

MVE165/MMG631

Linear and integer optimization with applications

Lecture 5

Linear programming duality and sensitivity analysis

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A linear program with optimal value z^*

$$\begin{array}{llll}
 z^* = \max & z := & 20x_1 & +18x_2 & & \text{weights} \\
 \text{subject to} & & 7x_1 & +10x_2 & \leq 3600 & (1) & v_1 \\
 & & 16x_1 & +12x_2 & \leq 5400 & (2) & v_2 \\
 & & & & x_1, x_2 & \geq 0 &
 \end{array}$$

[DRAW GRAPH]

- What is the largest possible value of z (i.e., z^*)?

Compute upper estimates of z^* , e.g.:

- Multiply (1) by 3:
 $\Rightarrow 21x_1 + 30x_2 \leq 10800 \quad \Rightarrow z^* \leq 10800$
- Multiply (2) by 1.5:
 $\Rightarrow 24x_1 + 18x_2 \leq 8100 \quad \Rightarrow z^* \leq 8100$
- Combine: $0.6 \times (1) + 1 \times (2)$:
 $\Rightarrow 20.2x_1 + 18x_2 \leq 7560 \quad \Rightarrow z^* \leq 7560$

A linear program with optimal value z^*

maximize	$z :=$	$20x_1 + 18x_2$			weights
subject to		$7x_1 + 10x_2 \leq 3600$	(1)		v_1
		$16x_1 + 12x_2 \leq 5400$	(2)		v_2
		$x_1, x_2 \geq 0$			

[DRAW GRAPH]

- Do better than guess—compute *optimal* weights!
- Value of estimate: $w = 3600v_1 + 5400v_2 \rightarrow \min$

Constraints on the weights

$$\begin{aligned}
 7v_1 + 16v_2 &\geq 20 \\
 10v_1 + 12v_2 &\geq 18 \\
 v_1, v_2 &\geq 0
 \end{aligned}$$

The best (lowest) possible upper estimate of z^*

$$\begin{array}{llllll} \text{minimize} & w := & 3600v_1 & + & 5400v_2 & \\ \text{subject to} & & 7v_1 & + & 16v_2 & \geq 20 \\ & & 10v_1 & + & 12v_2 & \geq 18 \\ & & & & v_1, v_2 & \geq 0 \end{array}$$

- A linear program! [DRAW GRAPH!!]
- It is called the *linear programming dual* of the original linear program

The lego model – the market problem

Consider the lego problem

$$\begin{array}{ll} \text{maximize} & z = 1600x_1 + 1000x_2 \\ \text{subject to} & 2x_1 + x_2 \leq 6 \\ & 2x_1 + 2x_2 \leq 8 \\ & x_1, x_2 \geq 0 \end{array}$$

- Option: Sell bricks instead of making furniture
- $v_1(v_2)$ = price of a large (small) brick
- The market wishes to *minimize the payment*: $\min 6v_1 + 8v_2$

Sell only if prices are high enough

- $2v_1 + 2v_2 \geq 1600$ – otherwise better to make tables
- $v_1 + 2v_2 \geq 1000$ – otherwise better to make chairs
- $v_1, v_2 \geq 0$ – don't sell at a negative price

A general linear program on “standard form”

A linear program with n non-negative variables, m equality constraints ($m < n$), and non-negative right-hand-sides

$$\begin{aligned} \text{maximize} \quad & z = \sum_{j=1}^n c_j x_j, \\ \text{subject to} \quad & \sum_{j=1}^n a_{ij} x_j = b_i, \quad i = 1, \dots, m, \\ & x_j \geq 0, \quad j = 1, \dots, n, \end{aligned}$$

where

$$\begin{aligned} x_j &\in \mathbb{R}, \quad j = 1, \dots, n, \\ a_{ij} &\in \mathbb{R}, \quad i = 1, \dots, m, \\ &\quad j = 1, \dots, n, \\ b_i &\geq 0, \quad i = 1, \dots, m, \\ c_j &\in \mathbb{R}, \quad j = 1, \dots, n. \end{aligned}$$

Or, on matrix form

$$\begin{aligned} \text{maximize} \quad & z = \mathbf{c}^T \mathbf{x}, \\ \text{subject to} \quad & \mathbf{A} \mathbf{x} = \mathbf{b}, \\ & \mathbf{x} \geq \mathbf{0}^n, \end{aligned}$$

where

$$\begin{aligned} \mathbf{x} &\in \mathbb{R}^n, \\ \mathbf{A} &\in \mathbb{R}^{m \times n}, \\ \mathbf{b} &\in \mathbb{R}_+^m, \\ \mathbf{c} &\in \mathbb{R}^n. \end{aligned}$$

Linear programming duality

To each primal linear program corresponds a dual linear program

(Primal)

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

(Dual)

$$\begin{aligned} &\text{maximize} && w = \mathbf{b}^T \mathbf{y} \\ &\text{subject to} && \mathbf{A}^T \mathbf{y} \leq \mathbf{c} \end{aligned}$$

The component forms of the primal and dual programs

(Primal)

$$\begin{aligned} \min \quad & z = \sum_{j=1}^n c_j x_j \\ \text{s.t.} \quad & \sum_{j=1}^n a_{ij} x_j = b_i, \quad i = 1, \dots, m \\ & x_j \geq 0, \quad j = 1, \dots, n \end{aligned}$$

(Dual)

$$\begin{aligned} \max \quad & w = \sum_{i=1}^m b_i y_i \\ \text{s.t.} \quad & \sum_{i=1}^m a_{ij} y_i \leq c_j, \\ & j = 1, \dots, n \end{aligned}$$

An example of linear programming duality

A primal linear program

minimize	$z =$	$2x_1$	$+3x_2$		weights/duals
subject to		$3x_1$	$+2x_2$	$= 14$	y_1
		$2x_1$	$-4x_2$	≥ 2	y_2
		$4x_1$	$+3x_2$	≤ 19	y_3
			x_1, x_2	≥ 0	

The corresponding dual linear program

maximize	$w =$	$14y_1$	$+2y_2$	$+19y_3$	weights/primals	
subject to		$3y_1$	$+2y_2$	$+4y_3$	≤ 2	x_1
		$2y_1$	$-4y_2$	$+3y_3$	≤ 3	x_2
		y_1			free	
			y_2		≥ 0	
				y_3	≤ 0	

maximization \iff minimization

dual program \iff primal program
 primal program \iff dual program

constraints \iff *variables*

\geq \iff ≤ 0

\leq \iff ≥ 0

$=$ \iff free

variables \iff *constraints*

≥ 0 \iff \geq

≤ 0 \iff \leq

free \iff $=$

The dual of the dual of any linear program equals the primal

Primal		Dual	
minimize	$z = \mathbf{c}^T \mathbf{x}$ (1a)	maximize	$w = \mathbf{b}^T \mathbf{y}$ (2a)
subject to	$\mathbf{Ax} = \mathbf{b}$ (1b)	subject to	$\mathbf{A}^T \mathbf{y} \leq \mathbf{c}$ (2b)
	$\mathbf{x} \geq \mathbf{0}^n$ (1c)		

Weak duality

[Th. 6.1]

Let \mathbf{x} be a feasible point in the primal (minimization) and \mathbf{y} be a feasible point in the dual (maximization). Then, it holds that

$$z = \mathbf{c}^T \mathbf{x} \geq \mathbf{b}^T \mathbf{y} = w$$

Proof: $z \underbrace{=}_{(1a)} \mathbf{c}^T \mathbf{x} \underbrace{\geq}_{(2b), (1c)} \mathbf{y}^T \mathbf{Ax} \underbrace{=}_{(1b)} \mathbf{y}^T \mathbf{b} \underbrace{=}_{(2a)} w. \quad \square$

In the course book, the primal is formulated with [inequality](#) constraints in (1b): adjust the dual and the proof for that case!

Primal

minimize $z = \mathbf{c}^T \mathbf{x}$
subject to $\mathbf{Ax} = \mathbf{b}$
 $\mathbf{x} \geq \mathbf{0}^n$

Dual

maximize $w = \mathbf{b}^T \mathbf{y}$
subject to $\mathbf{A}^T \mathbf{y} \leq \mathbf{c}$

Strong duality

[Th. 6.3]

In a pair of primal and dual linear programs, if one of them has an optimal solution, so does the other, and their optimal values are equal.

Primal

minimize $z = \mathbf{c}^T \mathbf{x}$
 subject to $\mathbf{Ax} = \mathbf{b}$
 $\mathbf{x} \geq \mathbf{0}^n$

Dual

maximize $w = \mathbf{b}^T \mathbf{y}$
 subject to $\mathbf{A}^T \mathbf{y} \leq \mathbf{c}$

Complementary slackness [Th. 6.5; proof in the course book]

If \mathbf{x} is *optimal in the primal* and \mathbf{y} is *optimal in the dual*, then it holds that

$$\mathbf{x}^T(\mathbf{c} - \mathbf{A}^T \mathbf{y}) = \mathbf{y}^T(\mathbf{b} - \mathbf{Ax}) = 0.$$

If \mathbf{x} is *feasible in the primal*, \mathbf{y} is *feasible in the dual*, and $\mathbf{x}^T(\mathbf{c} - \mathbf{A}^T \mathbf{y}) = \mathbf{y}^T(\mathbf{b} - \mathbf{Ax}) = 0$, then

\mathbf{x} and \mathbf{y} are optimal in their respective problems.

Primal	Dual
$z^* := \min z = \mathbf{c}_B^T \mathbf{x}_B + \mathbf{c}_N^T \mathbf{x}_N$	$w^* := \max w = \mathbf{b}^T \mathbf{y}$
subject to $\mathbf{B}\mathbf{x}_B + \mathbf{N}\mathbf{x}_N = \mathbf{b}$	subject to $\mathbf{B}^T \mathbf{y} \leq \mathbf{c}_B$
$\mathbf{x}_B \geq \mathbf{0}^m, \mathbf{x}_N \geq \mathbf{0}^{n-m}$	$\mathbf{N}^T \mathbf{y} \leq \mathbf{c}_N$

Duality theorem

[Th. 6.4]

Assume that $\mathbf{x}_B = \mathbf{B}^{-1}\mathbf{b}$ is an optimal basic (feasible) solution to the primal problem. Then $\mathbf{y}^T = \mathbf{c}_B^T \mathbf{B}^{-1}$ is an optimal solution to the dual problem and $z^* = w^*$.

Proof structure

[full proof in the course book]

- 1 $\mathbf{y}^T = \mathbf{c}_B^T \mathbf{B}^{-1}$ is feasible in the dual problem
- 2 The optimal objective values z^* and w^* are equal
- 3 Follows from complementarity: $(\mathbf{x}_B, \mathbf{x}_N)$ and \mathbf{y} are feasible in the primal and dual respective problem and $z^* = w^*$

Relations between primal and dual optimal solutions

primal (dual) problem \iff dual (primal) problem

unique and non-degenerate solution \iff unique and non-degenerate solution

unbounded solution \implies no feasible solutions

no feasible solutions \implies unbounded solution *or* no feasible solutions

degenerate solution \iff alternative solutions

Exercises on linear programming duality

- Formulate and solve graphically the dual of:

$$\begin{array}{ll} \text{minimize} & z = 6x_1 + 3x_2 + x_3 \\ \text{subject to} & 6x_1 - 3x_2 + x_3 \geq 2 \\ & 3x_1 + 4x_2 + x_3 \geq 5 \\ & x_1, x_2, x_3 \geq 0 \end{array}$$

- Then find the optimal primal solution
- Verify that the dual of the dual equals the primal

- B = index set of basic var's, N = index set of non-basic var's
 $\Rightarrow |B| = m$ and $|N| = n - m$
- Partition matrix/vectors: $\mathbf{A} = (\mathbf{B}, \mathbf{N})$, $\mathbf{x} = (\mathbf{x}_B, \mathbf{x}_N)$, $\mathbf{c} = (\mathbf{c}_B, \mathbf{c}_N)$
- The matrix \mathbf{B} (\mathbf{N}) contains the columns of \mathbf{A} corresponding to the index set B (N) — Analogously for \mathbf{x} and \mathbf{c}

Original linear program

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

Rewritten linear program

$$\begin{aligned} & \text{minimize } z = \mathbf{c}_B^T \mathbf{x}_B + \mathbf{c}_N^T \mathbf{x}_N \\ & \text{subject to } \mathbf{B}\mathbf{x}_B + \mathbf{N}\mathbf{x}_N = \mathbf{b}, \\ & \mathbf{x}_B \geq \mathbf{0}^m, \mathbf{x}_N \geq \mathbf{0}^{n-m} \end{aligned}$$

Substitute: $\mathbf{x}_B = \mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_N \implies$

$$\begin{aligned} & \text{minimize } z = \mathbf{c}_B^T \mathbf{B}^{-1}\mathbf{b} + [\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1}\mathbf{N}]\mathbf{x}_N \\ & \text{subject to } \mathbf{B}^{-1}\mathbf{b} - \mathbf{B}^{-1}\mathbf{N}\mathbf{x}_N \geq \mathbf{0}^m, \\ & \mathbf{x}_N \geq \mathbf{0}^{n-m} \end{aligned}$$

Optimality and feasibility (review)

Optimality condition (for minimization)

The basis B is *optimal* if $\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{N} \geq \mathbf{0}^{n-m}$
(marginal values = reduced costs ≥ 0)

If not, choose as *entering* variable $j \in N$ the one with the lowest (negative) value of the reduced cost $c_j - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{A}_j$

Feasibility condition

For all $i \in B$ it holds that $x_i = (\mathbf{B}^{-1} \mathbf{b})_i - (\mathbf{B}^{-1} \mathbf{A}_j)_i x_j$

Choose the *leaving* variable $i^* \in B$ according to

$$i^* = \arg \min_{i \in B} \left\{ \frac{(\mathbf{B}^{-1} \mathbf{b})_i}{(\mathbf{B}^{-1} \mathbf{A}_j)_i} \mid (\mathbf{B}^{-1} \mathbf{A}_j)_i > 0 \right\}$$

In the simplex tableau, we have

basis	$-z$	\mathbf{x}_B	\mathbf{x}_N	\mathbf{s}	RHS
$-z$	1	$\mathbf{0}$	$\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{N}$	$-\mathbf{c}_B^T \mathbf{B}^{-1}$	$-\mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{b}$
\mathbf{x}_B	$\mathbf{0}$	\mathbf{I}	$\mathbf{B}^{-1} \mathbf{N}$	\mathbf{B}^{-1}	$\mathbf{B}^{-1} \mathbf{b}$

- \mathbf{s} denotes possible slack variables [columns for \mathbf{s} are copies of certain columns for $(\mathbf{x}_B, \mathbf{x}_N)$]
 - The computations performed by the simplex algorithm involve matrix inversions (i.e., \mathbf{B}^{-1}) and *updates* of these
 - A non-basic (basic) variable enters (leaves) the basis \Rightarrow one column, \mathbf{A}_j , in \mathbf{B} is replaced by another, \mathbf{A}_k
 - Row operations \Leftrightarrow Updates of \mathbf{B}^{-1} (and of $\mathbf{B}^{-1} \mathbf{N}$, $\mathbf{B}^{-1} \mathbf{b}$, and $\mathbf{c}_B^T \mathbf{B}^{-1}$)
- \Rightarrow Efficient numerical computations are crucial for the performance of the simplex algorithm

Sensitivity analysis—changes in the optimal solution as functions of changes in the problem data (Ch. 5)

- How does the optimum change when the *right-hand-sides* (resources, e.g.) *change*?
- When the *objective coefficients* (prices, e.g.) *change*?

Assume that the basis B is optimal:

$$\begin{aligned} \text{minimize} \quad & z = \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{b} + [\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{N}] \mathbf{x}_N \\ \text{subject to} \quad & \mathbf{B}^{-1} \mathbf{b} - \mathbf{B}^{-1} \mathbf{N} \mathbf{x}_N \geq \mathbf{0}^m, \\ & \mathbf{x}_N \geq \mathbf{0}^{n-m}, \end{aligned}$$

where $\mathbf{x}_B = \mathbf{B}^{-1} \mathbf{b} - \mathbf{B}^{-1} \mathbf{N} \mathbf{x}_N$

Changes in the right-hand-side coefficients

Shadow price = dual price

[Def. 5.3]

The *shadow price* of a constraint is defined as the change in the optimal value as a function of the (marginal) change in the RHS. It equals the optimal value of the corresponding dual variable.

In AMPL: `display constraint_name.dual`

- Suppose \mathbf{b} changes to $\mathbf{b} + \Delta\mathbf{b}$

⇒ New optimal value:

$$z^{\text{new}} = \mathbf{c}_B^T \mathbf{B}^{-1} (\mathbf{b} + \Delta\mathbf{b}) = z + \mathbf{c}_B^T \mathbf{B}^{-1} \Delta\mathbf{b}$$

- The current basis is feasible if $\mathbf{B}^{-1} (\mathbf{b} + \Delta\mathbf{b}) \geq 0$
- If not: negative values will occur in the RHS of the simplex tableau
- The reduced costs are unchanged (positive, at optimum)
⇒ this can be resolved using the *dual simplex method*

Changes in the right-hand-side coefficients

A linear program

$$\begin{array}{llll} \text{minimize} & z = & -x_1 & -2x_2 \\ \text{subject to} & & -2x_1 & +x_2 \leq 2 \\ & & -x_1 & +2x_2 \leq 7 \\ & & x_1 & \leq 3 \\ & & & x_1, x_2 \geq 0 \end{array}$$

DRAW GRAPH

The optimal solution is given by

basis	-z	x_1	x_2	s_1	s_2	s_3	RHS
-z	1	0	0	0	1	2	13
x_2	0	0	1	0	$\frac{1}{2}$	$\frac{1}{2}$	5
x_1	0	1	0	0	0	1	3
s_1	0	0	0	1	$-\frac{1}{2}$	$\frac{3}{2}$	3

Changes in the right-hand-side coefficients

Change the right-hand-side according to

$$\begin{array}{ll} \text{minimize} & z = -x_1 - 2x_2 \\ \text{subject to} & -2x_1 + x_2 \leq 2 \\ & -x_1 + 2x_2 \leq 7 + \delta \\ & x_1 \leq 3 \\ & x_1, x_2 \geq 0 \end{array}$$

The change in the RHS is given by $\mathbf{B}^{-1}(0, \delta, 0)^T = (\frac{1}{2}\delta, 0, -\frac{1}{2}\delta)^T$
 \Rightarrow *new optimal tableau*:

basis	-z	x ₁	x ₂	s ₁	s ₂	s ₃	RHS
-z	1	0	0	0	1	2	13 + δ
x ₂	0	0	1	0	$\frac{1}{2}$	$\frac{1}{2}$	5 + $\frac{1}{2}\delta$
x ₁	0	1	0	0	0	1	3
s ₁	0	0	0	1	$-\frac{1}{2}$	$\frac{3}{2}$	3 - $\frac{1}{2}\delta$

- The current basis is feasible if $-10 \leq \delta \leq 6$ (i.e., if RHS ≥ 0)
- In AMPL: `display constraint_name.down, .current, .up`

Changes in the right-hand-side coefficients

Suppose $\delta = 8$. The simplex tableau then appears as

basis	$-z$	x_1	x_2	s_1	s_2	s_3	RHS
$-z$	1	0	0	0	1	2	21
x_2	0	0	1	0	$\frac{1}{2}$	$\frac{1}{2}$	9
x_1	0	1	0	0	0	1	3
s_1	0	0	0	1	$-\frac{1}{2}$	$\frac{3}{2}$	-1

- Dual simplex iteration: $s_1 = -1$ has to leave the basis
- Find smallest ratio between reduced cost (non-basic column) and (negative) elements in the “ s_1 -row” (to stay optimal)

s_2 will enter the basis — *new optimal* tableau:

basis	$-z$	x_1	x_2	s_1	s_2	s_3	RHS
$-z$	1	0	0	2	0	5	19
x_2	0	0	1	1	0	2	8
x_1	0	1	0	0	0	1	3
s_2	0	0	0	-2	1	-3	2

Changes in the objective coefficients

Reduced cost

The *reduced cost* of a non-basic variable defines the change in the objective value when the value of the corresponding variable is (marginally) increased.

The basis B is optimal if $\mathbf{c}_N^T - \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{N} \geq \mathbf{0}^{n-m}$ (i.e., marginal values = reduced costs ≥ 0)

In AMPL: `display variable_name.rc`

- Suppose \mathbf{c} changes to $\mathbf{c} + \Delta \mathbf{c}$
- The new optimal value:

$$z^{\text{new}} = (\mathbf{c}_B + \Delta \mathbf{c}_B)^T \mathbf{B}^{-1} \mathbf{b} = z + \Delta \mathbf{c}_B^T \mathbf{B}^{-1} \mathbf{b}$$

- The current basis is optimal if

$$(\mathbf{c}_N + \Delta \mathbf{c}_N)^T - (\mathbf{c}_B + \Delta \mathbf{c}_B)^T \mathbf{B}^{-1} \mathbf{N} \geq \mathbf{0}$$

- If not: more simplex iterations to find the optimal solution

Changes in the objective coefficients

Change the objective according to

$$\begin{array}{llll} \text{minimize} & z = & -x_1 & +(-2 + \delta)x_2 \\ \text{subject to} & & -2x_1 & +x_2 \leq 2 \\ & & -x_1 & +2x_2 \leq 7 \\ & & x_1 & \leq 3 \\ & & & x_1, x_2 \geq 0 \end{array}$$

The changes in the reduced costs are given by

$$-(\delta, 0, 0)\mathbf{B}^{-1}\mathbf{N} = (-\frac{1}{2}\delta, -\frac{1}{2}\delta) \Rightarrow \text{new optimal tableau:}$$

basis	-z	x_1	x_2	s_1	s_2	s_3	RHS
-z	1	0	0	0	$1 - \frac{1}{2}\delta$	$2 - \frac{1}{2}\delta$	$13 - 5\delta$
x_2	0	0	1	0	$\frac{1}{2}$	$\frac{1}{2}$	5
x_1	0	1	0	0	0	1	3
s_1	0	0	0	1	$-\frac{1}{2}$	$\frac{3}{2}$	3

- The current basis is optimal if $\delta \leq 2$ (i.e., if reduced costs ≥ 0)
- In AMPL: `display variable_name.down, .current, .up`

Changes in the objective coefficients

Suppose $\delta = 4 \Rightarrow$ new tableau:

basis	$-z$	x_1	x_2	s_1	s_2	s_3	RHS
$-z$	1	0	0	0	-1	0	-7
x_2	0	0	1	0	$\frac{1}{2}$	$\frac{1}{2}$	5
x_1	0	1	0	0	0	1	3
s_1	0	0	0	1	$-\frac{1}{2}$	$\frac{3}{2}$	3

Let s_2 enter and x_2 leave the basis. New optimal tableau:

basis	$-z$	x_1	x_2	s_1	s_2	s_3	RHS
$-z$	1	0	2	0	0	1	3
s_2	0	0	2	0	1	1	10
x_1	0	1	0	0	0	1	3
s_1	0	0	1	1	0	2	8