

University of Luxembourg

THESIS FOR THE BACHELOR OF MATHEMATICS

High Dimensional Regression Models

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Chapter 1

Introduction

1.1 The first section

1.1.1 The first subsection

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{1.1}$$

We define $\hat{\beta}$ as follows

$$\hat{\beta} := \arg\min_{\beta} \left\{ \frac{\|\mathbf{Y} - \mathbf{X}\beta\|_2^2}{n} + \lambda \|\beta\|_1 \right\}$$
 (1.2)

Lemma 1.1 (Basic Inequality).

$$\frac{\|\mathbf{X}(\hat{\beta} - \beta^0)\|_2^2}{n} + \lambda \|\hat{\beta}\|_1 \le 2\frac{\varepsilon^T \mathbf{X}(\hat{\beta} - \beta^0)}{n} + \lambda \|\beta^0\|_1$$

Proof. By definition of $\hat{\beta}$, we have that

$$\forall \beta \quad \frac{\|\mathbf{Y} - \mathbf{X}\hat{\beta}\|_2^2}{n} + \lambda \|\hat{\beta}\|_1 \leq \frac{\|\mathbf{Y} - \mathbf{X}\beta\|_2^2}{n} + \lambda \|\beta\|_1$$

In particular for $\beta = \beta^0$ we have

$$\frac{\|\mathbf{Y} - \mathbf{X}\hat{\beta}\|_{2}^{2}}{n} + \lambda \|\hat{\beta}\|_{1} \leq \frac{\|\mathbf{Y} - \mathbf{X}\beta^{0}\|_{2}^{2}}{n} + \lambda \|\beta^{0}\|_{1}$$

We now replace \mathbf{Y} using equation (1.1).

$$\frac{\|\mathbf{Y} - \mathbf{X}\hat{\boldsymbol{\beta}}\|_{2}^{2}}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{\|\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}^{0}\|_{2}^{2}}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|(\mathbf{X}\boldsymbol{\beta}^{0} + \boldsymbol{\varepsilon}) - \mathbf{X}\hat{\boldsymbol{\beta}}\|_{2}^{2}}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{\|(\mathbf{X}\boldsymbol{\beta}^{0} + \boldsymbol{\varepsilon}) - \mathbf{X}\boldsymbol{\beta}^{0}\|_{2}^{2}}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|\mathbf{X}(\boldsymbol{\beta}^{0} - \hat{\boldsymbol{\beta}}) + \boldsymbol{\varepsilon}\|_{2}^{2}}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{\|\mathbf{X}(\boldsymbol{\beta}^{0} - \boldsymbol{\beta}^{0}) + \boldsymbol{\varepsilon}\|_{2}^{2}}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|\mathbf{X}(\boldsymbol{\beta}^{0} - \hat{\boldsymbol{\beta}}) + \boldsymbol{\varepsilon}, \mathbf{X}(\boldsymbol{\beta}^{0} - \hat{\boldsymbol{\beta}}) + \boldsymbol{\varepsilon}\rangle}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{\|\boldsymbol{\varepsilon}\|_{2}^{2}}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|\mathbf{X}(\boldsymbol{\beta}^{0} - \hat{\boldsymbol{\beta}})\|_{2}^{2} + \|\boldsymbol{\varepsilon}\|_{2}^{2} + 2\langle \mathbf{X}(\boldsymbol{\beta}^{0} - \hat{\boldsymbol{\beta}}), \boldsymbol{\varepsilon}\rangle}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{\|\boldsymbol{\varepsilon}\|_{2}^{2}}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|\mathbf{X}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^{0})\|_{2}^{2}}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{2\langle \mathbf{X}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^{0}), \boldsymbol{\varepsilon}\rangle}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

$$\Rightarrow \frac{\|\mathbf{X}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^{0})\|_{2}^{2}}{n} + \lambda \|\hat{\boldsymbol{\beta}}\|_{1} \leq \frac{2\boldsymbol{\varepsilon}^{T}\mathbf{X}(\hat{\boldsymbol{\beta}} - \boldsymbol{\beta}^{0})}{n} + \lambda \|\boldsymbol{\beta}^{0}\|_{1}$$

Let

$$\mathscr{T} := \left\{ \max_{1 \le j \le p} 2 \frac{\left| \varepsilon^T \mathbf{X}^{(j)} \right|}{n} \le \lambda_0 \right\}$$

Lemma 1.2 (Lemma 6.2.). For all t > 0 and

$$\lambda_0 := 2\sigma \sqrt{\frac{t^2 + 2\log p}{n}}$$

we have

$$\mathbb{P}(\mathscr{T}) \geq 1 - 2 \exp\left[-t^2/2\right]$$

Proof. We define

$$V_j := \frac{\varepsilon^T \mathbf{X}^{(j)}}{\sqrt{n\sigma^2}}$$

Then we have

$$\mathbb{P}(\mathscr{T}) = \mathbb{P}\left(\left\{\max_{1 \le j \le p} 2 \frac{\left|\varepsilon^T \mathbf{X}^{(j)}\right|}{n} \le 2\sigma\sqrt{\frac{t^2 + 2\log p}{n}}\right\}\right)$$

$$= \mathbb{P}\left(\left\{\max_{1 \le j \le p} \frac{\varepsilon^T \mathbf{X}^{(j)}}{\sqrt{n\sigma^2}} \le \sqrt{t^2 + 2\log p}\right\}\right)$$

$$= \mathbb{P}\left(\left\{\max_{1 \le j \le p} |V_j| \le \sqrt{t^2 + 2\log p}\right\}\right)$$

$$= 1 - \mathbb{P}\left(\left\{\max_{1 \le j \le p} |V_j| > \sqrt{t^2 + 2\log p}\right\}\right)$$

Theorem 1.3 (Compatibility condition). We say that the compatibility condition is met for the set S_0 , if for some $\phi_0 > 0$, and for all β satisfying $\|\beta_{S_0^c}\|_1 \leq 3 \|\beta_{S_0}\|_1$, it holds that

 $\|\beta_{S_0}\|_1^2 \le \left(\beta^T \hat{\Sigma}\beta\right) s_0/\phi_0^2$

Theorem 1.4 (Theorem 6.1.). Suppose the compatibility condition holds for S_0 . Then on \mathcal{T} , we have for $\lambda \geq 2\lambda_0$,

$$\left\| \mathbf{X} \left(\hat{\beta} - \beta^0 \right) \right\|_2^2 / n + \lambda \left\| \hat{\beta} - \beta^0 \right\|_1 \le 4\lambda^2 s_0 / \phi_0^2$$

Theorem 1.5 (Compatibility condition for general sets). We say that the compatibility condition holds for the set S, if for some constant $\phi(S) > 0$, and for all β , with $\|\beta_{S^c}\|_1 \leq 3 \|\beta_S\|_1$, one has

$$\|\beta_S\|_1^2 \le \left(\beta^T \hat{\Sigma} \beta\right) |S|/\phi^2(S)$$

To be added

- how to get \hat{b} on page 101.
- where the χ^2 distribution comes from in page 101