Date: Thesday, November 6, 2018

Recap :

- An AR(P) model is stationary iff $AR(P) = nA(\infty)$.
 - 4 This is satisfied iff the zeros of the AR generating function lie outside the unit circle in the complex plane.
 - 40 This is called the "Stationarity Condition" for AR Models.
- An MA(9) model is only useful if it can be represented as an infinite order AR model (MA(9) = AR(00)).
 - 4 This is satisfied iff the zeros of the ma generating function lie outside the unit circle in the complex Plane.
 - up This is called the "invertibility condition" for MA models.

ARMA (P, 2) Models

2423 is an autoregressive moving average process of order p and q it:

Yt= \$114-1 + \$214-2 + ... + \$p1t-p + E+ + BE+-1 + ... + Ba E+-9

where $\{z_{\ell}\} \sim WN(0, \sigma^2)$ and the Φ s and Θ 's are constants to be estimated.

The model can also be stated in terms of its generating functions as follows:

where $\phi(z) = 1 - \phi_1 z - \dots - \phi_{p \geq p}$ is the generating function for the AR component, and $\Theta(z) = 1 + \Theta_1 \geq t \dots + \Theta_p \geq p$ is the generating function for the MR component.

Remarks:

- An Arma (P,q) model is not necessarily stationary, but we'd like it to be so that we can make model stationarity time series.
- An ARMA (P,q) model is not necessarily invertible, but we'd like it to be so that it can be written exclusively as a function of its own history,
- An ARMA (1,9) is stationary iff its AR component is stationary.
 - 4 we check this by determining whether the AR generating function $\phi(z)$ satisfies the stationarity conditions.
- · AN ARMA(P, g) is invertible iff its MA component is invertible.
 - 4 we check this by determining whether the MA generating function $\Theta(z)$ satisfies the invertibility conditions.

A feur more comments:

- $\cdot \quad AR(P) = ARMA(P, 0)$
- · MA(q) : ARMA (0,9)
- Model selection is determined by selecting appropriate orders p and q.
 - 4 We can use ACF and PACF plots to help with this, what we extect to see on these plots is the following:
 - · ACF: 2 Significant spikes + exponential decay.
 - · PACP : O significant spikes + exponential decay.



EXAMPLE: $\{Y_t\} \sim ARMA(1,2)$ $Y_t = \phi_1 Y_{t-1} + \epsilon_t + \Theta_1 \epsilon_{t-1} + \Theta_2 \epsilon_{t-2}$

Using backshift operator notation, find the generating functions and express this relationship in terms of them.

Solution:

 $Yt - \emptyset_1 Y_{t-1} = \xi_t + \Theta_{\xi_{t-1}} + \Theta_2 \xi_{t-2}$ $Yt (1 - \emptyset_1 G) = \xit (1 + \Theta_1 B + \Theta_2 B)$ $\emptyset B Y_t = \Theta(B) Y_t$

where
$$\phi(z) = 1 - \phi_1 z$$

 $\Theta(z) = 1 + \Theta_1 z + \Theta_2 z^2$

[BREAK]

EXAMPLE:
$$24t^{2} \sim ARMA(2,2)$$

 $8t = 8t - 1 + 0.58t - 2 + 5t + 0.25t - 1 + 0.75t - 2$
IS $34t^{2}$ Stationary and/or invertible?

Solution:

$$\begin{array}{rcl} \forall t - \forall t - 1 &= 0.5 \ \forall t - 2 &= \ \mathcal{E} + 0.2 \ \mathcal{E} + 1 &= 0.5 \ \mathcal{E} + -2 \\ (1 - 6 - 0.5 \ B^2) \ \forall t &= \ (1 + 0.2 \ B + 0.7 \ B^2) \ \mathcal{E} t \\ & \ \ensuremath{\emptyset} \mathcal{B} \ \forall t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ \forall t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ \forall t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ \forall t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ \forall t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ & \ \ensuremath{\square} t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ & \ \ensuremath{\square} t &= \ \ensuremath{\Theta} (B) \ \forall t \\ & \ \ensuremath{\square} \mathcal{B} \ & \ \ensuremath{\square} t &= \ \ensuremath{\square} (B) \ & \ \ensuremath{\square} t &= \ \ensuremath{\square} (B) \ & \ \ensuremath{\square} t &= \ \ensuremath{\square} (B) \ & \ \ensuremath{\square} t &= \ \ensuremath{\square} t \\ & \ \ensuremath{\square} \mathcal{B} \ & \ \ensuremath{\square} t &= \ensuremath{\square} t \\ & \ \ensuremath{\square} t \\ & \ensuremath{\square} t \\ & \ \ensuremath{\square} t \ & \ensurema$$

* $\phi(z) = 0$ iff $z = -(-1) \pm \sqrt{(-1)^2 - 4(-0.5)(1)}$ 2(-0.5)

$$= -1 \pm \sqrt{3}$$

 $z_1 = -2.73$ and $z_2 = 0.73$ $|z_1| = 2.73$ and $|z_2| = 0.73$

.: Zz lies inside the unit circle and so the Arma(2,2) model is not stationary.

(AR side of thing 5)

* $\Theta(z) = 0$ iff $z = -(0.2) \pm \sqrt{(0.2)^2 - 4(0.7)(1)}$ $= -0.2 \pm \sqrt{-2.76}$ $= -0.2 \pm \sqrt{2.76} i$ $= -0.2 \pm \sqrt{2.76} i$ 1.4 $Z_1 = -0.14 - 1.19 i \quad and \quad Z_2 = -0.14 + 1.19 i$ $|Z_1| = \sqrt{(-0.14)^2 + (-1.19)^2} = |Z_2| = 1.198$

Thus $|z_1| = |z_2| \ 71$, therefore the zeros lie outside the unit circle and this ARNA (2,2) model is invertible.

... This ARMA (2,2) model is invertible but not stationary.

[R]

Estimating Arma(P,q) Models

GOAL: TO estimate $\phi_1, \phi_2, ..., \phi_p, \Theta_1, \Theta_2, ..., \Theta_q, \sigma$ in the general Arma model:

 $\phi(B) Y = \Theta(B) Y$

(For Our Pulloses, we're going to assume M=0. Why? Because IRL, we usually have to do an overation to make our data from non-stationary to Stationary, and in doing so, we mean correct it to zero. More on that on Tuesday).

These parameters are estimated with observed data 241, 42,..., 4n3

Several methods of estimation exist. we'll focus on;

- (1) Maximum Likelihood Estimation
- (2) Least sanares Estimation

(It won't be as nice as LR, because everything is r.v)

ML Estimation

L

· TO do this, we need to make an assumption about the distribution of our data, and nence, the wn process.

$$\frac{1}{2} \sim MVN(\vec{0}, \sigma^{2} I_{n})$$

$$\frac{1}{2} \sim MVN(\vec{0}, \Gamma)$$

$$where \Gamma_{mxn} = \int \sigma(o) \sigma(1) \sigma(2) \cdots \sigma(n-1)$$

$$T(o) \sigma(1) \cdots \sigma(n-2)$$

$$\int \sigma(0)$$

$$\int \sigma(0)$$

$$T(o)$$

This results in the following likelihood function:

$$L(\phi_1, \phi_2, ..., \phi_p, \Theta_1, \Theta_2, ..., \Theta_q, \sigma) = \frac{1}{(2\pi)^{n_2} |\Gamma_{nxn}|^{\nu_2}} e^{\frac{1}{2} \frac{1}{\gamma} + \frac{1}{\gamma}} e^{\frac{1}{2} \frac{1}{\gamma} e^{\frac{1}{2} \frac{1}{\gamma} + \frac{1}{\gamma}} e^{\frac{1}{2} \frac{1}{\gamma} e^{\frac{1}{2} \frac{1}{\gamma} e^{\frac{1}{\gamma} + \frac{1}{\gamma}} e^{\frac{1}{2} \frac{1}{\gamma} e^{\frac{1}{2} \frac{1}{\gamma} e^{\frac{1}{\gamma} e$$

where
$$\vec{Y} = (Y_1, Y_2, ..., Y_n)^T$$
.

We want to maximize this function to obtain ML estimates of the parameters.

(It win he done numerically).