

Homework 3

Zhen

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Problem 1

Suppose f is a convex function and $S \subset \text{dom } f$ is a convex set. Let M be the set of global minima of f over S ,

$$M = \{\mathbf{x}^* \in S : f(\mathbf{x}^*) \leq f(\mathbf{x}), \forall \mathbf{x} \in S\}$$

Show that M is a convex set.

Proof:

Apparently, $M = \{\mathbf{x} : f(\mathbf{x}) = C\}$ where C is a const and $\forall \mathbf{x} \in C, f(\mathbf{x}) \geq C$.
 $\forall \mathbf{x}, \mathbf{y} \in M$ and $\theta \in (0, 1)$, we have

$$C \leq f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) \leq \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y}) = C,$$

which means that $f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) = C$.

Thus $\theta \mathbf{x} + \bar{\theta} \mathbf{y} \in M$ and M is convex.

Problem 2

Let f be convex. If $f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) = \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y})$ for some \mathbf{x}, \mathbf{y} and $\theta = \theta_0 \in (0, 1)$, then it holds for the same \mathbf{x}, \mathbf{y} and any $\theta \in [0, 1]$.

Proof by contradiction:

Without loss of generality, assume that $f(\theta_1 \mathbf{x} + \bar{\theta}_1 \mathbf{y}) < \theta_1 f(\mathbf{x}) + \bar{\theta}_1 f(\mathbf{y})$ where $\theta_1 \in (\theta_0, 1)$.

Then we have

$$\begin{aligned} \frac{\theta_0}{\theta_1} f(\theta_1 \mathbf{x} + \bar{\theta}_1 \mathbf{y}) + \left(1 - \frac{\theta_0}{\theta_1}\right) f(\mathbf{y}) &< \frac{\theta_0}{\theta_1} (\theta_1 f(\mathbf{x}) + \bar{\theta}_1 f(\mathbf{y})) + \left(1 - \frac{\theta_0}{\theta_1}\right) f(\mathbf{y}) \\ &= \theta_0 f(\mathbf{x}) + (1 - \theta_0) f(\mathbf{y}) \\ &= f(\theta_0 \mathbf{x} + \bar{\theta}_0 \mathbf{y}) \\ &= f\left(\frac{\theta_0}{\theta_1} (\theta_1 \mathbf{x} + \bar{\theta}_1 \mathbf{y}) + \left(1 - \frac{\theta_0}{\theta_1}\right) \mathbf{y}\right) \end{aligned}$$

Let $\theta_2 = \frac{\theta_0}{\theta_1}$, $\mathbf{x}_1 = (\theta_1 \mathbf{x} + \bar{\theta}_1 \mathbf{y})$ and $\mathbf{x}_2 = \mathbf{y}$. Thus we get

$$\theta_2 f(\mathbf{x}_1) + \bar{\theta}_2 f(\mathbf{x}_2) < f(\theta_2 \mathbf{x}_1 + \bar{\theta}_2 \mathbf{x}_2)$$

which deduce a contradiction.

Therefore, $\forall \theta \in (0, 1) : \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y}) \leq f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) \leq \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y})$.

Then $f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) = \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y})$, $\forall \theta \in (0, 1)$.

Problem 3

Determine if the following functions are convex, concave, or neither.

- (a) $f(\mathbf{x}) = f(x_1, x_2, x_3) = x_1^2 + x_1x_3 + x_2^2 + x_2x_3 + \frac{1}{2}x_3^2$ on \mathbb{R}^3

Solve: Convex.

Assume $f(\mathbf{x}) = \mathbf{x}^T \mathbf{A} \mathbf{x}$. By the fact that

$$f(\mathbf{x}) = \left(x_1 + \frac{1}{2}x_3\right)^2 + \left(x_2 + \frac{1}{2}x_3\right)^2$$

we have $\nabla^2 f = 2\mathbf{A} \succeq \mathbf{O}$. Therefore f is convex.

- (b) $f(\mathbf{x}) = f(x_1, x_2) = (x_1x_2)^{-1}$ on $\mathbb{R}_{++}^2 = \{(x_1, x_2) : x_1 > 0, x_2 > 0\}$

Solve: Convex.

Considering that: $\frac{\partial^2 f}{\partial x_1^2} = \frac{2}{x_1^3 x_2}$, $\frac{\partial^2 f}{\partial x_2^2} = \frac{2}{x_1 x_2^3}$, $\frac{\partial^2 f}{\partial x_1 \partial x_2} = \frac{1}{x_1^2 x_2^2}$

Then the eigenvalue λ_1, λ_2 of $\nabla^2 f$ satisfies that:

$$\left(\lambda - \frac{2}{x_1^3 x_2}\right)\left(\lambda - \frac{2}{x_1 x_2^3}\right) - \frac{1}{x_1^4 x_2^4} = 0, \quad i = 1, 2$$

Let $f(\lambda)$ denote **LHS** of the above equation. Then $f(\lambda) = 0$ is a parabola with an axis of symmetry $\lambda = \frac{1}{x_1^3 x_2} + \frac{1}{x_1 x_2^3} > 0$.

And considering that $f(0) > 0$ and $f(\lambda) = 0$ is of 2 unique solutions, we have $\lambda_1, \lambda_2 > 0$. Thus $\nabla^2 f \succeq \mathbf{O}$ and f is convex.

- (c) $f(x_1, x_2) = x_1 x_2^2$ on \mathbb{R}_{++}^2

Solve: Neither.

$$\nabla^2 f = \begin{pmatrix} 0 & 2x_2 \\ 2x_2 & 2x_1 \end{pmatrix}$$

Then the eigenvalue of $\nabla^2 f$ $\lambda_{\pm} = x_1 \pm \sqrt{x_1^2 + 4x_2^2}$. Thus f is neither convex nor concave ($\lambda_+ > 0$ while $\lambda_- < 0$).

- (d) $f(x_1, x_2) = x_1 x_2^{-1/2}$ on \mathbb{R}_{++}^2

Solve: Neither.

Considering that: $\frac{\partial^2 f}{\partial x_1^2} = 0$, $\frac{\partial^2 f}{\partial x_1 \partial x_2} = -\frac{1}{2x_2^{3/2}}$, $\frac{\partial^2 f}{\partial x_2^2} = \frac{3x_1}{4x_2^{5/2}}$.

Then the eigenvalue of $\nabla^2 f$

$$\lambda_{\pm} = \frac{1}{2} \left(\frac{3x_1}{4x_2^{5/2}} \pm \sqrt{\frac{9x_1^2}{16x_2^5} + \frac{1}{x_2^3}} \right)$$

Thus f is neither convex nor concave ($\lambda_+ > 0$ while $\lambda_- < 0$).

- (e) $f(x_1, x_2) = x_1^{\alpha} x_2^{1-\alpha}$ on \mathbb{R}_{++}^2

Solve: Concave.

Considering that

$$\nabla^2 f = -\alpha(1-\alpha)x_1^{\alpha-2}x_2^{-1-\alpha} \begin{bmatrix} x_2^2 & x_1 x_2 \\ x_1 x_2 & x_2^2 \end{bmatrix} \triangleq C(x_1, x_2, \alpha) \mathbf{A}$$

By the fact that $C(x_1, x_2, \alpha) < 0 \wedge \mathbf{A} \succeq \mathbf{O}$, $\nabla^2 f \preceq \mathbf{O}$ and f is concave.

Problem 4

Suppose $f_i : \mathbb{R} \rightarrow \mathbb{R}, i = 1, 2$, are strictly convex functions. Show that $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ defined by $f(x_1, x_2) = f_1(x_1) + f_2(x_2)$ is strictly convex over \mathbb{R}^2 , and in particular $f(x_1, x_2) = x_1^2 + x_2^4$ is strictly convex.

Proof:

$\forall \mathbf{x} = (x_1, x_2), \mathbf{y} = (y_1, y_2) \in \mathbb{R}^2$ and $\forall \theta \in (0, 1)$,

$$\begin{aligned} f(\theta \mathbf{x} + \bar{\theta} \mathbf{y}) &= f(\theta x_1 + \bar{\theta} y_1, \theta x_2 + \bar{\theta} y_2) \\ &= f_1(\theta x_1 + \bar{\theta} y_1) + f_2(\theta x_2 + \bar{\theta} y_2) \\ &\leq \theta f_1(x_1) + \bar{\theta} f_1(y_1) + \theta f_2(x_2) + \bar{\theta} f_2(y_2) \\ &= \theta f(\mathbf{x}) + \bar{\theta} f(\mathbf{y}) \end{aligned}$$

Therefore f is strictly convex.

Trivially, $f_1(x_1) = x_1^2$ and $f_2(x_2) = x_2^4$ are strictly convex. Then $f(x_1, x_2) = f_1(x_1) + f_2(x_2)$ is strictly convex.

Problem 5

Let $f : C \subset \mathbb{R}^n \rightarrow \mathbb{R}$ be a differentiable function defined on a nonempty open convex set C . Show that f is convex if and only if

$$\langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq 0, \forall \mathbf{x}, \mathbf{y} \in C$$

Proof:

f is convex

$$\iff \forall \text{direction } \mathbf{d}, \forall \mathbf{x} \in C, g(t) = f(\mathbf{x} + t\mathbf{d}) \text{ is convex on } \{t : \mathbf{x} + t\mathbf{d} \in C\}$$

$$\iff \forall \text{direction } \mathbf{d}, \forall \mathbf{x} \in C, g'(t) = \nabla f(\mathbf{x} + t\mathbf{d})^T \mathbf{d} \text{ is increasing on } \{t : \mathbf{x} + t\mathbf{d} \in C\}$$

$$\iff \forall \text{direction } \mathbf{d}, \forall \mathbf{x} \in C, \forall h, s \in \{t : \mathbf{x} + t\mathbf{d} \in C\}, [g'(h) - g'(s)](h - s) \geq 0$$

$$\iff \forall \text{direction } \mathbf{d}, \forall \mathbf{x} \in C, \forall h, s \in \{t : \mathbf{x} + t\mathbf{d} \in C\}, [\nabla f(\mathbf{x} + h\mathbf{d})^T \mathbf{d} - \nabla f(\mathbf{x} + s\mathbf{d})^T \mathbf{d}](h - s) \geq 0$$

$$\iff \forall \text{direction } \mathbf{d}, \forall \mathbf{x} \in C, \forall h, s \in \{t : \mathbf{x} + t\mathbf{d} \in C\}, [\nabla f(\mathbf{x} + h\mathbf{d})^T - \nabla f(\mathbf{x} + s\mathbf{d})^T][(\mathbf{x} + h\mathbf{d}) - (\mathbf{x} + s\mathbf{d})] \geq 0$$

$$\iff \forall \mathbf{x}, \mathbf{y} \in C, [\nabla f(\mathbf{x})^T - \nabla f(\mathbf{y})^T](\mathbf{x} - \mathbf{y}) \geq 0 \text{ (Note that: } \exists s, \mathbf{d}, \mathbf{x} = \mathbf{x} + 0\mathbf{d}, \mathbf{y} = \mathbf{x} + t\mathbf{d})$$

$$\iff \forall \mathbf{x}, \mathbf{y} \in C, \langle \nabla f(\mathbf{x}) - \nabla f(\mathbf{y}), \mathbf{x} - \mathbf{y} \rangle \geq 0$$