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# Convex Optimization Note

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## Abstract

convex optimization note based on the slides in SEEM5350: Numerical Optimization conducted by Shiqian Ma.

## 1 Proximal Gradient

Indicator function and norm

indicator of convex set  $C$ : conjugate is support function of  $C$

$$f(x) = \begin{cases} 0 & x \in C \\ +\infty & \text{otherwise} \end{cases}$$

$f^*(y) = \sup_x \langle x, y \rangle - f(x)$ , only when  $f(y) \in C$  can the conjugate function reach maximum:  
 $\sup_y \langle x, y \rangle$

so this the end of the proof.

inversely, conjugate of support function of closed convex set is indicator function

$$f(x) = S_C(x) = \sup_{y \in C} x^T y \quad f^*(y) = I_C(y)$$

proximal mapping of indicator function  $I_C$  is Euclidean projection on  $C$

$$\text{Prox}_{I_C}(x) = \operatorname{argmin}_{u \in C} \|u - x\|_2^2 = P_C(X)$$

### 1.1 Conjugate function

### 1.2 Norms

**conjugate of norm** is indicator function of dual norm ball:

$$f(x) = \|x\|, f^*(y) = I_B(y), (B = \{y \mid \|y\|_* \leq 1\})$$

proof: recall the definition of dual norm:

$$\|y\|_* = \sup_{\|x\| \leq 1} x^T y$$

to evaluate  $f^*(y) = \sup_x (y^T x - \|x\|)$ , we distinguish two cases:

- if  $\|y\|_* \leq 1$ , then (by Cauchy-Schwarz inequality)  
 $y^T x \leq \|x\|, \forall x$   
and equality holds if  $x=0$ ; therefore  $\sup_x (y^T x - \|x\|) = 0$
- if  $\|y\|_* > 1$ , therefore exists an  $x$  with  $\|x\| \leq 1, x^T y > 1$ ; then  
 $f^*(y) \geq y^T(tx) - \|tx\| = t(y^T x - \|x\|)$   
and rhs goes to infinity if  $t \rightarrow \infty$

**prox-operator** of norm: apply Moreau decomposition:

$$\text{prox}_{tf}(x) = x - t \text{prox}_{t^{-1}f^*}(\frac{x}{t}) = x - tP_B(\frac{x}{t}) = x - P_{tB}(x)$$

useful formula for  $\text{prox}_{t\|\cdot\|}$  when projection on  $tB = \{x \mid \|x\| \leq t\}$  is cheap.

for example, we can quickly calculate the  $\|\cdot\|_1, \|\cdot\|_2$  's prox-operator.

recall the projection of 2-norm:

Euclidian ball:  $C = \{x \mid \|x\|_2 \leq t\}$

$$P_C(x) = \frac{t}{\|x\|_2} x \quad \text{if } \|x\|_2 > t$$

$$P_C(x) = x, \quad \text{if } \|x\|_2 \leq t$$

therefore the proximal-operator of 2-norm is :

$$\text{prox}_{tf}(x) = \begin{cases} x - \frac{tx}{\|x\|_2} & \|x\|_2 > t \\ 0 & \text{otherwise} \end{cases}$$

**Acknowledgments**

**References**