

CSCI 6968 Weekly Participation 4

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1 Question

Consider the ordinary least square problem with L-1 norm.

$$\arg \min_{x \in \mathbb{R}} \frac{1}{2}(x - a)^2 + \lambda |x|$$

1. Argue that this is a convex optimization problem and has a unique solution given any a .

Solution:

We know that x^2 is a strictly convex function. $x - a$ is an affine function which is convex in nature, but $(x - a)^2$ is the composition of a strictly convex function and a convex function. So, it is also strictly convex. $|x|$ is a convex function. The sum of two convex functions is convex. Also, we can say this is strictly convex as we have a quadratic function. Alternatively, if we find the hessian of the function,

$$f(x) = \frac{1}{2}(x - a)^2 + \lambda |x|$$
$$\nabla^2 f(x) = 1 > 0$$

Hence, As the loss function is strictly convex, it can have a unique solution.

2. Let $S_\lambda(a)$ be the unique solution to this optimization problem, given an a . State Fermat's optimality condition as concisely as you can, using our rules for subdifferential manipulations.

Solution:

First, computing the subgradient of the loss function.

$$\partial f(x) = \begin{cases} \{x - a + \lambda\} & x > 0 \\ \{x - a - \lambda\} & x < 0 \\ [x - a - \lambda, x - a + \lambda] & x = 0 \end{cases}$$

So, according to Fermat's optimality condition, $x^* \in \arg \min_{x \in \mathbb{R}} f(x)$ iff $0 \in \partial f(x^*)$.

$$0 \in \partial f(x^*) = \begin{cases} \{x^* - a + \lambda\} & x^* > 0 \\ \{x^* - a - \lambda\} & x^* < 0 \\ [x^* - a - \lambda, x^* - a + \lambda] & x^* = 0 \end{cases}$$

3. Use Fermat's optimality condition to find an expression for $s_\lambda(a)$, and draw a plot of s_λ .

Solution:

$$s_{\lambda}(a) = \begin{cases} a - \lambda & x > \lambda \\ a + \lambda & x < -\lambda \\ 0 & -\lambda \leq x \leq \lambda \end{cases}$$

