

# On the invariance of certain estimators

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In this note,  $L_p$  estimators for the parameters in the linear model  $y = X\beta$  are considered. In particular, it is shown that these estimators are invariant under scale transformations on the dependent variable; that is, if  $\hat{\beta}(y, X)$  is an  $L_p$  estimator for  $\beta$ , then  $a\hat{\beta}(y, X) = \hat{\beta}(ay, X)$  for any nonzero scalar  $a$ . It is shown that this result does not extend to more general transformations on  $y$ , and the invariance property does not hold for general nonlinear models.

## 1. Invariance

Computing  $L_p$  estimators by linear functions on discrete data has received much attention in the literature in the past few years; recent articles have appeared for determining  $L_p$  estimators when  $p = 1, 2$ , and  $\infty$  (see Appa and Smith [1], Barrodale and Roberts [2], and Wagner [9]). The  $L_p$ -criteria for various values of  $p$  have been discussed by Barrodale and Roberts [3], Barrodale, Roberts, and Hunt [4], Ekblom and Henriksson [5], Forsythe [6], and Rice and White [8]. Several properties of  $L_1$  and  $L_\infty$  estimators are given in [1]; in [3] some properties of  $L_p$  estimators are established. This note will address itself to another property of any  $L_p$  estimator (for any  $p \neq 0$ ). In particular, it is shown that such estimators are invariant under scale transformations on the dependent

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variable. The concept of invariance is discussed by Fraser [7, p. 67] and is defined for scale transformations as:

DEFINITION.  $\hat{\beta}(y, X)$  is an invariant estimator for  $\beta$  if

$$a\hat{\beta}(y, X) = \hat{\beta}(ay, X).$$

The following lemma shows that under the  $L_p$ -criteria for any  $p (\neq 0)$  the  $L_p$  estimator,  $\hat{\beta}(y, X)$ , is invariant in the case of the linear model.

LEMMA. If  $\min_{\beta} \|y - X\beta\|^p = \|y - X\hat{\beta}\|^p$ , then for any scalar  $a \neq 0$ ,

$$(i) \min_{\delta} \|ay - X\delta\|^p = \|a\|^p \|y - X\hat{\beta}\|^p, \text{ and}$$

$$(ii) \hat{\delta} = a\hat{\beta}.$$

Proof. If  $\min_{\beta} \|y - X\beta\|^p = \|y - X\hat{\beta}\|^p$ , then

$$\begin{aligned} \min_{\delta} \|ay - X\delta\|^p &= \|a\|^p \min_{\delta} \left\| y - \frac{1}{a} X\delta \right\|^p \\ &= \|a\|^p \min_{\beta} \|y - X\beta\|^p, \end{aligned}$$

where

$$\begin{aligned} \beta &= \frac{1}{a} \delta \\ &= \|a\|^p \|y - X\hat{\beta}\|^p, \end{aligned}$$

and the result follows.

## 2. Summary and examples

When  $p = 1, 2$ , and  $\infty$ , the best  $L_p$  estimators of the location parameter in the model  $y = \beta_0$  correspond to the median, mean, and midrange, respectively ([1], [5], [7], and [8]). Hence, appealing to the lemma, for any scalar  $a (\neq 0)$ ,

$$ay_M, \overline{ay}, \text{ and } ay_{MR}$$

are optimal under  $L_1$ ,  $L_2$ , and  $L_\infty$ , respectively.

Consider the model  $y = \beta^3$ . This model is nonlinear with respect to the unknown parameter,  $\beta$ . Under the  $L_2$ -criterion

$$\hat{\beta} = (\bar{y})^{1/3},$$

and for any scalar  $a (\neq 0)$ ,

$$\hat{\beta}^* = (a\bar{y})^{1/3}.$$

Hence, the estimator is not invariant, but is invariant under the transformation  $\delta = \beta^3$ . In this case,

$$\frac{\hat{\delta}}{\delta} = \bar{y} \quad \text{and} \quad a\frac{\hat{\delta}}{\delta} = a\bar{y}.$$

When the nonlinear model is separable with respect to the unknown parameters, then the corresponding  $L_p$  estimator is invariant in view of the above transformation. The invariance property of the  $L_p$  estimators does not hold for general nonlinear models. For example, consider the model

$$y = \beta_1 e^{-\beta_2 x},$$

then for any optimal  $L_p$  estimator

$$\tilde{\beta} = (\tilde{\beta}_1, \tilde{\beta}_2)$$

and any  $a (\neq 0)$ ,

$$\tilde{\beta}^* = (a\tilde{\beta}_1, \tilde{\beta}_2).$$

In [4], models nonlinear in one parameter are discussed; for these models, the estimators are not invariant. Examples of these models are:

$$y = (\beta_0 + \beta_1 x) / (1 + \beta_2 x),$$

$$y = \beta_0 + \beta_1 / (1 + x)^{\beta_2},$$

and

$$y = e^{\beta_2 x} (\beta_0 + \beta_1 x) .$$

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