

Optimization Theory

Lecture 05

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1 Regularity Conditions

2 Second-Order Characterization

Optimal Condition

Theorem

Consider proper closed convex function f and closed convex set $\mathcal{C} \subseteq (\text{dom } f)^\circ$. A point $\mathbf{x}^* \in \mathcal{C}$ is a solution of convex optimization problem

$$\min_{\mathbf{x} \in \mathcal{C}} f(\mathbf{x})$$

if and only if

$$\mathbf{0} \in \partial(f(\mathbf{x}^*) + \mathbb{1}_{\mathcal{C}}(\mathbf{x}^*)).$$

Equivalently, there exists a subgradient $\mathbf{g}^* \in \partial f(\mathbf{x}^*)$, such that any $\mathbf{y} \in \mathcal{C}$ satisfies

$$\langle \mathbf{g}^*, \mathbf{y} - \mathbf{x}^* \rangle \geq 0.$$

In particular, the point \mathbf{x}^* is the solution of the problem in unconstrained case if

$$\mathbf{0} \in \partial f(\mathbf{x}^*).$$

Outline

1 Regularity Conditions

2 Second-Order Characterization

Regularity Conditions

The following regularity conditions are useful in the convergence analysis of convex optimization problems.

- 1 We say that a function $f : \mathcal{C} \rightarrow \mathbb{R}$ is G -Lipschitz continuous if for all $\mathbf{x}, \mathbf{y} \in \mathcal{C}$, we have

$$|f(\mathbf{x}) - f(\mathbf{y})| \leq G \|\mathbf{x} - \mathbf{y}\|_2.$$

- 2 We say a differentiable function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is L -smooth if it has L -Lipschitz continuous gradient. That is, for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$, we have

$$\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\|_2 \leq L \|\mathbf{x} - \mathbf{y}\|_2.$$

- 3 If the function

$$g(\mathbf{x}) = f(\mathbf{x}) - \frac{\mu}{2} \|\mathbf{x}\|_2^2$$

is convex for some $\mu > 0$, we say f is μ -strongly convex.

Strong Convexity

Theorem

The function $f : \mathcal{C} \rightarrow \mathbb{R}$ defined on convex set \mathcal{C} is μ -strongly-convex if and only if

$$f(\alpha \mathbf{x} + (1 - \alpha) \mathbf{y}) \leq \alpha f(\mathbf{x}) + (1 - \alpha) f(\mathbf{y}) - \frac{\mu \alpha (1 - \alpha)}{2} \|\mathbf{x} - \mathbf{y}\|_2^2$$

for all $\mathbf{x}, \mathbf{y} \in \mathcal{C}$ and $\alpha \in [0, 1]$.

Theorem

If a function f is differentiable on open set \mathcal{C} , then it is μ -strongly convex on \mathcal{C} if and only if

$$f(\mathbf{y}) \geq f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{\mu}{2} \|\mathbf{y} - \mathbf{x}\|_2^2$$

holds for any $\mathbf{x}, \mathbf{y} \in \mathcal{C}$.

Strong Convexity

If there exists some

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathcal{C}} f(\mathbf{x}),$$

then it is the unique minimizer.

Moreover, the solution is stable such that any approximate solution $\hat{\mathbf{x}}$ satisfying

$$f(\mathbf{x}) \leq f(\mathbf{x}^*) + \epsilon$$

leads to

$$\|\mathbf{x}^* - \hat{\mathbf{x}}\|_2^2 \leq \frac{2\epsilon}{\mu}.$$

Lipschitz Continuity and Smoothness

Theorem

A convex function f is G -Lipschitz continuous on $(\text{dom } f)^\circ$ if and only if

$$\|\mathbf{g}\|_2 \leq G$$

for all $\mathbf{g} \in \partial f(\mathbf{x})$ and $\mathbf{x} \in (\text{dom } f)^\circ$.

Theorem

A function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is L -smooth (possibly nonconvex), then it holds

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

holds for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$.

Theorem

A function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is convex and L -smooth, then we have

- ① $0 \leq f(\mathbf{y}) - f(\mathbf{x}) - \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle \leq \frac{L}{2} \|\mathbf{y} - \mathbf{x}\|_2^2$
- ② $f(\mathbf{x}) + \langle \nabla f(\mathbf{x}), \mathbf{y} - \mathbf{x} \rangle + \frac{1}{2L} \|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x})\|_2^2 \leq f(\mathbf{y})$
- ③ $\frac{1}{L} \|\nabla f(\mathbf{y}) - \nabla f(\mathbf{x})\|_2^2 \leq \langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle$

for any $\mathbf{x}, \mathbf{y} \in \mathbb{R}^d$.

Outline

1 Regularity Conditions

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Second-Order Characterization

Theorem (Smoothness and Convexity)

Let $f(\cdot)$ be a twice differentiable function defined on \mathbb{R}^d

- ① It is L -smooth if and only if $-L\mathbf{I} \preceq \nabla^2 f(\mathbf{x}) \preceq L\mathbf{I}$ for all $\mathbf{x} \in \mathbb{R}^d$.
- ② It is convex if and only if $\nabla^2 f(\mathbf{x}) \succeq \mathbf{0}$ for all $\mathbf{x} \in \mathbb{R}^d$.
- ③ It is μ -strongly-convex if and only if $\nabla^2 f(\mathbf{x}) \succeq \mu\mathbf{I}$ for all $\mathbf{x} \in \mathbb{R}^d$.

Sometimes, we say $f(\cdot)$ is ℓ -weakly convex if the function

$$g(\mathbf{x}) = f(\mathbf{x}) + \frac{\ell}{2} \|\mathbf{x}\|_2^2$$

is convex for some $\ell > 0$.

Theorem

Let $f : \mathbb{R}^d \rightarrow \mathbb{R}$ be a twice differentiable function. Suppose that $\nabla^2 f(\cdot)$ is continuous in an open neighborhood of $\mathbf{x}^* \in \mathbb{R}^d$.

① If \mathbf{x}^* is a local minimizer of $f(\cdot)$, then it holds that

$$\nabla f(\mathbf{x}^*) = \mathbf{0} \quad \text{and} \quad \nabla^2 f(\mathbf{x}^*) \succeq \mathbf{0}.$$

② If it holds that

$$\nabla f(\mathbf{x}^*) = \mathbf{0} \quad \text{and} \quad \nabla^2 f(\mathbf{x}^*) \succ \mathbf{0},$$

then the point \mathbf{x}^* is a strict local minimizer of $f(\cdot)$.

Second-Order Characterization

Some examples:

- ① For unconstrained quadratic problem

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{2} \mathbf{x}^\top \mathbf{A} \mathbf{x} - \mathbf{b}^\top \mathbf{x},$$

where $\mathbf{A} \in \mathbb{R}^{d \times d}$. We have

$$\nabla^2 f(\mathbf{x}) = \mathbf{A}.$$

- ② For regularized generalized linear model

$$\min_{\mathbf{x} \in \mathbb{R}^d} f(\mathbf{x}) \triangleq \frac{1}{n} \sum_{i=1}^n \phi_i(\mathbf{a}_i^\top \mathbf{x}) + \frac{\lambda}{2} \|\mathbf{x}\|_2^2.$$

where $\phi_i : \mathbb{R}^d \rightarrow \mathbb{R}$ is twice differentiable. We have

$$\nabla f(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n \phi'_i(\mathbf{a}_i^\top \mathbf{x}) \mathbf{a}_i + \lambda \mathbf{x} \quad \text{and} \quad \nabla^2 f(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n \phi''_i(\mathbf{a}_i^\top \mathbf{x}) \mathbf{a}_i \mathbf{a}_i^\top + \lambda \mathbf{I}.$$