

Problem 1

Let X has singular value decomposition $X = UDV^T$, where U and V are $N \times N$ and $p \times p$ orthogonal matrices, and $D = \text{diag}\{d_1, \dots, d_p\}$ with $d_1 \geq d_2 \geq \dots \geq d_p \geq 0$. Since $\lambda > 0$,

$$\begin{aligned} X^T X + \lambda I &= V(D^T D + \lambda I)V^T \\ &= V \begin{bmatrix} d_1^2 + \lambda & & \\ & \ddots & \\ & & d_p^2 + \lambda \end{bmatrix} V^T \\ (X^T X + \lambda I)^{-1} &= V \begin{bmatrix} \frac{1}{d_1^2 + \lambda} & & \\ & \ddots & \\ & & \frac{1}{d_p^2 + \lambda} \end{bmatrix} V^T \end{aligned}$$

So $X^T X + \lambda I$ is invertable.

Problem 2

According to Problem 1, let X has SVD $X = UDV^T$ and $(V)_{ij} = v_{ij}$.

$$\begin{aligned} \text{Cov}(\hat{\beta}^{\text{ridge}}) &= \sigma^2 (X^T X + \lambda I)^{-1} X^T X (X^T X + \lambda I)^{-1} \\ &= \sigma^2 V \begin{bmatrix} \frac{d_1^2}{(d_1^2 + \lambda)^2} & & \\ & \ddots & \\ & & \frac{d_p^2}{(d_p^2 + \lambda)^2} \end{bmatrix} V^T \\ \text{Var}(\hat{\beta}_i^{\text{ridge}}) &= \sigma^2 \sum_{k=1}^p \frac{d_k^2 v_{ik}^2}{(d_k^2 + \lambda)^2} \\ \text{Cov}(\hat{\beta}^{\text{OLS}}) &= \sigma^2 (X^T X)^{-1} \\ &= \sigma^2 V \begin{bmatrix} \frac{1}{d_1^2} & & \\ & \ddots & \\ & & \frac{1}{d_p^2} \end{bmatrix} V^T \\ \text{Var}(\hat{\beta}_i^{\text{OLS}}) &= \sigma^2 \sum_{k=1}^p \frac{v_{ik}^2}{d_k^2} \end{aligned}$$

Since $\lambda > 0$, for $k = 1, \dots, p$, $\frac{d_k^2}{(d_k^2 + \lambda)^2} < \frac{1}{d_k^2}$. So

$$\sum_{k=1}^p \frac{d_k^2 v_{ik}^2}{(d_k^2 + \lambda)^2} < \sum_{k=1}^p \frac{v_{ik}^2}{d_k^2}$$

That is to say, $\text{Var}(\hat{\beta}_i^{\text{ridge}}) < \text{Var}(\hat{\beta}_i^{\text{OLS}})$ for $j = 1, \dots, p$.

Problem 3

See [attachment](#).