

CONVEX ANALYSIS WORKSHOP

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1. CONVEX FUNCTIONS

I made this material referring to [1].

1.1. Definitions.

Definition 1.1.1 (Convex function): A function $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$ is convex if $\mathbf{dom} f$ is a convex set and

$$\forall \mathbf{x}, \mathbf{y} \in \mathbf{dom} f, \forall t \in [0, 1], f(t\mathbf{x} + (1-t)\mathbf{y}) \leq tf(\mathbf{x}) + (1-t)f(\mathbf{y}) \quad (1)$$

where $\mathbf{dom} f$ is the effective domain of f :

$$\mathbf{dom} f := \{\mathbf{x} \mid f(\mathbf{x}) < \infty\}. \quad (2)$$

Definition 1.1.2 (Non-decreasing and non-increasing): A function $f : \mathbb{R} \rightarrow \mathbb{R}$ is called *non-decreasing* if

$$\forall a, b \in \mathbb{R}, a \leq b \implies f(a) \leq f(b). \quad (3)$$

Likewise, a function $f : \mathbb{R} \rightarrow \mathbb{R}$ is called *non-increasing* if

$$\forall a, b \in \mathbb{R}, a \leq b \implies f(a) \geq f(b). \quad (4)$$

1.2. Lemma.

Lemma 1.2.1: Let $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}, g : \mathbb{R} \rightarrow \mathbb{R} \cup \{\infty\}, \mathbf{x}, \mathbf{y} \in \mathbb{R}^n, t \in [0, 1]$ and

$$g(t) = f(t\mathbf{y} + (1-t)\mathbf{x}). \quad (5)$$

Then, g is convex if and only if f is convex.

Proof: (\implies) Let $\theta \in [0, 1]$. For any $t_1, t_2 \in \mathbf{dom} g$,

$$\begin{aligned} & g(\theta t_1 + (1-\theta)t_2) \\ &= f((\theta t_1 + (1-\theta)t_2)\mathbf{y} + (1 - (\theta t_1 + (1-\theta)t_2))\mathbf{x}) \\ &= f(\theta t_1\mathbf{y} + (1-\theta)t_2\mathbf{y} + \mathbf{x} - \theta t_1\mathbf{x} - (1-\theta)t_2\mathbf{x}) \\ &= f(\theta t_1\mathbf{y} + \theta\mathbf{x} - \theta t_1\mathbf{x} + (1-\theta)t_2\mathbf{y} + (1-\theta)\mathbf{x} - (1-\theta)t_2\mathbf{x}) \quad (6) \\ &= f(\theta(t_1\mathbf{y} + (1-t_1)\mathbf{x}) + (1-\theta)(t_2\mathbf{y} + (1-t_2)\mathbf{x})) \\ &\leq \theta f(t_1\mathbf{y} + (1-t_1)\mathbf{x}) + (1-\theta)f(t_2\mathbf{y} + (1-t_2)\mathbf{x}) \\ &= \theta g(t_1) + (1-\theta)g(t_2) \end{aligned}$$

Thus, g is convex.

(\Leftarrow) Let $\mathbf{x}, \mathbf{y} \in \mathbf{dom} f$ and $t \in \mathbb{R}$. For any $\theta \in [0, 1]$,

$$\begin{aligned} f(\theta \mathbf{y} + (1 - \theta) \mathbf{x}) &= g(\theta) \\ &= g(\theta \cdot 1 + (1 - \theta) \cdot 0) \\ &\leq \theta g(1) + (1 - \theta) g(0) \\ &= \theta f(\mathbf{y}) + (1 - \theta) f(\mathbf{x}) \end{aligned} \tag{7}$$

Thus, f is convex. \square

1.3. Exercise.

Proposition 1.3.1 (Scalar composition): For $h : \mathbb{R} \rightarrow \mathbb{R} \cup \{\infty\}$, $g : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$, define $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$ by

$$f(\mathbf{x}) := h(g(\mathbf{x})) \tag{8}$$

with

$$\mathbf{dom} f = \{\mathbf{x} \in \mathbf{dom} g \mid g(\mathbf{x}) \in \mathbf{dom} h\}. \tag{9}$$

Then f is convex if

- h is convex and nondecreasing and g is convex, or
- h is convex and nonincreasing and g is concave.

Proof: First, we prove that f is convex if h is convex and nondecreasing and g is convex. Let $\mathbf{x}, \mathbf{y} \in \mathbf{dom} f$, and $t \in [0, 1]$. Since $\mathbf{x}, \mathbf{y} \in \mathbf{dom} f$, we have $\mathbf{x}, \mathbf{y} \in \mathbf{dom} g$ and $g(\mathbf{x}), g(\mathbf{y}) \in \mathbf{dom} h$. From convexity of g , $t\mathbf{x} + (1 - t)\mathbf{y} \in \mathbf{dom} g$. Then, since g is convex, we have

$$g(t\mathbf{x} + (1 - t)\mathbf{y}) \leq tg(\mathbf{x}) + (1 - t)g(\mathbf{y}) \tag{10}$$

Next, we prove that f is convex if h is convex and nonincreasing and g is concave. \square

REFERENCES

1. Boyd, S., Vandenberghe, L.: Convex Optimization. Cambridge University Press (2004)

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