Homework Assignment 7

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Problem 1. Write at least two necessary conditions and at least two sufficient conditions for a function $f: \mathbb{R}^n \to \mathbb{R}$ to be concave.

Solution. By definition, a function $f: \mathbb{R}^n \to \mathbb{R}$ is concave over the convex set $\Omega \subset \mathbb{R}^n$ if -f is convex over Ω . This definition will allow us to obtain results for concave functions by replacing f with -f in previously obtained results concerning convex functions.

Using this definition and Theorem 22.2, we see that the condition that if for all $\alpha \in (0,1)$ and for all $x, y \in \Omega$, we have that

$$f(\alpha \boldsymbol{x} + (1 - \alpha)\boldsymbol{y}) \ge \alpha f(\boldsymbol{x}) + (1 - \alpha)f(\boldsymbol{y})$$

is a necessary and sufficient condition for f to be concave on the convex set Ω .

Further, if the function f is \mathcal{C}^1 -smooth, we see from the above definition and Theorem 22.4 that the condition that if for all $\boldsymbol{x}, \boldsymbol{y} \in \Omega$, we have that

$$f(\boldsymbol{x}) \leq f(\boldsymbol{y}) + Df(\boldsymbol{x})(\boldsymbol{x} - \boldsymbol{y})$$

is a necessary and sufficient condition for f to be concave on the open convex set Ω .

Going one last step further, if the function f is \mathcal{C}^2 -smooth, we see from the above definition and Theorem 22.5 that the condition that if for all $\boldsymbol{x} \in \Omega$, the Hessian matrix $\boldsymbol{F}(\boldsymbol{x})$ of f at \boldsymbol{x} is a negative semi-definite matrix is a necessary and sufficient condition for f to be concave on the open convex set Ω .

Problem 2. Let $S \subset \mathbb{R}^n$ be a convex set and let $\boldsymbol{x}^* \in S$. Prove that a vector $\boldsymbol{d} \in \mathbb{R}^n$ is a feasible direction at \boldsymbol{x}^* (relative to S) if and only there exists $t_0 > 0$ such that $\boldsymbol{x}^* + t_0 \boldsymbol{d} \in S$ with $\boldsymbol{d} \neq \boldsymbol{0}$.

Solution. \Box

Problem 3. Recall that

$$\max\{\alpha,\beta\} := \begin{cases} \alpha & \text{if } \alpha \ge \beta \\ \beta & \text{if } \alpha < \beta \end{cases}.$$

Given two convex functions $f_1: \mathbb{R}^n \to \mathbb{R} \cup \{+\infty\}$ and $f_2: \mathbb{R}^n \to \mathbb{R} \cup \{+\infty\}$, prove that for $\boldsymbol{x} \in \mathbb{R}^n$, the function

$$f(x) := \max\{f_1(x), f_2(x)\}$$

is convex.

Solution. \Box

Problem 4. Consider the pair of linear programming problems in asymmetric duality:

(
$$P_a$$
) minimize $f(\boldsymbol{x}) = \boldsymbol{c}^\mathsf{T} \boldsymbol{x}$ (D_a) maximize $F(\boldsymbol{\lambda}) = \boldsymbol{\lambda}^\mathsf{T} \boldsymbol{b}$ subject to $A\boldsymbol{x} = \boldsymbol{b}$ subject to $\boldsymbol{\lambda}^\mathsf{T} A \leq \boldsymbol{c}^\mathsf{T}$ $\boldsymbol{x} \geq \boldsymbol{0}$

- a. Prove that (D_a) is a convex programming problem.
- b. Write the KKT conditions for (D_a) .
- c. Suppose that \boldsymbol{x}^* is feasible for (P_a) and $\boldsymbol{\lambda}^*$ is feasible for (D_a) . Use the KKT conditions to prove that if $(\boldsymbol{c}^{\mathsf{T}} \boldsymbol{\lambda}^{*\mathsf{T}} A) \boldsymbol{x}^* = 0$, then $\boldsymbol{\lambda}^*$ is optimal for (D_a) .

Solution. \Box