

1 Convex Functions

1.1 Definition and Basic Properties

Let C be a convex subset of \mathbb{R}^n . A function $f : C \rightarrow \mathbb{R}$ is called *convex* if

$$f(\alpha x + (1 - \alpha)y) \leq \alpha f(x) + (1 - \alpha)f(y), \forall x, y \in C, \forall \alpha \in [0, 1].$$

A function is called *strictly convex* if the inequality above is strict for all $x, y \in C$ with $x \neq y$, and all $\alpha \in (0, 1)$. A function is called *concave* if $(-f)$ is convex.

For a function $f : C \rightarrow \mathbb{R}$, we define the *level sets* of f to be $\{x \mid f(x) \leq \lambda\}$. If a function is convex, then all its level sets are also convex. However, the convexity of all level sets of a function does not necessarily imply the convexity of the function itself.

Examples of Convex Functions

The following functions are convex:

- (a) $f(x) := a'x + b$ for $x \in \mathbb{R}^n$, where $a \in \mathbb{R}^n$ and $b \in \mathbb{R}$.
- (b) $g(x) := \|x\|$ for $x \in \mathbb{R}^n$.
- (c) $h(x) := x^2$ for $x \in \mathbb{R}$.
- (d) $F(x) := \frac{1}{2}x'Ax$ for $x \in \mathbb{R}^n$, where A is a $n \times n$ symmetric positive semidefinite matrix. (i.e. $x'Ax \geq 0$ for all $x \in \mathbb{R}^n$)

1.2 Characterizations of Differentiable Convex Functions

We now give some characterizations of convexity for once or twice differentiable functions.

Proposition: Let C be a nonempty convex open set. Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be differentiable over an open set that contains C .

- (a) f is convex if and only if $f(z) \geq f(x) + \nabla f(x)'(z - x)$, for all $x, z \in C$.
- (b) f is strictly convex if and only if the above inequality is strict for $x \neq z$.

Proof. (\Leftarrow) Let $x, y \in C$, $\alpha \in [0, 1]$ and $z = \alpha x + (1 - \alpha)y$. We have,

$$f(x) \geq f(z) + \nabla f(z)'(x - z)$$

$$f(y) \geq f(z) + \nabla f(z)'(y - z).$$

Then,

$$\alpha f(x) + (1 - \alpha)f(y) \geq f(z)'(\alpha(x - z) + (1 - \alpha)(y - z)) = f(z) = f(\alpha x + (1 - \alpha)y)$$

Hence f is convex.

Conversely, suppose f is convex. For $x \neq z$, define $g : (0, 1] \rightarrow \mathbb{R}$ by

$$g(\alpha) = \frac{f(x + \alpha(z - x)) - f(x)}{\alpha}.$$

Consider α_1, α_2 with $0 < \alpha_1 < \alpha_2 < 1$. Let $\bar{\alpha} = \frac{\alpha_1}{\alpha_2}$ and $\bar{z} = x + \alpha_2(z - x)$. Then $f(x + \bar{\alpha}(z - x)) \leq \bar{\alpha}f(\bar{z}) + (1 - \bar{\alpha})f(x)$. So,

$$\frac{f(x + \bar{\alpha}(z - x)) - f(x)}{\bar{\alpha}} \leq f(\bar{z}) - f(x).$$

Therefore,

$$\frac{f(x + \alpha_1(z - x)) - f(x)}{\alpha_1} \leq \frac{f(x + \alpha_2(z - x)) - f(x)}{\alpha_2}.$$

So, $g(\alpha_1) \leq g(\alpha_2)$, that is, g is monotonically increasing.

Then $\nabla f(x)'(z - x) = \lim_{\alpha \downarrow 0} g(\alpha) \leq g(1) = f(z) - f(x)$. So we are done.

The proof for (b) is the same as (a), we just change all inequality to strict inequality. \square

As a consequence of the above proposition, we have a useful optimal condition for unconstrained optimization. Recall that in single variable calculus, if $f : \mathbb{R} \rightarrow \mathbb{R}$ is a differentiable convex function with $f'(x^*) = 0$, then x^* minimizes f . Here, we give a similar result.

Proposition: Let C be a nonempty convex set and let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a convex differentiable function over an open set that contains C . Then $x^* \in C$ minimizes f over C if and only if

$$\nabla f(x^*)'(z - x^*) \geq 0, \forall z \in C.$$

Proof. Suppose $\nabla f(x^*)'(z - x^*) \geq 0, \forall z \in C$, then by Prop 1.1.3(a), we have,

$$f(z) - f(x^*) \geq \nabla f(x^*)'(z - x^*) \geq 0, \forall z \in C.$$

Hence x^* indeed minimizes f over C .

Conversely, suppose x^* minimizes f over C . Suppose on the contrary that $\nabla f(x^*)'(z - x^*) < 0$ for some $z \in C$, then

$$\lim_{\alpha \downarrow 0} \frac{f(x^* + \alpha(z - x^*)) - f(x^*)}{\alpha} = \nabla f(x^*)'(z - x^*) < 0.$$

Then for sufficiently small α , we have $f(x^* + \alpha(z - x^*)) - f(x^*) < 0$, contradicting the optimality of x^* . \square

For twice continuously differentiable functions, we have the following characterization.

Proposition 2.1.5: Let C be a nonempty convex set $\subset \mathbb{R}^n$ and $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be twice continuously differentiable over an open set that contains C . Then:

- (a) If $\nabla^2 f(x)$ is positive semidefinite for all $x \in C$, then f is convex over C .
- (b) If $\nabla^2 f(x)$ is positive definite for all $x \in C$, then f is strictly convex over C .
- (c) If C is open and f is convex over C , then $\nabla^2 f(x)$ is positive semidefinite for all $x \in C$.

Proof. (a) For all $x, y \in C$,

$$f(y) = f(x) + \nabla f(x)'(y - x) + \frac{1}{2}(y - x)'\nabla^2 f(x + \alpha(y - x))(y - x)$$

for some $\alpha \in [0, 1]$. Since $\nabla^2 f$ is positive semidefinite, we have

$$f(y) \geq f(x) + \nabla f(x)'(y - x), \forall x, y \in C.$$

Hence, f is convex over C .

(b) We have $f(y) > f(x) + \nabla f(x)'(y - x)$ for all $x, y \in C$ with $x \neq y$ since $\nabla^2 f$ is positive definite.

(c) Assume there exist $x \in C$ and $z \in \mathbb{R}^n$ such that $z'\nabla^2 f(x)z < 0$. There exists $\epsilon > 0$ such that $x + \epsilon z \in C$ and $z'\nabla^2 f(x + \alpha\epsilon z)z < 0$ for all $\alpha \in [0, 1]$. Then

$$f(x + z) = f(x) + \nabla f(x)'z + z'\nabla^2 f(x + \alpha z)z < f(x) + \nabla f(x)'z.$$

This contradicts the convexity of f over C . Hence, $\nabla^2 f$ is indeed positive semidefinite over C . \square