

Final exam, High-dimensional Data Analysis, 2018 Spring [+32 points]

Not only answer but also calculation

Name:

+8 Q1 Ridge regression [+8]: Consider a model without an intercept:

$$Y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2), \quad i=1, \dots, n. \text{ Assume } \sum_{i=1}^n x_{i1} = \sum_{i=1}^n x_{i2} = 0 \text{ and } \sum_{i=1}^n x_{i1}^2 = \sum_{i=1}^n x_{i2}^2 = 1.$$

$$\text{Let } r_{12} = \sum_{i=1}^n x_{i1} x_{i2}, \quad r_{1y} = \sum_{i=1}^n x_{i1} Y_i, \text{ and } r_{2y} = \sum_{i=1}^n x_{i2} Y_i, \text{ and assume } r_{12} = r_{1y} = r_{2y} = 1/2.$$

+3 (1) [+3] Derive the ridge estimators $\hat{\beta}_{1\lambda}$ and $\hat{\beta}_{2\lambda}$ (your answer should be simplified)

$$\begin{aligned} L &= (y - X\beta)^T (y - X\beta) - \lambda \beta^T \beta \\ L &= -2X^T(y - X\beta) - 2\lambda \beta^T \beta \stackrel{\text{set}}{=} 0 \\ \Rightarrow \hat{\beta} &= (X^T X + \lambda I)^{-1} X^T y \end{aligned}$$

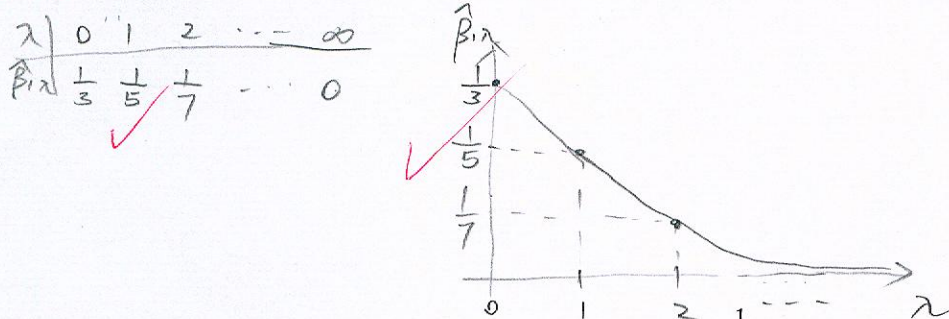
$$X = \begin{bmatrix} x_{11} & x_{12} \\ \vdots & \vdots \\ x_{n1} & x_{n2} \end{bmatrix} \quad X^T = \begin{bmatrix} x_{11} & \dots & x_{n1} \\ x_{12} & \dots & x_{n2} \end{bmatrix} \quad X^T X = \begin{bmatrix} \sum_{i=1}^n x_{i1}^2 & \sum_{i=1}^n x_{i1} x_{i2} \\ \sum_{i=1}^n x_{i1} x_{i2} & \sum_{i=1}^n x_{i2}^2 \end{bmatrix} = \begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix}$$

$$X^T y = \begin{bmatrix} \sum_{i=1}^n x_{i1} y_i \\ \sum_{i=1}^n x_{i2} y_i \end{bmatrix} = \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix}$$

$$\hat{\beta} = \left(\begin{bmatrix} 1 & 1/2 \\ 1/2 & 1 \end{bmatrix} + \lambda \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} 1+\lambda & 1/2 \\ 1/2 & 1+\lambda \end{bmatrix}^{-1} \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} \frac{1}{2\lambda+3} \\ \frac{1}{2\lambda+3} \end{bmatrix}$$

$$\therefore \hat{\beta}_{1\lambda} = \hat{\beta}_{2\lambda} = \frac{1}{2\lambda+3}$$

+2 (2) [+2] Draw the ridge trace for $\hat{\beta}_{1\lambda}$



+2 (3) [+2] Choose λ by setting $df_\lambda = 1$ and $r_{12} = \frac{1}{2}$.

$$\begin{aligned} df_\lambda &= \text{trace} [X (X^T X + \lambda I)^{-1} X^T] \\ &= \text{trace} [(X^T X + \lambda I)^{-1} X^T X] \\ &= \text{trace} \left(\frac{1}{(2\lambda+3)(2\lambda+1)} \begin{bmatrix} 4\lambda+3 & 2\lambda \\ 2\lambda & 4\lambda+3 \end{bmatrix} \right) = \frac{2(4\lambda+3)}{(2\lambda+3)(2\lambda+1)} \stackrel{\text{set}}{=} 1 \Rightarrow \lambda^2 = \frac{3}{4} \\ &\Rightarrow \lambda = \frac{\sqrt{3}}{2} \end{aligned}$$

+1 (4) [+1] Calculate the ridge estimates under the chosen value of λ .

$$\text{When } \lambda = \frac{\sqrt{3}}{2}$$

$$\hat{\beta}_{1\lambda} = \hat{\beta}_{2\lambda} = \frac{1}{2 \times \frac{\sqrt{3}}{2} + 3} = \frac{3 - \sqrt{3}}{6}$$

+8

Q2 Splines [+8]: Let $f(x) = \sum_{j=1}^k \beta_j M_j(x)$, where $M_j(x)$'s are the spline basis functions. For a knot sequence $\xi_1 < \xi_2 < \xi_3$ with $\Delta = \xi_2 - \xi_1 = \xi_3 - \xi_2$, let $z_i(t) = (t - \xi_i) / \Delta$ for $i = 1, 2$, and 3.

+2 (1) [+2] Write $\int f''(x)^2 dx$ in term of a quadratic form for $\beta = (\beta_1, \dots, \beta_k)^T$.

$$\begin{aligned} f(x) &= \sum_{j=1}^k \beta_j M_j(x) & \int f''(x)^2 dx & \\ f''(x) &= \sum_{j=1}^k \beta_j M_j''(x) & & \\ & & = \int \sum_{j=1}^k \beta_j M_j(x) \sum_{j'=1}^k \beta_{j'} M_{j'}(x) dx & = \sum_{j=1}^k \sum_{j'=1}^k \beta_j \beta_{j'} \int M_j(x) M_{j'}(x) dx \\ & & = \int \sum_{j=1}^k \sum_{j'=1}^k \beta_j \beta_{j'} M_j(x) M_{j'}(x) dx & = \beta^T \int M_j''(x) M_{j'}''(x) dx \beta \end{aligned}$$

+6 (2) [+6] Calculate $\int M_4''(t)^2 dt$,

where $M_4(t) = \frac{\mathbf{I}(\xi_1 \leq t < \xi_2)}{2\Delta} z_1(t)^3 + \frac{\mathbf{I}(\xi_2 \leq t < \xi_3)}{2\Delta} \{-7z_2(t)^3 + 3z_2(t)^2 + 3z_2(t) + 1\}$ $\mathbf{I}_1 = \mathbf{I}(\xi_1 \leq t < \xi_2)$
 $\mathbf{I}_2 = \mathbf{I}(\xi_2 \leq t < \xi_3)$

$$M_4(t) = \frac{\mathbf{I}_1}{2\Delta^2} z_1(t)^2 + \frac{\mathbf{I}_2}{2\Delta^2} \{-2z_2(t)^2 + 6z_2(t) + 3\}$$

$$M_4''(t) = \frac{3\mathbf{I}_1}{\Delta^3} z_1(t) + \frac{\mathbf{I}_2}{\Delta^3} \{-2z_2(t) + 3\}$$

$$\int M_4''(t)^2 dt = \int \left[\frac{3\mathbf{I}_1}{\Delta^3} z_1(t) + \frac{\mathbf{I}_2}{\Delta^3} \{-2z_2(t) + 3\} \right]^2 dt$$

$$= \int \frac{9\mathbf{I}_1}{\Delta^6} z_1(t)^2 dt + \int \frac{\mathbf{I}_2}{\Delta^6} \{-2z_2(t) + 3\}^2 dt$$

$$= \frac{9}{\Delta^6} \int_{\xi_1}^{\xi_2} z_1(t)^2 dt + \frac{9}{\Delta^6} \int_{\xi_2}^{\xi_3} \{7z_2(t) - 13\}^2 dt$$

$$49z_2^2 - 14z_2 + 1$$

$$= \frac{9}{\Delta^6} \left[\frac{\Delta}{3} \left(\frac{t - \xi_1}{\Delta} \right)^3 \right]_{\xi_1}^{\xi_2} + \left[\frac{49\Delta}{3} \left(\frac{t - \xi_2}{\Delta} \right)^3 - \frac{14\Delta}{2} \left(\frac{t - \xi_2}{\Delta} \right)^2 + \Delta \left(\frac{t - \xi_2}{\Delta} \right) \right]_{\xi_2}^{\xi_3}$$

$$= \frac{9}{\Delta^5} \left\{ \frac{1}{3} + \frac{49}{3} - \frac{14}{2} + 1 \right\} = \frac{96}{\Delta^5}$$

+8

Q3 Compound covariates [+8]: Consider a model without an intercept:

$$Y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \varepsilon_i, \quad \varepsilon_i \stackrel{iid}{\sim} N(0, \sigma^2), \quad i=1, \dots, n.$$

Assume $\sum_{i=1}^n x_{i1} = \sum_{i=1}^n x_{i2} = 0$ and $\sum_{i=1}^n x_{i1}^2 = \sum_{i=1}^n x_{i2}^2 = n$. Let $CC_i = \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2}$ be a compound covariate.

+2 (1) [+2] Derive $\hat{\beta}_1$ and $\hat{\beta}_2$ in the CC.

$$\hat{\beta}_1 = \underset{\beta_1}{\operatorname{argmax}} \sum_{i=1}^n (y_i - \beta_1 x_{i1})^2$$

$$L = \sum_{i=1}^n (y_i - \beta_1 x_{i1})^2$$

$$L' = -2 \sum_{i=1}^n x_{i1} (y_i - \beta_1 x_{i1}) \stackrel{\text{set } 0}{=} \Rightarrow \hat{\beta}_1 = \frac{\sum x_{i1} y_i}{\sum x_{i1}^2} = \frac{\sum x_{i1} y_i}{n}$$

the same as $\hat{\beta}_1$

$$\hat{\beta}_2 = \frac{\sum x_{i2} y_i}{\sum x_{i2}^2} = \frac{\sum x_{i2} y_i}{n}$$

+1 (2) [+1] Calculate $\sum_{i=1}^n CC_i$.

$$\sum_{i=1}^n CC_i = \sum_{i=1}^n (\hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2}) = \hat{\beta}_1 \sum x_{i1} + \hat{\beta}_2 \sum x_{i2} = 0$$

+5 (3) [+5] Let $\hat{Y}_i^{CC} = \hat{\gamma} CC_i$ be a predictor of Y_i . Derive $\hat{\gamma}$ in terms of $\hat{\beta}_1$, $\hat{\beta}_2$, and $r_{12} = \frac{1}{n} \sum_{i=1}^n x_{i1} x_{i2}$.

$$L = \sum_{i=1}^n (y_i - \hat{\gamma} CC_i)^2$$

$$L' = -2 \sum_{i=1}^n CC_i (y_i - \hat{\gamma} CC_i) \stackrel{\text{set } 0}{=} \Rightarrow \hat{\gamma} = \frac{\sum_{i=1}^n CC_i y_i}{\sum_{i=1}^n CC_i^2}$$

$$\Rightarrow \hat{\gamma} = \frac{\sum_{i=1}^n CC_i y_i}{\sum_{i=1}^n CC_i^2}$$

$$= \frac{\sum_{i=1}^n (\hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2}) y_i}{\sum_{i=1}^n (\hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2})^2}$$

$$= \frac{\hat{\beta}_1 \sum_{i=1}^n (x_{i1} y_i) + \hat{\beta}_2 \sum_{i=1}^n (x_{i2} y_i)}{\hat{\beta}_1^2 \sum_{i=1}^n x_{i1}^2 + \hat{\beta}_2^2 \sum_{i=1}^n x_{i2}^2 + 2 \hat{\beta}_1 \hat{\beta}_2 \sum_{i=1}^n x_{i1} x_{i2}}$$

$$\sum_{i=1}^n (x_{i1} y_i) = \hat{\beta}_1 \sum x_{i1}^2 = n \hat{\beta}_1^2$$
$$\sum_{i=1}^n (x_{i2} y_i) = \hat{\beta}_2 \sum x_{i2}^2 = n \hat{\beta}_2^2$$

$$= \frac{n \hat{\beta}_1^2 + n \hat{\beta}_2^2}{n \hat{\beta}_1^2 + n \hat{\beta}_2^2 + 2n r_{12} \hat{\beta}_1 \hat{\beta}_2}$$

$$= \frac{\hat{\beta}_1^2 + \hat{\beta}_2^2}{\hat{\beta}_1^2 + \hat{\beta}_2^2 + 2 \hat{\beta}_1 \hat{\beta}_2 r_{12}}$$

+8

Q4 Cross-validation [+8]: Data is given below:

y_i	x_i	h_i	\hat{y}_i
0	2	$\frac{25}{72}$	$\frac{13}{12}$
2	-2	$\frac{25}{72}$	$\frac{13}{12}$
3	0	$\frac{1}{8}$	$\frac{7}{4}$
4	-1	$\frac{13}{72}$	$\frac{25}{12}$
2	0	$\frac{1}{8}$	$\frac{7}{4}$
1	-2	$\frac{25}{72}$	$\frac{29}{12}$
0	1	$\frac{13}{72}$	$\frac{17}{12}$
2	2	$\frac{25}{72}$	$\frac{13}{12}$

$$X = \begin{bmatrix} 1 & 2 \\ 1 & -2 \\ 1 & 0 \\ 1 & -1 \\ 1 & 0 \\ 1 & -2 \\ 1 & 1 \\ 1 & 2 \end{bmatrix}$$

$$X^T X = \begin{bmatrix} 8 & 0 \\ 0 & 18 \end{bmatrix}$$

$$(X^T X)^{-1} = \begin{bmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{bmatrix}$$

$$X^T y = \begin{pmatrix} 14 \\ -6 \end{pmatrix}$$

$$X^T = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & -2 & 0 & -1 & 0 & -2 & 1 & 2 \end{bmatrix} \begin{bmatrix} 0 \\ 2 \\ 4 \\ 2 \\ 0 \\ 1 \\ 2 \\ 0 \end{bmatrix}$$

+2 (1) [+2] Compute the leverage h_i in the table above. Write the fraction (e.g., 1/2, not 0.5)

$$h_i = x_i^T (X^T X)^{-1} x_i$$

$$\textcircled{2}: (1 \ -2) \begin{pmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{pmatrix} \begin{pmatrix} 1 \\ -2 \end{pmatrix} = \frac{25}{72}$$

$$\textcircled{4}: (1 \ 1) \begin{pmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \frac{13}{72}$$

$$\textcircled{1}: (1 \ 2) \begin{pmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{pmatrix} \begin{pmatrix} 1 \\ 2 \end{pmatrix} = \frac{25}{72}$$

$$\textcircled{3}: (1 \ 0) \begin{pmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{pmatrix} \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \frac{1}{8}$$

$$\textcircled{5}: (1 \ -1) \begin{pmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{pmatrix} \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \frac{1}{72}$$

+2 (2) [+2] Compute the predictor \hat{y}_i in the above table

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

$$= \begin{bmatrix} \frac{1}{8} & 0 \\ 0 & \frac{1}{18} \end{bmatrix} \begin{pmatrix} 14 \\ -6 \end{pmatrix} = \begin{pmatrix} \frac{7}{4} \\ -\frac{1}{3} \end{pmatrix} \Rightarrow \hat{y}_i = \frac{7}{4} - \frac{1}{3} x_i$$

+2 (3) [+2] Compute the training MSE

$$MSE = \frac{1}{8} \sum_{i=1}^8 (y_i - \hat{y}_i)^2$$

$$= \frac{1}{8} \left\{ (0 - \frac{13}{12})^2 + (2 - \frac{29}{12})^2 + (3 - \frac{7}{4})^2 + (4 - \frac{25}{12})^2 + (2 - \frac{7}{4})^2 + (1 - \frac{29}{12})^2 + (0 - \frac{17}{12})^2 + (2 - \frac{13}{12})^2 \right\}$$

$$= \frac{1}{8} \left\{ (-\frac{13}{12})^2 + (-\frac{5}{12})^2 + (\frac{5}{4})^2 + (\frac{23}{12})^2 + (\frac{1}{4})^2 + (-\frac{17}{12})^2 + (-\frac{17}{12})^2 + (\frac{11}{12})^2 \right\}$$

+2 (4) [+2] Compute the testing MSE by LOOCV (use h_i)

$$LOOCV = \frac{1}{8} \sum_{i=1}^8 \left(\frac{y_i - \hat{y}_i}{1 - h_i} \right)^2$$

$$= \frac{1}{8} \left\{ \frac{169}{64} + \frac{25}{64} + \frac{100}{49} + \frac{19044}{3481} + \frac{4}{49} + \frac{10164}{2209} + \frac{10404}{3481} + \frac{4356}{2209} \right\}$$

$$= 2.5369$$