

1. Consider a linear regression model

说话:

$$y_i = x_{i1}\beta_1 + x_{i2}\beta_2 + \dots x_{ip}\beta_p + \epsilon_i, \quad i = 1, \dots, n.$$

The ridge regression is to apply squared penalty on the least squares estimate by minimizing

$$\min_{\beta} \sum_{i=1}^n (y_i - \sum_{j=1}^p x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^p \beta_j^2,$$

where $\lambda \geq 0$ is a tuning parameter. By convention, the response is centered and the covariates are standardized. The error term ϵ has zero mean. The resulting estimate is denoted by $\hat{\beta}^{\text{ridge}}$.

- Denote the design matrix by $\mathbf{X}_{n \times p} = (x_1, \dots, x_p)$. Derive the explicit expression of $\hat{\beta}^{\text{ridge}}$ in detailed steps.
 - Show the details how to compute the ridge solution via the singular value decomposition (SVD).
 - Show that there always exists a λ such that the mean squared error (MSE) of $\hat{\beta}^{\text{ridge}}$ is less than the MSE of $\hat{\beta}^{\text{ols}}$, the ordinary least square estimate. (Please provide detailed derivation of each step).
2. In the following, \mathbf{I}_m is an $m \times m$ identity matrix, $\mathbf{0}_m$ is an $m \times 1$ vector of zero elements, and $\mathbf{J}_m = \mathbf{1}_m \mathbf{1}_m'$, where $\mathbf{1}_m$ is an $m \times 1$ vector of 1's. You may use, without proof, the fact that

$$[\mathbf{I}_m + \phi \mathbf{J}_m]^{-1} = \left[\mathbf{I}_m - \frac{\phi}{1 + m\phi} \mathbf{J}_m \right].$$

- i. Consider the following linear model:

$$\begin{aligned} Y_{ijt} &= \gamma_i + \tau_j + \epsilon_{ijt}, \\ \epsilon_{ijt} &\sim N(0, \sigma_E^2), \gamma_i \sim N(0, \sigma_\gamma^2), i = 1, 2; j = 1, 2; t = 1, 2; \end{aligned} \quad (1)$$

where all random variables on the right hand side of the model are mutually independent. Write the model as $\mathbf{Y} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{X}\boldsymbol{\tau} + \boldsymbol{\epsilon}$, where

$$\mathbf{Y} = [Y_{111}, Y_{112}, Y_{121}, Y_{122}, Y_{211}, Y_{212}, Y_{221}, Y_{222}], \boldsymbol{\gamma} = [\gamma_1, \gamma_2], \boldsymbol{\tau} = [\tau_1, \tau_2]$$

and find \mathbf{Z}, \mathbf{X} . Next, find the variance-covariance matrix of $\mathbf{Z}\boldsymbol{\gamma} + \boldsymbol{\epsilon}$.

- State the distribution of \mathbf{Y} and find the best linear unbiased estimator of $\boldsymbol{\tau}$ in part (a). Give a condition for $\mathbf{C}'\boldsymbol{\tau}$ to be estimable under model (1), where \mathbf{C}' is $q \times p$ of rank q (and $q \geq 1$). Justify your answer.
- For given constant vector \mathbf{d} and estimable set of functions $\mathbf{C}'\boldsymbol{\tau}$, state a test statistic for testing

$$H_0 : \mathbf{C}'\boldsymbol{\tau} = \mathbf{d} \quad \text{versus} \quad H_1 : \mathbf{C}'\boldsymbol{\tau} \neq \mathbf{d},$$

where \mathbf{C}' is $q \times p$ of rank q (and $q \geq 1$). Find the expected value of the numerator of the test statistic.

- Let $\phi = \sigma_\gamma^2 / \sigma_E^2$ and let $\mathbf{C}' = [1, -1]$. Assuming that the distribution of your test statistic in part(c) is non-central F , does the power of this test depend on the value of σ_γ ? If so, in which way?