

Conditional likelihood  $f^n$ , conditioned on  $G_0 = 0$ , is

$$L(\tilde{\eta}) = \int_{x_n, \dots, x_1 | G_0 = 0} (x_n, \dots, x_1; \tilde{\eta} | G_0 = 0)$$

$$= \int_{x_n | x_{n-1}, \dots, x_1, G_0 = 0} \int_{x_{n-1}, \dots, x_1 | G_0 = 0}$$

$$= \int_{x_n | x_{n-1}, \dots, x_1, G_0 = 0} \int_{x_{n-1} | x_{n-2}, \dots, x_1, G_0 = 0} \int_{x_{n-2}, \dots, x_1 | G_0 = 0}$$

$$= \int_{x_1 | G_0 = 0} \prod_{t=2}^n \int_{x_t | x_{t-1}, \dots, x_1, G_0 = 0}$$

$$= \int_{x_1 | G_0 = 0} \prod_{t=2}^n \int_{x_t | \epsilon_{t-1}}$$

Thus, the conditional log likelihood  $f^n$  is

$$l(\tilde{\eta}) = -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n (x_t - \mu - \theta \epsilon_{t-1})^2$$

$$l(\tilde{\eta}) = -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n \epsilon_t^2$$

Note that

$$\epsilon_t = (x_t - \mu) - \theta \epsilon_{t-1}$$

$$\epsilon_t = (x_t - \mu) - \theta ((x_{t-1} - \mu) - \theta \epsilon_{t-2})$$

$$= (x_t - \mu) - \theta (x_{t-1} - \mu) + \theta^2 \epsilon_{t-2}$$

$$= (x_t - \mu) - \theta (x_{t-1} - \mu) + \theta^2 (x_{t-2} - \mu - \theta \epsilon_{t-3})$$

$$= (x_t - \mu) - \theta (x_{t-1} - \mu) + \theta^2 (x_{t-2} - \mu)$$

$$- \theta^3 \epsilon_{t-3}$$

⋮

$$\epsilon_t = (x_t - \mu) - \theta(x_{t-1} - \mu) + \theta^2(x_{t-2} - \mu) - \dots \\ \dots + (-\theta)^{t-1}(x_1 - \mu) + (-\theta)^t \epsilon_0$$

If  $\epsilon_0 = 0$  at the initialization,

$$\epsilon_t = \sum_{i=1}^t (x_i - \mu) (-\theta)^{t-i} \quad \text{and } l(\underline{\eta}) \text{ is}$$

$$l(\underline{\eta}) = -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n \left( \sum_{i=1}^t (x_i - \mu) (-\theta)^{t-i} \right)^2$$

$$\hat{\underline{\eta}}_{\text{CMLE}} = \underset{\underline{\eta}}{\text{arg max}} \quad l(\underline{\eta})$$

CMLEs are obtained using some iterative procedure.

### Exact MLE formulation

Let's look at the multivariate formulation.

$\underline{X} = (x_1, \dots, x_n)'$  realization from an  $n$ -dimensional multivariate normal

$$\text{i.e. } \underline{X} \sim N_n(\mu \underline{1}_n, \underline{\Omega})$$

$$\underline{\Omega} = E(\underline{X} - \mu \underline{1}_n)(\underline{X} - \mu \underline{1}_n)'$$

$$= \sigma^2 \begin{pmatrix} (1+\theta^2) & \theta & 0 & 0 & \dots & 0 \\ \theta & (1+\theta^2) & \theta & 0 & \dots & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & \cdot & \cdot & \cdot & \theta & -\theta \\ & & & & \theta & (1+\theta^2) \end{pmatrix}$$

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Likelihood  $f^n$ 

$$L(\underline{\eta}) = (2\pi)^{-n/2} |\underline{\Omega}|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{\mu} \underline{1}_n)' \underline{\Omega}^{-1} (\underline{x} - \underline{\mu} \underline{1}_n)\right)$$

log likelihood  $f^n$ 

$$l(\underline{\eta}) = -\frac{n}{2} \log 2\pi - \frac{1}{2} \log |\underline{\Omega}| - \frac{1}{2}(\underline{x} - \underline{\mu} \underline{1}_n)' \underline{\Omega}^{-1} (\underline{x} - \underline{\mu} \underline{1}_n)$$

Consider a factorization of  $\underline{\Omega}$  as

$$\underline{\Omega} = A D A' \quad (*)$$

$$A = \begin{pmatrix} 1 & & & & \\ \frac{\theta}{1+\theta^2} & 1 & & & \\ 0 & \frac{\theta(1+\theta^2)}{1+\theta^2+\theta^4} & 1 & & \\ & & & \ddots & \\ 0 & & & & 1 \end{pmatrix}$$

$\uparrow$   
 $\left( \frac{\theta(1+\theta^2+\dots+\theta^{2(n-2)})}{1+\theta^2+\dots+\theta^{2(n-1)}} \right)$

$$D = \sigma^2 \operatorname{diag}\left(1+\theta^2, \frac{1+\theta^2+\theta^4}{1+\theta^2}, \frac{1+\theta^2+\theta^4+\theta^6}{1+\theta^2+\theta^4}, \dots, \frac{1+\theta^2+\theta^4+\dots+\theta^{2n}}{1+\theta^2+\dots+\theta^{2(n-1)}}\right)$$

Using (\*) likelihood  $f^n$  is

$$L(\underline{\eta}) = (2\pi)^{-n/2} |A D A'|^{-1/2} \exp\left(-\frac{1}{2}(\underline{x} - \underline{\mu} \underline{1}_n)' (A')^{-1} D^{-1} A^{-1} (\underline{x} - \underline{\mu} \underline{1}_n)\right)$$

Note that  $|\underline{\Omega}| = |A D A'| = |A| |D| |A'| = |D| = \prod_{t=1}^n d_{tt}$

$$d_{tt} = \sigma^2 \frac{1 + \theta^2 + \dots + \theta^{2t}}{1 + \theta^2 + \dots + \theta^{2(t-1)}}$$

$$\text{let } \tilde{x}^0 = A^{-1} (\tilde{x} - \mu \mathbf{1}_n)$$

$$\text{i.e. } A \tilde{x}_0 = \tilde{x} - \mu$$

$$x_1^0 = x_1 - \mu$$

$$\vdots$$

$$x_t^0 = (x_t - \mu) - \frac{\theta(1 + \theta^2 + \dots + \theta^{2(t-2)})}{1 + \theta^2 + \dots + \theta^{2(t-1)}} x_{t-1}^0$$

$$L(\underline{\eta}) = (2\pi)^{-n/2} \left( \prod_{t=1}^n d_{tt} \right)^{-1/2} \exp \left( -\frac{1}{2} \sum_{t=1}^n \frac{x_t^0{}^2}{d_{tt}} \right)$$

$$\hat{\underline{\eta}}_{EMLE} = \arg \max_{\underline{\eta}} l(\underline{\eta}) ; l(\underline{\eta}) \text{ is the log likelihood}$$

Once again Iterative optimization techniques are used to obtain EMLE using the data  $(x_1, \dots, x_n)$

## MLE of Gaussian MA(q)

$$X_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}$$

$$\epsilon_t \stackrel{i.i.d.}{\sim} N(0, \sigma^2)$$

$$\underline{\eta} = (\mu, \theta_1, \dots, \theta_q, \sigma^2)' - \text{parameter vector}$$

## Conditional MLE formulation

Consider the likelihood conditional on the assumption that

$$\epsilon_0 = 0, \epsilon_{-1} = \epsilon_{-2} = \dots = \epsilon_{-(q-1)} = 0$$

(at the expected value of  $\epsilon_0, \epsilon_{-1}, \dots, \epsilon_{-(q-1)}$ )

Conditional likelihood (conditioned on  $\underline{\epsilon}_0 = (\epsilon_0, \epsilon_{-1}, \dots, \epsilon_{-(q-1)})' = \underline{0}$ )

$$L_c(\underline{\eta}) = f_{x_n, \dots, x_1 | \underline{\epsilon}_0 = \underline{0}}(x_n, \dots, x_1; \underline{\eta} | \underline{\epsilon}_0 = \underline{0})$$

$$= f_{x_n | x_{n-1}, \dots, x_1, \underline{\epsilon}_0 = \underline{0}} f_{x_{n-1} | \dots, x_1, \underline{\epsilon}_0 = \underline{0}}$$

$\vdots$

$$= f_{x_1 | \underline{\epsilon}_0 = \underline{0}} \left( \prod_{t=2}^n f_{x_t | x_{t-1}, \dots, x_1, \underline{\epsilon}_0 = \underline{0}} \right)$$

Note that  $x_1 | \underline{\epsilon}_0 = \underline{0} \sim N(\mu, \sigma^2)$

$\epsilon_t$  given  $x_t, x_{t-1}, \dots, \underline{\epsilon}_0$  can be expressed as

$$\epsilon_t = x_t - \mu - \theta_1 \epsilon_{t-1} - \dots - \theta_q \epsilon_{t-q}$$

$\forall t \geq 2$

$$x_t | x_{t-1}, \dots, x_1, \underline{\epsilon}_0 = \underline{0} \sim N(\mu + \theta_1 \epsilon_{t-1} + \dots + \theta_q \epsilon_{t-q}, \sigma^2)$$

## Conditional log likelihood

$$l_c(\underline{\eta}) = -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n (x_t - \mu - \theta_1 \epsilon_{t-1} - \dots - \theta_q \epsilon_{t-q})^2$$

$$l_c(\underline{\eta}) = -\frac{n}{2} \log 2\pi - \frac{n}{2} \log \sigma^2 - \frac{1}{2\sigma^2} \sum_{t=1}^n \epsilon_t^2$$

$$\hat{\underline{\eta}}_{\text{CMLE}} = \arg \max_{\underline{\eta}} l_c(\underline{\eta})$$

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Iterative methods used to obtain CMLEs. to

## Exact MLE formulation

$$\underline{X} = (x_1, \dots, x_n)' - \{x_t\} \text{ is Gaussian MA}(q)$$

$$\Rightarrow \underline{X} \sim N_n(\underline{\mu}, \underline{\Omega})$$

$$\underline{\mu} = E(\underline{X}) = \mu \underline{1}_n$$

$$\underline{\Omega} = \text{Cov}(\underline{X}) = E(\underline{X} - \underline{\mu})(\underline{X} - \underline{\mu})'$$

$$= \begin{pmatrix} \gamma_0 & \gamma_1 & & & 0 \\ \gamma_1 & \gamma_0 & \gamma_1 & & 0 \\ & \ddots & \ddots & \ddots & \vdots \\ & & \gamma_q & \ddots & \gamma_1 \\ 0 & & & \ddots & \gamma_0 \end{pmatrix}$$

$$\gamma_k = \begin{cases} \sigma^2 (\theta_k + \theta_{k+1} \theta_1 + \dots + \theta_q \theta_{q-k}), & k = 0, \dots, q \\ 0, & k > q \end{cases}$$

$\sigma^2 \omega$

Exact log likelihood  $f^n$

$$l(\underline{\eta}) = -\frac{n}{2} \log 2\pi - \frac{1}{2} \log |\underline{\Omega}| - \frac{1}{2} (\underline{x} - \underline{\mu})' \underline{\Omega}^{-1} (\underline{x} - \underline{\mu})$$

$$\hat{\underline{\eta}}_{EMLE} = \arg \max_{\underline{\eta}} l(\underline{\eta})$$

Note: Similar to MA(1), decomposition of  $\underline{\Omega}$  as  $\underline{\Omega} = A D A'$  leads to simplification of  $l(\underline{\eta})$ , expressing it explicitly in terms of the parameters  $\mu, \theta_1, \dots, \theta_q$  &  $\sigma^2$ .

Note: Iterative optimization techniques are used to obtain the EMLEs using  $l(\underline{\eta})$ .

Remark: Conditional LSE for MA model

Consider an invertible MA(1) ( $|\theta| < 1$ )

$$X_t = \mu + \epsilon_t + \theta \epsilon_{t-1}; \quad \underline{\eta} = (\mu, \theta)'$$

Ordinary LSE of  $\mu, \theta$  which is defined as

$$\hat{\underline{\eta}}_{OLS} = \arg \min_{\underline{\eta}} \frac{\sum_{t=2}^n (x_t - \mu - \theta \epsilon_{t-1})^2}{\sum_{t=2}^n \epsilon_t^2}$$

is not feasible since  $\epsilon_{t-1}$  is not observable

Let us put a condition that  $\epsilon_0$  is given (e.g.  $\epsilon_0 = 0$  if its expected value)

$$x_1 = \mu + \epsilon_1 + \theta \epsilon_0; \quad \epsilon_1 = (x_1 - \mu) - \theta \epsilon_0$$

$$x_2 = \mu + \epsilon_2 + \theta \epsilon_1; \quad \epsilon_2 = (x_2 - \mu) - \theta \epsilon_1$$

$$\epsilon_2 = (x_2 - \mu) - \theta((x_1 - \mu) - \theta \epsilon_0)$$

$$\text{i.e. } \epsilon_2 = (x_2 - \mu) - \theta(x_1 - \mu) + \theta^2 \epsilon_0$$

$$\vdots$$

$$x_{t-1} = \mu + \epsilon_{t-1} + \theta \epsilon_{t-2}$$

$$\epsilon_{t-1} = (x_{t-1} - \mu) - \theta \epsilon_{t-2}$$

$$= (x_{t-1} - \mu) - \theta((x_{t-2} - \mu) - \theta \epsilon_{t-3})$$

$$\vdots$$

$$\epsilon_{t-1} = \sum_{i=1}^{t-1} (x_i - \mu) (-\theta)^{t-1-i} \quad (\epsilon_0 = 0)$$

Conditional LSE of  $\mu$  &  $\theta$  is defined as

$$\hat{\eta}_{\sim \text{CLSE}} = \underset{\hat{\eta}}{\operatorname{argmin}} \sum_{t=2}^n \left( x_t - \mu - \theta \sum_{i=1}^{t-1} (x_i - \mu) (-\theta)^{t-1-i} \right)^2$$

Remark: CLSE for MA(q) can be framed in a similar manner.