

Lemma 3.7 Let $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$. Then for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have

$$\|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x}) - \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x})\|_2 \leq \frac{M}{2} \|\mathbf{y} - \mathbf{x}\|_2^2,$$

$$|f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle - \frac{1}{2} \langle \nabla^2 f(\mathbf{x})(\mathbf{y} - \mathbf{x}), \mathbf{y} - \mathbf{x} \rangle| \leq \frac{M}{6} \|\mathbf{y} - \mathbf{x}\|_2^3.$$

Lemma 3.8 Let $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$, with $\|\nabla^2 f(\mathbf{x}) - \nabla^2 f(\mathbf{y})\|_2 \leq M\|\mathbf{x} - \mathbf{y}\|_2$. Then

$$\nabla^2 f(\mathbf{x}) - M\|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I} \preceq \nabla^2 f(\mathbf{y}) \preceq \nabla^2 f(\mathbf{x}) + M\|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I}.$$

Proof:

Since $f \in \mathcal{C}_M^{2,2}(\mathbb{R}^n)$, $\|\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x})\|_2 \leq M\|\mathbf{y} - \mathbf{x}\|_2$. This means that the eigenvalues of the symmetric matrix $\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x})$ satisfy:

$$|\lambda_i(\nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x}))| \leq M\|\mathbf{y} - \mathbf{x}\|_2, \quad i = 1, 2, \dots, n.$$

Therefore,

$$-M\|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I} \preceq \nabla^2 f(\mathbf{y}) - \nabla^2 f(\mathbf{x}) \preceq M\|\mathbf{y} - \mathbf{x}\|_2 \mathbf{I}.$$

■

3.1 Exercises

1. Prove Lemma 3.7.

4 Optimality Conditions and Algorithms for Minimizing Functions

4.1 General Minimization Problem and Terminologies

Definition 4.1 We define the *general minimization problem* as follows

$$\begin{cases} \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & f_j(\mathbf{x}) \& 0, \quad j = 1, 2, \dots, m \\ & \mathbf{x} \in S, \end{cases} \quad (1)$$

where $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $f_j : \mathbb{R}^n \rightarrow \mathbb{R}$ ($j = 1, 2, \dots, m$), the symbol $\&$ could be $=$, \geq , or \leq , and $S \subseteq \mathbb{R}^n$.

Definition 4.2 The *feasible set* Q of (1) is

$$Q = \{\mathbf{x} \in S \mid f_j(\mathbf{x}) \& 0, \quad (j = 1, 2, \dots, m)\}.$$

In the following, we assume $S \equiv \mathbb{R}^n$.

- If $Q \equiv \mathbb{R}^n$, (1) is a *unconstrained optimization problem*.
- If $Q \subsetneq \mathbb{R}^n$, (1) is a *constrained optimization problem*.
- If all functionals $f(\mathbf{x}), f_j(\mathbf{x})$ are differentiable, (1) is a *smooth optimization problem*.
- If one of functionals $f(\mathbf{x}), f_j(\mathbf{x})$ is non-differentiable, (1) is a *non-smooth optimization problem*.
- If all constraints are linear $f_j(\mathbf{x}) = \langle \mathbf{a}_j, \mathbf{x} \rangle + b_j$ ($j = 1, 2, \dots, m$), (1) is a *linear constrained optimization problem*.

- In addition, if $f(\mathbf{x})$ is linear, (1) is a *linear programming problem*.
- In addition, if $f(\mathbf{x})$ is quadratic, (1) is a *quadratic programming problem*.
- If $f(\mathbf{x})$, $f_j(\mathbf{x})$ ($j = 1, 2, \dots, m$) are quadratic, (1) is a *quadratically constrained quadratic programming problem*.

Definition 4.3 \mathbf{x}^* is called a *global optimal solution* of (1) if $f(\mathbf{x}^*) \leq f(\mathbf{x})$, $\forall \mathbf{x} \in Q$. Moreover, $f(\mathbf{x}^*)$ is called the *global optimal value*. \mathbf{x}^* is called a *local optimal solution* of (1) if there exists an open ball $B(\mathbf{x}^*, \varepsilon) := \{\mathbf{x} \in \mathbb{R}^n \mid \|\mathbf{x} - \mathbf{x}^*\|_2 < \varepsilon\}$ such that $f(\mathbf{x}^*) \leq f(\mathbf{x})$, $\forall \mathbf{x} \in B(\mathbf{x}^*, \varepsilon) \cap Q$. Moreover, $f(\mathbf{x}^*)$ is called a *local optimal value*.

4.2 Complexity Bound for a Global Optimization Problem on the Unit Box

Consider one of the simplest problems in optimization, that is, minimizing a function on the n -dimensional box.

$$\begin{cases} \text{minimize} & f(\mathbf{x}) \\ \text{subject to} & \mathbf{x} \in B_n := \{\mathbf{x} \in \mathbb{R}^n \mid 0 \leq [\mathbf{x}]_i \leq 1, i = 1, 2, \dots, n\}. \end{cases} \quad (2)$$

To be coherent, we use the ℓ_∞ -norm:

$$\|\mathbf{x}\|_\infty = \max_{1 \leq i \leq n} |[\mathbf{x}]_i|.$$

Let us also assume that $f(\mathbf{x})$ is *Lipschitz continuous* on B_n :

$$|f(\mathbf{x}) - f(\mathbf{y})| \leq L \|\mathbf{x} - \mathbf{y}\|_\infty, \quad \forall \mathbf{x}, \mathbf{y} \in B_n.$$

Let us define a very simple method to solve (2), the **uniform grid method**.

Given a positive integer $p > 0$,

1. Form $(p+1)^n$ points

$$\mathbf{x}_{i_1, i_2, \dots, i_n} = \left(\frac{i_1}{p}, \frac{i_2}{p}, \dots, \frac{i_n}{p} \right)^T$$

where $(i_1, i_2, \dots, i_n) \in \{0, 1, \dots, p\}^n$.

2. Among all points $\mathbf{x}_{i_1, i_2, \dots, i_n}$, find a point $\bar{\mathbf{x}}$ which has the minimal value for the objective function.
3. Return the pair $(\bar{\mathbf{x}}, f(\bar{\mathbf{x}}))$ as the result.

Theorem 4.4 Let $f(\mathbf{x}^*)$ be the global optimal value for (2). Then the uniform grid method yields

$$f(\bar{\mathbf{x}}) - f(\mathbf{x}^*) \leq \frac{L}{2p}.$$

Proof:

Let \mathbf{x}^* be a global optimal solution. Then there are coordinates (i_1, i_2, \dots, i_n) such that $\mathbf{x} := \mathbf{x}_{i_1, i_2, \dots, i_n} \leq \mathbf{x}^* \leq \mathbf{x}_{i_1+1, i_2+1, \dots, i_n+1} =: \mathbf{y}$. Observe that $[\mathbf{y}]_i - [\mathbf{x}]_i = 1/p$ for $i = 1, 2, \dots, n$ and $[\mathbf{x}^*]_i \in [[\mathbf{x}]_i, [\mathbf{y}]_i]$ ($i = 1, 2, \dots, n$).

Consider $\hat{\mathbf{x}} = (\mathbf{x} + \mathbf{y})/2$ and form a new point $\tilde{\mathbf{x}}$ as:

$$[\tilde{\mathbf{x}}]_i := \begin{cases} [\mathbf{y}]_i, & \text{if } [\mathbf{x}^*]_i \geq [\hat{\mathbf{x}}]_i \\ [\mathbf{x}]_i, & \text{otherwise.} \end{cases}$$

It is clear that $|\tilde{x}_i - [x^*]_i| \leq 1/(2p)$ for $i = 1, 2, \dots, n$. Then $\|\tilde{x} - x^*\|_\infty = \max_{1 \leq i \leq n} |\tilde{x}_i - [x^*]_i| \leq 1/(2p)$. Since \tilde{x} belongs to the grid,

$$f(\tilde{x}) - f(x^*) \leq f(\tilde{x}) - f(x^*) \leq L\|\tilde{x} - x^*\|_\infty \leq L/(2p).$$

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Let us define our goal

Find $x \in B_n$ such that $f(x) - f(x^*) < \varepsilon$.
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Corollary 4.5 The number of iterations necessary for the problem (2) to achieve the above goal using the uniform grid method is at most

$$\left(\left\lfloor \frac{L}{2\varepsilon} \right\rfloor + 2 \right)^n.$$

Proof:

Take $p = \lfloor L/(2\varepsilon) \rfloor + 1$. Then, $p > L/(2\varepsilon)$ and from the previous theorem, $f(\tilde{x}) - f(x^*) \leq L/(2p) < \varepsilon$. Observe that we constructed $(p+1)^n$ points. ■

Consider the class of problems \mathcal{P} defined as follows:

Model:	$\min_{x \in B_n} f(x),$
Oracle:	$f(x)$ is ℓ_∞ -Lipschitz continuous on B_n . Only function values are available
Approximate solution:	Find $\bar{x} \in B_n$ such that $f(\bar{x}) - f(x^*) < \varepsilon$

Theorem 4.6 For $\varepsilon < \frac{L}{2}$, the number of iterations necessary for the class of problems \mathcal{P} using any method which uses only function evaluations is always at least $(\lfloor \frac{L}{2\varepsilon} \rfloor)^n$.

Proof:

Let $p = \lfloor \frac{L}{2\varepsilon} \rfloor$ (which is ≥ 1 from the hypothesis).

Suppose that there is a method which requires $N < p^n$ calls of the oracle to solve the problem in \mathcal{P} .

Then, there is a point $\hat{x} \in B_n = \{x \in \mathbb{R}^n \mid 0 \leq [x]_i \leq 1, i = 1, 2, \dots, n\}$ where there is no test points in the interior of $B := \{x \mid \hat{x} \leq x \leq \hat{x} + e/p\}$ where $e = (1, 1, \dots, 1)^T \in \mathbb{R}^n$.

Let $x^* := \hat{x} + e/(2p)$ and consider the function $\bar{f}(x) := \min\{0, L\|x - x^*\|_\infty - \varepsilon\}$. Clearly, \bar{f} is ℓ_∞ -Lipschitz continuous with constant L and its global minimum is $-\varepsilon$. Moreover, $\bar{f}(x)$ is non-zero valued only inside the box $B' := \{x \mid \|x - x^*\|_\infty \leq \varepsilon/L\}$.

Since $2p \leq L/\varepsilon$, $B' \subseteq \{x \mid \|x - x^*\|_\infty \leq 1/(2p)\} = B$.

Therefore, $\bar{f}(x)$ is equal to zero to all test points of our method and the accuracy of the method is ε .

If the number of calls of the oracle is less than p^n , the accuracy can not be better than ε . ■

Theorem 4.6 supports the claim that the *general optimization problem is unsolvable*.

Example 4.7 Consider a problem defined by the following parameters. $L = 2$, $n = 10$, and $\varepsilon = 0.01$.