

# Homework Assignment 3

## Problem 1. (15 points)

Consider the class of problems

$$\begin{aligned} & \underset{x}{\text{minimize}} && f(x) \\ & \text{subject to} && x \in X, \quad g_j(x) \leq u_j, \quad j = 1, \dots, r, \end{aligned}$$

where  $u = (u_1, \dots, u_r)$  is a vector parameterizing the right-hand side of the constraints. Given two distinct values  $\bar{u}$  and  $\tilde{u}$  of  $u$ , let  $\bar{f}$  and  $\tilde{f}$  be the corresponding optimal values, and assume that  $\bar{f}$  and  $\tilde{f}$  are finite. Assume further that  $\bar{\mu}$  and  $\tilde{\mu}$  are corresponding dual optimal solutions and that there is no duality gap. Show that

$$\tilde{\mu}'(\tilde{u} - \bar{u}) \leq \bar{f} - \tilde{f} \leq \bar{\mu}'(\tilde{u} - \bar{u}).$$

### Solution 1

$$\begin{aligned} D(\mu) &= \inf_{x \in X} \{f(x) + \mu' g(x)\}. \\ q(\mu, u) &= \inf_{x \in X} \{f(x) + \mu'(g(x) - u)\} = D(\mu) - \mu'u. \\ \bar{f} &= p(\bar{u}) = \sup_{\mu \geq 0} (D(\mu) - \mu'\bar{u}) = D(\bar{\mu}) - \bar{\mu}'\bar{u} \\ \tilde{f} &= p(\tilde{u}) = \sup_{\mu \geq 0} (D(\mu) - \mu'\tilde{u}) = D(\tilde{\mu}) - \tilde{\mu}'\tilde{u} \end{aligned}$$

where  $\bar{\mu}$  and  $\tilde{\mu}$  is the corresponding dual optimal solutions. We have:

$$\begin{aligned} \bar{f} &= D(\bar{\mu}) - \bar{\mu}'\bar{u} \geq D(\tilde{\mu}) - \tilde{\mu}'\bar{u} = (\tilde{f} + \tilde{\mu}'\tilde{u}) - \tilde{\mu}'\bar{u} = \tilde{f} + \tilde{\mu}'(\tilde{u} - \bar{u}). \\ \implies \tilde{\mu}'(\tilde{u} - \bar{u}) &\leq \bar{f} - \tilde{f}. \end{aligned}$$

Otherside is similar.

## Problem 2. (15 points)

Let  $g_j : R^n \mapsto R, j = 1, \dots, r$ , be convex functions over the nonempty convex subset of  $R^n$ . Show that the system

$$g_j(x) < 0, \quad j = 1, \dots, r,$$

has no solution within  $X$  if and only if there exists a vector  $\mu \in R^r$  such that

$$\begin{aligned} \sum_{j=1}^r \mu_j &= 1, \quad \mu \geq 0, \\ \mu' g(x) &\geq 0, \quad \forall x \in X. \end{aligned}$$

Hint: Consider the convex program

$$\begin{aligned} &\underset{x,y}{\text{minimize}} \quad y \\ &\text{subject to} \quad x \in X, y \in R, g_j(x) \leq y, \quad j = 1, \dots, r, \end{aligned} \tag{1}$$

**Solution 2** Consider the convex program

$$\begin{aligned} &\underset{x,y}{\text{minimize}} \quad y \\ &\text{subject to} \quad x \in X, y \in R, g_j(x) \leq y, \quad j = 1, \dots, r, \end{aligned} \tag{2}$$

Let  $v^*$  be the optimal value of this problem. The system  $g_j(x) < 0$  for  $j = 1, \dots, r$  has no solution in  $X$  if and only if for all  $x \in X$ ,  $\max_j g_j(x) \geq 0$ . This implies that the optimal value of the auxiliary problem satisfies  $v^* \geq 0$ .

Now, consider the Lagrangian of the auxiliary problem:

$$L(x, y, \lambda) = y + \sum_{j=1}^r \lambda_j (g_j(x) - y) = y \left( 1 - \sum_{j=1}^r \lambda_j \right) + \sum_{j=1}^r \lambda_j g_j(x).$$

The dual function:

$$q(\lambda) = \inf_{x \in X, y \in R} L(x, y, \lambda) = \begin{cases} \inf_{x \in X} \sum_{j=1}^r \lambda_j g_j(x) & \text{if } \sum_{j=1}^r \lambda_j = 1, \\ -\infty & \text{otherwise.} \end{cases}$$

Maximize  $q(\lambda)$  subject to  $\lambda \geq 0$  equivalent to:

$$\begin{aligned} &\underset{\lambda}{\text{maximize}} \quad \inf_{x \in X} \lambda' g(x) \\ &\text{subject to} \quad \sum_{j=1}^r \lambda_j = 1, \quad \lambda \geq 0. \end{aligned}$$

Let  $d^*$  be the dual optimal value. Then  $v^* = d^*$ . So

$$v^* \geq 0 \iff d^* \geq 0 \iff \sup_{\substack{\lambda \geq 0 \\ \sum \lambda_j = 1}} \left( \inf_{x \in X} \lambda' g(x) \right) \geq 0.$$

Since the feasible set for  $\lambda$  is compact, the supremum is attained by some vector  $\mu$ . Thus, the condition is equivalent to the existence of  $\mu \in R^r$  such that:

$$\sum_{j=1}^r \mu_j = 1, \quad \mu \geq 0, \quad \text{and} \quad \inf_{x \in X} \mu' g(x) \geq 0.$$

### Problem 3. (25 points)

Consider the problem

$$\begin{aligned} & \underset{x}{\text{minimize}} && f(x) \\ & \text{subject to} && x \in X, \quad g_i(x) \leq 0, i = 1, \dots, r, \end{aligned}$$

where  $X$  is a convex set, and  $f$  and  $g_i$ s are convex over  $X$ . Assume that the problem has at least one feasible solution. Show that the following are equivalent.

- (i) The dual optimal value  $q^* = \sup_{\mu \in R^r} q(\mu)$  is finite.
- (ii) The primal function  $p$  is proper.
- (iii) The set

$$M = \{(u, w) \in R^{r+1} \mid \text{there is an } x \in X \text{ such that } g(x) \leq u, f(x) \leq w\}$$

does not contain a vertical line.

**Solution 3** *The primal function defined as:*

$$p(u) = \inf\{f(x) \mid x \in X, g(x) \leq u\}.$$

We have  $p(0) < \infty$ , and  $p(u)$  is not identically  $+\infty$ .

**(ii)  $\iff$  (iii):** If  $p$  is proper, then  $p(u) > -\infty$  for all  $u$ . Therefore, there is no  $u$  for which  $(u, w) \in M$  for all  $w$ . Thus,  $M$  does not contain a vertical line. Conversely, if  $M$  does not contain a vertical line, then for every  $u$ , the values of  $w$  such that  $(u, w) \in M$  are bounded below. Thus  $p(u) > -\infty$  for all  $u$ . Since  $p$  is not identically  $+\infty$ ,  $p$  is proper.

**(ii)  $\implies$  (i):** If  $p$  is proper and convex, the conjugate of a proper convex function is proper. By Weak Duality,  $q(\mu) \leq p(0)$ . Since  $p$  is proper and a feasible solution exists,  $p(0)$  is finite. Thus  $\sup q(\mu) \leq p(0) < \infty$ .

**(i)  $\implies$  (ii):** If  $q^* = \sup q(\mu)$  is finite, then  $q(\mu) > -\infty$  for some  $\mu$ . Suppose  $p$  is not proper. Since feasible solutions exist, this means there exists  $\bar{u}$  such that  $p(\bar{u}) = -\infty$ . Then, for any  $\mu \geq 0$ :

$$q(\mu) \leq \inf_x \{f(x) + \mu' g(x)\} \leq p(\bar{u}) + \mu' \bar{u} = -\infty.$$

This contradicts the assumption that  $q^* > -\infty$ . Thus,  $p$  must be proper.

## Problem 4. (25 points)

Consider a proper convex function  $F$  of two vectors  $x \in R^n$  and  $y \in R^m$ . For a fixed  $(\bar{x}, \bar{y}) \in \text{dom}(F)$ , let  $\partial_x F(\bar{x}, \bar{y})$  and  $\partial_y F(\bar{x}, \bar{y})$  be the subdifferentials of the functions  $F(\cdot, \bar{y})$  and  $F(\bar{x}, \cdot)$  at  $\bar{x}$  and  $\bar{y}$ , respectively.

(a) Show that

$$\partial F(\bar{x}, \bar{y}) \subset \partial_x F(\bar{x}, \bar{y}) \times \partial_y F(\bar{x}, \bar{y})$$

and give an example showing that the inclusion may be strict in general.

(b) Assume that  $F$  has the form

$$F(x, y) = h_1(x) + h_2(y) + h(x, y),$$

where  $h_1$  and  $h_2$  are proper convex functions, and  $h$  is convex, real-valued, and differentiable. Show that the formula of part (a) holds with equality.

**Solution 4 (a)** Let  $(u, v) \in \partial F(\bar{x}, \bar{y})$ . By the definition:

$$F(x, y) \geq F(\bar{x}, \bar{y}) + u'(x - \bar{x}) + v'(y - \bar{y}), \quad \forall x, y.$$

Set  $y = \bar{y}$ :

$$F(x, \bar{y}) \geq F(\bar{x}, \bar{y}) + u'(x - \bar{x}).$$

This implies  $u \in \partial_x F(\bar{x}, \bar{y})$ . Similarly we have  $v \in \partial_y F(\bar{x}, \bar{y})$ . Thus,  $\partial F(\bar{x}, \bar{y}) \subset \partial_x F(\bar{x}, \bar{y}) \times \partial_y F(\bar{x}, \bar{y})$ .

**Example:** Consider  $F(x, y) = |x + y|$  at  $(\bar{x}, \bar{y}) = (0, 0)$ . The subdifferential of  $F$  at  $(0, 0)$  consists of vectors  $(u, v)$  such that  $|x + y| \geq ux + vy$ . This holds if and only if  $u = v$  and  $|u| \leq 1$ . Thus,  $\partial F(0, 0) = \{(u, u) \mid -1 \leq u \leq 1\}$ . But

$$\begin{aligned} F(x, 0) = |x| &\implies \partial_x F(0, 0) = [-1, 1] \\ F(0, y) = |y| &\implies \partial_y F(0, 0) = [-1, 1] \\ \implies \partial F(0, 0) &\subsetneq \partial_x F(0, 0) \times \partial_y F(0, 0) = [-1, 1] \times [-1, 1]. \end{aligned}$$

(b) Let  $F(x, y) = h_1(x) + h_2(y) + h(x, y)$ , we have:

$$\partial F(x, y) = \partial(h_1(x) + h_2(y)) + \nabla h(x, y).$$

Since  $h_1$  depends only on  $x$  and  $h_2$  only on  $y$ :

$$\partial(h_1(x) + h_2(y)) = \partial h_1(x) \times \partial h_2(y).$$

Also,  $\nabla h(x, y) = (\nabla_x h(x, y), \nabla_y h(x, y))$ . Thus:

$$\partial F(\bar{x}, \bar{y}) = \{(u_1 + \nabla_x h(\bar{x}, \bar{y}), u_2 + \nabla_y h(\bar{x}, \bar{y})) \mid u_1 \in \partial h_1(\bar{x}), u_2 \in \partial h_2(\bar{y})\}.$$

And:

$$\begin{aligned} \partial_x F(\bar{x}, \bar{y}) &= \partial_x(h_1(x) + h_2(\bar{y}) + h(\bar{x}, \bar{y})) = \partial h_1(\bar{x}) + \nabla_x h(\bar{x}, \bar{y}), \\ \partial_y F(\bar{x}, \bar{y}) &= \partial_y(h_1(\bar{x}) + h_2(y) + h(\bar{x}, \bar{y})) = \partial h_2(\bar{y}) + \nabla_y h(\bar{x}, \bar{y}). \end{aligned}$$

So:

$$\partial_x F \times \partial_y F = (\partial h_1(\bar{x}) + \nabla_x h) \times (\partial h_2(\bar{y}) + \nabla_y h) = \partial F(\bar{x}, \bar{y}).$$

## Problem 5. (20 points)

(Note: This exercise shows how a duality gap results in nondifferentiability of the dual function.)

Consider the problem

$$\begin{aligned} & \underset{x}{\text{minimize}} && f(x) \\ & \text{subject to} && x \in X, \quad g(x) \leq 0, \end{aligned}$$

and assume that for all  $\mu \geq 0$ , the infimum of the Lagrangian  $L(x, \mu)$  over  $X$  is attained by at least one  $x_\mu \in X$ . Show that if there is a duality gap, then the dual function  $q(\mu) = \inf_{x \in X} L(x, \mu)$  is nondifferentiable at every dual optimal solution.

Hint: If  $q$  is differentiable at a dual optimal solution  $\mu^*$ , by the theory of Section 5.3 in the textbook, we must have  $\partial q(\mu^*) / \partial \mu_j \leq 0$  and  $\mu_j^* \partial q(\mu^*) / \partial \mu_j = 0$  for all  $j$ . Use optimality conditions for  $\mu^*$ , together with any vector  $x_{\mu^*}$  that minimizes  $L(x, \mu^*)$  over  $X$ , to show that there is no duality gap.

**Solution 5** Assume that there is a duality gap, i.e.,  $q(\mu^*) < f(x^*)$ , and assume that the dual function  $q$  is differentiable at a dual optimal solution  $\mu^*$ .

$$\frac{\partial q(\mu^*)}{\partial \mu_j} \leq 0 \quad \forall j, \quad \text{and} \quad \mu_j^* \frac{\partial q(\mu^*)}{\partial \mu_j} = 0 \quad \forall j.$$

By the properties of the dual function, if the infimum in the definition of  $q(\mu)$  is attained at a unique point, the gradient is given by the constraint values at the minimizer of the Lagrangian. Specifically:

$$\nabla q(\mu^*) = g(x_{\mu^*}),$$

where  $x_{\mu^*}$  minimizes  $L(x, \mu^*)$  over  $X$ . Since  $g_j(x_{\mu^*}) \leq 0$  for all  $j$ ,  $x_{\mu^*}$  is a primal feasible solution. Since  $\mu_j^* g_j(x_{\mu^*}) = 0$  for all  $j$ , so we have complementary slackness.

$$q(\mu^*) = \inf_{x \in X} L(x, \mu^*) = L(x_{\mu^*}, \mu^*) = f(x_{\mu^*}) + \sum_{j=1}^r \mu_j^* g_j(x_{\mu^*}) = f(x_{\mu^*}).$$

Thus,  $q(\mu^*) = f(x_{\mu^*})$ , which contradicts the assumption of a duality gap. Therefore, if there is a duality gap, the dual function  $q$  cannot be differentiable at any dual optimal solution  $\mu^*$ .