

# Lecture 1 – Introduction to Duality

Module 6 – Duality in Linear Programming  
CS/ISyE/ECE 524



# LP Duality Module

## Learning Outcomes

By the end of this module, you should be able to...

- Find lower and upper bounds on any linear program's optimal objective
- Define duality in linear programs
  - Understand the relationship between primal and dual linear programs
  - State the strong duality theorem
- Perform sensitivity analysis on a linear program using duality
  - Understand relationship between duality and sensitivity analysis



# LP Duality

## Learning Outcomes

By the end of this module, you should be able to...

- Define complementary slackness
  - Use complementary slackness to find primal and/or dual solutions
- Write down the dual for the general form of the general min-cost network flow problem as well as specifically for
  - Longest path
  - Max flow
- Describe the real-world interpretation of the dual problem for some MCNF problems



# Bounds on optimal objective values

Recall the “Top Brass” model from the first class:

$$p^* \geq 12(1000) + 9(400) = 15600$$

Let's call the optimal objective value (max profit)  $p^*$

check feasibility:

$$4(1000) + 2(400) = 4800 \leq 4800 \quad \checkmark$$

$$(1000) + (400) = 1400 \leq 1750 \quad \checkmark$$

$$0 \leq 1000 \leq 1000 \quad \checkmark$$

$$0 \leq 400 \leq 1500 \quad \checkmark$$

Try (1000,400)

**Question:** Is there a way to find **bounds** on  $p^*$ ?

- Finding a *lower bound* is easy...we can use any feasible point!

**Every** feasible point gives a lower bound on the LP's optimal objective!

Finding the largest lower bound (best feasible point) amounts to solving the LP.



# Bounds on optimal objective values

What about upper bounds?

$$\begin{aligned} \max_{x_s, x_f} \quad & 12x_f + 9x_s \\ \text{s.t.} \quad & 4x_f + 2x_s \leq 4800 \\ & x_f + x_s \leq 1750 \\ & 0 \leq x_f \leq 1000 \\ & 0 \leq x_s \leq 1500 \end{aligned}$$

**Question:** What is the best upper bound we can find by combining constraints in this manner?

- Finding an *upper bound* is not so easy....
- We can use constraints:
  1. We know  $x_f \leq 1000$  and  $x_s \leq 1500$
  2. Thus,  $12x_f \leq 12 \times 1000 = 12000$  and  $9x_s \leq 9 \times 1500 = 13500$
  3. So  $p^* \leq 12,000 + 13500 = 25,500$
- 25,500 is very far away from the best lower bound 15,600
  - Can we do better?
  - 1. Rewrite:  $12x_f + 9x_s = x_f + (4x_f + 2x_s) + 7(x_f + x_s)$
  - 2. We know
$$x_f + (4x_f + 2x_s) + 7(x_f + x_s) \leq 1000 + 4800 + 7(1750)$$
  - 3. So  $p^* \leq 18,050$
- Combining constraints in different ways gives<sup>5</sup> us different upper bounds on  $p^*$



# Constraint multipliers

$$\begin{aligned} \max_{x_s, x_f} \quad & 12x_f + 9x_s \\ \text{s.t.} \quad & 4x_f + 2x_s \leq 4800 \\ & x_f + x_s \leq 1750 \\ & 0 \leq x_f \leq 1000 \\ & 0 \leq x_s \leq 1500 \end{aligned}$$

$$\lambda_4 x_s \geq \lambda_4 1500$$

**Question:** If we choose multipliers  $\lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0$ , what values are we “allowed” to use to find an upper bound on  $p^*$ ?

**Rephrased question:** For what values of  $\lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0$  is the following inequality *guaranteed* to hold for *any* feasible values of  $x_f, x_s$ ?

$$12x_f + 9x_s \leq \lambda_1(4x_f + 2x_s) + \lambda_2(x_f + x_s) + \lambda_3x_f + \lambda_4x_s \quad \lambda_4 \geq 0 \quad \leq 18045$$

In general, what we’ve been doing is:

**1.** Combine all constraints with different multipliers (that sum to at least 12 for  $x_f$  and 9 for  $x_s$ ):

- $0(4x_f + 2x_s) + 0(x_f + x_s) + 12x_f + 9x_s$
- $1(4x_f + 2x_s) + 7(x_f + x_s) + 1x_f + 0x_s$

**2.** Then plug in the maximum value the constraint can take:

- $0(4x_f + 2x_s) + 0(x_f + x_s) + 12x_f + 9x_s \leq 0 + 0 + 12(1000) + 9(1500) = 25,500$
- $1(4x_f + 2x_s) + 7(x_f + x_s) + 1x_f + 0x_s \leq 4800 + 7(1750) + 1000 + 0 = 18,050$

# Allowable constraint multipliers

$$\begin{aligned} \max_{x_f, x_s} \quad & 12x_f + 9x_s \\ \text{s.t.} \quad & 4x_f + 2x_s \leq 4800 \\ & x_f + x_s \leq 1750 \\ & 0 \leq x_f \leq 1000 \\ & 0 \leq x_s \leq 1500 \end{aligned}$$

**Question:** This gives us the allowable choices of  $\lambda$ , but if we want the **best upper bound**, how do we find the **best possible**  $\lambda$ ?

**Rephrased question:** Given that

$$\begin{aligned} p^* &\leq \lambda_1(4x_f + 2x_s) + \lambda_2(x_f + x_s) + \lambda_3x_f + \lambda_4x_s \\ &\leq \underline{4800\lambda_1 + 1750\lambda_2 + 1000\lambda_3 + 1500\lambda_4}, \end{aligned}$$

what choices of  $\lambda$  give us the smallest value for the right-hand side?

- First, let's rearrange the inequality to get a constant on one side:
$$12x_f + 9x_s \leq \lambda_1(4x_f + 2x_s) + \lambda_2(x_f + x_s) + \lambda_3x_f + \lambda_4x_s \Rightarrow 0 \leq x_f(4\lambda_1 + \lambda_2 + \lambda_3 - 12) + x_s(2\lambda_1 + \lambda_2 + \lambda_4 - 9)$$
- Next, because  $x_f, x_s \geq 0$ , the only way to guarantee this holds for *any* feasible solution is if:
  - $4\lambda_1 + \lambda_2 + \lambda_3 - 12 \geq 0$  **and**  $2\lambda_1 + \lambda_2 + \lambda_4 - 9 \geq 0$



# Best constraint multipliers

$$\begin{aligned} \max_{x_s, x_f} \quad & 12x_f + 9x_s \\ \text{s.t.} \quad & 4x_f + 2x_s \leq 4800 \\ & x_f + x_s \leq 1750 \\ & x_f \leq 1000 \\ & x_s \leq 1500 \\ & x_f, x_s \geq 0 \end{aligned}$$

Let's recap. We want to find values of  $\lambda_1, \lambda_2, \lambda_3, \lambda_4$  such that:

- $\lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0$  (otherwise things get funky with plugging in upper bounds on constraints)
- $4\lambda_1 + \lambda_2 + \lambda_3 \geq 12, 2\lambda_1 + \lambda_2 + \lambda_4 \geq 9$  (so we can guarantee we have an upper bound)
- The value  $4800\lambda_1 + 1750\lambda_2 + 1000\lambda_3 + 1500\lambda_4$  is as small as possible.

We can rewrite this more compactly:

This is just an LP!

$$\begin{aligned} \min_{\lambda_1, \lambda_2, \lambda_3, \lambda_4} \quad & 4800\lambda_1 + 1750\lambda_2 + 1000\lambda_3 + 1500\lambda_4 \\ \text{s.t.} \quad & 4\lambda_1 + \lambda_2 + \lambda_3 \geq 12 \\ & 2\lambda_1 + \lambda_2 + \lambda_4 \geq 9 \\ & \lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0 \end{aligned}$$





# Duality

(Or, the part where Prof. Smith always gets really excited)

## Primal problem

$$\begin{aligned} \max_{x_s, x_f} \quad & 12x_f + 9x_s \\ \text{s.t.} \quad & 4x_f + 2x_s \leq 4800 \\ & x_f + x_s \leq 1750 \\ & x_f \leq 1000 \\ & x_s \leq 1500 \\ & x_f, x_s \geq 0 \end{aligned}$$

The problem of finding the lambda multipliers that give the best upper bound is called the **dual problem**. The original LP is called the **primal problem**.

## Dual problem

$$\begin{aligned} \min_{\lambda_1, \lambda_2, \lambda_3, \lambda_4} \quad & 4800\lambda_1 + 1750\lambda_2 + 1000\lambda_3 + 1500\lambda_4 \\ \text{s.t.} \quad & 4\lambda_1 + \lambda_2 + \lambda_3 \geq 12 \\ & 2\lambda_1 + \lambda_2 + \lambda_4 \geq 9 \\ & \lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0 \end{aligned}$$

**Fact:** Every primal LP has an associated dual!

Some observations:

- Primal is max, dual is min
- There is a dual variable for every primal constraint
- There is a dual constraint for every primal variable
- (any feasible primal point)  $\leq p^* \leq d^* \leq$  (any feasible dual point)



# Duality in Top Brass with matrices

## Primal problem

$$\begin{aligned} \max_{f,s} \quad & \begin{bmatrix} 12 \\ 9 \end{bmatrix}^T \begin{bmatrix} f \\ s \end{bmatrix} \\ \text{s.t.} \quad & \begin{bmatrix} 4 & 2 \\ 1 & 1 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} f \\ s \end{bmatrix} \leq \begin{bmatrix} 4800 \\ 1750 \\ 1000 \\ 1500 \end{bmatrix} \\ & f, s \geq 0 \end{aligned}$$

## Dual problem

$$\begin{aligned} \min_{\lambda} \quad & \begin{bmatrix} 4800 \\ 1750 \\ 1000 \\ 1500 \end{bmatrix}^T \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} \\ \text{s.t.} \quad & \begin{bmatrix} 4 & 1 & 1 & 0 \\ 2 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \end{bmatrix} \geq \begin{bmatrix} 12 \\ 9 \end{bmatrix} \\ & \lambda_1, \lambda_2, \lambda_3, \lambda_4 \geq 0 \end{aligned}$$

In Julia: [Top Brass Dual](#)



# General LP Duality

## Primal problem (P)

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

## Dual problem (D)

$$\begin{aligned} \min_{\lambda} \quad & b^T \lambda \\ \text{s.t.} \quad & A^T \lambda \geq c \\ & \lambda \geq 0 \end{aligned}$$

**Challenge:** See if you can prove the Weak Duality Theorem for the general case.

*Hint:* This is exactly what we did for Top Brass.

**Theorem (Weak Duality):** If  $x$  and  $\lambda$  are feasible points of (P) and (D) (respectively), then:

$$c^T x \leq p^* \leq d^* \leq b^T \lambda$$

**Theorem (Strong Duality):** If either  $p^*$  or  $d^*$  exist and are finite, then:

$$p^* = d^*$$



# Possible outcomes for Primal/Dual pairs

## Primal problem (P)

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

## Dual problem (D)

$$\begin{aligned} \min_{\lambda} \quad & b^T \lambda \\ \text{s.t.} \quad & A^T \lambda \geq c \\ & \lambda \geq 0 \end{aligned}$$

**Question:** Given Weak Duality, which primal/dual combinations are possible?

$$p^* \leq d^*, \quad p^* = d^*$$

1. Optimal  $p^*$  is attained
2. (P) is unbounded:  $p^* = \infty$
3. (P) is infeasible:  $p^* = -\infty$

1. Optimal  $d^*$  is attained
2. (D) is unbounded:  $d^* = -\infty$
3. (D) is infeasible:  $d^* = \infty$

P	D
1	1
2	3
3	2
3	3

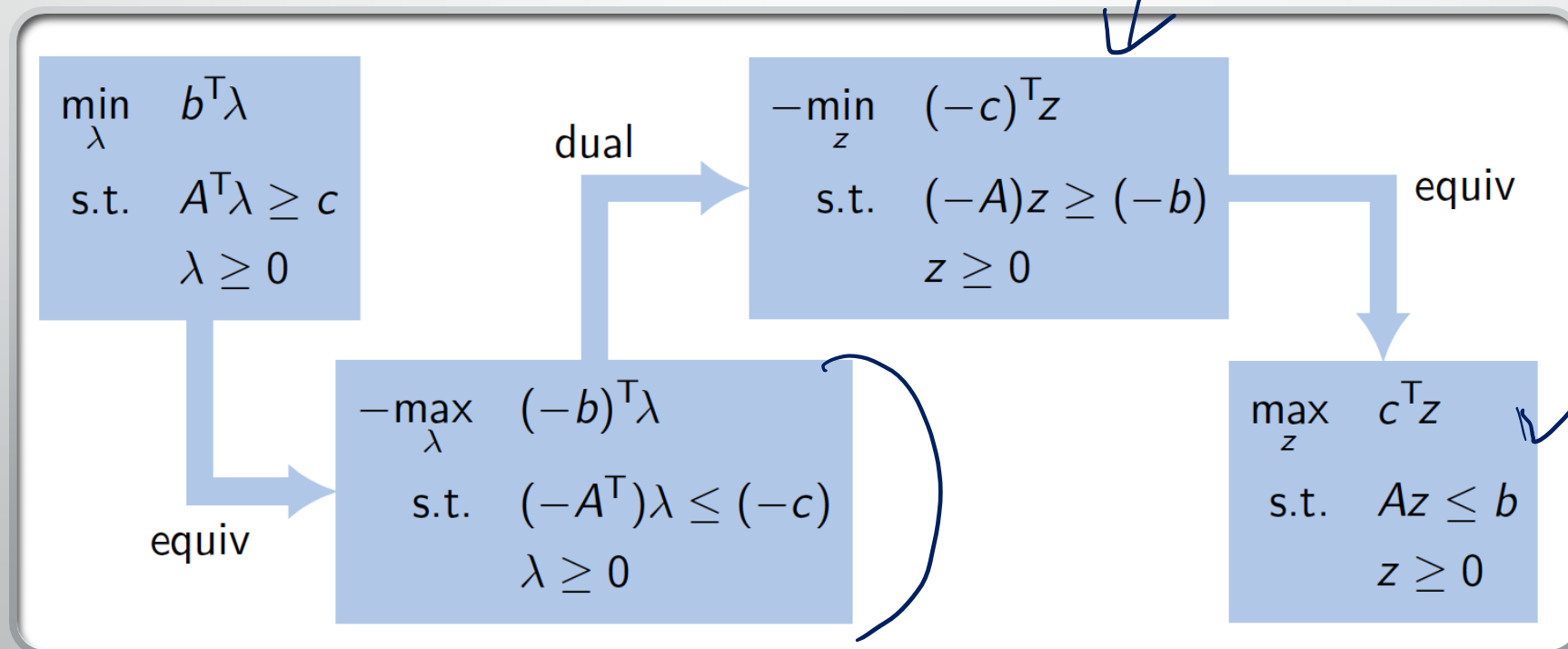


# What if your LP is not in standard form?

If your LP is not in standard form and you need to take the dual:

1. Convert the LP to standard form
2. Write the dual
3. Make any simplifications

**Exercise:** What is the dual of the dual?



# Common primal/dual pairs

Standard form:

$$\begin{array}{ll} \max_x & c^T x \\ \text{s.t.} & Ax \leq b \\ & x \geq 0 \end{array} \quad \begin{array}{c} \text{dual} \\ \longleftrightarrow \end{array} \quad \begin{array}{ll} \min_{\lambda} & b^T \lambda \\ \text{s.t.} & \lambda \geq 0 \\ & A^T \lambda \geq c \end{array}$$

Free form:

$$\begin{array}{ll} \max_x & c^T x \\ \text{s.t.} & Ax \leq b \\ & x \text{ free} \end{array} \quad \begin{array}{c} \text{dual} \\ \longleftrightarrow \end{array} \quad \begin{array}{ll} \min_{\lambda} & b^T \lambda \\ \text{s.t.} & \lambda \geq 0 \\ & A^T \lambda = c \end{array}$$

Mixed constraints:

$$\begin{array}{ll} \max_x & c^T x \\ \text{s.t.} & Ax \leq b \\ & Fx = g \\ & x \text{ free} \end{array} \quad \begin{array}{c} \text{dual} \\ \longleftrightarrow \end{array} \quad \begin{array}{ll} \min_{\lambda, \mu} & b^T \lambda + g^T \mu \\ \text{s.t.} & \lambda \geq 0 \\ & \mu \text{ free} \\ & A^T \lambda + F^T \mu = c \end{array}$$



# Dual Rules

Here are some useful rules for transitioning between primal and dual problems (either side can be primal or dual):

## Minimization

Nonnegative variable  $\geq$

Nonpositive variable  $\leq$

Free variable

Inequality constraint  $\geq$

Inequality constraint  $\leq$

Equality constraint  $=$

## Maximization

Inequality constraint  $\leq$

Inequality constraint  $\geq$

Equality constraint  $=$

Nonnegative variable  $\geq$

Nonpositive variable  $\leq$

Free variable

## Key:

Dual variables  $\equiv$  Primal constraints

Dual constraints  $\equiv$  Primal variables



# The same information but in math

$$\max_x c^T x \quad (\text{max})$$

$$\text{s.t. } Ax \leq b \quad (\text{constraint } \leq)$$

$$x \geq 0 \quad (\text{variable } \geq)$$

$$\min_{\lambda} b^T \lambda \quad (\text{min})$$

$$\text{s.t. } \lambda \geq 0 \quad (\text{variable } \geq)$$

$$A^T \lambda \geq c \quad (\text{constraint } \geq)$$

LP primal-dual pair with every possible situation:

$$\max_{x,y,z} c^T x + d^T y + f^T z$$

$$\text{s.t. } Ax + By + Cz \leq p$$

$$Dx + Ey + Fz \geq q$$

$$Gx + Hy + Jz = r$$

$$x \geq 0$$

$$y \leq 0$$

$$z \text{ free}$$

$$\min_{\lambda,\eta,\mu} p^T \lambda + q^T \eta + r^T \mu$$

$$\text{s.t. } \lambda \geq 0$$

$$\eta \leq 0$$

$$\mu \text{ free}$$

$$A^T \lambda + D^T \eta + G^T \mu \geq c$$

$$B^T \lambda + E^T \eta + H^T \mu \leq d$$

$$C^T \lambda + F^T \eta + J^T \mu = f$$





# The real question: so what?

- Why should we care about the dual? (Other than the fact that it's really cool, of course!)
- Sometimes the dual is much easier to solve than the primal:
  - The dual is much easier than the primal in this case
  - Many solvers take advantage of duality to get solutions quickly
- Duality is very closely related to the idea of **sensitivity**: how *sensitive* is a solution to changes in the problem data? (e.g., if you change a constraint, how much does it affect the objective?)

$\begin{array}{ll}\max_{x,y,z} & 3x + y + 2z \\ \text{s.t.} & x + 2y + z \leq 2 \\ & x, y, z \geq 0\end{array}$	$\longleftrightarrow$ dual $\longleftrightarrow$	$\begin{array}{ll}\min_{\lambda} & 2\lambda \\ \text{s.t.} & \lambda \geq 3 \\ & 2\lambda \geq 1 \\ & \lambda \geq 2 \\ & \lambda \geq 0\end{array}$
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