

$$2. \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \leq \frac{1}{\mu} \|f'(\mathbf{x}) - f'(\mathbf{y})\|_2^2, \quad \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n.$$

Proof:

Let us fix $\mathbf{x} \in \mathbb{R}^n$, and define the function $\phi(\mathbf{y}) = f(\mathbf{y}) - \langle f'(\mathbf{x}), \mathbf{y} \rangle$. Clearly, $\phi \in \mathcal{S}_\mu^1(\mathbb{R}^n)$. Also, one minimal solution is \mathbf{x} . Therefore,

$$\begin{aligned} \phi(\mathbf{x}) &= \min_{\mathbf{v} \in \mathbb{R}^n} \phi(\mathbf{v}) \geq \min_{\mathbf{v} \in \mathbb{R}^n} \left[\phi(\mathbf{y}) + \langle \phi'(\mathbf{y}), \mathbf{v} - \mathbf{y} \rangle + \frac{\mu}{2} \|\mathbf{v} - \mathbf{y}\|_2^2 \right] \\ &= \phi(\mathbf{y}) - \frac{1}{2\mu} \|\phi'(\mathbf{y})\|_2^2 \end{aligned}$$

as wished. Adding two copies of the 1 with \mathbf{x} and \mathbf{y} interchanged, we get 2. ■

The converse of Theorem 6.18 is not valid. For instance, consider $f(x_1, x_2) = x_1^2 - x_2^2$, $\mu = 1$. Then the inequalities 1. and 2. are satisfied but $f \notin \mathcal{S}_\mu^1(\mathbb{R}^2)$ for any $\mu > 0$.

Theorem 6.19 Let f be a twice continuously differentiable function. Then $f \in \mathcal{S}_\mu^2(\mathbb{R}^n)$ if and only if

$$f''(\mathbf{x}) \succeq \mu \mathbf{I}, \quad \forall \mathbf{x} \in \mathbb{R}^n.$$

Proof:

Left for exercise. ■

Corollary 6.20 Let f be a twice continuously differentiable function. Then $f \in \mathcal{S}_{\mu,L}^{2,1}(\mathbb{R}^n)$ if and only if

$$L\mathbf{I} \succeq f''(\mathbf{x}) \succeq \mu \mathbf{I}, \quad \forall \mathbf{x} \in \mathbb{R}^n.$$

Theorem 6.21 If $f \in \mathcal{S}_{\mu,L}^{1,1}(\mathbb{R}^n)$, then

$$\frac{\mu L}{\mu + L} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{\mu + L} \|f'(\mathbf{x}) - f'(\mathbf{y})\|_2^2 \leq \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle, \quad \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n.$$

Proof:

If $\mu = L$, from Theorem 6.17 and the definition of $\mathcal{C}_\mu^1(\mathbb{R}^n)$,

$$\begin{aligned} \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle &\geq \frac{\mu}{2} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{\mu}{2} \|\mathbf{x} - \mathbf{y}\|_2^2 \\ &\geq \frac{\mu}{2} \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{2\mu} \|f'(\mathbf{x}) - f'(\mathbf{y})\|_2^2, \end{aligned}$$

and the result follows.

If $\mu < L$, let us define $\phi(\mathbf{x}) = f(\mathbf{x}) - \frac{\mu}{2} \|\mathbf{x}\|_2^2$. Then $\phi'(\mathbf{x}) = f'(\mathbf{x}) - \mu \mathbf{x}$ and $\langle \phi'(\mathbf{x}) - \phi'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle = \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle - \mu \|\mathbf{x} - \mathbf{y}\|_2^2 \leq (L - \mu) \|\mathbf{x} - \mathbf{y}\|_2^2$ since $f \in \mathcal{C}_L^{1,1}(\mathbb{R}^n)$. Also $\langle \phi'(\mathbf{x}) - \phi'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \mu \|\mathbf{x} - \mathbf{y}\|_2^2 - \mu \|\mathbf{x} - \mathbf{y}\|_2^2 = 0$ due to Theorem 6.17. Therefore, from Theorem 6.13, $\phi \in \mathcal{F}_{L-\mu}^{1,1}(\mathbb{R}^n)$.

We have now $\langle \phi'(\mathbf{x}) - \phi'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq \frac{1}{L-\mu} \|\phi'(\mathbf{x}) - \phi'(\mathbf{y})\|_2^2$ from Theorem 6.13. Therefore

$$\begin{aligned} \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle &\geq \mu \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{L-\mu} \|f'(\mathbf{x}) - f'(\mathbf{y}) - \mu(\mathbf{x} - \mathbf{y})\|_2^2 \\ &= \mu \|\mathbf{x} - \mathbf{y}\|_2^2 + \frac{1}{L-\mu} \|f'(\mathbf{x}) - f'(\mathbf{y})\|_2^2 - \frac{2\mu}{L-\mu} \langle f'(\mathbf{x}) - f'(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \\ &\quad + \frac{\mu^2}{L-\mu} \|\mathbf{x} - \mathbf{y}\|_2^2, \end{aligned}$$

and the result follows after some simplifications. ■

6.5 Exercises

1. Given a convex set $S \subseteq \mathbb{R}^n$ and an arbitrary norm $\|\cdot\|$ in \mathbb{R}^n , define the distance of a point $\mathbf{x} \in \mathbb{R}^n$ to the set S as

$$\text{dist}(\mathbf{x}, S) := \inf_{\mathbf{y} \in S} \|\mathbf{x} - \mathbf{y}\|.$$

Show that the distance function $\text{dist}(\mathbf{x}, S)$ is convex in \mathbf{x} .

2. Prove Theorem 6.4.
3. Prove Theorem 6.8.
4. Prove Lemma 6.9.
5. Prove Theorem 6.7.
6. Prove Corollary 6.16.
7. Prove Theorem 6.17.
8. Prove Theorem 6.19.

7 Worse Case Analysis for Gradient Based Methods

7.1 Lower Complexity Bound for the class $\mathcal{F}_L^{\infty,1}(\mathbb{R}^n)$

Gradient Based Method: Iterative method \mathcal{M} generated by a sequence such that

$$\mathbf{x}_k \in \mathbf{x}_0 + \text{Lin}\{f'(\mathbf{x}_0), f'(\mathbf{x}_1), \dots, f'(\mathbf{x}_{k-1})\}, \quad k \geq 1.$$

Consider the problem class as follows

Model:	$\min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x})$
Oracle:	$f \in \mathcal{F}_L^{1,1}(\mathbb{R}^n)$
Approximate solution:	Only function and gradient values are available Find $\bar{\mathbf{x}} \in \mathbb{R}^n$ such that $f(\bar{\mathbf{x}}) - f(\mathbf{x}^*) < \varepsilon$

Theorem 7.1 For any $1 \leq k \leq \frac{n-1}{2}$, and any $\mathbf{x}_0 \in \mathbb{R}^n$, there exists a function $f \in \mathcal{F}_L^{\infty,1}(\mathbb{R}^n)$ such that for any gradient based method of type \mathcal{M} , we have

$$\begin{aligned} f(\mathbf{x}_k) - f^* &\geq \frac{3L\|\mathbf{x}_0 - \mathbf{x}^*\|_2^2}{32(k+1)^2}, \\ \|\mathbf{x}_k - \mathbf{x}^*\|_2^2 &\geq \frac{1}{8}\|\mathbf{x}_0 - \mathbf{x}^*\|_2^2, \end{aligned}$$

where \mathbf{x}^* is the minimum of $f(\mathbf{x})$ and $f^* := f(\mathbf{x}^*)$.

Proof:

This type of methods are invariant with respect to a simultaneous shift of all objects in the space of variables. Therefore, we can assume that $\mathbf{x}_0 = \mathbf{0}$.

Consider the family of quadratic functions

$$f_k(\mathbf{x}) = \frac{L}{4} \left\{ \frac{1}{2} \left[[\mathbf{x}]_1^2 + \sum_{i=1}^{k-1} ([\mathbf{x}]_i - [\mathbf{x}]_{i+1})^2 + [\mathbf{x}]_k^2 \right] - [\mathbf{x}]_1 \right\}, \quad k = 1, 2, \dots, \left\lfloor \frac{n-1}{2} \right\rfloor.$$