

$$h_y(x) = \langle y, x \rangle$$

$$h_y: x \rightarrow \langle y, x \rangle$$

$$\|x\|_p = \left(\sum_{i=1}^n |x_i|^p \right)^{\frac{1}{p}}$$

Dual Norm.

$$\|z\|_* := \sup_{\|x\| \leq 1} \langle z, x \rangle.$$

Hölder's Inequality.

$$\forall z, x \in \mathbb{R}^d. \quad |\langle z, x \rangle| \leq \|z\|_* \|x\| \quad \checkmark \text{ fix } x$$

$$\text{pf: } \|z\|_* = \sup_{\|x\| \leq 1} \langle z, x \rangle = \sup_x \langle z, \frac{x}{\|x\|} \rangle \geq \frac{1}{\|x\|} \langle z, x \rangle. \quad \langle z, x \rangle = \|z\|_* \|x\|.$$

$$\text{Set } x \rightarrow -x. \quad \langle z, x \rangle \geq -\|z\|_* \|x\|. \quad \Rightarrow |\langle z, x \rangle| \leq \|z\|_* \|x\|.$$

$\|\cdot\|_p$ and $\|\cdot\|_q$ are duals when $\frac{1}{p} + \frac{1}{q} = 1$. $\|\cdot\|_2$ is its own dual.
 $\|\cdot\|_1$ and $\|\cdot\|_\infty$ are dual to each other.

In \mathbb{R}^d , all ℓ_p norms are equivalent. In particular,

$$\forall x \in \mathbb{R}^d, p \geq 1, r > p: \|x\|_r \leq \|x\|_p \leq d^{\frac{1}{p} - \frac{1}{r}} \|x\|_r.$$

However, choice of norm affects how algorithm performance depends on dimension d .

Lower semicontinuous.

$$f: \mathbb{R}^d \rightarrow \overline{\mathbb{R}}, \quad \text{l.s.c. at } x \in \mathbb{R}^d \quad \text{if} \quad f(x) \leq \liminf_{y \rightarrow x} f(y).$$

Indicator of a closed set is l.s.c.

$$I_{\mathcal{X}}(x) = \begin{cases} 0 & x \in \mathcal{X} \\ \infty & x \notin \mathcal{X}. \end{cases}$$

$$\min_{x \in \mathcal{X}} f(x) \equiv \min_{x \in \mathbb{R}^d} \{ f(x) + I_{\mathcal{X}}(x) \}. \quad \dots \text{Unify constrained and unconstrained optimization.}$$

Convex Function.

f is convex $\Leftrightarrow \text{epi}(f)$ is convex set.

Proper : $f: \mathbb{R}^d \rightarrow \overline{\mathbb{R}}$. f is proper means $\exists x \in \mathbb{R}^d$ st. $f(x) \in \mathbb{R}$.

$f: \mathbb{R}^d \rightarrow \overline{\mathbb{R}}$ is convex & proper $\Rightarrow \text{dom}(f)$ is convex.