

MA 5037: Optimization Methods and Applications

Duality



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The primal problem and its Lagrangian function

We explore the dual problem by considering the general model:

$$\begin{aligned} f^* = \min \quad & f(x) \\ \text{subject to} \quad & g_i(x) \leq 0, \quad i = 1, 2, \dots, m, \\ & h_j(x) = 0, \quad j = 1, 2, \dots, p, \\ & x \in X, \end{aligned} \tag{1}$$

where $f, g_i, h_j (i = 1, 2, \dots, m, j = 1, 2, \dots, p)$ are functions defined on the set $X \subseteq \mathbb{R}^n$. Problem (1) will be referred to as the primal problem.

The Lagrangian function of the problem is defined as

$$L(x, \lambda, \mu) = f(x) + \sum_{i=1}^m \lambda_i g_i(x) + \sum_{j=1}^p \mu_j h_j(x), \quad (x \in X, \lambda \in \mathbb{R}_+^m, \mu \in \mathbb{R}^p)$$

where $\lambda_1, \lambda_2, \dots, \lambda_m$ are nonnegative Lagrange multipliers associated with the inequality constraints, and $\mu_1, \mu_2, \dots, \mu_p$ are the Lagrange multipliers associated with the equality constraints.

Definition of the dual problem

The dual objective function $q : \mathbb{R}_+^m \times \mathbb{R}^p \rightarrow \mathbb{R} \cup \{-\infty\}$ is defined to be

$$q(\lambda, \mu) = \min_{x \in X} L(x, \lambda, \mu). \quad (2)$$

There may be values of (λ, μ) for which $q(\lambda, \mu) = -\infty$, we define the domain of the dual objective function as

$$\text{dom}(q) = \{(\lambda, \mu) \in \mathbb{R}_+^m \times \mathbb{R}^p : q(\lambda, \mu) > -\infty\}.$$

Then the dual problem is given by

$$q^* = \max q(\lambda, \mu) \quad \text{subject to } (\lambda, \mu) \in \text{dom}(q). \quad (3)$$

That is,

$$q^* = \max_{(\lambda, \mu) \in \text{dom}(q)} \min_{x \in X} L(x, \lambda, \mu).$$

Convexity of the dual problem

Theorem: Consider the problem (1) with f, g_i, h_j ($i = 1, 2, \dots, m$, $j = 1, 2, \dots, p$) being functions defined on the set $X \subseteq \mathbb{R}^n$, and let q be the function defined in (2). Then we have

- (a) $\text{dom}(q) = \{(\lambda, \mu) \in \mathbb{R}_+^m \times \mathbb{R}^p : q(\lambda, \mu) > -\infty\}$ is a convex set,
- (b) $q(\lambda, \mu) = \min_{x \in X} L(x, \lambda, \mu)$ is a concave function over $\text{dom}(q)$.

Proof:

(a) Taking $(\lambda_1, \mu_1), (\lambda_2, \mu_2) \in \text{dom}(q)$ and $\alpha \in [0, 1]$, we have

$$\min_{x \in X} L(x, \lambda_1, \mu_1) > -\infty \quad \text{and} \quad \min_{x \in X} L(x, \lambda_2, \mu_2) > -\infty.$$

Since $L(x, \lambda, \mu)$ is affine with respect to λ and μ , we obtain

$$\begin{aligned} & q(\alpha\lambda_1 + (1-\alpha)\lambda_2, \alpha\mu_1 + (1-\alpha)\mu_2) \\ &= \min_{x \in X} L(x, \alpha\lambda_1 + (1-\alpha)\lambda_2, \alpha\mu_1 + (1-\alpha)\mu_2) \\ &= \min_{x \in X} (\alpha L(x, \lambda_1, \mu_1) + (1-\alpha)L(x, \lambda_2, \mu_2)). \end{aligned}$$

Proof of the convexity of the dual problem

Therefore, we have

$$\begin{aligned} & q(\alpha\lambda_1 + (1-\alpha)\lambda_2, \alpha\mu_1 + (1-\alpha)\mu_2) \\ & \geq \alpha \min_{x \in X} L(x, \lambda_1, \mu_1) + (1-\alpha) \min_{x \in X} L(x, \lambda_2, \mu_2) \\ & = \alpha q(\lambda_1, \mu_1) + (1-\alpha)q(\lambda_2, \mu_2) > -\infty. \end{aligned}$$

Hence, $\alpha(\lambda_1, \mu_1) + (1-\alpha)(\lambda_2, \mu_2) \in \text{dom}(q)$, and the convexity of $\text{dom}(q)$ is established.

(b) As noted in the proof of part (a), $L(x, \lambda, \mu)$ is an affine function with respect to (λ, μ) . In particular, it is a concave function with respect to (λ, μ) .

Since $q(\lambda, \mu)$ is the minimum of concave functions, it must be concave. \square

Weak duality theorem

Theorem: Consider the primal problem (1) and its dual problem (3). Then $q^* \leq f^*$, where q^* and f^* are optimal dual and primal values, respectively.

Proof: Let us denote the feasible set of the primal problem by

$$S = \{x \in X : g_i(x) \leq 0, h_j(x) = 0, 1 \leq i \leq m, 1 \leq j \leq p\}.$$

Then for any $(\lambda, \mu) \in \mathbb{R}_+^m \times \mathbb{R}^p$, we have

$$\begin{aligned} q(\lambda, \mu) &= \min_{x \in X} L(x, \lambda, \mu) \leq \min_{x \in S} L(x, \lambda, \mu) \\ &= \min_{x \in S} \left(f(x) + \sum_{i=1}^m \lambda_i g_i(x) + \sum_{j=1}^p \mu_j h_j(x) \right) \\ &\leq \min_{x \in S} f(x). \end{aligned}$$

We thus obtain that

$$q(\lambda, \mu) \leq \min_{x \in S} f(x) = f^*$$

for any $(\lambda, \mu) \in \mathbb{R}_+^m \times \mathbb{R}^p$. By taking the maximum over (λ, μ) , we have $q^* \leq f^*$. \square

Supporting hyperplane theorem

Theorem: Let $C \subseteq \mathbb{R}^n$ be a convex set with nonempty interior and let $\mathbf{y} \notin C$. Then there exists $\mathbf{0} \neq \mathbf{p} \in \mathbb{R}^n$ such that

$$\mathbf{p}^\top \mathbf{x} \leq \mathbf{p}^\top \mathbf{y} \text{ for any } \mathbf{x} \in C.$$

Proof: Since $\mathbf{y} \notin C \supseteq \text{int}(C) = \text{int}(\text{cl}(C))$, it follows that $\mathbf{y} \notin \text{int}(\text{cl}(C))$. Therefore, there exists a sequence $\{\mathbf{y}_k\}_{k \geq 1}$ satisfying $\mathbf{y}_k \notin \text{cl}(C)$ such that $\mathbf{y}_k \rightarrow \mathbf{y}$ as $k \rightarrow \infty$.

Since $\text{cl}(C)$ is convex and closed, it follows by the strict separation theorem (Theorem 10.1) that there exists $\mathbf{0} \neq \mathbf{p}_k \in \mathbb{R}^n$ such that

$$\mathbf{p}_k^\top \mathbf{x} < \mathbf{p}_k^\top \mathbf{y}_k, \quad \forall \mathbf{x} \in \text{cl}(C).$$

Dividing the latter inequality by $\|\mathbf{p}_k\| \neq 0$, we obtain

$$\frac{\mathbf{p}_k^\top}{\|\mathbf{p}_k\|} (\mathbf{x} - \mathbf{y}_k) < 0, \quad \forall \mathbf{x} \in \text{cl}(C). \quad (4)$$

Proof of the supporting hyperplane theorem (cont'd)

Since the sequence $\{\frac{\mathbf{p}_k}{\|\mathbf{p}_k\|}\}_{k \geq 1}$ is bounded, it follows that there exists a subsequence $\{\frac{\mathbf{p}_k}{\|\mathbf{p}_k\|}\}_{k \in T}$ such that $\frac{\mathbf{p}_k}{\|\mathbf{p}_k\|} \rightarrow \mathbf{p}$ as $k \xrightarrow{T} \infty$ for some $\mathbf{p} \in \mathbb{R}^n$. Hence, $\|\mathbf{p}\| = 1$ and in particular $\mathbf{p} \neq \mathbf{0}$. Taking the limit as $k \xrightarrow{T} \infty$ in inequality (4), we obtain that

$$\mathbf{p}^\top (\mathbf{x} - \mathbf{y}) \leq 0, \quad \forall \mathbf{x} \in cl(\mathbf{C}),$$

which implies the result since $\mathbf{C} \subseteq cl(\mathbf{C})$. \square

Separation of two convex sets

Theorem: Let $C_1, C_2 \subseteq \mathbb{R}^n$ be two convex sets with nonempty interior such that $C_1 \cap C_2 = \emptyset$. Then there exists $\mathbf{0} \neq \mathbf{p} \in \mathbb{R}^n$ for which

$$\mathbf{p}^\top \mathbf{x} \leq \mathbf{p}^\top \mathbf{y}, \quad \forall \mathbf{x} \in C_1, \mathbf{y} \in C_2.$$

Proof: The set $C_1 - C_2$ is a convex set with nonempty interior, and since $C_1 \cap C_2 = \emptyset$, it follows that $\mathbf{0} \notin C_1 - C_2$. By the supporting hyperplane theorem, it follows that there exists $\mathbf{0} \neq \mathbf{p} \in \mathbb{R}^n$ such that

$$\mathbf{p}^\top (\mathbf{x} - \mathbf{y}) \leq \mathbf{p}^\top \mathbf{0} = 0, \quad \forall \mathbf{x} \in C_1, \mathbf{y} \in C_2,$$

which is the same as the desired result. \square

A nonlinear version of Farkas lemma

Theorem (nonlinear Farkas lemma): *Let $X \subseteq \mathbb{R}^n$ be a convex set and let f, g_1, g_2, \dots, g_m be convex functions over X . Assume that there exists $\hat{x} \in X$ such that*

$$g_i(\hat{x}) < 0, \quad i = 1, 2, \dots, m.$$

Let $c \in \mathbb{R}$. Then the following two claims are equivalent.

(a) *The following implication holds :*

$$x \in X, \quad g_i(x) \leq 0, \quad i = 1, 2, \dots, m \implies f(x) \geq c.$$

(b) *There exist $\lambda_1, \lambda_2, \dots, \lambda_m \geq 0$ such that*

$$\min_{x \in X} \left(f(x) + \sum_{i=1}^m \lambda_i g_i(x) \right) \geq c. \quad (5)$$

Proof of the nonlinear Farkas lemma

(b) \Rightarrow (a): Suppose that there exist $\lambda_1, \lambda_2, \dots, \lambda_m \geq 0$ such that (5) holds. Let $x \in X$ satisfy $g_i(x) \leq 0, i = 1, 2, \dots, m$. Then by (5) we have

$$f(x) + \sum_{i=1}^m \lambda_i g_i(x) \geq c.$$

Since $g_i(x) \leq 0$ and $\lambda_i \geq 0$ for $i = 1, 2, \dots, m$,

$$f(x) \geq c - \sum_{i=1}^m \lambda_i g_i(x) \geq c.$$

(a) \Rightarrow (b): Assume that (a) holds. Consider the following two sets:

$$S := \{u = (u_0, u_1, \dots, u_m) : \exists x \in X \text{ s.t. } f(x) \leq u_0, g_i(x) \leq u_i, 1 \leq i \leq m\},$$

$$T := \{(u_0, u_1, \dots, u_m) : u_0 < c, u_1 \leq 0, u_2 \leq 0, \dots, u_m \leq 0\}.$$

Proof of the nonlinear Farkas lemma (cont'd)

Note that S and T are convex with nonempty interiors and by (a), $S \cap T = \emptyset$. Therefore, by the separation theorem of two convex sets, it follows that there exists a vector $\mathbf{a} = (a_0, a_1, \dots, a_m)^\top \neq \mathbf{0}$ such that

$$\min_{(u_0, u_1, \dots, u_m) \in S} \sum_{j=0}^m a_j u_j \geq \max_{(u_0, u_1, \dots, u_m) \in T} \sum_{j=0}^m a_j u_j. \quad (6)$$

Claim: $\mathbf{a} \geq \mathbf{0}$. Consider the RHS of (6). Suppose that there exists an $a_i < 0$. By taking u_i to be a negative number tending to $-\infty$ while fixing all the other components as zeros, we obtain that the RHS of (6) is ∞ , which is a contradiction.

Since $\mathbf{a} \geq \mathbf{0}$, it follows that **RHS of (6) = $a_0 c$** , and we thus obtain

$$\min_{(u_0, u_1, \dots, u_m) \in S} \sum_{j=0}^m a_j u_j \geq a_0 c. \quad (7)$$

Proof of the nonlinear Farkas lemma (cont'd)

We will show that $a_0 > 0$. Suppose in contradiction that $a_0 = 0$. Then

$$\min_{(u_0, u_1, \dots, u_m) \in S} \sum_{j=1}^m a_j u_j \geq 0.$$

Since we can take $u_i = g_i(\hat{x})$, $i = 1, 2, \dots, m$, it leads to

$$\sum_{j=1}^m a_j g_j(\hat{x}) \geq 0.$$

which is impossible since $g_j(\hat{x}) < 0 \forall j$ and $\mathbf{a} = (a_0, a_1, \dots, a_m)^\top \neq \mathbf{0}$.

Now we can divide (7) by $a_0 > 0$ to obtain

$$\min_{(u_0, u_1, \dots, u_m) \in S} \left(u_0 + \sum_{j=1}^m \tilde{a}_j u_j \right) \geq c, \quad \tilde{a}_j := \frac{a_j}{a_0}. \quad (8)$$

Proof of the nonlinear Farkas lemma (cont'd)

Define a subset $\tilde{S} \subseteq S$ by

$$\begin{aligned}\tilde{S} &:= \{u = (u_0, u_1, \dots, u_m) : \exists x \in X \text{ s.t. } f(x) = u_0, g_i(x) = u_i, 1 \leq i \leq m\} \\ &= \{(f(x), g_1(x), \dots, g_m(x)) : x \in X\}. \quad (\star)\end{aligned}$$

Then we have

$$\begin{aligned}\min_{(u_0, u_1, \dots, u_m) \in S} \left(u_0 + \sum_{j=1}^m \tilde{a}_j u_j \right) &\leq \min_{(u_0, u_1, \dots, u_m) \in \tilde{S}} \left(u_0 + \sum_{j=1}^m \tilde{a}_j u_j \right) \\ \text{by } (\star) &= \min_{x \in X} \left(f(x) + \sum_{j=1}^m \tilde{a}_j g_j(x) \right),\end{aligned}$$

which combined with (8) yields the desired result

$$\min_{x \in X} \left(f(x) + \sum_{j=1}^m \tilde{a}_j g_j(x) \right) \geq c. \quad \square$$

Strong duality of convex problems (inequality constraints)

Theorem: *Consider the optimization problem*

$$\begin{aligned} f^* &= \min f(x) \\ \text{subject to } & g_i(x) \leq 0, \ i = 1, 2, \dots, m, \\ & x \in X, \end{aligned} \tag{9}$$

where X is a convex set and $f, g_i, i = 1, 2, \dots, m$, are convex functions over X . Suppose that there exists $\hat{x} \in X$ for which $g_i(\hat{x}) < 0, i = 1, 2, \dots, m$. Suppose that problem (9) has a finite optimal value. Then the optimal value of the dual problem

$$q^* = \max\{q(\lambda) : \lambda \in \text{dom}(q)\}, \tag{10}$$

where

$$q(\lambda) = \min_{x \in X} L(x, \lambda),$$

is attained, and the optimal values of the primal and dual problems are the same:

$$f^* = q^*.$$

Proof of the strong duality of convex problems

Since problem (9) has a finite optimal value, we have $f^* > -\infty$. It follows that the following implication holds:

$$x \in X, \quad g_i(x) \leq 0, \quad i = 1, 2, \dots, m \implies f(x) \geq f^*.$$

By the nonlinear Farkas's lemma, there exist $\tilde{\lambda}_1, \tilde{\lambda}_2, \dots, \tilde{\lambda}_m \geq 0$ such that

$$q(\tilde{\lambda}) = \min_{x \in X} \left(f(x) + \sum_{j=1}^m \tilde{\lambda}_j g_j(x) \right) \geq f^*,$$

which combined with the weak duality theorem yields

$$q^* \geq q(\tilde{\lambda}) \geq f^* \geq q^*.$$

Hence, $f^* = q^*$ and $\tilde{\lambda}$ is an optimal solution of the dual problem. \square

Complementary slackness conditions

Theorem: Consider problem (9) and assume that $f^* = q^*$, where q^* is the optimal value of the dual problem given by (10). If \mathbf{x}^* and λ^* are optimal solutions of the primal and dual problems, respectively, then

$$\begin{aligned}\mathbf{x}^* &\in \arg \min L(\mathbf{x}, \lambda^*), \\ \lambda_i^* g_i(\mathbf{x}^*) &= 0, \quad i = 1, 2, \dots, m.\end{aligned}$$

Proof: First, we have

$$\begin{aligned}q^* &= q(\lambda^*) = \min_{\mathbf{x} \in X} L(\mathbf{x}, \lambda^*) \leq L(\mathbf{x}^*, \lambda^*) \\ &= f(\mathbf{x}^*) + \sum_{i=1}^m \lambda_i^* g_i(\mathbf{x}^*) \leq f(\mathbf{x}^*) = f^*.\end{aligned}$$

Since $f^* = q^*$, all the inequalities in the above chain are satisfied as equalities. It follows that $\mathbf{x}^* \in \arg \min L(\mathbf{x}, \lambda^*)$, $\sum_{i=1}^m \lambda_i^* g_i(\mathbf{x}^*) = 0$. Because of $\lambda_i^* \geq 0$ and $g_i(\mathbf{x}^*) \leq 0 \forall i = 1, 2, \dots, m$, we obtain $\lambda_i^* g_i(\mathbf{x}^*) = 0 \forall i = 1, 2, \dots, m$. \square