

Exercise 1. For $y \in \mathbb{R}^n$, $X \in \mathbb{R}^{n \times n}$ and $\lambda > 0$, derive the formula to implement a subgradient step for the Ridge Regression

$$\argmin_{\alpha} \frac{1}{2} \|y - X\alpha\|_2^2 + \lambda \|\alpha\|_2^2$$

— The Lasso

$$\argmin_{\alpha} \frac{1}{2} \|y - X\alpha\|_2^2 + \lambda \|\alpha\|_1$$

Relaxation:

Initialize α vector

← Warm start

for i in range(n):

$$\alpha_i = \argmin_{\alpha_i} \|y - X\alpha\|_2^2 + \lambda \|\alpha\|_2^2$$

explicit formula

Optimal descent

Initialize α vector

while not done:

$$\begin{aligned} \text{subdifferential} &= \text{subdifferential}(f(\alpha)) \\ i &= \text{max index (subdifferential)} \\ \alpha_i &= \argmin_{\alpha_i} \|y - X\alpha\|_2^2 + \lambda \|\alpha\|_2^2 \end{aligned}$$

Relaxation: more steps required

+ easier to implement (no subdifferentials → error prone)

CV time + ?

Fix $i \rightarrow$ calculate optimal i -th coordinate given all the others

$$\argmin_{\alpha_i} \frac{1}{2} \|y - X_{-i}\alpha_{-i} - \alpha_i x_i\|_2^2 + \lambda \|\alpha\|_2^2$$

$$\argmin_{\alpha_i} \frac{1}{2} \|y - X_{-i}\alpha_{-i} - \alpha_i x_i\|_2^2 + \lambda \alpha_i^2$$

$$\left[\text{Reminder: } \argmin_{\alpha} \frac{1}{2} \|X\alpha - y\|_2^2 + \lambda \|\alpha\|_2^2 = (X^T X + \lambda I)^{-1} X^T y \right]$$

$$= (x_i^T x_i + \lambda)^{-1} x_i^T D$$

$$= \frac{x_i^T D}{\|x_i\|_2^2 + \lambda}$$

$$\left[\text{Reminder: } \argmin_{\alpha \in \mathbb{R}} \frac{1}{2} \|X\alpha - y\|_2^2 + \lambda |\alpha| = \text{sign}(\langle x, y \rangle) \left(\frac{|\langle x, y \rangle| - \lambda}{\|x\|_2^2} \right)_+ \right]$$

$$\argmin_{\alpha_i} \frac{1}{2} \|X\alpha - y\|_2^2 + \lambda \|\alpha\|_2^2$$

$$= \argmin_{\alpha_i} \frac{1}{2} \|y - X_{-i}\alpha_{-i} - \alpha_i x_i\|_2^2 + \lambda \alpha_i^2$$

$$= \text{sign}(\langle x_i, D \rangle) \left(\frac{|\langle x_i, D \rangle| - \lambda}{\|x_i\|_2^2} \right)_+$$