1)$$

$$M: y(t) = -ay(t-1) + \eta(t) \quad \eta(t) \sim \text{WN}(0, \lambda^2) \quad \text{AR}(1) \\ (\text{Hyp. } |a| < 1)$$

a^* that minimize $\bar{J}(a)$, λ^2^* ?

$$\begin{aligned} 1. \hat{y}(t|t-1) &= \frac{C_m(z) - A_m(z)}{C_m(z)} y(t) \\ &\stackrel{z^{-1}}{=} \frac{1 - (1 + az^{-1})}{1} y(t) \\ &\stackrel{z^{-1}}{=} -ay(t-1) \end{aligned}$$

$$\begin{aligned} 2. \varepsilon(t) &= y(t) - \hat{y}(t|t-1) = y(t) + ay(t-1) = (1 + az^{-1}) y(t) \\ &\stackrel{z^{-1}}{=} (1 + az^{-1}) \left(1 + \frac{1}{3} z^{-1} \right) e(t) \\ &\stackrel{z^{-1}}{=} \left(1 + \left(\frac{1}{3} + a \right) z^{-1} + \frac{1}{3} az^{-2} \right) e(t) \end{aligned}$$

$$3. \bar{J}(a) = \mathbb{E}[\varepsilon(t)^2] = 1 + \frac{1}{9} + a^2 + \frac{2}{3}a + \frac{1}{9}a^2$$

$$\frac{d\bar{J}}{da} = \frac{2}{3} + \frac{20}{9}a = 0 \implies a^* = -\frac{3}{10}$$

$$\lambda^2^* = \bar{J}(a^*) = 1 + \left(\frac{1}{3} - \frac{3}{10} \right)^2 + \left(\frac{1}{9} \cdot \frac{9}{100} \right) = \frac{91}{90} \approx 1.01$$

(similar to the variance of the WN that generates the data)

Alternative way: (YULE-WALKER PROCEDURE)

$$\varepsilon(t) = y(t) - \hat{y}(t|t-1) = y(t) + ay(t-1)$$

$$\begin{aligned} \mathbb{E}[\varepsilon(t)^2] &= \mathbb{E}[(y(t) + ay(t-1))^2] = \underbrace{\mathbb{E}[y(t)^2]}_{\delta_y(0)} + a^2 \underbrace{\mathbb{E}[y(t-1)^2]}_{\delta_y(0)} + 2a \underbrace{\mathbb{E}[y(t)y(t-1)]}_{\delta_y(1)} \\ &= (1 + a^2) \delta_y(0) + 2a \delta_y(1) \end{aligned}$$

$$\frac{d\mathbb{E}[\varepsilon(t)^2]}{da} = 2a \delta_y(0) + 2 \delta_y(1) = 0 \implies a^* = -\frac{\delta_y(1)}{\delta_y(0)}$$

$$\delta y(0) = \mathbb{E}[(e(t) + \frac{1}{3}e(t-1))^2] = \mathbb{E}[e(t)^2] + \frac{1}{3}\mathbb{E}[e(t-1)^2] = 1 + \frac{1}{9} = \frac{10}{9}$$

$$\delta y(1) = \mathbb{E}[y(t)y(t-1)] = \mathbb{E}[(e(t) + \frac{1}{3}e(t-1))(e(t-1) + \frac{1}{3}e(t-2))]$$

$$\stackrel{?}{=} \mathbb{E}\left[\frac{1}{3}e(t-1)^2\right] = \frac{1}{3}$$

all the other simplifies ($=0$)

$$\Rightarrow a^* = -\frac{\sqrt{3}}{10g} = -\frac{3}{10}$$

Remark: Identify a system MA(1) :

- family model AR(1) : $\lambda^{2*} = 1.05$

- family model AR(2) : $\lambda^{2*} = 1.011$

If we increase the order of the family the result is better.

smaller : AR(2) is better than AR(1)
(obvious since $AR(1) \subset AR(2)$)

(EX.)

$$S: y(t) = \frac{1}{3}y(t-1) + u(t-1) + \underbrace{y(t)}_{\text{exogenous input}} - \frac{1}{2}y(t-1)$$

$$y \sim WN(0, 1) \quad u \sim WN(0, 1) \quad \left. \begin{array}{l} \\ \end{array} \right\} \perp$$

$$\Rightarrow ARMAX(1, 1, 1)$$

$$M: y(t) = -ay(t-1) + bu(t-1) + e(t)$$

$$e \sim WN(0, \lambda^2)$$

$$\Rightarrow AR(1, 1)$$

$$\bar{J}(\theta) = \mathbb{E}[\varepsilon(t, \theta)^2], \quad \theta^* = \begin{bmatrix} a \\ b \end{bmatrix}, \quad \lambda^{2*}?$$

$$1. \quad \boxed{\hat{y}(t+k|t) = \frac{\tilde{F}(z)}{C(z)}y(t) + \frac{B(z)\mathbb{E}(z)}{C(z)}u(t)}$$

$$c(z) = A(z)\mathbb{E}(z) + z^{-k}\tilde{F}(z)$$

$\mathbb{E}(z) = \text{result of the long division for } k\text{-steps}$

$z^{-k}\tilde{F}(z) = \text{remainder of the long division}$

So we compute the long division (1-step, ARX model) :

$$\begin{array}{r} 1 \\ 1+az^{-1} \\ \hline 1-az^{-1} \end{array} \quad \begin{array}{r} 1+az^{-1} \\ \hline 1 \end{array} \quad \Rightarrow \quad \begin{array}{l} c(z) = 1 \\ B(z) = b^* \\ \tilde{F}(z) = -a^* \\ \mathbb{E}(z) = 1^* \end{array}$$

$$\Rightarrow \hat{y}(t+1|t) = -ay(t) + bu(t)$$

$$2. \quad \varepsilon(t, \theta) = y(t) - \hat{y}(t|t-1) = y(t) + ay(t-1) - bu(t-1)$$

$$3. \quad \mathbb{E}[\varepsilon(t, \theta)^2] = \mathbb{E}[(y(t) + ay(t-1) - bu(t-1))^2]$$

$$\stackrel{?}{=} \mathbb{E}[y(t)^2] + a^2\mathbb{E}[y(t-1)^2] + b^2\mathbb{E}[u(t-1)^2] + 2a\mathbb{E}[y(t)y(t-1)] +$$

$$-2b\mathbb{E}[y(t)u(t-1)] - 2ab\mathbb{E}[y(t-1)u(t-1)]$$

$$\mathbb{E}[\varepsilon(t)^2] = \delta_y(0) + a^2 \delta_y(1) + b^2 + 2a \delta_y(1) - 2b \mathbb{E}[y(t) u(t-1)] - 2ab \mathbb{E}[y(t-1) u(t-1)]$$

~~$\mathbb{E}[y(t) u(t-1)] =$~~

~~$= \mathbb{E}[-ay(t-2) + bu(t-2) + e(t-1)] u(t-1) =$~~

~~$= -a \mathbb{E}[y(t-2) u(t-1)] + b \mathbb{E}[u(t-2) u(t-1)] + \mathbb{E}[e(t-1) u(t-1)]$~~

~~$y(t-2) = f(e(t-2), \dots)$~~

↓ and $\mathbb{E}=0$

~~$\mathbb{E}[y(t-1) u(t-1)] =$~~

~~$= \mathbb{E}[(-2y(t-1) + bu(t-1) + e(t)) u(t-1)] =$~~

~~$= -2a \mathbb{E}[y(t-1) u(t-1)] + \mathbb{E}[u(t-1)^2] + \mathbb{E}[e(t) u(t-1)]$~~

↓ checked on the right

$$\begin{aligned}\mathbb{E}[\varepsilon(t)^2] &= (1+a^2) \delta_y(0) + 2a \delta_y(1) + b^2 - 2b \\ &\stackrel{\downarrow}{=} (1+a^2) \delta_y(0) + 2a \delta_y(1) + b^2 - 2b\end{aligned}$$

WE HAVE TO TAKE THE REAL $y(t)$, NOT THE MODEL:

- $\mathbb{E}[y(t-1) u(t-1)] = 0$
- $\mathbb{E}[y(t) u(t-1)] = 1$

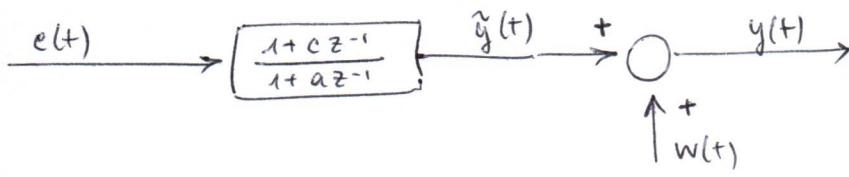
$$\begin{cases} \frac{\partial \mathbb{E}[\varepsilon(t)^2]}{\partial a} = 2a \delta_y(0) + 2 \delta_y(1) = 0 \\ \frac{\partial \mathbb{E}[\varepsilon(t)^2]}{\partial b} = 2b - 2 \mathbb{E}[y(t) u(t-1)] = 0 \end{cases} \implies \begin{cases} a^* = -\frac{\delta_y(1)}{\delta_y(0)} \\ b^* = \mathbb{E}[y(t) u(t-1)] \stackrel{\downarrow}{=} 1 \end{cases}$$

$$\begin{aligned}\mathbb{E}[y(t) y(t)] &= \delta_y(0) &= \frac{69}{32} \\ \mathbb{E}[y(t) y(t-1)] &= \delta_y(1) &= \frac{7}{32} \\ \mathbb{E}[y(t) u(t-1)] &= \mathbb{E}\left[\left(\frac{1}{3}y(t-1) + u(t-1) + y(t) - \frac{1}{2}y(t-1)\right) u(t-1)\right] \\ &= \frac{1}{3} \mathbb{E}[y(t-1) u(t-1)] + \underbrace{\mathbb{E}[u(t-1)^2]}_1 + \underbrace{\mathbb{E}[y(t) u(t-1)]}_1 - \frac{1}{2} \mathbb{E}[y(t-1) u(t-1)] \\ &= \frac{1}{3} \mathbb{E}\left[\left(\frac{1}{3}y(t-2) + u(t-2) - y(t-1) - \frac{1}{2}y(t-2)\right) u(t-1)\right] \\ &\stackrel{\downarrow}{=} 1\end{aligned}$$

$$\implies \begin{cases} a^* = -\frac{\delta_y(1)}{\delta_y(0)} = -\frac{7}{69} \\ b^* = \mathbb{E}[y(t) u(t-1)] = 1 \end{cases}$$

to find with the information about the real system

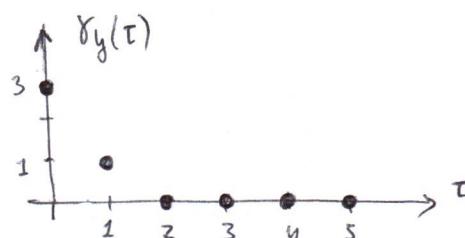
(Ex.)



$$\begin{aligned} e(t) &\sim WN(0, 1) \\ w(t) &\sim WN(0, s) \\ |a| &< 1, \quad c \in \mathbb{R} \\ e(t) &\perp w(t) \end{aligned}$$

1. Identify a, c s.t. $\gamma_y(\tau)$ is :

$$\gamma_y(\tau) = \begin{cases} 3 & \tau = 0 \\ 1 & |\tau| = 1 \\ 0 & |\tau| \geq 2 \end{cases}$$



The process is MA(1) (looking at the covariance function)

$$\Rightarrow a = 0$$

$$\Rightarrow y(t) = (1 + c z^{-1}) e(t) + w(t)$$

$$\begin{aligned} \mathbb{E}[(y(t))^2] &= \mathbb{E}[(e(t) + c e(t-1) + w(t))^2] \\ &\stackrel{\perp}{=} \mathbb{E}[e(t)^2] + c^2 \mathbb{E}[e(t-1)^2] + \mathbb{E}[w(t)^2] \quad (\text{the others are } 0) \\ &\stackrel{\perp}{=} 1 + c^2 + 1 \\ &\stackrel{\perp}{=} \gamma_y(0) = 3 \quad \Rightarrow \quad c^2 = 1 \quad \Rightarrow \quad c = \pm 1 \end{aligned}$$

$$\begin{aligned} \mathbb{E}[y(t)y(t-1)] &= \gamma_y(1) = 1 \\ &\stackrel{\perp}{=} \mathbb{E}[(e(t) + c e(t-1) + w(t))(e(t-1) + c e(t-2) + w(t-1))] \\ &\stackrel{\perp}{=} \mathbb{E}[c e(t-1)^2] \\ &\stackrel{\perp}{=} c \quad \Rightarrow \quad c = 1 \end{aligned}$$

2. Identify a, c if $\gamma_y(0) = 5$, $\gamma_y(\tau) = 0 \quad \tau \neq 0$.

$$\Rightarrow y(t) \sim WN(0, 5)$$

$$\Rightarrow y(t) = w(t) + \boxed{\frac{1 + c z^{-1}}{1 + a z^{-1}}} e(t)$$

this must be an
ALL PASS filter

$$\Rightarrow c = \frac{1}{a}$$

$$\Rightarrow \frac{1 + c z^{-1}}{1 + a z^{-1}} e(t) \sim WN(0, c^2) := \eta \sim WN(0, c^2)$$

$$\Rightarrow \mathbb{E}[y(t)^2] = \mathbb{E}[w(t)^2] + \mathbb{E}[\eta(t)^2] = 1 + c^2 = 5 \Rightarrow c = \pm 2$$

$$a = \pm \frac{1}{2}$$

(Ex.) (Prediction)

$$y(t) = \frac{(1-2z^{-1})(1+\frac{1}{4}z^{-1})(1-\frac{1}{4}z^{-1})}{(1-\frac{1}{2}z^{-1})} e(t) \quad e(t) \sim WN(0, 1)$$

Canonical? Predictors?

$$y(t) = \frac{\left(\frac{z-2}{z}\right)\left(\frac{z+\frac{1}{4}}{z}\right)\left(\frac{z-\frac{1}{4}z}{z}\right)}{\left(\frac{z-\frac{1}{2}z}{z}\right)} = \cancel{\frac{(z-2)}{z}} \frac{(z+\frac{1}{4})}{z} \frac{(z-\frac{1}{4})}{z} \frac{z}{(z-\frac{1}{2})} e(t)$$

- monic
 - same degree
 - no simplifications
 - zeros & poles?

We have a band zero to remove (All-pass filter)

$$y(t) = \frac{(1 - 2z^{-1})(1 + \frac{1}{4}z^{-1})(1 - \frac{1}{9}z^{-1})}{(1 - \frac{1}{2}z^{-1})} e(t)$$

$$\Rightarrow y(t) = \left(1 - \frac{1}{16}z^{-2}\right)y(t) \quad y(t) \sim WN(0, q)$$

We use the long division:

$$\begin{array}{c|c} \begin{array}{cc} 1 & az^{-1} \\ & -\frac{1}{16}z^{-2} \end{array} & I \\ \hline \begin{array}{cc} 1 & az^{-1} \\ & -\frac{1}{16}z^{-2} \end{array} & 1 + az^{-1} - \frac{1}{16}z^{-2} \\ \hline \begin{array}{cc} 1 & az^{-1} \\ & -\frac{1}{16}z^{-2} \end{array} & \begin{array}{l} \curvearrowleft k=3 \text{ steps} \\ \curvearrowright k=2 \text{ steps} \\ \curvearrowright k=1 \text{ steps} \end{array} \\ \hline \begin{array}{cc} 1 & -\frac{1}{16}z^{-2} \\ & -\frac{1}{16}z^{-2} \end{array} & \\ \hline & \end{array}$$

→ the predictor for $k=3$ is 0

$$k=1 : \quad y(t) = \left(1 + \frac{\alpha z^{-1} - \frac{1}{16} z^{-2}}{1} \right) \eta(t)$$

$$= \left(1 + \alpha z^{-1} - \frac{1}{16} z^{-2} \right) \eta(t)$$

$$\hat{y}(t|t-1) = \left(az^{-1} - \frac{1}{16}z^{-2}\right) y(t) \quad (\text{from noise})$$

$$\hat{y}(t|t-1) = \left(az^{-1} - \frac{1}{16}z^{-2}\right) \cdot \left(\frac{1}{1 - \frac{1}{16}z^{-2}}\right) y(t) \quad (\text{from data})$$

$$\hat{y}(t|t-1) = \frac{-\frac{1}{16}z^{-2}}{1 - \frac{1}{16}z^{-2}} y(t) \quad (\text{since } a=1)$$

$$\hat{y}(t|t-1) = \frac{1}{16} \hat{y}(t-2|t-3) - \frac{1}{16} y(t-2) \quad (\text{time domain})$$

$$k=2 : \quad y(t) = \left[(1 + az^{-1}) + \frac{(-\frac{1}{16}z^{-2})}{1} \right] y(t)$$

$$\begin{aligned}\hat{y}(t|t-2) &= \frac{-\frac{1}{16}z^{-2}}{1} y(t) && \text{(from noise)} \\ &= \frac{-\frac{1}{16}z^{-2}}{1 - \frac{1}{16}z^{-2}} y(t) && \text{(from data)}\end{aligned}$$

$$\hat{y}(t|t-2) = \frac{1}{16} \hat{y}(t-2|t-4) - \frac{1}{16} y(t-2) \quad \text{(time domain)}$$

$$k=3 : \quad y(t) = \left[(1 + az^{-1} - \frac{1}{16}z^{-2}) + 0 \right] y(t)$$

$$\hat{y}(t|t-3) = 0$$

Analysis of the prediction error?

$$\begin{aligned}\mathbb{E}[\varepsilon(t|t-k)^2] &= \mathbb{E}[(\mathbb{E}[z] y(t))^2] \\ &= \begin{cases} \bullet k=1 : \quad \mathbb{E}[\varepsilon(t|t-1)^2] = \mathbb{E}[y(t)^2] = 4 \\ \bullet k=2 : \quad \mathbb{E}[\varepsilon(t|t-2)^2] = \mathbb{E}[(1 + az^{-1}) y(t)]^2 = 4 \\ \bullet k=3 : \quad \mathbb{E}[\varepsilon(t|t-3)^2] = \mathbb{E}[y(t)^2] = \left(1 + \frac{1}{16}\right) 4 = 4.016 \end{cases}\end{aligned}$$

(EX.) Identification

$$S: \quad y(t) = -0.5 y(t-1) + \xi(t) \quad \xi(t) \sim WN(0, 1)$$

$$M: \quad y(t) = a y(t-2) + e(t) \quad e(t) \sim WN(0, \lambda^2)$$

a in order to minimize the 1-step ahead predictor error?

$$\hat{y}(t|t-1) = a y(t-2)$$

$$\varepsilon(t|t-1) = y(t) - \hat{y}(t|t-1) = y(t) - a y(t-2)$$

$$\begin{aligned}\mathbb{E}[\varepsilon(t|t-1)^2] &= \mathbb{E}[(y(t) - a y(t-2))^2] \\ &= \mathbb{E}[y(t)^2] + a^2 \mathbb{E}[y(t-2)^2] - 2a \mathbb{E}[y(t) y(t-2)] \\ &= \gamma_y(0) + a^2 \gamma_y(0) - 2a \gamma_y(2)\end{aligned}$$

$$\frac{\partial J}{\partial a} = 2a \gamma_y(0) - 2 \gamma_y(2) = 0 \implies a^* = \frac{\gamma_y(2)}{\gamma_y(0)}$$

$$\gamma_y(0) = \frac{1}{1-a^2} = \frac{1}{1-(0.5)^2} = \frac{4}{3}$$

\uparrow a in $y(t)$ of S,
not $y(t)$ of M
EULER-WALKER FORMULA

$$\gamma_y(1) = -0.5 \gamma_y(0)$$

$$\gamma_y(2) = -0.5 (-0.5 \gamma_y(0)) = 0.25 \gamma_y(0)$$

$$\Rightarrow a^* = 0.25$$

(Ex.)

$$y(t) = 3 + v(t)$$

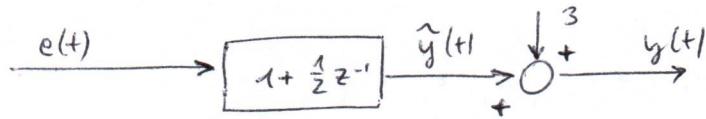
find the optimal predictor if : $(\hat{y}(t|t-k) = ?)$

1. $v(t) \sim WN(0,1)$:

$$\Rightarrow y(t) \sim WN(3,4)$$

$$\Rightarrow \hat{y}(t|t-k) = \mathbb{E}[y(t)] = 3$$

2. $v(t) = e(t) + \frac{1}{2}e(t-1)$ $e(t) \sim WN(0,1)$:



We first consider the DEBIAS PROCESS. : $y(t) = \hat{y}(t) + 3$

$$k=1 : \hat{y}(t|t-1) = \frac{\frac{1}{2}}{1 + \frac{1}{2}z^{-1}} \hat{y}(t-1)$$

$$\begin{aligned} \hat{y}(t|t-1) &= \frac{\frac{1}{2}}{1 + \frac{1}{2}z^{-1}} (y(t-1) - 3) + 3 \\ &= \frac{\frac{1}{2}}{1 + \frac{1}{2}z^{-1}} y(t-1) - \frac{\frac{3}{2}}{\frac{3}{2}} + 3 \\ &\quad \text{by theorem of the GAIN} \\ &= -\frac{1}{2} \hat{y}(t-1|t-2) + \frac{1}{2} y(t-1) + 2 \end{aligned}$$

ATTENTION when we don't have a null mean

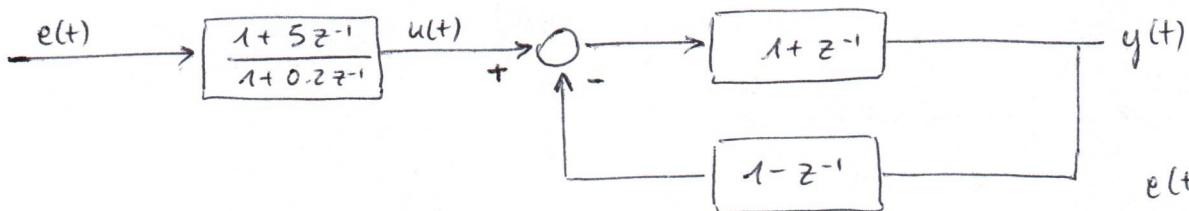
$$k=2 : \hat{y}(t) = e(t) + \frac{1}{2}e(t-1)$$

$(k \geq 2)$

$$\Rightarrow \hat{y}(t|t-2) = \mathbb{E}[\hat{y}(t)] = 0$$

$$\Rightarrow \hat{y}(t|t-2) = \mathbb{E}[y(t)] = 3$$

(Ex.) (Rias colte)



$$e(t) \sim WN(0,1)$$

$$u(t) = \frac{1 + 5z^{-1}}{1 + \frac{1}{5}z^{-1}} e(t)$$

$u(t) \sim WN(0, 25)$
since it's an
all pass filter

$$\Rightarrow \Gamma_u(\omega) = 25 \quad \forall \omega$$

$$u(t) = \frac{(z+5)}{z} \frac{z \cdot 5}{(5z+1)} e(t) = \frac{(z+5)}{\left(z + \frac{1}{5}\right)} e(t)$$

$$y(t) = (1 - z^{-1})(u(t) - (1 - z^{-1})y(t))$$

$$\downarrow \frac{1 - z^{-1}}{1 + (1 - z^{-1})z} u(t) = \frac{z(z-1)}{2z^2 - 2z + 1} u(t)$$

$$\downarrow \frac{z(z-1)}{z\left(z - \frac{1}{2} - j\frac{1}{2}\right)\left(z - \frac{1}{2} + j\frac{1}{2}\right)} u(t)$$

$$z_{1/2} = \frac{1}{2} \pm j\frac{1}{2}$$

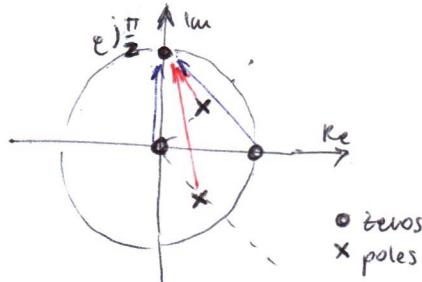
$$\Gamma_y(\omega) = |W(e^{j\omega})|^2 \Gamma_u(\omega)$$

$$\downarrow \frac{|e^{j\omega}(e^{j\omega}-1)|^2}{|(e^{j\omega}-\frac{1}{2}-j\frac{1}{2})|^2 |e^{j\omega}-\frac{1}{2}+j\frac{1}{2}|^2} \cdot \frac{25}{4}$$

We use the graphical approach:

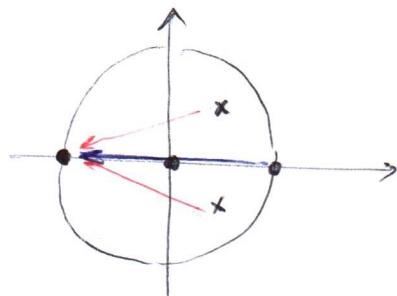
$$\omega = 0 : \Gamma_y(0) = 0$$

$$\omega = \frac{\pi}{2} :$$



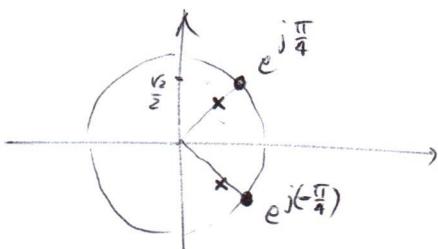
$$\Gamma_y\left(\frac{\pi}{2}\right) = \frac{25}{4} \cdot \frac{1 \cdot (\sqrt{2})^2}{\left(\sqrt{\left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^2}\right)^2} \left(\sqrt{\left(\frac{1}{2}\right)^2 + \left(\frac{3}{2}\right)^2}\right)^2 \\ = 10$$

$$\omega = \pi :$$

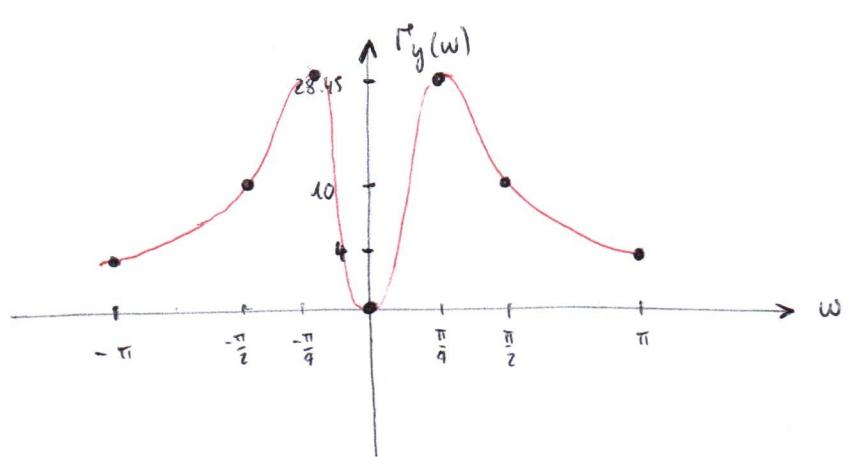


$$\Gamma_y(\pi) = \frac{25}{4} \cdot \frac{1^2 \cdot 2^2}{\left(\sqrt{\left(\frac{1}{2}\right)^2 + \left(\frac{3}{2}\right)^2}\right)^2 \cdot 2} = 4$$

Since we have poles in the unit disc we evaluate the closest points to these poles:



$$\Gamma_y\left(\frac{\pi}{4}\right) = \frac{25}{4} \cdot \frac{1^2 \cdot \left(\sqrt{(1-\frac{\sqrt{2}}{2})^2 + (\frac{\sqrt{2}}{2})^2}\right)^2}{\left(1 - \frac{\sqrt{2}}{2}\right)^2 \left(\sqrt{\left(\frac{\sqrt{2}}{2} - \frac{1}{2}\right)^2 + \left(\frac{1}{2} + \frac{\sqrt{2}}{2}\right)^2}\right)^2} \\ = \frac{25}{4} \cdot \frac{(2-\sqrt{2})}{(3-2\sqrt{2})} \approx 28.45$$



(last exercise on Beep)