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ORIGINAL ARTICLE

Adjusted ridge estimator and comparison with Kibria's method in linear regression

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Abstract This paper proposes an adjusted ridge regression estimator for β for the linear regression model. The merit of the proposed estimator is that it does not require estimating the ridge parameter k unlike other existing estimators. We compared our estimator with an ordinary least squares (LS) estimator and with some well known estimators proposed by Hoerl and Kennard (1970), ordinary ridge regression (RR) estimator and generalized ridge regression (GR) and some estimators proposed by Kibria (2003) among others. A simulation study has been conducted and compared for the performance of the estimators in the sense of smaller mean square error (MSE). It appears that the proposed estimator is promising and can be recommended to the practitioners.
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1. Introduction

Regression analysis is one of the frequently used tools for forecasting in almost all disciplines; hence estimation of unknown parameters is a common interest for many users. These estimates can be found by various estimation methods. The easiest and the most common method of them is the ordinary least squares (LS) technique, which minimizes the squared distance between the estimated and observed values. Multicollinearity among the explanatory variables in the regression model is an important problem that exhibits serious undesirable effects on the analysis faced in applications. The LS estimator is sensitive to number 'errors', namely, there is an 'explosion' of the sampling variance of the estimators. Alternative estimators are designed to combat multicollinearity-yield-biased estimators.

One of the popular numerical techniques to deal with multicollinearity is the ridge regression due to Hoerl and Kennard (1970). Ridge regression approach has been studied by McDonald and Galarneau (1975), Swindel (1976), Lawless (1978), Singh and Chaubey (1987), Sarkar (1992), Saleh and Kibria (1993), Kibria (2003), Khalaf and Shukur (2005), Zhong and Yang (2007), Batah et al. (2008), Yan (2008), Yan and Zhao (2009), Muniz and Kibria (2009), Yang and Chang (2010), Khalaf (2012) and Dorugade (2014) and others. Ridge Regression estimator has been the benchmarked for almost all the estimators developed later in this context. Most of the researchers compare superiority of their suggested estimators with LS, RR, GR and other existing methods in terms of minimum MSE criterion in the presence of multicollinearity. In this article, our primary aim is to suggest an estimator by modifying the ordinary ridge regression (RR) estimator avoiding the computation of ridge parameter and secondly to evaluate the performance of our estimator with LS, RR and GR estimators in the presence of sever or extremely sever multicollinearity.

This article is organized as follows: in Section 2, we define model and parameter estimation methods with their bias and

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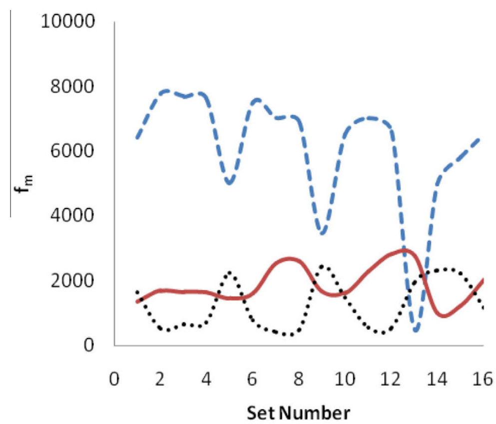

Figure 1 "f_m" for AR, RR and GR estimators ($\rho = 0.95$, $p = 3$ and $\beta = (10, 4, 1, 8)'$).

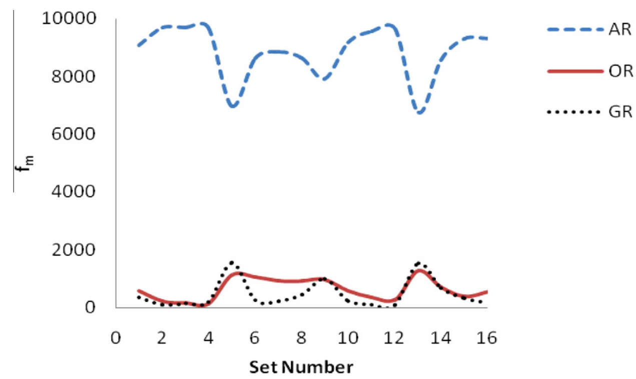

Figure 3 "f_m" for AR, RR and GR estimators ($\rho = 0.999$, $p = 3$ and $\beta = (14, 5, 2, 6)'$).

MSE. In Section 3, we have proposed biased estimator. We compare our new estimator in the MSE sense, with the RR estimator, in the same section. In Section 4, performances of the proposed estimators with respect to the scalar MSE criterion compared to LS, RR and GR estimators are evaluated on basis of the Monte Carlo Simulation results. Influence of choice of k to compute RR on the proposed estimator AR is also studied in the same section. Finally, article ends with some concluding remarks.

2. Model specifications and the estimators

We consider the linear regression model with p predictors and n observations:

$$Y = X\beta + \varepsilon, \tag{1}$$

where $Y = (Y_1, Y_2, \ldots, Y_n)'$, $\beta = (\beta_1, \beta_2, \ldots, \beta_p)'$, $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n)'$and $X = (x_1, x_2, \ldots, x_p)$. ε_i's are independently and identically distributed as normal with mean 0 and variance σ^2. Assume that the Y_i's are centered and the covariates x_i's are standardized. Let Λ and T be the matrices of eigen values and eigen vectors of $X'X$, respectively, satisfying $T'X'XT = \Lambda = \text{diagonal}(\lambda_1, \lambda_2, \ldots, \lambda_p)$, where λ_i being the ith eigenvalue of $X'X$ and $T'T = TT' = I_p$. We obtain the equivalent model

$$Y = Z\alpha + \varepsilon, \tag{2}$$

where $Z = XT$, it implies that $Z'Z = \Lambda$, and $\alpha = T'\beta$ (see Montgomery et al., 2001).

Then LS estimator of α is given by

$$\hat{\alpha}_{LS} = (Z'Z)^{-1}Z'Y = \Lambda^{-1}Z'Y. \tag{3}$$

Therefore, LS estimator of β is given by

$$\hat{\beta}_{LS} = T\hat{\alpha}_{LS}.$$

2.1. Generalized ridge regression estimator (GR)

In order to combat multicollinearity and improve the LS estimator, Hoerl and Kennard (1970) suggested an alternative estimator by adding a ridge parameter k to the diagonal elements of the least square estimator. They also suggested generalized ridge regression (GR) estimator by using separate ridge parameter for each regressor in the ridge regression. Also, if the optimal values for biasing constants differ significantly from each other, then this estimator has the potential to save a greater amount of MSE than the LS estimator (Stephen and Christopher, 2001).

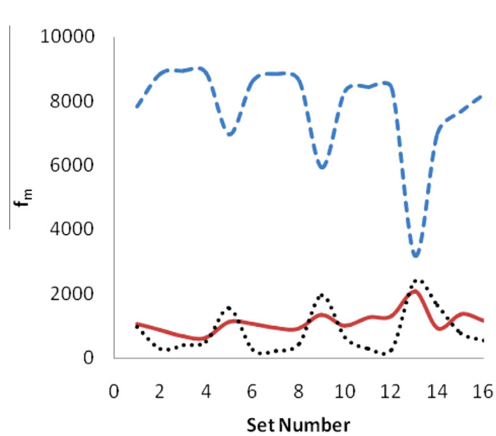

Figure 2 "f_m" for AR, RR and GR estimators ($\rho = 0.99$, $p = 3$ and $\beta = (7, 4, 1, 8)'$).

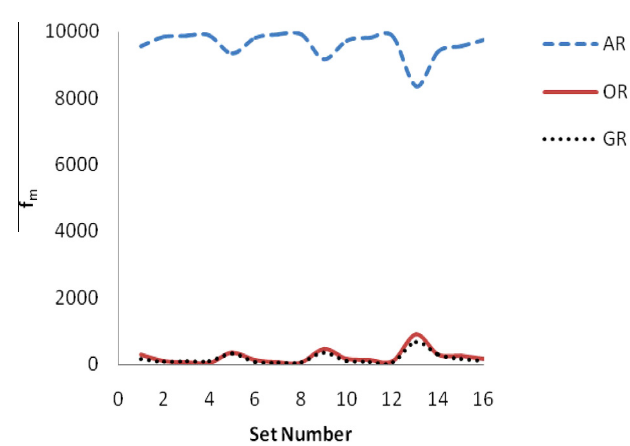

Figure 4 "f_m" for AR, RR and GR estimators ($\rho = 0.9999$, $p = 3$ and $\beta = (10, 1, 1, 4)'$).

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