

EECS 127/227AT Optimization Models in Engineering
Spring 2020

Discussion 9

1. Magic with constraints

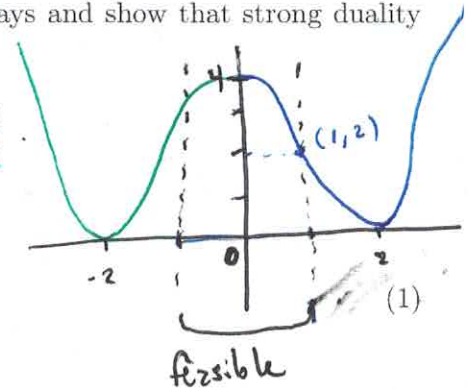
In this question, we will represent a problem in two different ways and show that strong duality holds in one case but doesn't hold in the other.

Let

$$f_0(x) \doteq \begin{cases} x^3 - 3x^2 + 4, & x \geq 0 \\ -x^3 - 3x^2 + 4, & x < 0 \end{cases}$$

(a) Consider the minimization problem

$$\begin{aligned} p^* &= \inf_{x \in \mathbb{R}} f_0(x) \\ \text{s.t. } &-1 \leq x, \quad x \leq 1. \end{aligned}$$



i. Show that $p^* = 2$ and the set of optimizers $x \in \mathcal{X}^*$ is $\mathcal{X}^* = \{-1, 1\}$ by examining the "critical" points, i.e., points where the gradient is zero, points on the boundaries, and $\pm\infty$.

$$x = \pm\infty, \pm 2, \textcircled{0}, \textcircled{\pm 1}$$

$$p^* = 2 \text{ attained at } x \in \{-1, 1\}.$$

ii. Show that the dual problem can be represented as

$$d^* = \sup_{\lambda_1, \lambda_2 \geq 0} g(\vec{\lambda}),$$

where

$$g(\vec{\lambda}) = \min \{g_1(\vec{\lambda}), g_2(\vec{\lambda})\},$$

with

$$g_1(\vec{\lambda}) = \inf_{x \geq 0} x^3 - 3x^2 + 4 - \lambda_1(x+1) + \lambda_2(x-1) \quad h_1(x, \vec{\lambda})$$

$$g_2(\vec{\lambda}) = \inf_{x < 0} -x^3 - 3x^2 + 4 - \lambda_1(x+1) + \lambda_2(x-1) \quad h_2(x, \vec{\lambda})$$

$$\begin{aligned} g(\vec{\lambda}) &= \inf_{x \in \mathbb{R}} \underbrace{f_0(x)}_{\text{piecewise}} + \lambda_1(-1-x) + \lambda_2(x-1) \\ &= \min \left(\inf_{x \geq 0} \mathcal{L}(x, \vec{\lambda}), \inf_{x < 0} \mathcal{L}(x, \vec{\lambda}) \right) \end{aligned}$$

iii. Next, show that

$$g_1(\bar{\lambda}) \leq -3\lambda_1 + \lambda_2$$

$$g_2(\bar{\lambda}) \leq \lambda_1 - 3\lambda_2.$$

Use this to show that $g(\bar{\lambda}) \leq 0$ for all $\lambda_1, \lambda_2 \geq 0$.

$$g_1(\lambda) \leq \cancel{-3x^2} h(x, \lambda) \text{ at any feasible } x.$$

$$x=2 \Rightarrow g_1(\lambda) \leq -3\lambda_1 + \lambda_2$$

$$x=-2 \Rightarrow g_2(\lambda) \leq \lambda_1 - 3\lambda_2$$

iv. Show that $g(\bar{0}) = 0$ and conclude that $d^* = 0$.

$$d^* = \max_{\lambda} g(\bar{\lambda})$$

$$g(\bar{0}) = \min \{g_1(\bar{0}), g_2(\bar{0})\}$$

$$= \min \left\{ \inf_{x \geq 0} x^3 - 3x^2 + 4, \inf_{x < 0} -x^3 - 3x^2 + 4 \right\}$$

$$= \min \{0, 0\} = 0 \Rightarrow d^* = \sup_{\lambda} 0 = 0$$

more math

v. Does strong duality hold?

$$\left. \begin{array}{l} p^* = 2 \\ d^* = 0 \end{array} \right\} \Rightarrow \text{NO!}$$

(b) Now, consider a problem equivalent to the minimization in (1):

$$p^* = \inf_{x \in \mathbb{R}} f_0(x) \quad (2)$$

$$\text{s.t. } x^2 \leq 1.$$

Observe that $p^* = 2$ and the set of optimizers $x \in \mathcal{X}^*$ is $\mathcal{X}^* = \{-1, 1\}$, since this problem is equivalent to the one in part (a).

i. Show that the dual problem can be represented as

$$d^* = \sup_{\lambda \geq 0} g(\lambda),$$

where

$$g(\lambda) = \min(g_1(\lambda), g_2(\lambda)),$$

with

$$g_1(\lambda) = \inf_{x \geq 0} x^3 - 3x^2 + 4 + \lambda(x^2 - 1) \quad h(x, \lambda)$$

$$g_2(\lambda) = \inf_{x < 0} -x^3 - 3x^2 + 4 + \lambda(x^2 - 1).$$

ii. Show that $g_1(\lambda) = g_2(\lambda) = \begin{cases} 4 - \lambda, & \lambda \geq 3 \\ -\frac{4}{27}(3 - \lambda)^3 + 4 - \lambda, & 0 \leq \lambda < 3. \end{cases}$

skip in sol'n

$$x = 0, +\infty, \nabla_x h(x, \lambda) = 0 \Rightarrow 3x^2 - 2(3 - \lambda)x = 0$$

$$\Rightarrow \underline{x = 0} \text{ or } \underline{x = \frac{2}{3}(3 - \lambda)}$$

iii. Conclude that $d^* = 2$ and the optimal $\lambda = \frac{3}{2}$.

iv. Does strong duality hold?

$$\underline{d^* = 2 = p^*} \Rightarrow \underline{\text{YES}} \text{ strong duality!}$$

If you have a nonconvex problem you want to solve, try different equivalent specifications of your constraints.

2. Linear programming

Express the following problems as LPs.

(a)

→ slack variables!

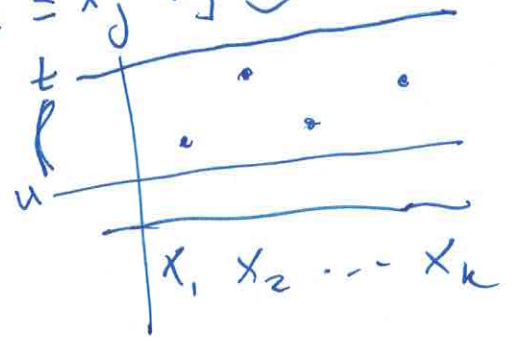
$$\begin{aligned} \min & c^T x \\ \text{s.t.} & Ax \leq b \\ & x \leq 0? \end{aligned}$$

$$\begin{aligned} \min_{\vec{x} \in \mathbb{R}^k} & \left[\max_{i=1, \dots, k} x_i - \min_{j=1, \dots, k} x_j \right] \\ \text{s.t.} & A\vec{x} = \vec{b} \end{aligned}$$

$$\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_k \end{bmatrix}$$

$$\min_{\vec{x}, t, u} [t - u]$$

$$\begin{aligned} \text{s.t.} \quad t & \geq \max_i x_i \Leftrightarrow t \geq x_i \quad \forall i \\ u & \leq \min_j x_j \Leftrightarrow u \leq x_j \quad \forall j \\ Ax & = b \end{aligned}$$



(b)

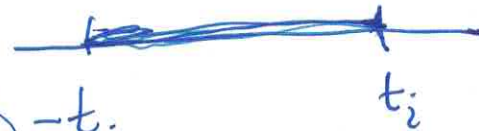
$$\begin{aligned} \min_{\vec{x} \in \mathbb{R}^k} & \sum_{i=1}^k |x_i| \\ \text{s.t.} & A\vec{x} = \vec{b} \end{aligned}$$

$$\min_{\vec{x}, \vec{t}} \sum_{i=1}^k t_i$$

$$\text{s.t.} \quad A\vec{x} = \vec{b}$$

$$t_i \geq |x_i|$$

$$\begin{aligned} & \swarrow \searrow \\ x_i & \leq t_i \quad x_i \geq -t_i \end{aligned}$$



$$\min_{\vec{x}, \vec{t}} \sum t_i \Leftrightarrow \mathbf{1}^T \vec{t}$$

$$\begin{aligned} \text{s.t.} \quad A\vec{x} & = \vec{b} \\ x_i & \leq t_i, \quad x_i \geq -t_i \quad \forall i \end{aligned} //$$