

proof: $f^*(y)$ is convex, where $f^*(y) = \max_{x \in \mathbb{R}^n} y^T x - f(x)$

Let's denote $g_x(y) := y^T x - f(x)$. Note that

function $g_x(y)$ is linear w.r.t y . Thus $g_x(y)$ is convex w.r.t y . By convexity of $g_x(y)$ we

have

$$g_x(tz + (1-t)s) \leq t g_x(z) + (1-t) g_x(s) \quad \forall x \in \mathbb{R}^n$$

Let's take the maximum

$$\max_{x \in \mathbb{R}^n} g_x(tz + (1-t)s) \leq \max_{x \in \mathbb{R}^n} t g_x(z) + (1-t) g_x(s)$$

$$\leq t \max_{x \in \mathbb{R}^n} g_x(z) + (1-t) \max_{x \in \mathbb{R}^n} g_x(s)$$

~~By~~ By definition we have that

$$f^*(y) = \max_{x \in \mathbb{R}^n} g_x(y)$$

Thus using the above inequality we get

$$f^*(tz + (1-t)s) \leq t f^*(z) + (1-t) f^*(s)$$

$\Rightarrow f^*(y)$ is convex.

Convex conjugate of ℓ_1 -norm

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$$F^*(\gamma) = \max_x x^T \gamma - \|x\|_1$$
$$= \max_x \sum_{i=1}^n x_i y_i - \sum_{i=1}^n |x_i|$$

$$= \max_x \sum_{i=1}^n x_i y_i - |x_i|$$

$$= \sum_{i=1}^n \max_{x_i} x_i y_i - |x_i|$$

using separability
of the function w.r.t
 x_i .)

Let's work with $\max_{x_i} x_i y_i - |x_i| = \max_{x_i} x_i y_i - x_i \text{sign}(x_i)$

$$= \max_{x_i} x_i (y_i - \text{sign}(x_i))$$

Say $y_i > 1$ then if $x_i = +\infty$ the maximum

is $+\infty$

Say $y_i < -1$ then if $x_i = -\infty$ the maximum

is $+\infty$.

say $-1 \leq y_i \leq 1$ then maximum is attained for $x_i = 0$ which gives maximum value equal to zero. Thus

$$\max_{x_i} x_i y_i - |x_i| = \begin{cases} 0 & \text{if } |y_i| \leq 1 \\ +\infty & \text{otherwise} \end{cases}$$

Thus

$$f^*(y) = \sum_{i=1}^n \max_{x_i} x_i y_i - |x_i| = \begin{cases} 0 & \text{if } \|y\|_\infty \leq 1 \\ +\infty & \text{otherwise} \end{cases}$$

Proof that : $f(x) - HD \leq f_H(x) \leq f(x)$

Let's prove the upper bound.

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$$f_{\mu}(x) = \max_{y \in \text{dom } f^*} x^T y - f^*(y) - \mu \partial(y)$$

$$\leq \max_{y \in \text{dom } f^*} x^T y - f^*(y) + \max_{y \in \text{dom } f^*} -\mu \partial(y)$$

$$= f(x) + \max_{y \in \text{dom } f^*} -(-\mu \partial(y))$$

$$= f(x) - \min_{y \in \text{dom } f^*} \mu \partial(y)$$

But we assumed that $\min_{y \in \text{dom } f^*} \partial(y) = 0$, thus
we get

$$f_{\mu}(x) \leq f(x).$$

proof $f(x) - \mu D \leq f_H(x) \leq f(x)$

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where $D = \sup_{y \in \text{dom } f^*} \partial(y)$

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We assumed that $\text{dom } f^* \subseteq \mathbb{R}^n$ is closed and bounded. This means that $\text{dom } f^*$ is compact. We also assumed that $\partial(y)$ is continuous. These assumptions imply that

$$\max_{y \in \text{dom } f^*} \partial(y) < +\infty \Rightarrow D < +\infty, \quad \left[\text{Weierstrass extreme value theorem} \right]$$

Let's prove $f(x) - \mu D \leq f_H(x)$:

$$\begin{aligned} f_H(x) &= \max_{y \in \text{dom } f^*} x^T y - f^*(y) - \mu \partial(y) \\ &\geq \max_{y \in \text{dom } f^*} x^T y - f^*(y) - \mu \cdot D \\ &= f(x) - \mu D \end{aligned}$$