

Introduction to Time Series Analysis. Lecture 10.

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Forecasting.

1. The innovations representation.
2. Recursive method: Innovations algorithm.

Review: One-step-ahead linear prediction

$$X_{n+1}^n = \phi_{n1} X_n + \phi_{n2} X_{n-1} + \cdots + \phi_{nn} X_1$$

$$\Gamma_n \phi_n = \gamma_n,$$

$$P_{n+1}^n = \mathbb{E} (X_{n+1} - X_{n+1}^n)^2 = \gamma(0) - \gamma_n' \Gamma_n^{-1} \gamma_n,$$

$$\Gamma_n = \begin{bmatrix} \gamma(0) & \gamma(1) & \cdots & \gamma(n-1) \\ \gamma(1) & \gamma(0) & & \gamma(n-2) \\ \vdots & & \ddots & \vdots \\ \gamma(n-1) & \gamma(n-2) & \cdots & \gamma(0) \end{bmatrix},$$

$$\phi_n = (\phi_{n1}, \phi_{n2}, \dots, \phi_{nn})', \quad \gamma_n = (\gamma(1), \gamma(2), \dots, \gamma(n))'.$$

The innovations representation

Instead of writing the best linear predictor as

$$X_{n+1}^n = \phi_{n1} X_n + \phi_{n2} X_{n-1} + \cdots + \phi_{nn} X_1,$$

we can write

$$X_{n+1}^n = \theta_{n1} \underbrace{(X_n - X_n^{n-1})}_{\text{innovation}} + \theta_{n2} (X_{n-1} - X_{n-1}^{n-2}) + \cdots + \theta_{nn} (X_1 - X_1^0).$$

This is still linear in X_1, \dots, X_n .

The innovations are uncorrelated:

$$\text{Cov}(X_j - X_j^{j-1}, X_i - X_i^{i-1}) = 0 \text{ for } i \neq j.$$

Comparing representations: $U_n = X_n - X_n^{n-1}$ versus X_n

$$\begin{pmatrix} U_1 \\ U_2 \\ \vdots \\ U_n \end{pmatrix} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ -\phi_{11} & 1 & & 0 \\ \vdots & & \ddots & \\ -\phi_{n-1,n-1} & -\phi_{n-1,n-2} & \cdots & 1 \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{pmatrix}$$

$$\begin{pmatrix} X_1^0 \\ X_2^1 \\ \vdots \\ X_n^{n-1} \end{pmatrix} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ \theta_{11} & 0 & & 0 \\ \vdots & & \ddots & \\ \theta_{n-1,n-1} & \theta_{n-1,n-2} & \cdots & 0 \end{pmatrix} \begin{pmatrix} U_1 \\ U_2 \\ \vdots \\ U_n \end{pmatrix}$$

Innovations Algorithm

$$X_1^0 = 0, \quad X_{n+1}^n = \sum_{i=1}^n \theta_{ni} (X_{n+1-i} - X_{n+1-i}^{n-i}).$$

NB: error in text.

$$\theta_{n,n-i} = \frac{1}{P_{i+1}^i} \left(\gamma(n-i) - \sum_{j=0}^{i-1} \theta_{\textcolor{red}{i},\textcolor{red}{i-j}} \theta_{n,n-j} P_{j+1}^j \right).$$

$$P_1^0 = \gamma(0) \quad P_{n+1}^n = \gamma(0) - \sum_{i=0}^{n-1} \theta_{n,n-i}^2 P_{i+1}^i.$$

Innovations Algorithm: Example

$$\theta_{n,n-i} = \frac{1}{P_{i+1}^i} \left(\gamma(n-i) - \sum_{j=0}^{i-1} \theta_{i,i-j} \theta_{n,n-j} P_{j+1}^j \right).$$

$$P_1^0 = \gamma(0) \quad P_{n+1}^n = \gamma(0) - \sum_{i=0}^{n-1} \theta_{n,n-i}^2 P_{i+1}^i.$$

$$\theta_{1,1} = \gamma(1)/P_1^0, \quad P_2^1 = \gamma(0) - \theta_{1,1}^2 P_1^0$$

$$\theta_{2,2} = \gamma(2)/P_1^0, \quad \theta_{2,1} = (\gamma(1) - \theta_{1,1} \theta_{2,2} P_1^0) / P_2^1,$$

$$P_3^2 = \gamma(0) - (\theta_{2,2}^2 P_1^0 + \theta_{2,1}^2 P_2^1)$$

$$\theta_{3,3}, \quad \theta_{3,2}, \quad \theta_{3,1}, \quad P_4^3, \dots$$

Predicting h steps ahead using innovations

The innovations representation for the one-step-ahead forecast is

$$P(X_{n+1}|X_1, \dots, X_n) = \sum_{i=1}^n \theta_{ni} (X_{n+1-i} - X_{n+1-i}^{n-i}),$$

What is the innovations representation for $P(X_{n+h}|X_1, \dots, X_n)$?

Fact: If $h \geq 1$ and $1 \leq i \leq n$, we have

$$\text{Cov}(X_{n+h} - P(X_{n+h}|X_1, \dots, X_{n+h-1}), X_i) = 0.$$

Thus, $P(X_{n+h} - P(X_{n+h}|X_1, \dots, X_{n+h-1})|X_1, \dots, X_n) = 0$.

That is, the best prediction of X_{n+h} is the
best prediction of the one-step-ahead forecast of X_{n+h} .

Predicting h steps ahead using innovations

$$\begin{aligned} & P(X_{n+h}|X_1, \dots, X_n) \\ &= P(P(X_{n+h}|X_1, \dots, X_{n+h-1})|X_1, \dots, X_n) \\ &= P\left(\sum_{i=1}^{n+h-1} \theta_{n+h-1,i} (X_{n+h-i} - X_{n+h-i}^{n+h-i+1}) | X_1, \dots, X_n\right) \\ &= \sum_{i=1}^{n+h-1} \theta_{n+h-1,i} P((X_{n+h-i} - X_{n+h-i}^{n+h-i+1}) | X_1, \dots, X_n) \\ &= \sum_{i=h}^{n+h-1} \theta_{n+h-1,i} P((X_{n+h-i} - X_{n+h-i}^{n+h-i+1}) | X_1, \dots, X_n) \\ &= \sum_{i=h}^{n+h-1} \theta_{n+h-1,i} (X_{n+h-i} - X_{n+h-i}^{n+h-i+1}) \end{aligned}$$

Predicting h steps ahead using innovations

$$\begin{aligned} P(X_{n+1}|X_1, \dots, X_n) &= \sum_{i=1}^n \theta_{ni} (X_{n+1-i} - X_{n+1-i}^{n-i}) \\ P(X_{n+h}|X_1, \dots, X_n) &= \sum_{j=h}^{n+h-1} \theta_{n+h-1,j} (X_{n+h-j} - X_{n+h-j}^{n+h-j+1}) \\ &= \sum_{i=1}^n \theta_{n+h-1,h-1+i} (X_{n+1-i} - X_{n+1-i}^{n-i}) \\ (j = i + h - 1) \end{aligned}$$

Mean squared error of h -step-ahead forecasts

From orthogonality of the predictors and the error,

$$\mathbb{E}((X_{n+h} - P(X_{n+h}|X_1, \dots, X_n)) P(X_{n+h}|X_1, \dots, X_n)) = 0.$$

That is, $\mathbb{E}(X_{n+h} P(X_{n+h}|X_1, \dots, X_n)) = \mathbb{E}(P(X_{n+h}|X_1, \dots, X_n)^2)$.

Hence, we can express the mean squared error as

$$\begin{aligned} P_{n+h}^n &= \mathbb{E}(X_{n+h} - P(X_{n+h}|X_1, \dots, X_n))^2 \\ &= \gamma(0) + \mathbb{E}(P(X_{n+h}|X_1, \dots, X_n))^2 \\ &\quad - 2\mathbb{E}(X_{n+h} P(X_{n+h}|X_1, \dots, X_n)) \\ &= \gamma(0) - \mathbb{E}(P(X_{n+h}|X_1, \dots, X_n))^2. \end{aligned}$$

Mean squared error of h -step-ahead forecasts

But the innovations are uncorrelated, so

$$\begin{aligned} P_{n+h}^n &= \gamma(0) - \mathbb{E} (P(X_{n+h}|X_1, \dots, X_n))^2 \\ &= \gamma(0) - \mathbb{E} \left(\sum_{j=h}^{n+h-1} \theta_{n+h-1,j} (X_{n+h-j} - X_{n+h-j}^{n+h-j-1}) \right)^2 \\ &= \gamma(0) - \sum_{j=h}^{n+h-1} \theta_{n+h-1,j}^2 \mathbb{E} (X_{n+h-j} - X_{n+h-j}^{n+h-j-1})^2 \\ &= \gamma(0) - \sum_{j=h}^{n+h-1} \theta_{n+h-1,j}^2 P_{n+h-j}^{n+h-j-1}. \end{aligned}$$