

More on the Calculations of Yule-Walker equations

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Recall that PACF at lag k may be thought of as the k -th regression coefficient in the following regression

$$z_{k+1} = \phi_{k,1}z_k + \phi_{k,2}z_{k-1} + \dots + \phi_{k,k}z_1 + e_t, \quad k = 1, 2, 3, \dots, n.$$

And, as discussed in class, we can calculate the partial autocorrelation functions (PACF) using the Cramer's rule which requires calculating complicated determinants for large k . Alternatively, we can calculate PACF using a recursive method, Durbin-Levinson algorithm. Specifically, the Durbin-Levinson recursive may be summarized below.

$$\begin{aligned} \boldsymbol{\phi}_1 &= \phi_{1,1}, & \phi_{1,1} &= \frac{\gamma(1)}{\gamma(0)} = \rho(1) \\ \boldsymbol{\phi}_k &= \begin{pmatrix} \boldsymbol{\phi}_{k-1} - \phi_{k,k} \tilde{\boldsymbol{\phi}}_{k-1} \\ \phi_{k,k} \end{pmatrix}, & \phi_{k,k} &= \frac{\gamma(k) - \boldsymbol{\phi}_{k-1}' \tilde{\boldsymbol{\gamma}}_{k-1}}{\gamma(0) - \boldsymbol{\phi}_{k-1}' \boldsymbol{\gamma}_{k-1}}, \end{aligned}$$

where $\boldsymbol{\phi}_k = (\phi_{k,1}, \dots, \phi_{k,k})'$, $\tilde{\boldsymbol{\phi}}_k = (\phi_{k,k}, \dots, \phi_{k,1})'$, $\boldsymbol{\gamma}_k = (\gamma(1), \dots, \gamma(k))'$, and $\tilde{\boldsymbol{\gamma}}_k = (\gamma(k), \dots, \gamma(1))'$, $k = 1, 2, \dots, n$. Alternatively, we may calculate the Durbin-Levinson algorithm using

$$\begin{aligned} \hat{\phi}_{11} &= \hat{\rho}_1, & (1) \\ \hat{\phi}_{k+1,k+1} &= \frac{\hat{\rho}_{k+1} - \sum_{j=1}^k \hat{\phi}_{kj} \hat{\rho}_{k+1-j}}{1 - \sum_{j=1}^k \hat{\phi}_{kj} \hat{\rho}_j}, & (2) \\ \hat{\phi}_{k+1,j} &= \hat{\phi}_{kj} - \hat{\phi}_{k+1,k+1} \hat{\phi}_{k,k+1-j}, & j = 1, \dots, k. \quad (3) \end{aligned}$$

Example (Wei, 2005, pp. 21-23)

Suppose that we observe the following sample autocorrelation functions¹

$$\hat{\rho}_1 = -0.188, \quad \hat{\rho}_2 = -0.201, \quad \hat{\rho}_3 = 0.181, \dots$$

Using Equations (1) to (3), we have

1. $k = 0$:

$$\hat{\phi}_{11} = \hat{\rho}_1 = -0.188$$

2. $k = 1$:

$$\phi_{2,2} = \frac{\hat{\rho}_{1+1} - \hat{\phi}_{1,1}\hat{\rho}_1}{1 - \hat{\phi}_{1,1}\hat{\rho}_1} = \frac{\hat{\rho}_2 - \hat{\rho}_1^2}{1 - \hat{\rho}_1^2} = -0.245$$

$$\hat{\phi}_{2,1} = \hat{\phi}_{1,1} - \hat{\phi}_{2,2} \hat{\phi}_{1,1} = -0.234$$

3. $k = 2$:

$$\hat{\phi}_{\underbrace{2+1,2+1}_k}^{\underbrace{33}_{j=1}} = \frac{\hat{\rho}_{2+1} - \sum_{j=1}^2 \hat{\phi}_{2j} \hat{\rho}_{2+1-j}}{1 - \sum_{j=1}^2 \hat{\phi}_{2j} \hat{\rho}_j} = \frac{\hat{\rho}_3 - \hat{\phi}_{21}\hat{\rho}_2 - \hat{\phi}_{22}\hat{\rho}_1}{1 - \hat{\phi}_{21}\hat{\rho}_1 - \hat{\phi}_{22}\hat{\rho}_2} = 0.097$$

$$\hat{\phi}_{3,\underbrace{1}_{j=1}} = \hat{\phi}_{2,\underbrace{1}_{j=1}} - \hat{\phi}_{2+1,2+1} \hat{\phi}_{2,2+1-\underbrace{1}_{j=1}} = \hat{\phi}_{2,1} - \hat{\phi}_{3,3} \hat{\phi}_{2,2}$$

$$\hat{\phi}_{3,\underbrace{2}_{j=2}} = \hat{\phi}_{2,\underbrace{2}_{j=2}} - \hat{\phi}_{3,3} \hat{\phi}_{2,2+1-\underbrace{2}_{j=2}} = \hat{\phi}_{2,2} - \hat{\phi}_{3,3} \hat{\phi}_{2,1}$$

4. $k = 3, 4, \dots, n$

¹ Like ACF, the sample autocorrelation functions are symmetric around the origin $k = 0$ since

$$\hat{\rho}_k = \frac{\sum_{t=1}^{n-k} (z_t - \bar{z})(z_{t+k} - \bar{z})}{\sum_{t=1}^n (z_t - \bar{z})^2} = \frac{\sum_{t=k+1}^n (z_t - \bar{z})(z_{t-k} - \bar{z})}{\sum_{t=1}^n (z_t - \bar{z})^2} = \hat{\rho}_{-k}.$$