

The process y_t is called a moving average (MA) process if

$$y_t = e_t + c_1 e_{t-1} + \ldots + c_q e_{t-q} = C(z)e_t$$

where C(z) is a monic polynomial of order q (in z^{-1}), i.e.,

$$C(z) = 1 + c_1 z^{-1} + \ldots + c_q z^{-q}$$

with $c_q \neq 0$, and e_t is a zero-mean white noise process with variance σ_e^2 .

An MA(q) process will satisfy

$$m_y = E\{C(z)e_t\} = 0$$

$$r_y(k) = \begin{cases} \sigma_e^2 \left(c_k + c_1 c_{k+1} + \dots + c_{q-k} c_q\right) & \text{if } |k| \le q \\ 0 & \text{if } |k| > q \end{cases}$$

$$\phi_y(\omega) = \sigma_e^2 \left| C(\omega) \right|^2$$

where $C(\omega)$ indicates that C(z) is evaluated at frequency $\omega,$ i.e., $z=e^{i\omega}.$

In particular, note that $r_y(k) = 0$ for |k| > q.

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Example:

Consider the (real-valued) MA(1) process $y_t = e_t + c_1 e_{t-1}$, i.e., $C(z) = 1 + c_1 z^{-1}$. The auto-covariance of y_t is

$$r_y(0) = \sigma_e^2 (1 + c_1^2)$$

 $r_y(1) = \sigma_e^2 c_1$
 $r_y(k) = 0$, for $|k| > 1$

with $r_y(k) = r_y(-k)$, $\forall k$. Similarly, the PSD of y_t is

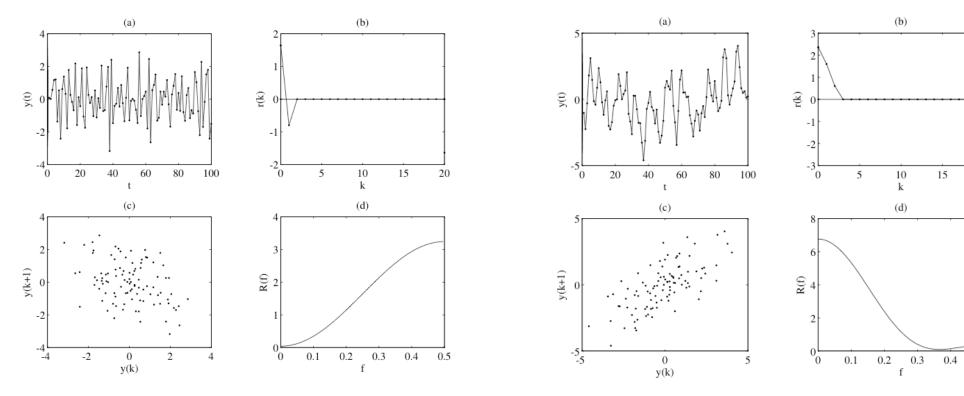
$$\phi_y(\omega) = \sigma_e^2 |1 + c_1 e^{-i\omega}|^2$$

$$= \sigma_e^2 (c_1 e^{i\omega} + 1 + c_1^2 + c_1 e^{-i\omega})$$

$$= \sigma_e^2 (1 + c_1^2 + 2c_1 \cos(\omega))$$

for $\omega = 2\pi f$, with $-0.5 < f \le 0.5$

The roots of C(z) will determine the locations of the nulls in $\phi_y(\omega)$.



MA(1)–process Y(t) = e(t) - 0.8e(t-1); (a) realisation, (b) covf. func., (c) scatter-plot and (d) spectral density.

MA(2)-process
$$Y(t) = e(t) + e(t-1) + 0.6e(t-2)$$
.

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0.5



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$$V\{\hat{\rho}_y(k)\} = \frac{1}{N} \left(1 + 2(\hat{\rho}_y^2(1) + \dots + \hat{\rho}_y^2(q)) \right)$$

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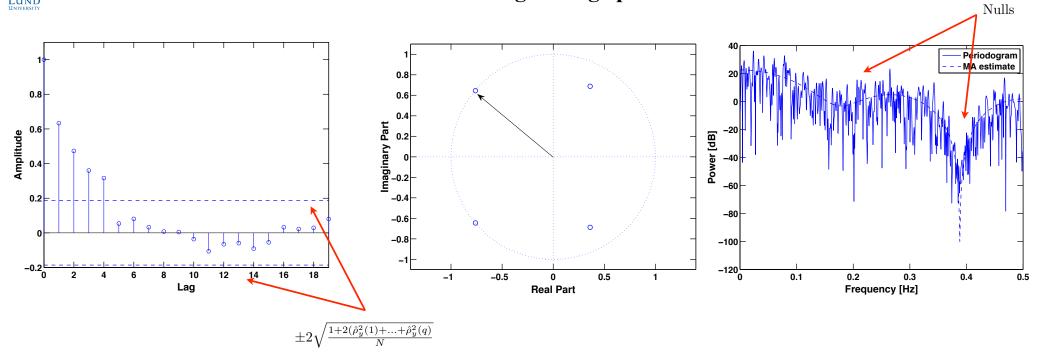
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The (approximative) 95% confidence interval for an $\mathrm{MA}(q)$ process can be expressed as

$$\hat{\rho}_e(k) \approx 0 \pm 2\sqrt{\frac{1 + 2(\hat{\rho}_y^2(1) + \dots + \hat{\rho}_y^2(q))}{N}}$$
 for $|k| \ge q + 1$

For white noise, i.e., q = 0, this simplifies to $\hat{\rho}_e(k) \approx 0 \pm 2/\sqrt{N}$.

Use the provided function acf. Remember that you can use help acf to learn more on how to use it.



Example:

As far as we can tell, this is the ACF of an MA(4) process, i.e.,

$$C(z) = 1 + c_1 z^{-1} + c_2 z^{-2} + c_3 z^{-3} + c_4 z^{-4}$$

As $\phi_y(\omega) = \sigma_e^2 |C(\omega)|^2$, the roots of C(z) determines where the nulls of the PSD will be located. If $y_t \in \mathbb{R}$, these will be symmetric; the PSD will thus have two nulls for the positive frequencies.