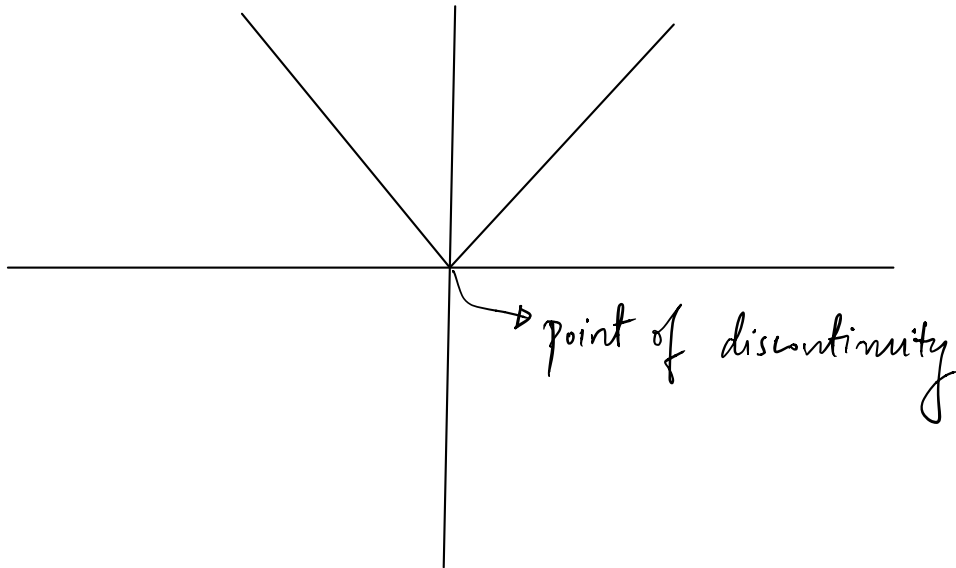


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Answer :  $L(w) = \frac{1}{2} \|x-w\|_2^2 + \lambda \|w\|_1$

This function is continuous on both positive and negative sides except at zero. This is shown below.



Because of this we cannot differentiate  $L(w)$  directly. We need to split  $L(w)$  into ranges (ve & -ve)

$$\|w\|_1 = \begin{cases} +w & \text{if } w > 0 \\ -w & \text{if } w < 0 \\ 0 & \text{otherwise} \end{cases}$$

$$L(w) = \frac{1}{2} \|x - w\|_2^2 + \lambda \|w\|_1$$

Differentiate  $L(w)$  in the positive range of  $w$

$$L(w) = \frac{1}{2} \|x - w\|_2^2 + \lambda \sum w_i$$

where all  $w_i$  are positive

This  $L(w)$  can be differentiated.

$$\frac{dL(w)}{dw} = \frac{1}{2} \cdot 2 \cdot (x - w)(-1) + \lambda$$

$$0 = -(x - w) + \lambda$$

$$x - w = \lambda$$

$$\boxed{w = x - \lambda}$$

$$\text{Here, } w_i > 0 \quad \therefore (x - \lambda) > 0 \rightarrow \boxed{x > \lambda}$$

|||  $\therefore$  Differentiate  $L(w)$  in the negative range of  $w$

$$L(w) = \frac{1}{2} \|x - w\|_2^2 - \lambda \sum w_i$$

$$\frac{dL(w)}{dw} = (-1)(x - w) - \lambda$$

$$(w - x) - \lambda = 0$$

$$w - x = \lambda$$

$$\boxed{w = \lambda + x}$$

Here,  $w < 0$

$$\lambda + x < 0 \rightarrow \lambda < -x \rightarrow \boxed{x < -\lambda}$$

So, the optimal values of  $w$  are

$$w_i^* = \begin{cases} x - \lambda & x > \lambda \\ x + \lambda & x < -\lambda \\ 0 & \text{otherwise} \end{cases}$$

① Answer :

a) All parameters  $w$  are free to be determined

$R(w) = \text{Elastic Net}$

This allows all parameters  $w$  to be determined.  $L_1$  and  $L_2$  can be controlled using  $\lambda_1$  and  $\lambda_2$ . Therefore all values of lasso or ridge are possible.

b)  $w$  should be sparse

$R(w) = L_1 \text{ Norm}$

The reason for using  $L_1$  norm is its shape. It has spikes that occur at sparse points. If this is used to get a solution it is very likely to touch a point on the spike tip. Thereby giving a sparse solution.

c) The coefficients of  $w$  should be small in magnitude on average

$R(w) = L_2 \text{ Norm}$ .  $L_2 \text{ Norm}$  minimizes all the coefficients without making them zero and minimization of the coefficients will be lesser than that of  $L_1$ .

d) For most indices  $j$ ,  $w_j$  should be equal to  $w_{j-1}$

$$R(w) = \sum_{i=1}^{d-1} (w_i - w_{i+1})^2$$

e)  $w$  should have no negative-valued coefficients

$$R(w) = L_1 \text{ Norm}$$