THE CHINESE UNIVERSITY OF HONG KONG Department of Mathematics MATH4230 2024-25 Lecture 12 February 19, 2025 (Wednesday)

1 Recall

Convex Function

Definition 1. Let $f : X \to \mathbb{R}$, where X is a convex subset of \mathbb{R}^n . Then f is **convex** if and only if for any $x, y \in X$ and $\lambda \in (0, 1)$,

$$f(\lambda x + (1 - \lambda)y) \le \lambda f(x) + (1 - \lambda)f(y).$$

Also, we discussed the following lemma yesterday.

Lemma 1. Let $X \subseteq \mathbb{R}^n$ be non-empty convex set.

1. If $f : X \to \mathbb{R}$ is differentiable, then

$$f(x)$$
 is convex $\iff f(y) \ge f(x) + \langle \nabla f(x), y - x \rangle, \quad \forall x, y \in X$

2. If $f : X \to \mathbb{R}$ is twice differentiable, then

f(x) is convex $\iff \nabla^2 f(x) \ge 0, \ \forall x \in X$

where $\nabla f^2(x) \ge 0$ denotes the Hessian matrix of f is positive semidefinite.

2 Non-differentiable Convex Functions

Definition 2. Let X be a convex set and $f : X \to \mathbb{R}$ be a function. A vector $w \in \mathbb{R}^n$ is called a **subgradient** of f at point $x \in X$ if

$$f(y) \ge f(x) + w^T(y - x), \ \forall y \in X$$

We denote $\partial f(x) = \{ \text{all subgradient of } f \text{ at } x \}.$

Definition 3. The epigraph of $f : X \to \mathbb{R}$ is defined by

 $epi(f) := \{(x,t) : x \in X, t \ge f(x)\} \subseteq X \times \mathbb{R} \subseteq \mathbb{R}^n \times \mathbb{R}$

Lemma 2. Let X be a convex set and $f : X \to \mathbb{R}$ be a function. Then

 $f \text{ is convex} \iff epi(f) \text{ is convex.}$

Proof. " \implies " Let $(x_1, t_1), (x_2, t_2) \in epi(f)$ and $\lambda \in (0, 1)$. Then, by definition, we have

$$t_1 \ge f(x_1)$$
 and $t_2 \ge f(x_2)$

This implies that

$$\lambda t_1 + (1 - \lambda)t_2 \ge \lambda f(x_1) + (1 - \lambda)f(x_2) \ge f(\lambda x_1 + (1 - \lambda)x_2)$$
$$\implies (\lambda x_1 + (1 - \lambda)x_2, \ \lambda t_1 + (1 - \lambda)t_2) \in \operatorname{epi}(f)$$

Thus, epi(f) is convex.

" \Leftarrow " Suppose f is not convex, then there exists $x_1, x_2 \in X$ and $\lambda \in (0, 1)$ such that

$$f(\lambda x_1 + (1 - \lambda)x_2) > \lambda f(x_1) + (1 - \lambda)f(x_2)$$

At the same time, $(x_1, t_1), (x_2, t_2) \in epi(f)$ for $t_1 = f(x_1), t_2 = f(x_2)$. Then it implies that

$$\implies \lambda t_1 + (1 - \lambda)t_2 < f(\lambda x_1 + (1 - \lambda)x_2)$$
$$\implies (\lambda x_1 + (1 - \lambda)x_2, \ \lambda t_1 + (1 - \lambda)t_2) \notin \operatorname{epi}(f)$$

This would lead to epi(f) is not convex.

Proposition 3. Let $X \subseteq \mathbb{R}^n$ be convex and $f : X \to \mathbb{R}$ be a function.

- 1. If $\partial f(x) \neq \emptyset$, for any $x \in X$, then f is convex.
- 2. If f is convex, then $\partial f(x) \neq \emptyset$ for any $x \in ri(X)$.

Proof. 1. Let $x, y \in X$ and $\lambda \in (0, 1)$. Define $z := \lambda x + (1 - \lambda)y$. Since the subgradient of f(z) is non-empty, i.e. $\partial f(z) \neq \emptyset$, there exist $w \in \partial f(z)$. By definition, we have $f(y) \ge f(z) + w^T(y - z)$ for all $y \in X$. Therefore, we have

$$\begin{cases} f(y) \ge f(z) + w^T (y - z) & (1) \\ f(x) \ge f(z) + w^T (x - z) & (2) \end{cases}$$

Multiplying (1) by $(1 - \lambda)$ and (2) by λ then sum together yields

$$\begin{split} \lambda f(x) + (1-\lambda)f(y) &\geq f(z) + w^T \left(\lambda(x-z) + (1-\lambda)(y-z)\right) \\ &= f(z) + w^T \left[\lambda \left((1-\lambda)x + (\lambda-1)y\right) + (1-\lambda)(-\lambda x + (\lambda)y)\right] \\ &= f(z) + w^T(0) \\ &= f(z) \\ f\left(\lambda x + (1-\lambda)y\right) &\leq \lambda f(x) + (1-\lambda)f(y) \end{split}$$

This proves that f is convex.

2. If f is convex, then by the previous lemma, the epigraph epi(f) is also convex. Let x ∈ ri(X), then z := (x, f(x)) ∈ epi(f) ⊆ ℝⁿ⁺¹. Since z + (0, -ε) = (x, f(x) - ε) ∉ epi(f), ∀ε > 0, then the point z is lying on the relative boundary of epi(f). By the separation theorem, there exist (w, v) ∈ ℝⁿ × ℝ such that

$$\langle (w,v), z \rangle \ge \langle (w,v), (y,t) \rangle, \quad \forall (y,t) \in \operatorname{epi}(f) \\ \iff w^T x + v f(x) \ge w^T y + v t, \quad \forall y \in X, \, t \ge f(y)$$
 (*)

Then, we claim the followings:

- We must have $v \leq 0$, otherwise $\lim_{t \to +\infty} vt = +\infty$ and the inequality fail to satisfy.
- Also, we have $v \neq 0$, otherwise $w^T x \ge w^T y$ for any $y \in X$. This implies

$$w^T x \ge w^T \underbrace{(x + \varepsilon w)}_{\in X} = w^T x + \varepsilon \|w\|^2$$

and contradiction occurs since $\varepsilon \|w\|^2 > 0$.

From the above, we can conclude that v < 0. Since $w^T x + v f(x) \ge w^T y + vt$, $\forall y \in X, t \ge f(y)$, dividing both sides by v < 0 yields:

$$\frac{w^T}{v}x + f(x) \le \frac{w^T}{v}y + t, \ \forall y \in X, \ t \ge f(y)$$

Letting t = f(y) in (*), we obtain

$$f(y) \ge f(x) + \left(\frac{w^T}{v}\right)(y-x), \ \forall y \in X$$

which implies that

$$\frac{w}{v} \in \partial f(x), \ \forall x \in \operatorname{ri}(X).$$

— End of Lecture 12 —