

## Homework 4: Lagrangian Duality

**Exercise 1** Consider a general optimization problem of the form

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && g_j(x) \leq 0, \quad j = 1, \dots, m, \\ & && h_i(x) = 0, \quad i = 1, \dots, p, \\ & && x \in X, \end{aligned}$$

where  $X \subseteq \mathfrak{R}^n$ ,  $f : \mathfrak{R}^n \rightarrow \mathfrak{R}$ , each  $g_j : \mathfrak{R}^n \rightarrow \mathfrak{R}$ , and each  $h_i : \mathfrak{R}^n \rightarrow \mathfrak{R}$ . Assume that the optimal value  $f^*$  of the problem is finite. Consider the dual problem obtained by assigning a Lagrange multiplier  $\mu_j \geq 0$  for each constraint  $g_j(x) \leq 0$  and a Lagrange multiplier  $\lambda_i \geq 0$  for each constraint  $h_i(x) = 0$ . Show the lower bounding property

$$q(\mu, \lambda) \leq f^*,$$

where  $q$  is the dual function,  $\mu = [\mu_1, \dots, \mu_m]^T$  and  $\lambda = [\lambda_1, \dots, \lambda_p]^T$ .

**Exercise 2** Consider an LP in the standard form

$$\begin{aligned} & \text{minimize} && c^T x \\ & \text{subject to} && Ax = b, \\ & && x \geq 0, \end{aligned}$$

and its corresponding dual

$$\begin{aligned} & \text{maximize} && b^T p \\ & \text{subject to} && A^T p \leq c. \end{aligned}$$

where  $x \in \mathfrak{R}^n$ ,  $b \in \mathfrak{R}^m$ , and  $A \in \mathfrak{R}^m \times \mathfrak{R}^n$ . Transform the dual in a minimization problem and find its dual. Show that this dual (of the dual) is the same as the original LP.

**Exercise 3** Consider the following optimization problem in  $\mathfrak{R}^2$ :

$$\begin{aligned} & \text{minimize} && e^{-x_2} \\ & \text{subject to} && \|x\| \leq x_1, \quad x_2 \geq 0. \end{aligned}$$

- What is the constraint set? What is the optimal value of the problem?
- Consider a dual problem obtained by assigning a Lagrange multiplier only to the constraint  $x_2 \geq 0$ . What is the dual optimal value? Is there a duality gap?
- Consider a dual problem obtained by assigning a Lagrange multiplier only to the constraint  $\|x\| \leq x_1$ . What is the dual optimal value in this case? Is there a duality gap?
- What is your interpretation of the meaning of the results obtained in (b) and (c)?

**Exercise 4** Prove the following **Relax-all rule**: Given a minimization problem

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && g_j(x) \leq 0, \quad j = 1, \dots, m, \\ & && x \in \mathbb{R}^n, \end{aligned}$$

where  $X \subseteq \mathbb{R}^n$ ,  $f : \mathbb{R}^n \rightarrow \mathbb{R}$ , and each  $g_j : \mathbb{R}^n \rightarrow \mathbb{R}$ . Assume that the optimal value  $f^*$  of the problem is finite.

Consider a dual problem obtained by assigning a Lagrange multiplier  $\mu_j > 0$  to each constraint  $g_j(x) \leq 0$ , and assume that there is no duality gap, i.e.,  $q^* = f^*$ . Then, there is no duality gap when considering any other dual problem obtained by assigning Lagrange multipliers  $\mu_j > 0$  to constraints  $g_j(x) \leq 0$  with  $j \in J$  for a subset  $J \subset \{1, \dots, m\}$ . Specifically, for any  $J \subset \{1, \dots, m\}$ , the partial dual problem

$$\begin{aligned} & \text{maximize} && \tilde{q}(\tilde{\mu}) \\ & \text{subject to} && \tilde{\mu}_j(x) \geq 0, \quad j \in J \end{aligned} \tag{1}$$

with

$$q(\tilde{\mu}) = \inf_{g_j(x) \leq 0, j \notin J} \left\{ f(x) + \sum_{j \in J} \tilde{\mu}_j g_j(x) \right\},$$

we have  $\tilde{q}^* = f^*$ , where  $\tilde{q}^*$  is the optimal value of the partial dual problem in (1).

**Exercise 5** (Analytic centering) Consider the following problem

$$\begin{aligned} & \text{minimize} && -\sum_{i=1}^m \ln(b_i - a_i^T x) \\ & \text{subject to} && x \in \mathbb{R}^n, \end{aligned} \tag{2}$$

with domain  $\{x \in \mathbb{R}^n \mid a_i^T x < b_i, i = 1, \dots, m\}$ . Derive its dual problem by first introducing new variables  $y_i$  and then introducing equality constraints  $y_i = b_i - a_i^T x$  for  $i = 1, \dots, m$ .

Remark: The solution to the problem in (2) is known as **analytic center** of the linear inequalities  $a_i^T x \leq b_i$ ,  $i = 1, \dots, m$ . The function  $-\ln(b_i - a_i^T x)$  is referred to as a **log-barrier** function. This function plays an important role in the interior point method, which we study later on.

**Exercise 6** Consider the following problem

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && g_j(x) \leq 0, \quad j = 1, \dots, m, \end{aligned} \tag{3}$$

where the function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  and each  $g_j : \mathbb{R}^n \rightarrow \mathbb{R}$  are differentiable and convex. Let  $h_j : \mathbb{R} \rightarrow \mathbb{R}$  be increasing differentiable convex functions. Show that

$$\phi(x) = f(x) + \sum_{j=1}^m h_j(g_j(x))$$

is convex.

Suppose that  $\tilde{x}$  minimizes  $\phi(x)$  over  $\mathbb{R}^n$ . Show how to use  $\tilde{x}$  to find a feasible vector for the dual of the problem in (3).