

## Moving Average

$$X_t = \frac{1}{3} (\omega_{t-1} + \omega_t + \omega_{t+1}), \quad \omega_t \sim WN(\sigma_\omega^2)$$

$$\mu_t = E[X_t] = \frac{1}{3} E[\omega_{t-1} + \omega_t + \omega_{t+1}] = 0$$

$$\gamma(s,t) = \text{COV} \left[ X_s - \mu_s, X_t - \mu_t \right] =$$

$$= \frac{1}{9} E \left[ (\omega_{s-1} + \omega_s + \omega_{s+1}) (\omega_{t-1} + \omega_t + \omega_{t+1}) \right]$$

$$= \begin{cases} \frac{3}{9} \sigma_\omega^2 & |s-t| = 0 \\ \frac{2}{9} \sigma_\omega^2 & |s-t| = 1 \\ \frac{1}{9} \sigma_\omega^2 & |s-t| = 2 \\ 0 & \text{else} \end{cases}$$

Alternatively,

write the model as a linear process:

$$X_t = \mu + \sum_{j=-\infty}^{\infty} \psi_j w_{t-j}$$

where

$$\psi_{-1} = 1/3$$

$$\psi_0 = 1/3$$

$$\psi_1 = 1/3$$

$$\psi_j = 0 \quad \text{else}$$

$$\begin{aligned} E[X_t] &= \mu \\ \gamma(h) &= \sigma_w^2 \sum_{j=-\infty}^{\infty} \psi_{j+h} \psi_j = \begin{cases} 3/9 \sigma_w^2 & h=0 \\ 2/9 \sigma_w^2 & |h|=1 \\ 1/9 \sigma_w^2 & |h|=2 \\ 0 & \text{else} \end{cases} \end{aligned}$$

# Autoregressive Model

Example:  $y_t = \alpha + \varphi y_{t-1} + \omega_t$ ,  $\omega_t \sim WN(\sigma_\omega^2)$

and assume  $|\varphi| < 1$ .

For the moment, <sup>↑  $\phi$</sup>  assume stationarity.

$$E[y_t] = \alpha + \varphi E[y_{t-1}] + 0$$

$$\mu = \alpha + \varphi \cdot \mu$$

(because of stationarity)

$$\mu - \varphi \mu = \alpha$$

$$\mu(1 - \varphi) = \alpha$$

$$\mu = \alpha / (1 - \varphi)$$

$$\gamma_0 = \text{Var}(\underline{y}_t) = \varphi^2 \text{Var}(y_{t-1}) + \sigma_w^2$$

$$\gamma_0 = \varphi^2 \gamma_0 + \sigma_w^2 \quad (\text{stationarity})$$

$$\gamma_0 (1 - \varphi^2) = \sigma_w^2$$

$$\gamma_0 = \sigma_w^2 / (1 - \varphi^2)$$

$$\gamma_1 = \text{cov}(y_{t-1}, \underline{y}_t) = \text{cov}(y_{t-1}, \underline{\varphi y_{t-1} + w_t})$$

$$\gamma_1 = \varphi \gamma_0$$

$$\gamma_2: \text{cov}(y_{t-2}, \underline{y}_t) = \text{cov}(y_{t-2}, \underline{\varphi y_{t-1} + w_t})$$

$$\gamma_2 = \varphi \gamma_1 = \varphi^2 \gamma_0$$

etc ...

Now let's do the same thing using the linear process formulation.

$$y_t = \mu + \sum_{j=-\infty}^{\infty} \psi_j w_{t-j}$$

where  $\psi_j = \varphi^j$   $j = 0, 1, 2, \dots$

and  $\psi_j = 0$  else.

~~Notice~~ Notice that  $\sum_{j=-\infty}^{\infty} |\psi_j| < \infty$

if and only if  $|\varphi| < 1$ .

$$\begin{aligned}\gamma(h) &= \sigma_w^2 \sum_{j=0}^{\infty} \psi_j \psi_{j+h} \\ &= \sigma_w^2 \sum_{j=0}^{\infty} (\varphi^j \cdot \varphi^{j+h}) \\ &= \sigma_w^2 \sum_{j=0}^{\infty} \varphi^{2j+h} = \frac{\sigma_w^2}{1-\varphi^2} \cdot \varphi^h \\ &= \varphi^h \cdot \gamma(0).\end{aligned}$$

## Estimation of mean

Need stationary model in order to be able to do anything:

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$$

## Estimation of covariances

$$\hat{\gamma}(-h) = \hat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-h} (x_{t+h} - \hat{\mu})(x_t - \hat{\mu})$$

## Estimation of auto correlations

$$\hat{\rho}(h) = \frac{\hat{\gamma}(h)}{\hat{\gamma}(0)}$$

$$h = \dots -2, -1, 0, 1, 2, \dots$$

Theorem: Under general conditions,  
for a white noise process,  $\{w_t\}$ ,

$$\sqrt{n} (\hat{\rho}(h) - 0) \xrightarrow{D} N(0, 1)$$

for all  $h$ .

So, we can test the hypothesis

$$H_0: \rho(h) = 0$$

by checking whether  $|\hat{\rho}(h)| < \pm \frac{2}{\sqrt{n}}$



$G_n$ , a joint test (for many values of  $h$ ),

$$n \cdot \sum_{h=1}^H |\hat{\rho}^{(h)}|^2 \xrightarrow{D} \chi^2_H$$

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In R: given  $x[1] \dots x[t]$

$x_{\text{bar}} = \text{mean}(x)$

$\text{cov} = \text{acf}(x)$