# 6.253: Convex Analysis and Optimization Homework 5

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## Problem 1

Consider the convex programming problem

minimize  $f(x)$ subject to  $x \in X$ ,  $q(x) \leq 0$ ,

of Section 5.3, and assume that the set  $X$  is described by equality and inequality constraints as

$$
X = \{x \mid h_i(x) = 0, i = 1, \ldots, \bar{m}, g_j(x) \le 0, j = r + 1, \ldots, \bar{r}\}.
$$

Then the problem can alternatively be described without an abstract set constraint, in terms of all of the constraint functions

$$
h_i(x) = 0, \quad i = 1, \ldots, \bar{m}, \qquad g_j(x) \leq 0, \quad j = 1, \ldots, \bar{r}.
$$

We call this the *extended representation* of (P). Show if there is no duality gap and there exists a dual optimal solution for the extended representation, the same is true for the original problem.

#### Solution.

Assume that there exists a dual optimal solution in the extended representation. Thus there exist nonnegative scalars  $\lambda_1^*, \ldots, \lambda_m^*, \lambda_{m+1}^*, \ldots, \lambda_{\overline{n}}^*$  and  $\mu_1^*, \ldots, \mu_r^*, \mu_{r+1}^*, \ldots, \mu_{\overline{r}}^*$  such that

$$
f^* = \inf_{x \in R^n} \left\{ f(x) + \sum_{i=1}^{\bar{m}} \lambda_i^* h_i(x) + \sum_{j=1}^{\bar{r}} \mu_j^* g_j(x) \right\},\,
$$

from which we have

$$
f^* \le f(x) + \sum_{i=1}^{\bar{m}} \lambda_i^* h_i(x) + \sum_{j=1}^{\bar{r}} \mu_j^* g_j(x), \qquad \forall \ x \in R^n.
$$

For any  $x \in X$ , we have  $h_i(x) = 0$  for all  $i = 1, \ldots, \overline{m}$ , and  $g_j(x) \leq 0$  for all  $j = r + 1, \ldots, \overline{r}$ , so that  $\mu_j^* g_j(x) \leq 0$  for all  $j = r + 1, \ldots, \overline{r}$ . Therefore, it follows from the preceding relation that

$$
f^* \le f(x) + \sum_{j=1}^r \mu_j^* g_j(x), \qquad \forall \ x \in X.
$$

Taking the infimum over all  $x \in X$ , it follows that

$$
f^* \leq \inf_{x \in X} \left\{ f(x) + \sum_{j=1}^r \mu_j^* g_j(x) \right\}
$$
  
\n
$$
\leq \inf_{x \in X, g_j(x) \leq 0, j=1,\dots,r} \left\{ f(x) + \sum_{j=1}^r \mu_j^* g_j(x) \right\}
$$
  
\n
$$
\leq \inf_{\substack{x \in X, h_i(x) = 0, i=1,\dots,m \\ g_j(x) \leq 0, j=1,\dots,r}} f(x)
$$
  
\n
$$
= f^*.
$$

Hence, equality holds throughout above, showing that the scalars  $\lambda_1^*, \ldots, \lambda_m^*, \mu_1^*, \ldots, \mu_r^*$  constitute a dual optimal solution for the original representation.

## Problem 2

Consider the class of problems

minimize  $f(x)$ subject to  $x \in X$ ,  $g_j(x) \le u_j$ ,  $j = 1, \ldots, r$ ,

where  $u = (u_1, \ldots, u_r)$  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.

We have 
$$
\bar{f} = \inf_{x \in X} \{f(x) + \bar{\mu}'(g(x) - \bar{u})\},
$$

$$
f = \inf_{x \in X} \{f(x) + \mu'(g(x) - u)\}.
$$

Let  $\bar{q}(\mu)$  denote the dual function of the problem corresponding to  $\bar{u}$ :

$$
\bar{q}(\mu) = \inf_{x \in X} \{ f(x) + \mu'(g(x) - \bar{u}) \}.
$$

We have

$$
\bar{f} - f = \inf_{x \in X} \{ f(x) + \bar{\mu}'(g(x) - \bar{u}) \} - \inf_{x \in X} \{ f(x) + \mu'(g(x) - u) \}
$$
\n
$$
= \inf_{x \in X} \{ f(x) + \bar{\mu}'(g(x) - \bar{u}) \} - \inf_{x \in X} \{ f(x) + \mu'(g(x) - \bar{u}) \} + \mu'(u - \bar{u})
$$
\n
$$
= \bar{q}(\bar{\mu}) - \bar{q}(\mu) + \mu'(u - \bar{u})
$$
\n
$$
\geq \mu'(u - \bar{u}),
$$

where the last inequality holds because  $\bar{\mu}$  maximizes  $\bar{q}$ .

This proves the left-hand side of the desired inequality. Interchanging the roles of  $\bar{f}$ ,  $\bar{u}$ ,  $\bar{\mu}$ , and  $f, u, \mu$ , shows the desired right-hand side.

## Problem 3

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

$$
g_j(x) < 0, \qquad j = 1, \ldots, r,
$$

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

$$
\sum_{j=1}^{r} \mu_j = 1, \qquad \mu \ge 0,
$$
  

$$
\mu' g(x) \ge 0, \qquad \forall x \in X.
$$

Hint: Consider the convex program

minimize 
$$
y
$$
  
subject to  $x \in X$ ,  $y \in R$ ,  $g_j(x) \le y$ ,  $j = 1,...,r$ .

#### Solution.

The dual function for the problem in the hint is

$$
q(\mu) = \inf_{y \in R, x \in X} \left\{ y + \sum_{j=1}^{r} \mu_j (g_j(x) - y) \right\}
$$
  
= 
$$
\begin{cases} \inf_{x \in X} \sum_{j=1}^{r} \mu_j g_j(x) & \text{if } \sum_{j=1}^{r} \mu_j = 1, \\ -\infty & \text{if } \sum_{j=1}^{r} \mu_j \neq 1. \end{cases}
$$

The problem in the hint satisfies the Slater condition, so the dual problem has an optimal solution  $\mu^*$  and there is no duality gap.

Clearly the problem in the hint has an optimal value that is greater or equal to 0 if and only if the system of inequalities

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

has no solution within  $X$ . Since there is no duality gap, we have

$$
\max_{\mu \ge 0, \, \sum_{j=1}^r \mu_j = 1} q(\mu) \ge 0
$$

if and only if the system of inequalities  $g_j(x) < 0$ ,  $j = 1, \ldots, r$ , has no solution within X. This is equivalent to the statement we want to prove.

## Problem 4

Consider the problem

$$
\begin{array}{ll}\text{minimize} & f(x) \\ \text{subject to} & x \in X, \quad g(x) \le 0, \end{array}
$$

where X is a convex set, and f and  $g_i$  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

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

does not contain a vertical line.

#### Solution.

We note that  $-q$  is closed and convex, and that

$$
q(\mu) = \inf_{u \in R^r} \{p(u) + \mu'u\}, \qquad \forall \ \mu \in R^r.
$$

Since  $q(\mu) \leq p(0)$  for all  $\mu \in \mathbb{R}^r$ , given the feasibility of the problem [i.e.,  $p(0) < \infty$ ], we see that  $q^*$  is finite if and only if q is proper. Since q is the conjugate of  $p(-u)$  and p is convex, by the Conjugacy Theorem,  $q$  is proper if and only if  $p$  is proper. Hence (i) is equivalent to (ii).

We note that the epigraph of p is the closure of M. Hence, given the feasibility of the problem, (ii) is equivalent to the closure of M not containing a vertical line. Since  $M$  is convex, its closure does not contain a line if and only if M does not contain a line (since the closure and the relative interior of  $M$  have the same recession cone). Hence (ii) is equivalent to (iii).

## Problem 5

Consider a proper convex function F of two vectors  $x \in \mathbb{R}^n$  and  $y \in \mathbb{R}^m$ . For a fixed  $(\bar{x}, \bar{y}) \in$  $dom(F)$ , 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.

(a) We have  $(g_x, g_y) \in \partial F(\bar{x}, \bar{y})$  if and only if

$$
F(x,y) \ge F(\bar{x}, \bar{y}) + g'_x(x-\bar{x}) + g'_y(y-\bar{y}), \qquad \forall x \in R^n, y \in R^m.
$$

By setting  $y = \bar{y}$ , we obtain that  $g_x \in \partial_x F(\bar{x}, \bar{y})$ , and by setting  $x = \bar{x}$ , we obtain that  $g_y \in$  $\partial_y F(\bar{x}, \bar{y}),$  so that  $(g_x, g_y) \in \partial_x F(\bar{x}, \bar{y}) \times \partial_y F(\bar{x}, \bar{y}).$ 

For an example where the inclusion is strict, consider any function whose subdifferential is not a Cartesian product at some point, such as  $F(x, y) = |x + y|$  at points  $(\bar{x}, \bar{y})$  with  $\bar{x} + \bar{y} = 0$ . (b) Since  $F$  is the sum of functions of the given form, we have

$$
\partial F(\bar{x}, \bar{y}) = \{ (g_x, 0) \mid g_x \in \partial h_1(\bar{x}) \} + \{ (0, g_y) \mid g_y \in \partial h_2(\bar{y}) \} + \{ \nabla h(\bar{x}, \bar{y}) \}
$$

[the relative interior condition of the proposition is clearly satisfied]. Since

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

the result follows.

## Problem 6

This exercise shows how a duality gap results in nondifferentiability of the dual function. Consider the problem

$$
\begin{array}{ll}\text{minimize} & f(x) \\ \text{subject to} & x \in X, \quad g(x) \le 0, \end{array}
$$

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, we must have  $\partial q(\mu^*)/\partial \mu_i \leq 0$  and  $\mu_i^* \partial q(\mu^*)/\partial \mu_i = 0$  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.

To obtain a contradiction, assume that q is differentiable at some dual optimal solution  $\mu^* \in M$ , where  $M = {\mu \in R^r \mid \mu \geq 0}.$  Then

$$
\nabla q(\mu^*)(\mu^* - \mu) \ge 0, \qquad \forall \ \mu \ge 0.
$$

If  $\mu_i^* = 0$ , then by letting  $\mu = \mu^* + \gamma e_j$  for a scalar  $\gamma \ge 0$ , and the vector  $e_j$  whose jth component is 1 and the other components are 0, from the preceding relation we obtain  $\partial q(\mu^*)/\partial \mu_j \leq 0$ . Similarly, if  $\mu_j^* > 0$ , then by letting  $\mu = \mu^* + \gamma e_j$  for a sufficiently small scalar  $\gamma$  (small enough so that  $\mu^* + \gamma e_j \in M$ , from the preceding relation we obtain  $\partial q(\mu^*)/\partial \mu_j = 0$ . Hence

$$
\partial q(\mu^*)/\partial \mu_j \leq 0,
$$
  $\forall j = 1,...,r,$   
 $\mu_j^* \partial q(\mu^*)/\partial \mu_j = 0,$   $\forall j = 1,...,r.$ 

Since q is differentiable at  $\mu^*$ , we have that

$$
\nabla q(\mu^*) = g(x^*),
$$

for some vector  $x^* \in X$  such that  $q(\mu^*) = L(x^*, \mu^*)$ . This and the preceding two relations imply that  $x^*$  and  $\mu^*$  satisfy the necessary and sufficient optimality conditions for an optimal primal and dual optimal solution pair. It follows that there is no duality gap, a contradiction.

## Problem 7

Consider the problem

minimize 
$$
f(x) = 10x_1 + 3x_2
$$
  
subject to  $5x_1 + x_2 \ge 4, x_1, x_2 = 0$  or 1,

(a) Sketch the set of constraint-cost pairs  $\{(4 - 5x_1 - x_2, 10x_1 + 3x_2)|x_1, x_2 = 0 \text{ or } 1\}.$ 

(b)Describe the corresponding MC/MC framework as per Section 4.2.3.

(c) Solve the problem and its dual, and relate the solutions to your sketch in part (a).

#### Solution.

(a) The set of constraint-cost pairs contains 4 points:  $(-2,13)$ ,  $(-1,10)$ ,  $(3,3)$ ,  $(4,0)$ .<br>(b) To each of these 4 points we add the first orphant and we get the  $\overline{M}$  set.

(c) The primal optimal solution is  $x^* = (1,0)$  and the primal optimal cost is  $p^* = 10$ . The dual function is easily found to be:

$$
q(\mu) = \begin{cases} 4\mu & \text{if } \mu \leq 2, \\ 10 - \mu & \text{if } 2 \leq \mu \leq 3, \\ 13 - 2\mu & \text{if } 3 \leq \mu. \end{cases}
$$

Therefore  $q^* = 8$ . This is the intersection of the line segment connecting the points  $(4,0)$ ,  $(-1,10)$ with the y-axis.

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