

CO 250: Introduction to Optimization

Module 4: Duality Theory (Strong Duality)

Recap: Weak Duality

(P_{\max})			(P_{\min})	
max	$c^T x$	\leq constraint	≥ 0 variable	min $b^T y$ subject to $A^T y \leq c$ $y \geq 0$
subject to	$Ax \leq b$ $x \geq 0$	$=$ constraint	free variable	
		\geq constraint	≤ 0 variable	
		≥ 0 variable	\geq constraint	
		free variable	$=$ constraint	
		≤ 0 variable	\leq constraint	

Last lecture: we described a method to construct the dual of a general linear program.

E.g.: consider the primal LP, (P), on the right – a **max LP** that falls in the **first two columns** of the table.

→ The dual of (P) is a **min LP**.

$$\begin{aligned}
 &\max (2, -1, 3)x && (P) \\
 &\text{s.t. } \begin{pmatrix} 1 & 0 & -1 \\ 0 & -2 & 1 \\ 1 & 1 & 0 \end{pmatrix} x \begin{matrix} \leq \\ = \\ \geq \end{matrix} \begin{pmatrix} 2 \\ 1 \\ -2 \end{pmatrix} \\
 &x_1 \geq 0, x_2 \leq 0, x_3 \text{ free}
 \end{aligned}$$

Recap: Weak Duality

(P_{\max})			(P_{\min})	
max	$c^T x$	\leq constraint	≥ 0 variable	min $b^T y$ subject to $A^T y \preceq c$ $y \succeq 0$
subject to	$Ax \preceq b$ $x \succeq 0$	$=$ constraint	free variable	
		\geq constraint	≤ 0 variable	
		≥ 0 variable	\geq constraint	
		free variable	$=$ constraint	
		≤ 0 variable	\leq constraint	

$$\max (2, -1, 3)x \quad (P)$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & -1 \\ 0 & -2 & 1 \\ 1 & 1 & 0 \end{pmatrix} x \begin{matrix} \leq \\ = \\ \geq \end{matrix} \begin{pmatrix} 2 \\ 1 \\ -2 \end{pmatrix}$$

$$x_1 \geq 0, x_2 \leq 0, x_3 \text{ free}$$

$$\min (2, 1, -2)y \quad (D)$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & 0 & 1 \\ 0 & -2 & 1 \\ -1 & 1 & 0 \end{pmatrix} y \begin{matrix} \geq \\ \leq \\ = \end{matrix} \begin{pmatrix} 2 \\ -1 \\ 3 \end{pmatrix}$$

$$y_1 \geq 0, y_2 \text{ free}, y_3 \leq 0$$

Recap: Weak Duality

$$\begin{array}{ll} \max (2, -1, 3)x & \text{(P)} \\ \text{s.t. } \begin{pmatrix} 1 & 0 & -1 \\ 0 & -2 & 1 \\ 1 & 1 & 0 \end{pmatrix} x \begin{matrix} \leq \\ = \\ \geq \end{matrix} \begin{pmatrix} 2 \\ 1 \\ -2 \end{pmatrix} \\ x_1 \geq 0, x_2 \leq 0, x_3 \text{ free} \end{array} \quad \begin{array}{ll} \min (2, 1, -2)y & \text{(D)} \\ \text{s.t. } \begin{pmatrix} 1 & 0 & 1 \\ 0 & -2 & 1 \\ -1 & 1 & 0 \end{pmatrix} y \begin{matrix} \geq \\ \leq \\ = \end{matrix} \begin{pmatrix} 2 \\ -1 \\ 3 \end{pmatrix} \\ y_1 \geq 0, y_2 \text{ free}, y_3 \leq 0 \end{array}$$

Weak Duality Theorem

if \bar{x} is feasible for (P) and \bar{y} is feasible for (D),

$$\implies c^T \bar{x} \leq b^T \bar{y}$$

If $c^T \bar{x} = b^T \bar{y}$, then **both** \bar{x} and \bar{y} are optimal.

This Lecture: Strong Duality

(P_{\max})			(P_{\min})		
max	$c^T x$	\leq constraint	≥ 0 variable	min	$b^T y$
subject to		$=$ constraint	free variable	subject to	
		\geq constraint	≤ 0 variable		
	$Ax \leq b$	≥ 0 variable	\geq constraint		$A^T y \leq c$
	$x \geq 0$	free variable	$=$ constraint		$y \geq 0$
		≤ 0 variable	\leq constraint		

Question

Can we always find feasible solutions \bar{x} and \bar{y} to a primal-dual pair, (P_{\max}) , (P_{\min}) , such that $c^T \bar{x} = b^T \bar{y}$?

Strong Duality Theorem

If (P_{\max}) has an optimal solution \bar{x} , then (P_{\min}) has an optimal solution \bar{y} such that $c^T \bar{x} = b^T \bar{y}$.

Strong Duality – for LPs in SEF

Let us prove the **Strong Duality Theorem** in the special case where (P) is in SEF.

Let's assume (P) has an optimal solution.

→ 2-Phase Simplex terminates with an optimal basis B (Why?)

We can rewrite (P) for basis B :

$$\begin{aligned} \max z &= \bar{y}^T b + \bar{c}^T x & (P') \\ \text{s.t. } x_B + A_B^{-1} A_N x_N &= A_B^{-1} b \\ x &\geq 0 \end{aligned}$$

Thus, $\bar{x}_N = 0$ and $\bar{x}_B = A_B^{-1} b$

$$\begin{aligned} \max c^T x & & (P) \\ \text{s.t. } Ax &= b \\ x &\geq 0 \end{aligned}$$

$$\begin{aligned} \min b^T y & & (D) \\ \text{s.t. } A^T y &\geq c \end{aligned}$$

where:

$$\begin{aligned} \bar{y} &= A_B^{-T} c_B \\ \bar{c}^T &= c^T - \bar{y}^T A \end{aligned}$$

Strong Duality – for LPs in SEF

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$$\begin{aligned} \max c^T x & & (P) \\ \text{s.t. } Ax &= b \\ x &\geq 0 \end{aligned}$$

Thus, $\bar{x}_N = 0$ and $\bar{x}_B = A_B^{-1} b$

$$\begin{aligned} \min b^T y & & (D) \\ \text{s.t. } A^T y &\geq c \end{aligned}$$

Recall that (P) and (P') are equivalent!

→ \bar{x} has same value in (P) and (P')

$$\begin{aligned} c^T \bar{x} &= \bar{y}^T b + \bar{c}^T \bar{x} \\ &= \bar{y}^T b + \bar{c}_N^T \bar{x}_N \\ &= b^T \bar{y} \end{aligned}$$

where:

$$\begin{aligned} \bar{y} &= A_B^{-T} c_B \\ \bar{c}^T &= c^T - \bar{y}^T A \end{aligned}$$

Goal: Show that \bar{y} is dual feasible.

Strong Duality – for LPs in SEF

We can rewrite (P) for basis B :

$$\begin{aligned} \max \quad & z = \bar{y}^T b + \bar{c}^T x \\ \text{s.t.} \quad & x_B + A_B^{-1} A_N x_N = A_B^{-1} b \\ & x \geq 0 \end{aligned} \quad (\text{P}')$$

$$\begin{aligned} \max \quad & c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned} \quad (\text{P})$$

Thus, $\bar{x}_B = A_B^{-1} b$ and $\bar{x}_N = 0$ and $c^T \bar{x} = b^T \bar{y}$.

$$\begin{aligned} \min \quad & b^T y \\ \text{s.t.} \quad & A^T y \geq c \end{aligned} \quad (\text{D})$$

Note that B is an optimal basis $\rightarrow \bar{c} \leq 0$

$$\rightarrow c^T - \bar{y}^T A \leq 0$$

where:

$$\begin{aligned} \bar{y} &= A_B^{-T} c_B \\ \bar{c}^T &= c^T - \bar{y}^T A \end{aligned}$$

Equivalently, $A^T \bar{y} \geq c$,
meaning \bar{y} is dual feasible!

Strong Duality Theorem

Strong Duality Theorem

Let (P) and (D) be a **primal-dual pair** of LPs. If (P) has an optimal solution, then (D) has one, and their objective values equal.

Note: (P) is feasible and (D) is feasible \longrightarrow (P) cannot be unbounded
Fundamental Theorem of LP \longrightarrow (P) has an optimal solution.

Subtly different version via previous results:

Strong Duality Theorem – Feasibility Version

Let (P) and (D) be primal-dual pair of LPs. If **both are feasible**, then both have optimal solutions of the same objective value.

Possible Outcomes of Primal-Dual Pair (P), (D)

(D)(P)	optimal solution	unbounded	infeasible
optimal solution	possible ①	impossible ②	impossible ③
unbounded	impossible ④	impossible ⑤	possible ⑥
infeasible	impossible ⑦	possible ⑧	possible ⑨

- ①, ⑥, and ⑧ many examples exist
- ② follows directly from Weak Duality as follows:

Suppose, **for a contradiction**, that (D) has an optimal solution \bar{y} .

$c^T \bar{x} \leq b^T \bar{y}$ for all feasible primal solutions \bar{x}
by Weak Duality \rightarrow (P) is bounded!

Similar arguments apply to ④ and ⑤

- ③, ⑦ follow directly from Strong Duality
- I'll leave ⑨ for you to do as an exercise!

$$\begin{aligned} \max \quad & c^T x \quad (P) \\ \text{s.t.} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

$$\begin{aligned} \min \quad & b^T y \quad (D) \\ \text{s.t.} \quad & A^T y \geq c \end{aligned}$$

Strong Duality Theorem

Let (P) and (D) be a **primal-dual pair** of LPs. If (P) has an optimal solution, then (D) has one, and their objective values equal.

(D)(P)	optimal solution	unbounded	infeasible
optimal solution	possible ①	impossible ②	impossible ③
unbounded	impossible ④	impossible ⑤	possible ⑥
infeasible	impossible ⑦	possible ⑧	possible ⑨