

Problem Set 4

Econ 211C

Question 1 50 points
Hamilton, problem 13.2.

Solution: For any $ARMA(p, q)$ process, let $r = \max(p, q + 1)$. [13.1.22] and [13.1.23] in Hamilton tell us that the state equation and the observation equation are respectively,

$$\boldsymbol{\xi}_{t+1} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{r-1} & \phi_r \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \boldsymbol{\xi}_t + \begin{bmatrix} \varepsilon_{t+1} \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad (1)$$

$$y_t = \mu + \begin{bmatrix} 1 & \theta_1 & \theta_2 & \cdots & \theta_{r-1} \end{bmatrix} \boldsymbol{\xi}_t, \quad (2)$$

where

$$\boldsymbol{\xi}_t = \begin{bmatrix} (1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_r L^r)^{-1} \varepsilon_t \\ (1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_r L^r)^{-1} \varepsilon_{t-1} \\ \vdots \\ (1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_r L^r)^{-1} \varepsilon_{t-r+1} \end{bmatrix}.$$

If y_t is an $AR(p)$ process, then we have $r = \max(p, q + 1) = p$ and $\theta_1 = \theta_2 = \cdots = \theta_{p-1} = 0$. In general, an $AR(p)$ process can be expressed as

$$(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p)(y_t - \mu) = \varepsilon_t, \quad \forall t,$$

which implies

$$(1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p)^{-1} \varepsilon_t = y_t - \mu, \quad \forall t.$$

Substituting this last expression into $\boldsymbol{\xi}_t$ in Equations (1) and (2) gives us

$$\begin{bmatrix} y_{t+1} - \mu \\ y_t - \mu \\ \vdots \\ y_{t-p+2} - \mu \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_{p-1} & \phi_p \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \begin{bmatrix} y_t - \mu \\ y_{t-1} - \mu \\ \vdots \\ y_{t-p+1} - \mu \end{bmatrix} + \begin{bmatrix} \varepsilon_{t+1} \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

$$y_t = \mu + \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} y_t - \mu \\ y_{t-1} - \mu \\ \vdots \\ y_{t-p+1} - \mu \end{bmatrix},$$

which are [13.1.14] and [13.1.15], respectively. If y_t is an $MA(1)$ process, we have $r = \max(p, q + 1) = q + 1 = 2$ and $\phi_1 = \phi_2 = 0$. Now,

$$(1 - \phi_1 L - \phi_2 L^2)^{-1} \varepsilon_t = (1 - 0 \times L - 0 \times L^2)^{-1} \varepsilon_t = \varepsilon_t, \quad \forall t.$$

Substituting this last expression into ξ_t in Equations (1) and (2) gives us

$$\begin{bmatrix} \varepsilon_{t+1} \\ \varepsilon_t \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \varepsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{t+1} \\ 0 \end{bmatrix},$$

$$y_t = \mu + \begin{bmatrix} 1 & \theta \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \varepsilon_{t-1} \end{bmatrix},$$

which are [13.1.17] and [13.1.18], respectively.

Question 2 50 points
Hamilton, problem 13.4.

Solution:

Given the model specified in [13.4.3] and [13.4.4], it's clear that $F = 0$. As a result

$$K_t \equiv F P_{t|t-1} H (H' P_{t|t-1} H + R)^{-1} = 0.$$

The initial conditions of the Kalman recursions are

$$\hat{\xi}_{1|0} = E(\xi_1) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$P_{1|0} = E[(\xi_1 - E(\xi_1))(\xi_1 - E(\xi_1))'] = Q = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}$$

and $\forall t \geq 1$,

$$\hat{\xi}_{t+1|t} = F \hat{\xi}_{t|t-1} + K_t (y_t - A' x_t - H' \hat{\xi}_{t|t-1}) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$P_{t+1|t} = F P_{t|t-1} F' + Q = Q = \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix}.$$

And in turn we have

$$\begin{aligned} |\mathbf{H}'\mathbf{P}_{t|t-1}\mathbf{H} + \mathbf{R}| &= \left| \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \mathbf{0} \right| = \sigma_1^2 + \sigma_2^2, \\ \mathbf{y}_t - \mathbf{A}'\mathbf{x}_t - \mathbf{H}'\hat{\boldsymbol{\xi}}_{t|t-1} &= y_t - 0 = y_t. \end{aligned}$$

Substituting into [13.4.1] gives us

$$\begin{aligned} & f_{\mathbf{Y}_t|\mathbf{X}_t, \mathbf{Y}_{t-1}}(\mathbf{y}_t|\mathbf{x}_t, \mathbf{Y}_{t-1}) \\ &= (2\pi)^{-n/2} |\mathbf{H}'\mathbf{P}_{t|t-1}\mathbf{H} + \mathbf{R}|^{-1/2} \\ & \quad \times \exp \left\{ -\frac{1}{2} \left(\mathbf{y}_t - \mathbf{A}'\mathbf{x}_t - \mathbf{H}'\hat{\boldsymbol{\xi}}_{t|t-1} \right)' (\mathbf{H}'\mathbf{P}_{t|t-1}\mathbf{H} + \mathbf{R})^{-1} \left(\mathbf{y}_t - \mathbf{A}'\mathbf{x}_t - \mathbf{H}'\hat{\boldsymbol{\xi}}_{t|t-1} \right) \right\} \\ &= (2\pi)^{-1/2} (\sigma_1^2 + \sigma_2^2)^{-1/2} \exp \left[-\frac{y_t^2}{2(\sigma_1^2 + \sigma_2^2)} \right]. \end{aligned}$$

Hence, the sample log-likelihood [13.4.4] becomes

$$\begin{aligned} \sum_{t=1}^T \log f_{\mathbf{Y}_t|\mathbf{X}_t, \mathbf{Y}_{t-1}}(\mathbf{y}_t|\mathbf{x}_t, \mathbf{Y}_{t-1}) &= \sum_{t=1}^T \log \left\{ (2\pi)^{-1/2} (\sigma_1^2 + \sigma_2^2)^{-1/2} \exp \left[-\frac{y_t^2}{2(\sigma_1^2 + \sigma_2^2)} \right] \right\} \\ &= -\frac{T}{2} \log(2\pi) - \frac{T}{2} \log(\sigma_1^2 + \sigma_2^2) - \frac{\sum_{t=1}^T y_t^2}{2(\sigma_1^2 + \sigma_2^2)}, \end{aligned}$$

which is exactly [13.4.5].