BIOS:7600 Homework 3

Chuan Lu

February 16, 2019

1. Problem 1.8

(a) Show that

$$\lim_{\lambda \to 0^+} \frac{\partial}{\partial \lambda} \sum_{j} \operatorname{Var}(\hat{\beta}_j) = -2 \frac{\sigma^2}{n} \sum_{j} d_j^{-2}.$$

Proof. Let $\frac{1}{n}X^{\top}X = QDQ^{\top}$. Then

$$\begin{aligned} \operatorname{Var}(\hat{\beta}) &= \sigma^{2} W X^{\top} X W = \sigma^{2} \frac{1}{n} (Q D Q^{\top} + n \lambda I)^{-1} n Q D Q^{\top} \frac{1}{n} (Q D Q^{\top} + n \lambda I)^{-1} \\ &= \sigma^{2} \frac{1}{n} Q (D + \lambda I)^{-1} D (D + \lambda I)^{-1} Q^{-1} \\ &= \sigma^{2} \frac{1}{n} Q \operatorname{diag} \{ \frac{d_{i}}{(d_{i} + \lambda)^{2}} \} Q^{-1}. \end{aligned}$$

Hence,

$$\frac{\partial}{\partial \lambda} \operatorname{Var}(\hat{\beta}_j) = \frac{\partial}{\partial \lambda} \left(\frac{\sigma^2}{n} \frac{d_j}{(d_j + \lambda)^2} \right) = \frac{\sigma^2}{n} d_j \frac{-2d_j - 2\lambda}{(d_j + \lambda)^4},$$

and

$$\lim_{\lambda \to 0^+} \frac{\partial}{\partial \lambda} \sum_j \mathrm{Var}(\hat{\beta}_j) = \lim_{\lambda \to 0^+} \sum_j \frac{\sigma^2}{n} d_j \frac{-2d_j}{d_j^4} = -2 \frac{\sigma^2}{n} \sum_j d_j^{-2}.$$

(b) Show that $\lim_{\lambda \to 0^+} \frac{\partial}{\partial \lambda} \text{Bias}^2(\hat{\beta}) = 0$.

Proof. First

$$MSE(\hat{\beta}) = \sum Var(\hat{\beta}_j) + \sum Bias^2(\hat{\beta}_j).$$

By (1.17) in https://arxiv.org/pdf/1509.09169;Lecture,

$$MSE(\hat{\beta}) = \sigma^{2} tr\{\frac{1}{n} Q A^{-1} D A^{-1} Q^{\top}\} + \beta^{\top} Q (A^{-1} D - I)^{\top} (A^{-1} D - I) Q^{\top} \beta,$$

where $A = D + \frac{1}{n}\lambda I$. By (a) we know the first term is just $Var(\hat{\beta})$, so

$$\begin{aligned} \operatorname{Bias}^2(\hat{\beta}) &= \beta^\top Q (A^{-1}D - I)^\top (A^{-1}D - I) Q^\top \beta \\ &= \alpha^\top \operatorname{diag}\{\frac{\frac{1}{n^2}\lambda}{(d_i + \frac{1}{n}\lambda)^2}\}\alpha, \end{aligned}$$

where $\alpha = Q^{\top}\beta$. Then

$$\lim_{\lambda \to 0^+} \frac{\partial}{\partial \lambda} \mathrm{Bias}^2(\hat{\beta}) = \lim_{\lambda \to 0^+} \alpha^\top \mathrm{diag} \{ \frac{\frac{2}{n^2} \lambda (d_i + \frac{1}{n} \lambda)^2 - \frac{2}{n^3} \lambda^2 (d_i + \frac{1}{n} \lambda)^2}{(d_i + \frac{1}{n} \lambda)^4} \} \alpha = 0.$$

2. Problem 1.10

Proof. By the definition of linear fitting models,

$$y_{i} - \hat{f}_{(-i)}(x_{i}) = y_{i} - \sum_{j=1, j \neq i}^{n} \tilde{s}_{ij} y_{j} = y_{i} - \sum_{j=1, j \neq i}^{n} \frac{s_{ij}}{1 - s_{ii}} y_{j}$$

$$= \frac{1}{1 - s_{ii}} y_{i} - \sum_{j=1}^{n} \frac{s_{ij}}{1 - s_{ii}} y_{j}$$

$$= \frac{y_{i} - \hat{f}(x_{i})}{1 - s_{ii}}.$$

Hence the equality holds.

3. Problem 1.11

(a) Based on OLS model, the most important variables are as follows: (ranked in descending order):

- hfa
- \bullet age
- aro
- $\begin{array}{l} \bullet \ \ \text{wght} \\ \bullet \ \ \text{afe} \end{array}$
- inc
- mc

wiiz

For ridge regression, we choose $\lambda = 0.1482021$ based on the results of GCV (varies from 10^{-5} to 10^{5}). The most important variables are:

- \bullet hfa
- age
- aro
- \bullet inc
- wght

- \bullet whz
- rr
- (b) For OLS model, the regression coefficient for age is -0.4096032, while for ridge regression, the coefficient is -0.2893046. This is mainly from the significant correlation of age with other variables (which is similar with Example 1.2).
- (c) The coefficients for both variables with both models are as follows: I think the influence of both variables on pneumonia should look

	absu	afe
OLS	-0.02698383	0.1531287
Ridge	0.0357972	0.08959214

similar since absu and afe are similar behaviours. In this case, I think the estimates of ridge regression should be more reasonable.