

Q: What is $\hat{\beta}^{\text{lasso}}$ for $Y = X\beta + \varepsilon$ where X is orthonormal design matrix

Orthonormal design matrix:

$$X$$

 $N \times p$

see also
example 6.4
in WNVW

$$\begin{matrix} X^T X & = & I \\ \uparrow & & \uparrow \\ p \times N & N \times p & p \times p \end{matrix}$$

← $\text{corr} = 0$ all pairs of x 's

$$\min_{\beta} \left((Y - X\beta)^T (Y - X\beta) + \lambda \sum_{j=1}^p |\beta_j| \right)$$

$$= \min_{\beta} \left(Y^T Y - 2\beta^T \underbrace{X^T Y}_{\hat{\beta}_{LS}} + \beta^T \underbrace{X^T X}_I \beta + \lambda \sum |\beta_j| \right)$$

$$\hat{\beta}_{LS} = (\underbrace{X^T X}_I)^{-1} X^T Y = X^T Y$$

$$\propto \min_{\beta} \left(-2\beta^T \hat{\beta}_{LS} + \beta^T \beta + \lambda \sum |\beta_j| \right)$$

$$\underbrace{\beta_1 \hat{\beta}_{LS1} + \beta_2 \hat{\beta}_{LS2} + \dots}_{\beta_1^2 + \beta_2^2 + \dots}$$

$$= \min_{\beta} \left(-2 \sum_{j=1}^p \beta_j \cdot \hat{\beta}_{LSj} + \sum_{j=1}^p \beta_j^2 + \lambda \sum_{j=1}^p |\beta_j| \right)$$

$$= \min_{\beta_1, \dots, \beta_p} \sum_{j=1}^p \left(-2\beta_j \hat{\beta}_{LSj} + \beta_j^2 + \lambda |\beta_j| \right)$$

$$= \sum_{j=1}^p \min_{\beta_j} \left(-2\beta_j \hat{\beta}_{LSj} + \beta_j^2 + \lambda |\beta_j| \right)$$

can handle each j separately!

Let $\text{loss}(\beta_j) = -2\hat{\beta}_{LSj}\beta_j + \beta_j^2 + \lambda|\beta_j| \leftarrow \text{minimize wrt } \beta_j$

Dropping j 's and LS for ease of notation.

We want to find $\underline{\beta}$ such that $-2\hat{\beta}\beta + \beta^2 + \lambda|\beta|$ is minimal

$\beta \geq 0$

$$-2\hat{\beta}\beta + \beta^2 + \lambda\beta = \beta^2 - 2(\hat{\beta} - \frac{1}{2}\lambda)\beta + (\hat{\beta} - \frac{1}{2}\lambda)^2 - (\hat{\beta} - \frac{1}{2}\lambda)^2$$

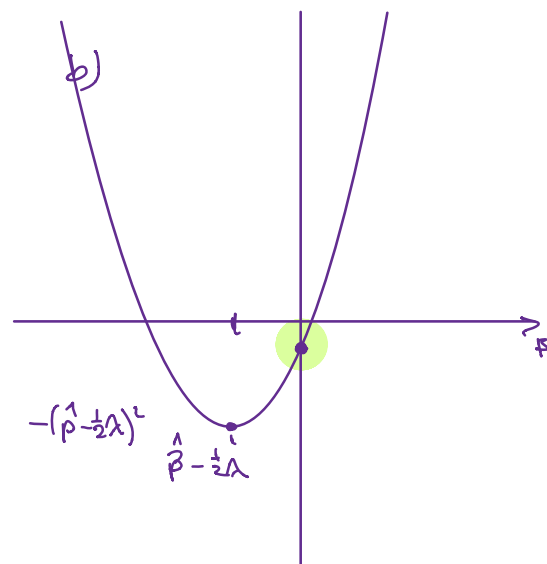
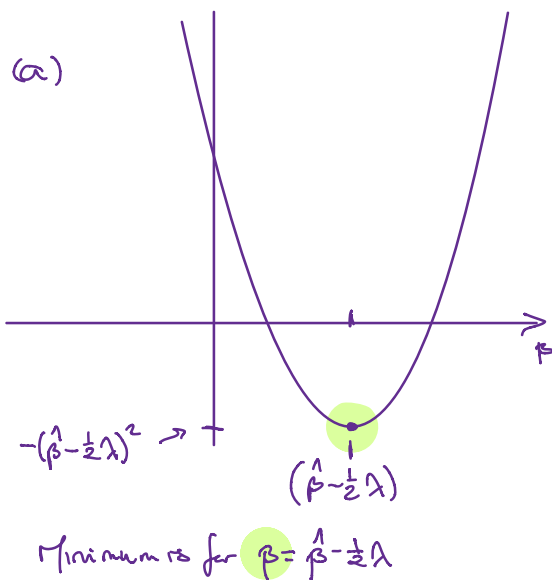
completing sq.

$$= (\beta - (\hat{\beta} - \frac{1}{2}\lambda))^2 - (\hat{\beta} - \frac{1}{2}\lambda)^2$$

$$(\beta - a)^2 - a^2$$

Look at $(\hat{\beta} - \frac{1}{2}\lambda) \geq 0$
(a)

$(\hat{\beta} - \frac{1}{2}\lambda) < 0$
(b)



We required that $\beta \geq 0$, thus
revers the minimum is at $\beta = 0$

In conclusion: for $\beta \geq 0$

$$\beta = \max(\hat{\beta} - \frac{1}{2}\lambda, 0) \text{ gives the minimum}$$

$$\underline{\beta < 0} \quad -2\hat{\rho}\beta + \beta^2 - \lambda\beta = \beta^2 - 2(\hat{\rho} + \frac{1}{2}\lambda)\beta + (\hat{\rho} + \frac{1}{2}\lambda)^2 - (\hat{\rho} + \frac{1}{2}\lambda)^2$$

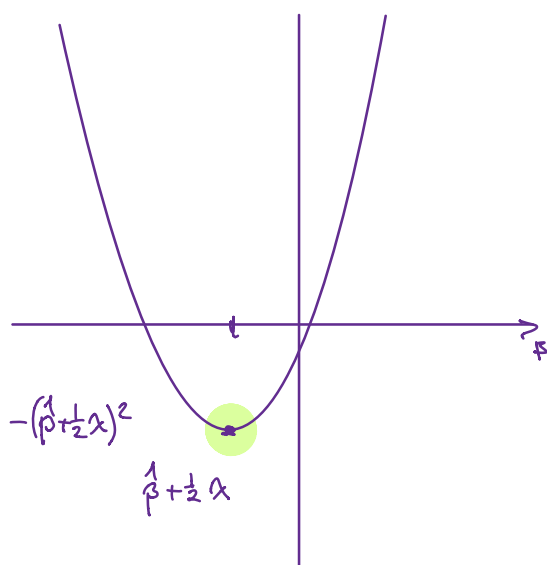
$$= (\beta - (\hat{\rho} + \frac{1}{2}\lambda))^2 - (\hat{\rho} + \frac{1}{2}\lambda)^2$$

$$(b - a)^2 - a^2$$

$$a = \hat{\rho} + \frac{1}{2}\lambda$$

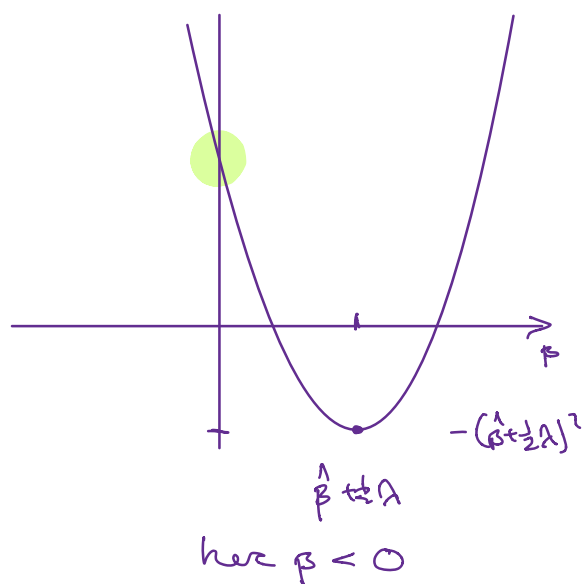
Some type of argument as above: Among $\beta \geq 0$ we find the minimum at $\beta = \min(\hat{\rho} + \frac{1}{2}\lambda, 0)$

(a) $\hat{\rho} + \frac{1}{2}\lambda \leq 0$



minimum at $\beta = (\hat{\rho} + \frac{1}{2}\lambda)$

(b) $\hat{\rho} + \frac{1}{2}\lambda > 0$



minimum at $\beta = 0$

$$\beta = \min(\hat{\rho} + \frac{1}{2}\lambda, 0)$$

We need to combine the two results:

$$\begin{aligned}\beta &= \max(\hat{\beta} - \frac{1}{2}\Lambda, 0) && \text{for } \beta \geq 0 \\ \beta &= \min(\hat{\beta} + \frac{1}{2}\Lambda, 0) && \text{for } \beta < 0 \quad (\text{could be } \beta \leq 0 \text{ really})\end{aligned}$$

And prefer to do that conditional on values of $\hat{\beta}$ and not of β (as so far)

$$\hat{\beta} < -\frac{1}{2}\Lambda : \quad \beta = \hat{\beta} + \frac{1}{2}\Lambda$$

\uparrow i.e. negative

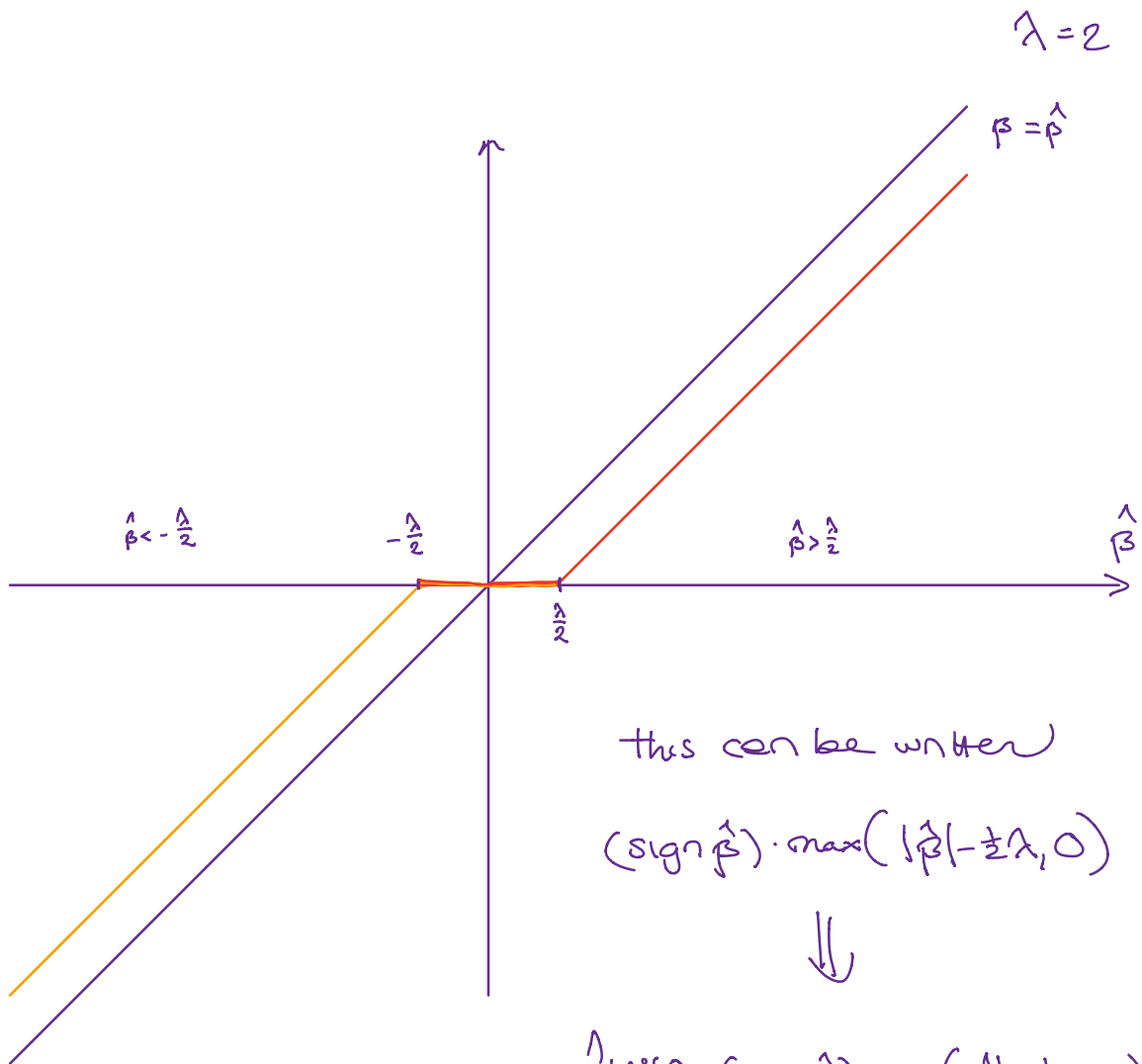
$$-\frac{1}{2}\Lambda \leq \hat{\beta} \leq \frac{1}{2}\Lambda : \quad \beta = 0$$

$$\hat{\beta} \geq \frac{1}{2}\Lambda : \quad \beta = \hat{\beta} - \frac{1}{2}\Lambda$$

\uparrow i.e. positive

\Rightarrow this is combined into

$$\begin{aligned}& \text{sgn}(\hat{\beta}) \cdot \max(|\hat{\beta}| - \frac{1}{2}\Lambda, 0) \\ &= \text{sgn}(\hat{\beta}) \left(|\hat{\beta}| - \frac{1}{2}\Lambda \right)_+\end{aligned}$$



this can be written

$$(\text{sign } \hat{\beta}) \cdot \max(|\hat{\beta}| - \frac{1}{2}\lambda, 0)$$

\Downarrow

$$\hat{\beta}^{\text{Lasso}} = (\text{sign } \hat{\beta}) \max(|\hat{\beta}| - \frac{1}{2}\lambda, 0)$$

$$= (\text{sign } \hat{\beta}) (|\hat{\beta}| - \frac{1}{2}\lambda)_+$$

NB: $\hat{\beta} = \hat{\beta}_{\text{LS}_j}$ and $\hat{\beta}^{\text{Lasso}} = \hat{\beta}_{\text{Lasso}_j}$