

Homework 3

Due date: Wednesday, Apr. 26, 2017 (at the beginning of class)

You are allowed to drop 1 subproblem without penalty. In addition, up to 1 bonus point will be awarded to each subproblem for clean, well-organized, and elegant solutions.

1. Proximal minimization (40 points)

Recall that the proximal operator of a convex function h is defined as

$$\text{prox}_h(\mathbf{x}) := \arg \min_{\mathbf{z}} \left\{ \frac{1}{2} \|\mathbf{x} - \mathbf{z}\|^2 + h(\mathbf{z}) \right\}$$

(a) Suppose that $f(\mathbf{x}) = \|\mathbf{x}\|_2$. Show that

$$\text{prox}_{\lambda f}(\mathbf{x}) := \left(1 - \frac{\lambda}{\|\mathbf{x}\|_2} \right)_+ \mathbf{x},$$

where $(a)_+ := \max\{a, 0\}$.

(b) Suppose that $f(\mathbf{x}) = h(\mathbf{x}) + \frac{\rho}{2} \|\mathbf{x} - \mathbf{a}\|^2$. Show that

$$\text{prox}_{\lambda f}(\mathbf{x}) := \text{prox}_{\frac{\lambda}{1+\lambda\rho} h} \left(\frac{1}{1+\lambda\rho} \mathbf{x} + \frac{\lambda\rho}{1+\lambda\rho} \mathbf{a} \right).$$

(c) Suppose that $f(\mathbf{x}) = h(\mathbf{x}) + \mathbf{a}^\top \mathbf{x} + \mathbf{b}$. Show that

$$\text{prox}_{\lambda f}(\mathbf{x}) := \text{prox}_{\lambda h}(\mathbf{x} - \lambda \mathbf{a}).$$

(d) Show that a point \mathbf{x}^* is the minimizer of $h(\cdot)$ if and only if

$$\mathbf{x}^* = \text{prox}_h(\mathbf{x}^*).$$

This simple observation is the motivation of the so-called *proximal minimization algorithm*, which finds the optimizer of h by the iterative procedure

$$\mathbf{x}^{t+1} = \text{prox}_{\lambda h}(\mathbf{x}^t).$$

2. Restricted isometry properties (30 points)

Recall that the restricted isometry constant $\delta_s \geq 0$ of \mathbf{A} is the smallest constant such that

$$(1 - \delta_s) \|\mathbf{x}\|_2^2 \leq \|\mathbf{A}\mathbf{x}\|_2^2 \leq (1 + \delta_s) \|\mathbf{x}\|_2^2 \quad (1)$$

holds for all s -sparse vector $\mathbf{x} \in \mathbb{R}^p$.

(a) Show that

$$|\langle \mathbf{A}\mathbf{x}_1, \mathbf{A}\mathbf{x}_2 \rangle| \leq \delta_{s_1+s_2} \|\mathbf{x}_1\|_2 \|\mathbf{x}_2\|_2$$

for all pairs of \mathbf{x}_1 and \mathbf{x}_2 that are supported on disjoint subsets $S_1, S_2 \subset \{1, \dots, n\}$ with $|S_1| \leq s_1$ and $|S_2| \leq s_2$.

(b) For any \mathbf{u} and \mathbf{v} , show that

$$|\langle \mathbf{u}, (\mathbf{I} - \mathbf{A}^\top \mathbf{A})\mathbf{v} \rangle| \leq \delta_s \|\mathbf{u}\| \cdot \|\mathbf{v}\|,$$

where s is the cardinality of $\text{support}(\mathbf{u}) \cup \text{support}(\mathbf{v})$.

(c) Suppose that each column of \mathbf{A} has unit norm. Show that $\delta_2 = \mu(\mathbf{A})$, where $\mu(\mathbf{A})$ is the mutual coherence of \mathbf{A} .

3. Statistical dimension (10 points) Recall that for any convex cone \mathcal{K} , its statistical dimension and Gaussian width are defined respectively as

$$\text{stat-dim}(\mathcal{K}) := \mathbb{E}[\|\mathcal{P}_{\mathcal{K}}(\mathbf{g})\|^2]$$

and

$$w(\mathcal{K}) := \mathbb{E} \left[\sup_{\mathbf{z} \in \mathcal{K}, \|\mathbf{z}\|=1} \langle \mathbf{z}, \mathbf{g} \rangle \right],$$

where $\mathbf{g} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$ and $\mathcal{P}_{\mathcal{K}}$ denotes the projection to \mathcal{K} as

$$\mathcal{P}_{\mathcal{K}}(\mathbf{g}) = \arg \min_{\mathbf{z} \in \mathcal{K}} \|\mathbf{g} - \mathbf{z}\|.$$

(a) Prove that $w^2(\mathcal{K}) \leq \text{stat-dim}(\mathcal{K})$.

(b) (Optional (10 bonus points)) Prove the reverse inequality $\text{stat-dim}(\mathcal{K}) \leq w^2(\mathcal{K}) + 1$.
hint: Let $f(\cdot)$ be a function that is Lipschitz with respect to the Euclidean norm:

$$|f(\mathbf{u}) - f(\mathbf{v})| \leq M \|\mathbf{u} - \mathbf{v}\| \quad \forall \mathbf{u}, \mathbf{v}.$$

Then, $\text{Var}(f(\mathbf{g})) \leq M^2$.