

DERIVATION OF REGRESSION TRANSFORMATION MATRICES FOR FIRST AND HIGHER ORDER AUTOREGRESSIVE DISTURBANCES*

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I. Introduction

It is well known that if a linear regression model has disturbance terms generated by a first order autoregressive process we can transform it into a standard linear model by use of the transformation matrix.

$$(1.1) \quad T = \begin{bmatrix} \sqrt{1-\rho^2} & 0 & 0 \cdots 0 & 0 \\ -\rho & 1 & 0 \cdots 0 & 0 \\ 0 & -\rho & 1 \cdots 0 & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 \cdots 1 & 0 \\ 0 & 0 & 0 \cdots \rho & 1 \end{bmatrix}$$

where ρ is the autoregressive coefficient. (See [3, p. 67], [4, p. 260], [5] and [7, p. 253].) The matrix T is related to the covariance matrix of disturbance terms by

$$(1.2) \quad V(u) = \sigma_0^2 (T' T)^{-1}$$

where u is the vector of the disturbance terms, and σ_0^2 is defined later. We can easily verify that the matrix T is really a correct transformation matrix.

We can get $V(u)$ directly from the definition of autocorrelation. Because $V(u)$ is a positive definite symmetric matrix we can apply the procedure of triangular decomposition or Cholesky's method to get the inverse, $V^{-1}(u)$. (See [6, Sec. 1-4].) Because $V^{-1}(u)$ is a positive definite symmetric band matrix of width 1 (see eq. (2.20) below), the Cholesky decomposition into lower triangular matrix with positive diagonal elements gives $\sigma_0 T$ which has the same band width, 1. (See [6, Theorem 1-13].) Thus we get T from $V(u)$.

*The author is grateful to Prof. Donald Ebbeler for useful comments and suggestions.

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The same procedure applies to higher order autoregression models. But the procedure of derivation of T from $V(u)$ is tedious and inefficient even for the first order case.

In this paper I will develop an alternative procedure which leads to the matrix T directly in a more efficient way. Here I will illustrate the procedure for the first and second order autoregressive models. The extension to higher order models is straightforward.

II. The First-Order Autoregression Model

Assume that observations are arranged in the order of successive time periods. Assume that the disturbances are generated by a first order autoregressive process which is described by the following equation:

$$(2.1) \quad u_t = \rho u_{t-1} + v_t, \quad t = \dots -2, -1, 0, 1, 2, \dots$$

where

$$(2.2) \quad |\rho| < 1,$$

$$(2.3) \quad E(v_t) = 0,$$

and

$$(2.4) \quad V(v_t) = \sigma_0^2, \quad \text{Cov}(v_s, v_t) = 0 \text{ for } s \neq t.$$

An implication derived from (2.1) is

$$(2.5) \quad u_t = v_t + \rho v_{t-1} + \rho^2 v_{t-2} + \dots$$

from which we get

$$(2.6) \quad V(u_t) = E(u_t^2) = \frac{\sigma_0^2}{1 - \rho^2}$$

and especially when $t=0$,

$$(2.7) \quad V(u_0) = \frac{\sigma_0^2}{1 - \rho^2}.$$

Now, the equation (2.1) can be rewritten as

$$v_t = \rho u_{t-1} + u_t$$

or in matrix form for n observations,

$$(2.8) \quad \begin{bmatrix} v_1 \\ v_2 \\ \cdot \\ \cdot \\ v_n \end{bmatrix} = \begin{bmatrix} -\rho & 1 & 0 & 0 \cdots 0 & 0 & 0 \\ 0 & -\rho & 1 & 0 \cdots 0 & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & 0 & -\rho & 1 & 0 \\ 0 & 0 & 0 & 0 \cdots 0 & -\rho & 1 \end{bmatrix} \cdot \begin{bmatrix} u_0 \\ u_1 \\ \cdot \\ \cdot \\ u_n \end{bmatrix}$$

If we define

III. The Second-Order Autoregression Model

Assume that the disturbances are generated by a second order autoregressive process described by the equation,

$$(3.1) \quad u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + v_t, \quad t = \dots -2, -1, 0, 1, 2, \dots$$

where ρ_1 and ρ_2 satisfy the following constraints:

$$(3.2) \quad \begin{aligned} \rho_2 + \rho_1 &< 1 \\ \rho_2 - \rho_1 &< 1 \\ -1 &< \rho_2 < 1. \end{aligned}$$

Further we assume that

$$(3.3) \quad E(v_t) = 0$$

$$(3.4) \quad V(v_t) = \sigma_0^2, \quad Cov(v_s, v_t) = 0 \text{ for } s \neq t.$$

We can derive from the above that (see [2, pp. 60-62])

$$(3.5) \quad V(u_t) = \frac{1 - \rho_2}{1 + \rho_2} \frac{\sigma_0^2}{(1 - \rho_2)^2 - \rho_1^2}$$

and

$$(3.6) \quad Cov(u_t, u_{t-1}) = \frac{1}{1 + \rho_2} \frac{\sigma_0^2 \rho_1}{(1 - \rho_2)^2 - \rho_1^2}.$$

Especially we have the covariance matrix,

$$(3.7) \quad V(u^0) = \frac{1}{1 + \rho_2} \frac{\sigma_0^2}{(1 - \rho_2)^2 - \rho_1^2} \begin{bmatrix} 1 - \rho_2 & \rho_1 \\ \rho_1 & 1 - \rho_2 \end{bmatrix}$$

where $u^0 = (u_{-1} u_0)'$.

Now equation (3.1) can be rewritten as

$$v_t = -\rho_2 u_{t-2} - \rho_1 u_{t-1} + u_t, \quad t = \dots -2, -1, 0, 1, 2, \dots$$

or, in matrix form for n observations,

$$(3.8) \quad \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ \cdot \\ \cdot \\ v_n \end{bmatrix} = \begin{bmatrix} -\rho_2 & -\rho_1 & 1 & 0 \cdots 0 & 0 \\ 0 & -\rho_2 & -\rho_1 & 1 \cdots 0 & 0 \\ 0 & 0 & -\rho_2 & -\rho_1 \cdots 0 & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & 0 & -\rho_1 & 1 \end{bmatrix} \begin{bmatrix} u_{-1} \\ u_0 \\ u_1 \\ \cdot \\ \cdot \\ u_n \end{bmatrix}$$

If we define

$$v = (v_1 \ v_2 \ v_3 \ \cdots \ v_n)'$$

$$P = \begin{bmatrix} -\rho_2 & 0 & 0 \cdots 0 \\ -\rho_1 & -\rho_2 & 0 \cdots 0 \end{bmatrix}$$

$$R = \begin{pmatrix} 1 & 0 & \vdots & 0 & 0 \cdots \cdots 0 & 0 \\ -\rho_1 & 1 & \vdots & 0 & 0 \cdots \cdots 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ -\rho_2 & -\rho_1 & \vdots & 1 & 0 \cdots \cdots 0 & 0 \\ 0 & -\rho_2 & \vdots & -\rho_1 & 1 \cdots \cdots 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \vdots & 0 & 0 & -\rho_2 & -\rho_1 & 1 \end{pmatrix} = \begin{pmatrix} R_{11} & 0 \\ R_{21} & R_{22} \end{pmatrix}$$

$$u = (u_1 \ u_2 \ u_3 \ \cdots \ u_n)'$$

and

$$w = u + Pu^0,$$

then the relation (3.8) becomes

$$(3.9) \quad w = Ru.$$

Because R is nonsingular we have

$$(3.10) \quad u = R^{-1}w.$$

Therefore if we have the covariance matrix of w , $V(w)$, we can express the covariance matrix of u as

$$(3.11) \quad V(u) = R^{-1}V(w)R'^{-1}.$$

But

$$(3.12) \quad w = v + Pu^0$$

and v and u^0 are uncorrelated. Therefore we have

$$(3.13) \quad V(w) = V(v) + PV(u^0)P' = \sigma_0^2 I + \frac{\sigma_0^2}{1+\rho_2} \frac{1}{(1-\rho_2)^2 - \rho_1^2} P \begin{pmatrix} 1-\rho_2 & \rho_1 \\ \rho_1 & 1-\rho_2 \end{pmatrix} P' = \sigma_0^2 Q$$

where

$$Q = \begin{pmatrix} Q_{11} & 0 \\ 0 & I \end{pmatrix}$$

and

$$Q_{11} = \frac{1}{1+\rho_2} \frac{1}{(1-\rho_2)^2 - \rho_1^2} \begin{pmatrix} 1-\rho_2 & \rho_1\rho_2 \\ \rho_1\rho_2 & (1-\rho_1^2) - \rho_2(1+\rho_1^2) \end{pmatrix}$$

The inverse of Q_{11} is

$$(3.14) \quad Q_{11}^{-1} = \begin{pmatrix} (1+\rho_2)[(1-\rho_1^2) - \rho_2(1+\rho_1^2)] & -(1+\rho_2)\rho_1\rho_2 \\ -(1+\rho_2)\rho_1\rho_2 & 1-\rho_2^2 \end{pmatrix}$$

Because Q or Q_{11}^{-1} is a positive definite symmetric matrix under condition (3.2), we can find a triangular matrix s_{11} such that

$$S_{11} = \begin{pmatrix} s_{11} & 0 \\ s_{21} & s_{22} \end{pmatrix}, \quad s_{ii} > 0, \quad i=1, 2,$$

and

$$S_{11}'S_{11} = \begin{pmatrix} s_{11}^2 + s_{21}^2 & s_{21}s_{22} \\ s_{21}s_{22} & s_{22}^2 \end{pmatrix} = Q_{11}^{-1}.$$

The result of this evaluation is

$$S_{11} = \begin{pmatrix} \sqrt{\frac{(1-\rho_2)^2 - \rho_1^2}{(1-\rho_2)}(1+\rho_2)} & 0 \\ -\frac{\sqrt{\rho_1^2 \rho_2^2 (1+\rho_2)}}{(1-\rho_2)} & \sqrt{1-\rho_2^2} \end{pmatrix}$$

If we define

$$S = \begin{pmatrix} S_{11} & 0 \\ 0 & I \end{pmatrix}$$

then

$$(3.15) \quad Q_{11} = S_{11}^{-1} S_{11}'^{-1} \quad \text{and} \quad Q = S^{-1} S'^{-1}.$$

Combining (3.11), (3.13) and (3.15), we get

$$(3.16) \quad V(u) = \sigma_0^2 R^{-1} S^{-1} S'^{-1} R'^{-1} = \sigma_0^2 (T'T)^{-1}$$

where

$$(3.17) \quad T = SR.$$

From (3.16) we can easily see that

$$(3.18) \quad V^{-1}(u) = \sigma_0^{-2} T'T.$$

Now the evaluation of matrices T , $V^{-1}(u)$, and $V(u)$ is straightforward.

From the definitions of S and R we get

$$(3.19) \quad T = SR = \begin{pmatrix} S_{11} & 0 \\ 0 & I \end{pmatrix} \begin{pmatrix} R_{11} & 0 \\ R_{21} & R_{22} \end{pmatrix} = \begin{pmatrix} S_{11}R_{11} & 0 \\ R_{21} & R_{22} \end{pmatrix}$$

$$= \begin{pmatrix} s_{11} & 0 & \vdots & 0 & 0 & \cdots & \cdots & 0 & 0 \\ s_{21} - \rho_1 s_{22} & s_{22} & \vdots & 0 & 0 & \cdots & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & 1 & 0 & \cdots & \cdots & 0 & 0 \\ 0 & -\rho_2 & \vdots & -\rho_1 & 1 & \cdots & \cdots & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \vdots & 0 & 0 & \cdots & \cdots & 1 & 0 \\ 0 & 0 & \vdots & 0 & 0 & -\rho_2 & -\rho_1 & 1 \end{pmatrix}$$

where

$$s_{21} - \rho_1 s_{22} = -\frac{\sqrt{\rho_1^2 (1+\rho_2)}}{(1-\rho_2)}.$$

The matrix T transforms a second order autocorrelation model

$$(3.20) \quad y = X\beta + u$$

into a standard linear model

$$(3.21) \quad Ty = TX\beta + Tu$$

in the sense that the covariance matrix of the disturbance vector, Tu , is a scalar matrix, i.e.,

$$(3.22) \quad V(Tu) = TV(u)T' = \sigma_0^2 T(T'T)^{-1}T' = \sigma_0^2 TT^{-1}T'^{-1}T' = \sigma_0^2 I. \quad (2)$$

If we want $V^{-1}(u)$ and $V(u)$ we can evaluate them according to (3.18) and (3.16), respectively.

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(2) Amemiya[1] suggests a simpler type of transformation matrix, $(R_{21} \ R_{22})$. But such a transformation lacks an optimal property which T has. (See [5]).