

1. [B&V, problem 3.14] We say the function  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  is *convex-concave* if  $f(x, z)$  is a concave function of  $z$ , for each fixed  $x$ , and a convex function of  $x$ , for each fixed  $z$ . We also require its domain to have the product form  $\text{dom } f = A \times B$ , where  $A \subseteq \mathbb{R}^n$  and  $B \subseteq \mathbb{R}^m$  are convex.

- (a) Give a second-order condition for a twice differentiable function  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  to be convex-concave, in terms of its Hessian  $\nabla^2 f(x, z)$ .
- (b) Suppose that  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  is convex-concave and differentiable, with  $\nabla f(\tilde{x}, \tilde{z}) = 0$ . Show that the *saddle-point property* holds: for all  $x, z$ , we have

$$f(\tilde{x}, z) \leq f(\tilde{x}, \tilde{z}) \leq f(x, \tilde{z}).$$

(This can be used to show that  $f$  satisfies the *strong max-min property*:

$$\sup_z \inf_x f(x, z) = \inf_x \sup_z f(x, z),$$

with the common value being  $f(\tilde{x}, \tilde{z})$ .)

- (c) Now suppose that  $f : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$  is differentiable, but not necessarily convex-concave, and the saddle-point property holds at  $\tilde{x}, \tilde{z}$ :

$$f(\tilde{x}, z) \leq f(\tilde{x}, \tilde{z}) \leq f(x, \tilde{z})$$

for all  $x, z$ . Show that  $\nabla f(\tilde{x}, \tilde{z}) = 0$ .

2. [B&V, problem 3.22] Use the composition rules to show that the following function is convex.

$$f(x, u, v) = -\log(uv - x^T x) \quad \text{on} \quad \text{dom } f = \{(x, u, v) \mid uv > x^T x, u, v > 0\}.$$

Hint: Use the convexity of the quadratic-over-linear function.

3. [B&V, problem 3.32] In general the product or ratio of two convex functions is not convex. However, there are some results that apply to functions on  $\mathbb{R}$ . Prove the following.

- (a) If  $f$  and  $g$  are convex, both nondecreasing (or nonincreasing), and positive functions on an interval, then  $fg$  is convex.
- (b) If  $f$  and  $g$  are concave, positive, with one nondecreasing and the other nonincreasing, then  $fg$  is concave.
- (c) If  $f$  is convex, nondecreasing, and positive, and  $g$  is concave, nonincreasing, and positive, then  $f/g$  is convex.

4. [B&V, problem 4.1] Consider the optimization problem

$$\begin{aligned} & \text{minimize} && f_0(x_1, x_2) \\ & \text{subject to} && 2x_1 + x_2 \geq 1 \\ & && x_1 + 3x_2 \geq 1 \\ & && x_1 \geq 0, \quad x_2 \geq 0. \end{aligned}$$

Make a sketch of the feasible set. For each of the following objective functions, give an optimal point  $x^*$  and the optimal value  $p^* = f_0(x^*)$ . [In some cases the optimal value may be achieved by a set of points rather than a single point; in such cases determine the optimal *set*.]

- (a)  $f_0(x_1, x_2) = x_1 + x_2$ .
- (b)  $f_0(x_1, x_2) = -x_1 - x_2$ .
- (c)  $f_0(x_1, x_2) = x_1$ .
- (d)  $f_0(x_1, x_2) = \max\{x_1, x_2\}$ .
- (e)  $f_0(x_1, x_2) = x_1^2 + 9x_2^2$ .

5. [B&V, problem 4.6] A convex optimization problem can have only *linear* equality constraint functions. In some special cases, however, it is possible to handle convex equality constraint functions, i.e., constraints of the form  $g(x) = 0$ , where  $g$  is convex. We explore this idea in this problem.

Consider the optimization problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && h(x) = 0, \end{aligned} \tag{1}$$

where  $f_i$  and  $h$  are convex functions with domain  $\mathbb{R}^n$ . Unless  $h$  is affine, this is *not* a convex optimization problem. Consider the related problem

$$\begin{aligned} & \text{minimize} && f_0(x) \\ & \text{subject to} && f_i(x) \leq 0, \quad i = 1, \dots, m \\ & && h(x) \leq 0, \end{aligned} \tag{2}$$

where the convex equality constraint has been relaxed to a convex inequality. [A change in a constraint is said to be a relaxation if it enlarges the constraint set.] This problem is, of course, convex.

Now suppose we can guarantee that at any optimal solution  $x^*$  of the convex problem (2), we have  $h(x^*) = 0$ , i.e., the inequality  $h(x) \leq 0$  is always active at the solution. Then we can solve the (nonconvex) problem (1) by solving the convex problem (2).

Show that this is the case if there is an index  $r$  such that

- $f_0$  is monotonically increasing in  $x_r$
- $f_1, \dots, f_m$  are nondecreasing in  $x_r$
- $h$  is monotonically decreasing in  $x_r$ .