

Modern Statistical Methods — Example Sheet 3

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In all of the below, assume that any design matrices X are $n \times p$ and have their columns centred and then scaled to have ℓ^2 -norm \sqrt{n} , and that any responses $Y \in \mathbb{R}^n$ are centred.

Question 1. *When proving the theorems on the prediction error of the Lasso, we started with the so-called basic inequality that*

$$\frac{1}{2n} \|X(\beta^0 - \hat{\beta})\|_2^2 \leq \frac{1}{n} \varepsilon^\top X(\hat{\beta} - \beta^0) + \lambda \|\beta^0\|_1 - \lambda \|\hat{\beta}\|_1.$$

Show that in fact we can improve this to

$$\frac{1}{n} \|X(\beta^0 - \hat{\beta})\|_2^2 \leq \frac{1}{n} \varepsilon^\top X(\hat{\beta} - \beta^0) + \lambda \|\beta^0\|_1 - \lambda \|\hat{\beta}\|_1.$$

Proof. By the KKT conditions, we there exists $\hat{\nu} \in \mathbb{R}^p$ with $\|\hat{\nu}\|_\infty \leq 1$ and $\langle \hat{\nu}, \hat{\beta} \rangle = \|\hat{\beta}\|_1$ such that

$$\begin{aligned} \frac{1}{n} X^\top (Y - X\hat{\beta}) &= \lambda \hat{\nu} \\ \frac{1}{n} X^\top (X(\beta^0 - \hat{\beta}) + \varepsilon) &= \lambda \hat{\nu} \\ \frac{1}{n} X^\top X(\beta^0 - \hat{\beta}) &= -\frac{1}{n} X^\top \varepsilon + \lambda \hat{\nu} \\ \frac{1}{n} (\beta^0 - \hat{\beta})^\top X^\top X(\beta^0 - \hat{\beta}) &= -\frac{1}{n} (\beta^0 - \hat{\beta})^\top X^\top \varepsilon + \lambda (\beta^0 - \hat{\beta})^\top \hat{\nu} \\ \frac{1}{n} \|X(\beta^0 - \hat{\beta})\|_2^2 &= \frac{1}{n} \varepsilon^\top X(\hat{\beta} - \beta^0) + \lambda \langle \hat{\nu}, \beta^0 \rangle - \lambda \|\hat{\beta}\|_1, \end{aligned}$$

and now plugging in $\langle \beta^0, \hat{\nu} \rangle \leq \|\beta^0\|_1 \|\hat{\nu}\|_\infty \leq \|\beta^0\|_1$ yields the result. \square

Question 2. *Under the assumptions of Theorem 23 on the prediction and estimation properties of the Lasso under a compatibility condition, show that, with probability $1 - 2p^{-(A^2/8-1)}$, we have*

$$\frac{1}{n} \|X(\beta^0 - \hat{\beta})\|_2^2 \leq \frac{9A^2 \log(p)}{4\varphi^2} \frac{\sigma^2 s}{n}.$$