6.253: Convex Analysis and Optimization Homework 5

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Problem 1

Consider the convex programming problem

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

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

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

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

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

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 $\lambda_1^*, \ldots, \lambda_m^*, \lambda_{m+1}^*, \ldots, \lambda_{\bar{m}}^*$ and $\mu_1^*, \ldots, \mu_r^*, \mu_{r+1}^*, \ldots, \mu_{\bar{r}}^*$ such that

$$f^* = \inf_{x \in \mathbb{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

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

For any $x \in X$, we have $h_i(x) = 0$ for all $i = 1, ..., \bar{m}$, and $g_j(x) \leq 0$ for all $j = r + 1, ..., \bar{r}$, so that $\mu_j^* g_j(x) \leq 0$ for all $j = r + 1, ..., \bar{r}$. 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

$$f^* \leq \inf_{x \in X} \left\{ f(x) + \sum_{j=1}^r \mu_j^* g_j(x) \right\}$$

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

$$\leq \inf_{\substack{x \in X, \ h_i(x) = 0, \ i=1, \dots, r \\ g_j(x) \leq 0, \ j=1, \dots, r}} f(x)$$

$$= f^*.$$

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

 $\begin{array}{ll} \underset{x}{\text{minimize}} & f(x)\\ \text{subject to} & x \in X, \qquad g_j(x) \leq u_j, \ j=1,\ldots,r, \end{array}$

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

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

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

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

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, μ , shows the desired right-hand side.

Problem 3

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

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

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

$$\begin{array}{ll} \underset{x,y}{\text{minimize}} & y\\ \text{subject to} & x \in X, , \quad y \in R, \qquad g_j(x) \leq y, \quad j = 1, \ldots, r \end{array}$$

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 μ^* 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 $g_j(x) < 0, j = 1, ..., r$, has no solution within X. This is equivalent to the statement we want to prove.

Problem 4

Consider the problem

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

where X is a convex set, and f and g_j 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

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

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

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

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

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

the result follows.

Problem 6

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

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

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 μ^* , by the theory of Section 5.3, 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 μ^* , together with any vector x_{μ^*} 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 $M = \{\mu \in \mathbb{R}^r \mid \mu \ge 0\}$. Then

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

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

$$\partial q(\mu^*)/\partial \mu_j \le 0, \qquad \forall \ j = 1, \dots, r,$$

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

Since q is differentiable at μ^* , 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 μ^* 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

$$\begin{array}{ll} \underset{x}{\text{minimize}} & f(x) = 10x_1 + 3x_2\\ \text{subject to} & 5x_1 + x_2 \ge 4, x_1, x_2 = 0 \text{ or } 1, \end{array}$$

(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).

(b) To each of these 4 points we add the first orphant and we get the 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:

$$q(\mu) = \begin{cases} 4\mu & if\mu \le 2, \\ 10 - \mu & if2 \le \mu \le 3, \\ 13 - 2\mu & if3 \le \mu. \end{cases}$$

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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