

Estimación de la función Media, Autocovarianza y autocorrelación parcial.

$$\hat{\mu}, \mu = E[z_t] \rightarrow \hat{\mu} = \bar{z} = \frac{1}{n} \sum_{i=1}^n z_n$$

z_t es un proceso estacionario

No es un proceso de variables indep.

El estimado $\hat{\mu}$ es inseguro

$$E[\hat{\mu}] = E[\bar{z}] = E\left[\frac{1}{n} \sum_{i=1}^n z_n\right] = \frac{1}{n} \sum_{i=1}^n \mu = \mu$$

$$\text{Var}(\hat{\mu}) = \text{Var}(\bar{z}) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n z_n\right) \sim \cancel{\frac{\text{Var}(z_n)}{n}}$$

$$= \frac{1}{n^2} \sum_{t=1}^n \sum_{s=1}^n \text{Cov}(z_t, z_s) = \frac{1}{n^2} \sum_{t=1}^n \sum_{s=1}^n \gamma_{t-s}$$

$$t = s + n$$

$$t - s = n$$

$$t = 1, 2, \dots, n$$

$$s = 1, 2, \dots, n$$

t	s	t-s=k
1	1	0
1/2	2	1/2
2	2	0

$$\frac{1}{n} \sum_{k=1}^n \gamma_k$$

$$= \frac{1}{n^2} \sum_{k=1}^n (n \gamma_k) \Rightarrow \text{multiplicamos } \times \gamma_0$$

$$\text{Dividimos } \times \gamma_0$$

$$= \frac{\gamma_0}{n} \sum_{k=1}^n \rho_k \left\{ \frac{\gamma_k}{\gamma_0} \right\}$$

$$\Rightarrow \text{Si } \lim_{n \rightarrow \infty} \frac{\gamma_0}{n} \sum_{k=1}^n \rho_k < \infty \Rightarrow$$

Sabremos que $\hat{\mu}$ es un estimado-consistente de μ .

$$\left| \frac{1}{n} \sum_{k=1}^n p_k \right| = \left| \frac{1}{n} \sum_{k=1}^N p_k + \frac{1}{n} \sum_{k=N+1}^n p_k \right|$$

$$\leq \left| \frac{1}{n} \sum_{k=1}^N p_k \right| + \left| \frac{1}{n} \sum_{k=N+1}^n p_k \right|$$

$$\leq \frac{1}{n} \sum_{k=1}^N |p_k| + \frac{1}{n} \sum_{k=N+1}^n |p_k|$$

Vamos a escoger N tal que

$$|p_k| \leq \epsilon/4$$

$$\leq \frac{1}{n} \sum_{k=1}^N |p_k| + \frac{1}{n} \cdot \frac{\epsilon}{4} \cdot (n - N + 1) < \infty$$

$n \rightarrow \infty$

Resultado del tipo ergódico

$$n \rightarrow \infty \quad X_t^{(n)} \rightarrow X_t$$

Estimador para la fn. de autocovarianza.

$$\hat{\gamma}_k = \frac{1}{n} \sum_{t=1}^{n-k} (z_t - \bar{z})(z_{t+k} - \bar{z}) \quad \checkmark$$

$$\hat{\hat{\gamma}}_k = \frac{1}{n-k} \sum_{t=1}^{n-k} (z_t - \bar{z})(z_{t+k} - \bar{z})$$

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0}$$

Datos

\bar{z}_t

t	z_t	z_{t+1}	z_{t+1}	z_{t+2}
1	13	8	-	15
2	8	15	13	4
3	15	4	8	4
4	4	4	15	12
5	4	12	4	11
6	12	11	4	-
7	11	-	12	-

$$\hat{\rho}_1 = \frac{\text{Cov}(z_{t+1}, z_t)}{\sqrt{\text{Var}(z_{t+1})} \sqrt{\text{Var}(z_t)}} = \frac{\frac{1}{n} \sum (z_t - \bar{z})(z_{t+1} - \bar{z})}{\sqrt{\frac{1}{n} \sum (z_t - \bar{z})^2} \sqrt{\frac{1}{n} \sum (z_{t+1} - \bar{z})^2}}$$

$\hat{\rho}_1 \approx -0.188$

$\hat{\rho}_t = \hat{\rho}_{-t}$

Sample PACF (Estimador de la función de autocorrelación parcial)

$$P_K = \hat{\phi}_{KK}$$

$$\hat{\phi}_{1,1} = \hat{P}_{1,1}$$

$$\hat{\phi}_{K+1,K+1} = \frac{\hat{P}_{K+1} - \sum_{j=1}^K \hat{\phi}_{Kj} \hat{P}_{K+1-j}}{1 - \sum_{j=1}^K \hat{\phi}_{Kj} \hat{P}_j}$$

Durbin (1960)

$$\hat{\phi}_{K+1,j} = \hat{\phi}_{Kj} - \hat{\phi}_{K+1,K+1} \hat{\phi}_{K,K+1-j} \quad ; j=1, 2, \dots, K$$

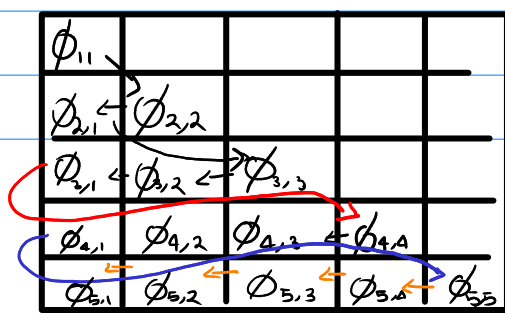
$$\hat{\phi}_{2,2} = \hat{\phi}_{1+1,1+1} = \frac{\hat{P}_2 - \sum_{j=1}^1 \hat{\phi}_{1j} \hat{P}_{2-j}}{1 - \sum_{j=1}^1 \hat{\phi}_{1j} \hat{P}_j}$$

$$= \frac{\hat{P}_2 - \hat{\phi}_{1,1} \hat{P}_1}{1 - \hat{\phi}_{1,1} \hat{P}_1}$$

$$\hat{\phi}_{1+1,1}$$

$$\hat{\phi}_{2,1} = \hat{\phi}_{1,1} - \hat{\phi}_{2,2} \hat{\phi}_{1,1}$$

$$\hat{\phi}_{3,3} = \hat{\phi}_{2+1,2+1} = \frac{\hat{P}_3 - \sum_{j=1}^2 \hat{\phi}_{2,j} \hat{P}_{3-j}}{1 - \sum_{j=1}^2 \hat{\phi}_{2,j} \hat{P}_j} = \frac{\hat{P}_3 - \hat{\phi}_{2,1} \hat{P}_2 - \hat{\phi}_{2,2} \hat{P}_1}{1 - \hat{\phi}_{2,1} \hat{P}_1 - \hat{\phi}_{2,2} \hat{P}_2}$$



$$\hat{\phi}_{4,4}^{\hat{K}_{3+1}, \hat{K}_{3+1}} = \frac{\hat{P}_4 - \sum_{j=1}^3 \phi_{3,j} \hat{P}_{4-j}}{1 - \sum_{j=1}^3 \phi_{3,j} \hat{P}_j} = \frac{\hat{P}_4 - \phi_{3,1} P_3 - \phi_{3,2} P_2 - \phi_{3,3} P_1}{1 - \phi_{3,1} P_1 - \phi_{3,2} P_2 - \phi_{3,3} P_3}$$

$$(\hat{P}_1, \hat{P}_2, \dots, \hat{P}_n)$$

$$n=1 \quad \phi_{1,1} = \hat{P}_1$$

$$\phi_{n,n}$$

$$n=k \quad \phi_{k,k} = \frac{\hat{P}_k}{1 - \sum_{j=1}^{k-1} \phi_{k,j} \hat{P}_j}$$

$$\phi_{K, K+j} = \frac{\hat{P}_{K+j} - \sum_{i=1}^j \phi_{K, K+i-j} \hat{P}_{K+i-j}}{1 - \sum_{i=1}^{K-1} \phi_{K,i} \hat{P}_i}$$

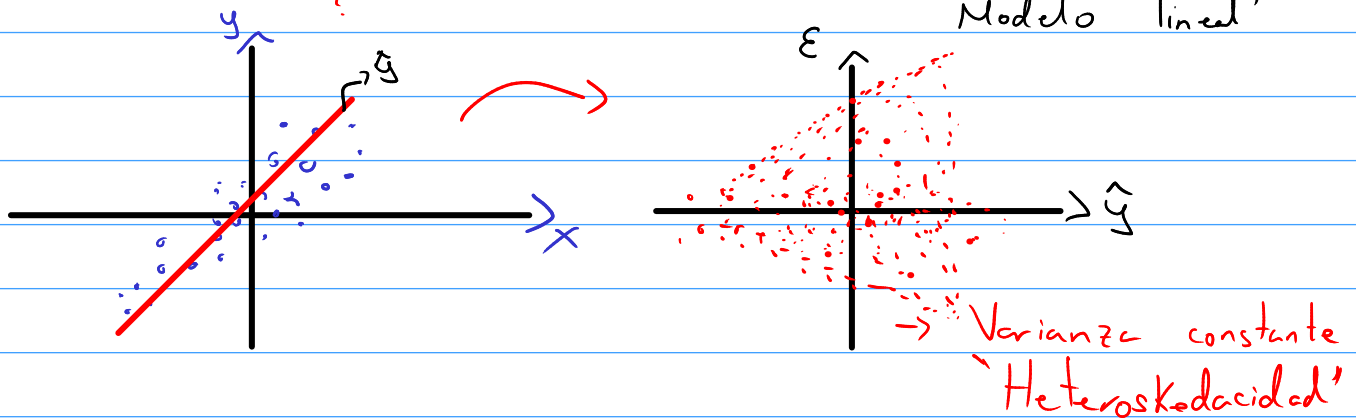
$$(0.3, 0.4, 0.1)$$

$$\phi_{1,1} = 0.3$$

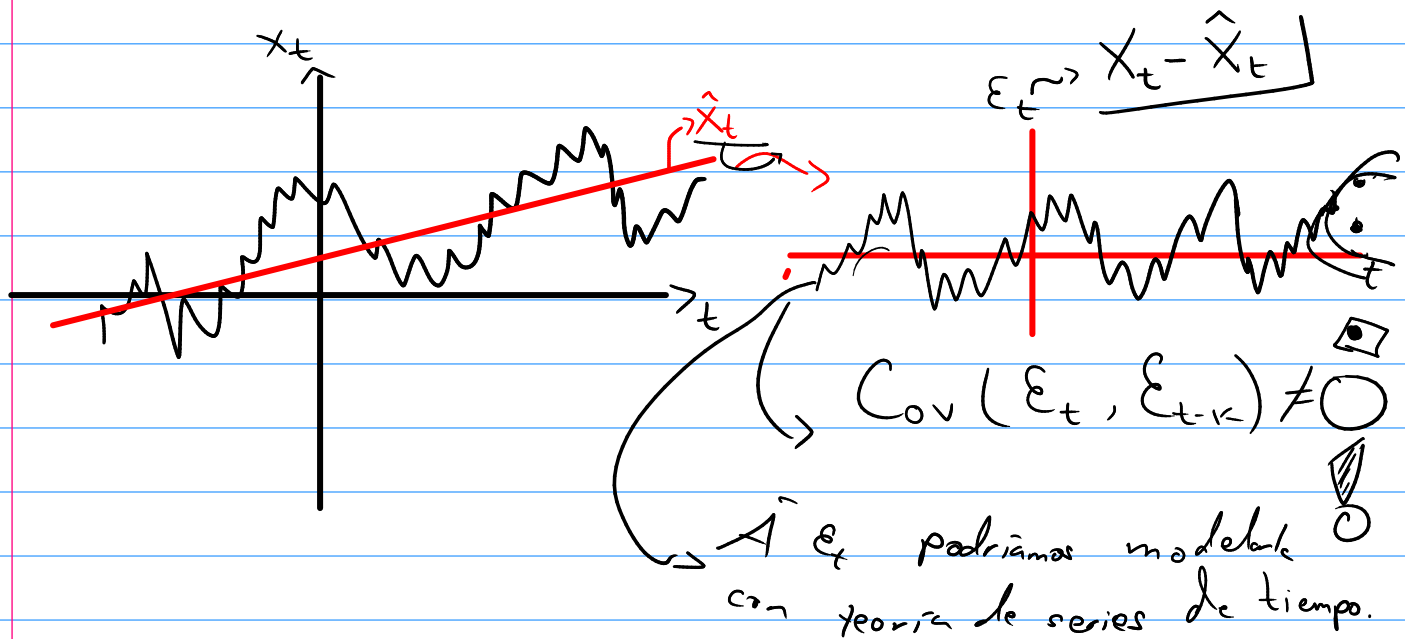
$$\phi_{2,2} = \frac{0.4 - 0.3(0.3)}{1 - 0.3(0.3)} = \frac{0.4 - (0.3)^2}{1 - (0.3)^2}$$

Modelos ARIMA

$$Y = \alpha X + \underbrace{\varepsilon}_{?} ; \varepsilon \sim N(0, \sigma^2) \quad \left. \vphantom{Y = \alpha X + \varepsilon} \right\} \begin{array}{l} \text{Modelo de} \\ \text{regresión lineal} \\ \text{"Modelo lineal"} \end{array}$$



$$\varepsilon_t \leadsto \text{Cov}(\varepsilon_t, \varepsilon_{t-k}) = 0 \quad \forall k > 0 \quad \rightarrow \text{No autocorrelación.}$$



Procesos Autorregresivos
(AR)

Procesos de medias móviles
(MA)

Procesos Autorregresivos con medias móviles
(ARMA)

Procesos autorregresivos Integrados con medias móviles
(ARIMA)

Procesos autorregresivos Integrados Estacionarios con medias móviles
(SARIMA)

Introducción a los modelos autoregresivos (AR)

Intuición: La información a tiempo t este influida por los p -últimos valores, es decir $\{X_{t-1}, X_{t-2}, \dots, X_{t-p}\}$

Ejemplo:

$$X_t = X_{t-1} - 0.9X_{t-2} + w_t \quad w_t \sim WN(0, \sigma^2)$$

↳ AR(2)

Un modelo autoregresivo de orden p (AR(p)) va a definirse de la siguiente forma:

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + w_t, \quad w_t \sim WN(0, \sigma^2)$$

$\{\phi_1, \dots, \phi_p\}$ parámetros donde $\phi_i \in \mathbb{R}$, $i=1, 2, \dots, p$
 $\phi_p \neq 0$

Otra forma de nombrar a un proceso AR(p) es la siguiente.

$$X_t = \phi_1 B X_t + \phi_2 B^2 X_t + \dots + \phi_p B^p X_t + w_t$$
$$= X_t (\phi_1 B + \phi_2 B^2 + \dots + \phi_p B^p) + w_t$$

B^n es el operador "lag", donde $B^n X_t = X_{t-n}$

$$w_t = X_t (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p)$$

$$w_t = \phi(B) X_t$$

↳ $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ } Operador autoregresivo

Supongamos que tenemos un proceso AR(1)

$$x_t = \phi x_{t-1} + w_t \quad \forall t \in (-\infty, \dots, 0, \dots, \infty) \cap \mathbb{N}$$

Iterando hacia atrás.

$$\begin{aligned} x_t &= \phi (\phi x_{t-2} + w_{t-1}) + w_t = \phi^2 x_{t-2} + w_t + \phi w_{t-1} \\ &= \phi^3 x_{t-3} + w_t + \phi w_{t-1} + \phi^2 w_{t-2} = \dots = \phi^k x_{t-k} + \underbrace{\sum_{j=1}^{k-1} \phi^j w_{t-j}} \end{aligned}$$

→ Si x_t es un proceso estacionario y además $|\phi| < 1$

Podemos representar un proceso AR(1) como un proceso lineal de la sig. form.

$$\underline{x_t = \sum_{j=0}^{\infty} \phi^j w_{t-j}} \quad \text{Principio de causalidad.}$$

$$\lim_{k \rightarrow \infty} \mathbb{E} \left[\left(x_t - \sum_{j=0}^{\infty} \phi^j w_{t-j} \right)^2 \right] = \lim_{k \rightarrow \infty} \phi^{2k} \mathbb{E} [x_{t-k}^2] = 0$$

$|\phi| < 1$

$\{x_t\}$ una sucesión de v.c.s. $x_t \xrightarrow{L^2} x$ si

$$\lim_{k \rightarrow \infty} \mathbb{E} [(x_t - x)^2] = 0$$

$$\lim_{k \rightarrow \infty} \mathbb{E} \left[\left(x_t - \sum_{j=0}^{\infty} \phi^j w_{t-j} \right)^2 \right] = \lim_{k \rightarrow \infty} \mathbb{E} \left[x_t^2 - 2x_t \sum_{j=0}^{\infty} \phi^j w_{t-j} + \left(\sum_{j=0}^{\infty} \phi^j w_{t-j} \right)^2 \right]$$

$$\lim_{K \rightarrow \infty} \mathbb{E}[X_t^2] + \mathbb{E}\left[\left(\sum_{j=0}^{\infty} \phi^j w_{t-j}\right)^2\right]$$

$$= \gamma_0 + \lim_{K \rightarrow \infty} \mathbb{E}\left[\left(\sum_{j=0}^{\infty} \phi^j w_{t-j}\right)^2\right] = \gamma_0 + \lim_{K \rightarrow \infty} \sum_{i=1}^{\infty} \text{Var}(\phi^i w_{t-i})$$

$$\text{Var}\left(\sum \phi^j w_{t-j}\right) = \gamma_0 + \lim_{K \rightarrow \infty} \sum_{i=1}^{\infty} \phi^{2i} \text{Var}(w_{t-i})$$

$$\gamma_0 = \phi^0 \gamma_0 = \phi^0 \text{Var}(w_t)$$

$$= \lim_{K \rightarrow \infty} \sum_{i=0}^K \phi^{2i} \text{Var}(w_{t-i}) = \lim_{K \rightarrow \infty} \sum_{i=1}^K \phi^{2i} \text{Var}(X_t) \leq$$

la suma sea absolutamente sumable.

$$\sum_{i=1}^{\infty} |a_i| \leftrightarrow 0$$

$\leq \lim_{K \rightarrow \infty} \sum |\phi^{2i}| \text{Var}(X_t) \rightarrow 0$

$$X_t = \sum_{k=1}^{\infty} \phi^k w_{t-k} \quad |\phi| < 1$$

Apéndice A del Shumway

