

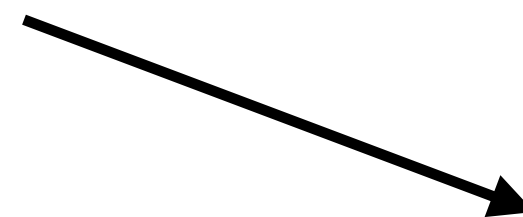
ORF522 – Linear and Nonlinear Optimization

8. Linear optimization duality

Ed Forum

$$\begin{aligned} \min_x c^T x \\ \text{st } Ax \leq b \end{aligned} \rightarrow g(y) = \min_x c^T x + y^T (Ax - b) \\ = c^T x^* + \underbrace{y^T (Ax^* - b)}_{\leq 0} \\ \leq c^T x^*$$

- Why are the dual variables ≥ 0 for inequalities?
- Why is the case of the both primal and dual infeasible an ~~exception~~ to strong duality?
- Are there other examples where strong duality does not hold? Yes!



$$\begin{aligned} \text{minimize} \quad & -2x_1 + x_2 \\ \text{subject to} \quad & x_1 - x_2 \leq 1 \\ & -x_1 + x_2 \leq -2 \\ & x_1, x_2 \geq 0 \end{aligned}$$

Recap

Optimal objective values

Primal

$$\begin{aligned} &\text{minimize} && c^T x \\ &\text{subject to} && Ax \leq b \end{aligned}$$

p^* is the primal optimal value

Primal infeasible: $p^* = +\infty$

Primal unbounded: $p^* = -\infty$

Dual

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y + c = 0 \\ &&& y \geq 0 \end{aligned}$$

d^* is the dual optimal value

Dual infeasible: $d^* = -\infty$

Dual unbounded: $d^* = +\infty$

Relationship between primal and dual

$p^* \geq d^*$

	$p^* = +\infty$	p^* finite	$p^* = -\infty$
$d^* = +\infty$	primal inf. dual unb.	/ / / / /	/ / / / /
d^* finite		optimal values equal	/ / / / /
$d^* = -\infty$	exception		primal unb. dual inf

EXCLUDED
BY
STRONG
DUALITY

- Upper-right excluded by **weak duality**
- (1, 1) and (3, 3) proven by **weak duality**
- (3, 1) and (2, 2) proven by **strong duality**

Today's agenda

Readings: [Chapter 4, LO][Chapter 11, LP]

- Two-person zero-sum games
- Farkas lemma
- Complementary slackness
- Dual simplex method

Two-person zero-sum games

Rock paper scissors

Rules

At count to three declare one of: Rock, Paper, or Scissors

Winners

Identical selection is a draw, otherwise:

- Rock beats (“dulls”) scissors
- Scissors beats (“cuts”) paper
- Paper beats (“covers”) rock

Extremely popular: world RPS society, USA RPS league, etc.

Two-person zero-sum game

- Player 1 (P1) chooses a number $i \in \{1, \dots, m\}$ (one of m actions)
- Player 2 (P2) chooses a number $j \in \{1, \dots, n\}$ (one of n actions)

Two players make their choice independently

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Two players make their choice independently

Rule

Player 1 pays A_{ij} to player 2

$A \in \mathbf{R}^{m \times n}$ is the **payoff matrix**

Rock, Paper, Scissors

$$A = \begin{array}{c} \text{R} \\ \text{P} \\ \text{S} \end{array} \begin{array}{ccc} \text{R} & \text{P} & \text{S} \\ \left[\begin{array}{ccc} 0 & 1 & -1 \\ -1 & 0 & 1 \\ 1 & -1 & 0 \end{array} \right] \end{array}$$

Mixed (randomized) strategies

Deterministic strategies can be systematically defeated

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Randomized strategies

- P1 chooses randomly according to distribution x :

x_i = probability that P1 selects action i

- P2 chooses randomly according to distribution y :

y_j = probability that P2 selects action j

Mixed (randomized) strategies

Deterministic strategies can be systematically defeated

Randomized strategies

- P1 chooses randomly according to distribution x :

x_i = probability that P1 selects action i

- P2 chooses randomly according to distribution y :

y_j = probability that P2 selects action j

Expected payoff (from P1 P2), if they use mixed-strategies x and y ,

$$\sum_{i=1}^m \sum_{j=1}^n x_i y_j A_{ij} = x^T A y$$

Mixed strategies and probability simplex

Probability simplex in \mathbf{R}^k

$$P_k = \{p \in \mathbf{R}^k \mid p \geq 0, \quad \mathbf{1}^T p = 1\}$$

Mixed strategy

For a game player, a mixed strategy is a distribution over all possible deterministic strategies.

The **set of all mixed strategies** is the probability simplex $\longrightarrow x \in P_m, \quad y \in P_n$

Optimal mixed strategies

P1: optimal strategy x^* is the solution of

$$\begin{array}{ll} \text{minimize} & \max_{y \in P_n} x^T A y \\ \text{subject to} & x \in P_m \end{array}$$

P2: optimal strategy y^* is the solution of

$$\begin{array}{ll} \text{maximize} & \min_{x \in P_m} x^T A y \\ \text{subject to} & y \in P_n \end{array}$$

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$$\begin{array}{ll} \text{minimize} & \max_{j=1, \dots, n} (A^T x)_j \\ \text{subject to} & x \in P_m \end{array}$$

$$y \rightarrow e_j$$



P2: optimal strategy y^* is the solution of

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Inner problem over
deterministic
strategies (**vertices**)

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$$\begin{array}{ll} \text{maximize} & \min_{i=1, \dots, m} (A y)_i \\ \text{subject to} & y \in P_n \end{array}$$

Optimal strategies x^* and y^* can be computed using **linear optimization**

Minmax theorem

Theorem

$$\overbrace{\max_{y \in P_n} \min_{x \in P_m} x^T A y}^{P_2} = \overbrace{\min_{x \in P_m} \max_{y \in P_n} x^T A y}^{P_1}$$

Minmax theorem

Theorem

$$\max_{y \in P_n} \min_{x \in P_m} x^T A y = \min_{x \in P_m} \max_{y \in P_n} x^T A y$$

Proof

The optimal x^* is the solution of

$$\begin{aligned} &\text{minimize} && t \\ &\text{subject to} && A^T x \leq t \mathbf{1} \\ &&& \mathbf{1}^T x = 1 \\ &&& x \geq 0 \end{aligned}$$

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The two LPs are **duals** and by **strong duality** the equality follows. ■

Nash equilibrium

Theorem

$$\max_{y \in P_n} \min_{x \in P_m} x^T A y = \min_{x \in P_m} \max_{y \in P_n} x^T A y$$

Consequence

The pair of mixed strategies (x^*, y^*) attains the **Nash equilibrium** of the two-person matrix game, i.e.,

$$x^T A y^* \geq x^{*T} A y^* \geq x^{*T} A y, \quad \forall x \in P_m, \forall y \in P_n$$

Example

$$A = \begin{bmatrix} 4 & 2 & 0 & -3 \\ -2 & -4 & -3 & 3 \\ -2 & -3 & 4 & 1 \end{bmatrix}$$

$$\min_i \max_j A_{ij} = 3 > -2 = \max_j \min_i A_{ij}$$

Example

$$A = \begin{bmatrix} 4 & 2 & 0 & -3 \\ -2 & -4 & -3 & 3 \\ -2 & -3 & 4 & 1 \end{bmatrix}$$

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Optimal mixed strategies

$$x^* = (0.37, 0.33, 0.3), \quad y^* = (0.4, 0, 0.13, 0.47)$$

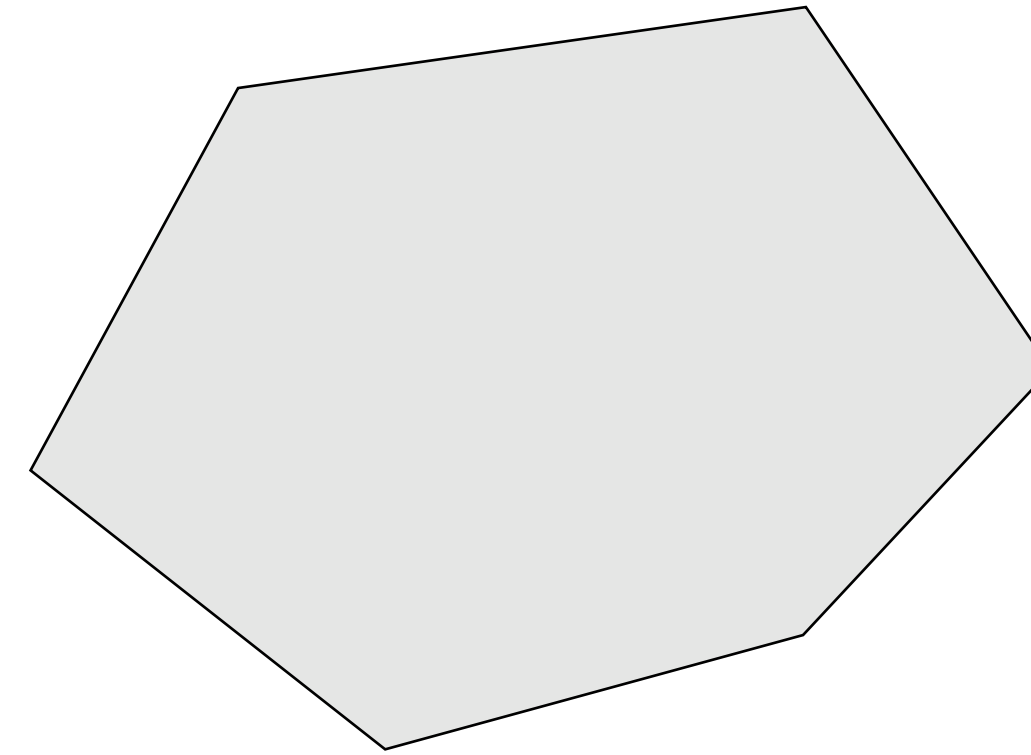
Expected payoff

$$x^{*T} A y^* = 0.2$$

Farkas lemma

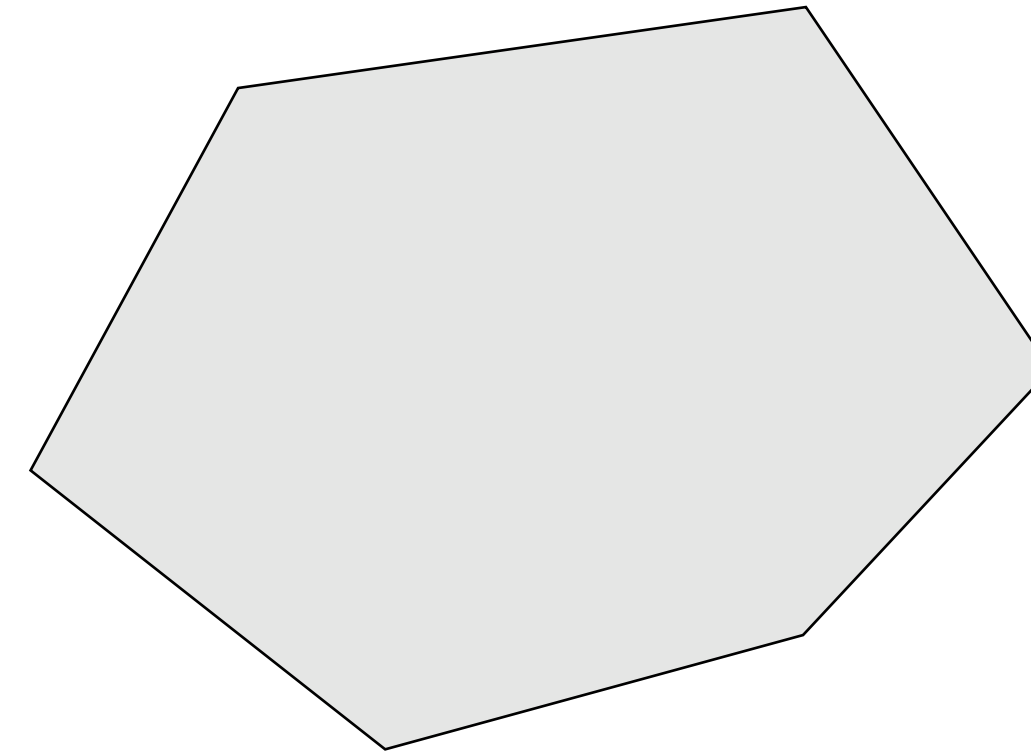
Feasibility of polyhedra

$$P = \{x \mid Ax = b, \quad x \geq 0\}$$



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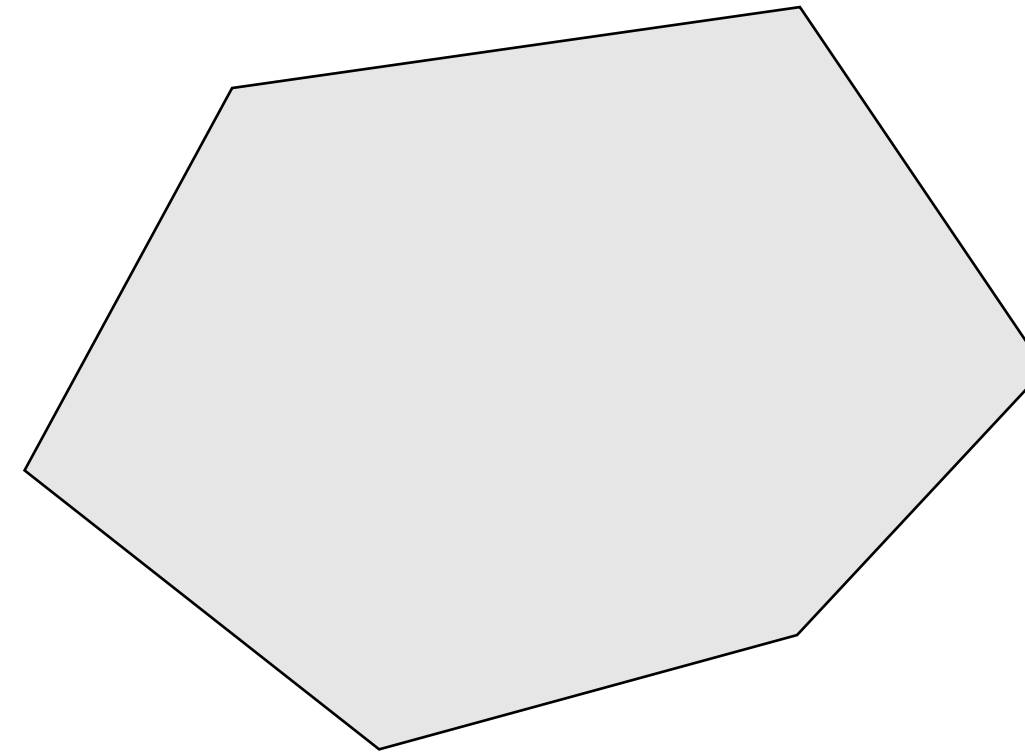


How to show that P is **feasible**?

Easy: we just need to provide an $x \in P$, i.e., a **certificate**

Feasibility of polyhedra

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How to show that P is **feasible**?

Easy: we just need to provide an $x \in P$, i.e., a **certificate**

How to show that P is **infeasible**?

Farkas lemma

Theorem

Given A and b , exactly one of the following statements is true:

1. There exists an x with $Ax = b, x \geq 0$
2. There exists a y with $A^T y \geq 0, b^T y < 0$

Farkas lemma

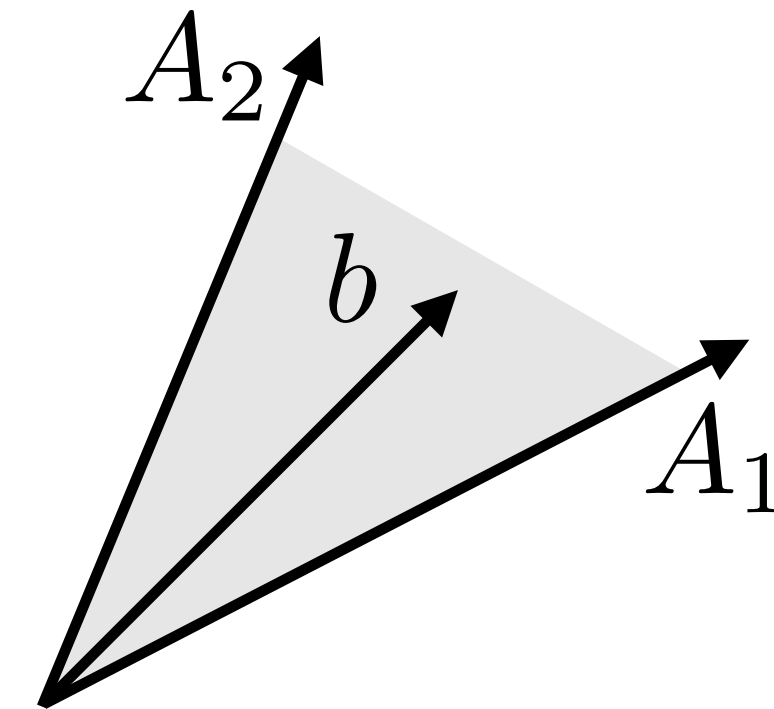
Geometric interpretation

1. First alternative

There exists an x with $Ax = b, x \geq 0$

$$b = \sum_{i=1}^n x_i A_i, \quad x_i \geq 0, \quad i = 1, \dots, n$$

b is in the cone generated by the columns of A



Farkas lemma

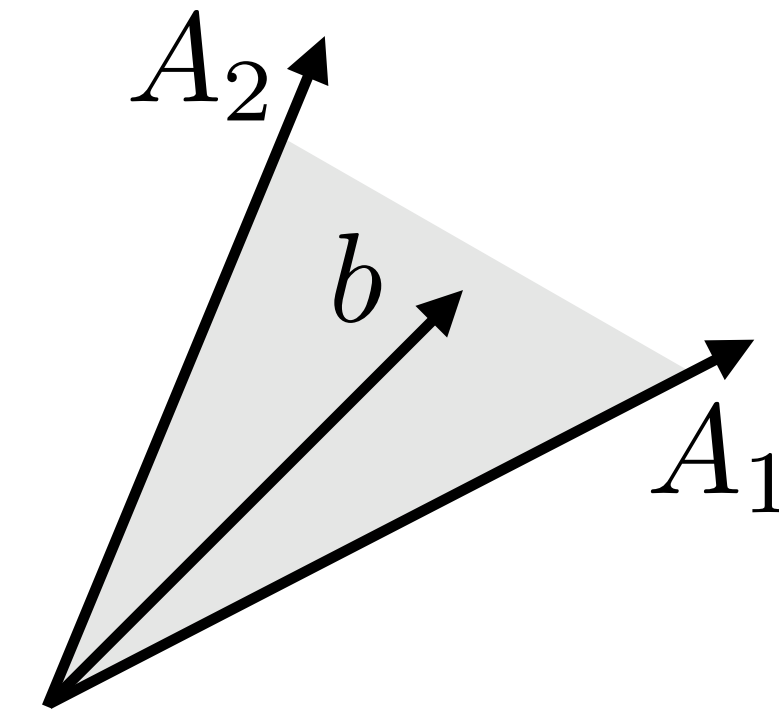
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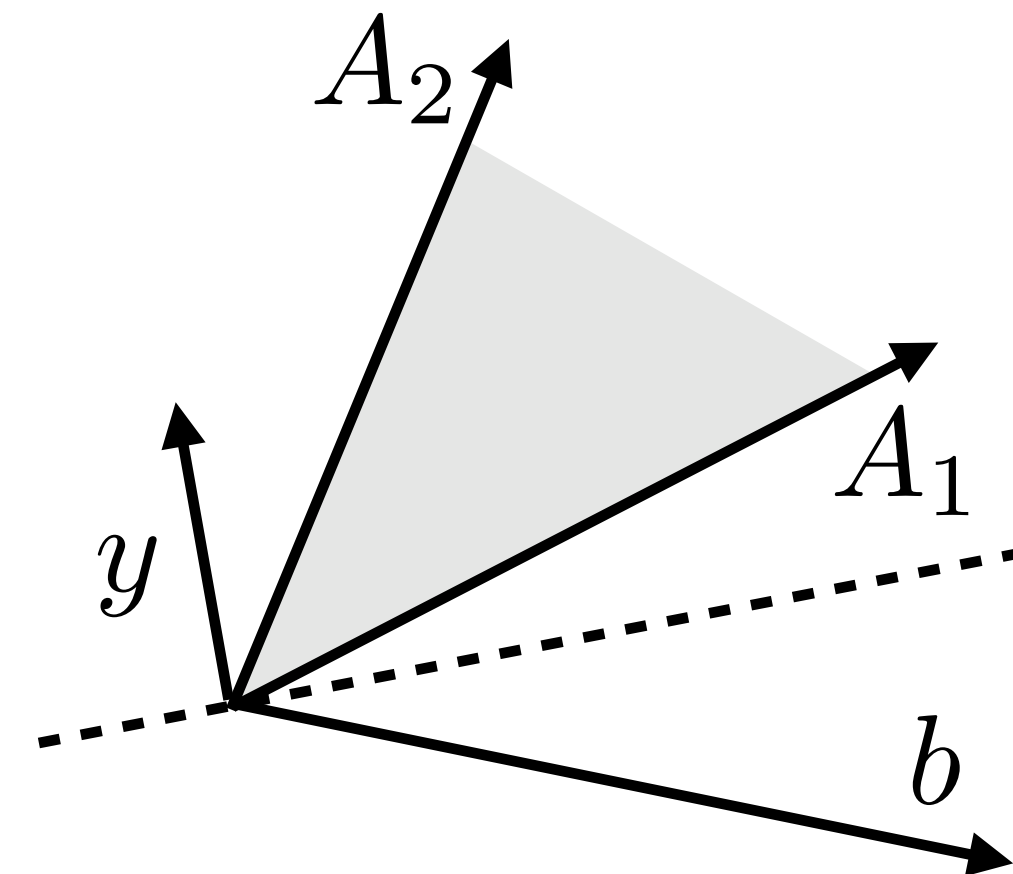


2. Second alternative

There exists a y with $A^T y \geq 0, b^T y < 0$

$$y^T A_i \geq 0, \quad i = 1, \dots, m, \quad y^T b < 0$$

The hyperplane $y^T z = 0$
separates b from A_1, \dots, A_n



Farkas lemma

Proof

1 and 2 cannot be both true (easy)

$$\underbrace{x \geq 0, Ax = b}_1 \text{ and } \underbrace{y^T A \geq 0}_2 \longrightarrow y^T b = \underbrace{y^T Ax}_{\geq} \underbrace{\geq 0}_{>0}$$

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$$x \geq 0, Ax = b \text{ and } y^T A \geq 0 \quad \longrightarrow \quad y^T b = y^T Ax \geq 0$$

1 and 2 cannot be both false (duality)

Primal

$$\begin{aligned} &\text{minimize} && 0 \\ &\text{subject to} && Ax = b \\ &&& x \geq 0 \end{aligned}$$

Dual

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y \geq 0 \end{aligned}$$

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$$b^T y \geq 0 \text{ for all } y \text{ such that } A^T y \geq 0$$

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$$\text{There exists } y \text{ such that } A^T y \geq 0 \text{ and } b^T y < 0$$

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y is an
**infeasibility
certificate**

Complementary slackness

Optimality conditions

Primal

$$\begin{aligned} &\text{minimize} && c^T x \\ &\text{subject to} && Ax \leq b \end{aligned}$$

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x and y are **primal** and **dual** optimal if and only if

- x is **primal feasible**: $Ax \leq b$
- y is **dual feasible**: $A^T y + c = 0$ and $y \geq 0$
- The **duality gap** is zero: $c^T x + b^T y = 0$

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Can we **relate** x and y (not only the objective)?

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Theorem

Primal, dual feasible x, y are optimal if and only if

$$y_i (b_i - a_i^T x) = 0, \quad i = 1, \dots, m$$

i.e., at optimum, $b - Ax$ and y have a **complementary sparsity** pattern:

$$\begin{aligned} y_i > 0 &\Rightarrow a_i^T x = b_i \\ a_i^T x < b_i &\Rightarrow y_i = 0 \end{aligned}$$

Complementary slackness

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The duality gap at primal feasible x and dual feasible y can be written as

$$c^T x + b^T y = (-A^T y)^T x + b^T y = (b - Ax)^T y = \sum_{i=1}^m y_i (b_i - a_i^T x) = 0$$

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Since all the elements of the sum are nonnegative, they must all be 0 ■

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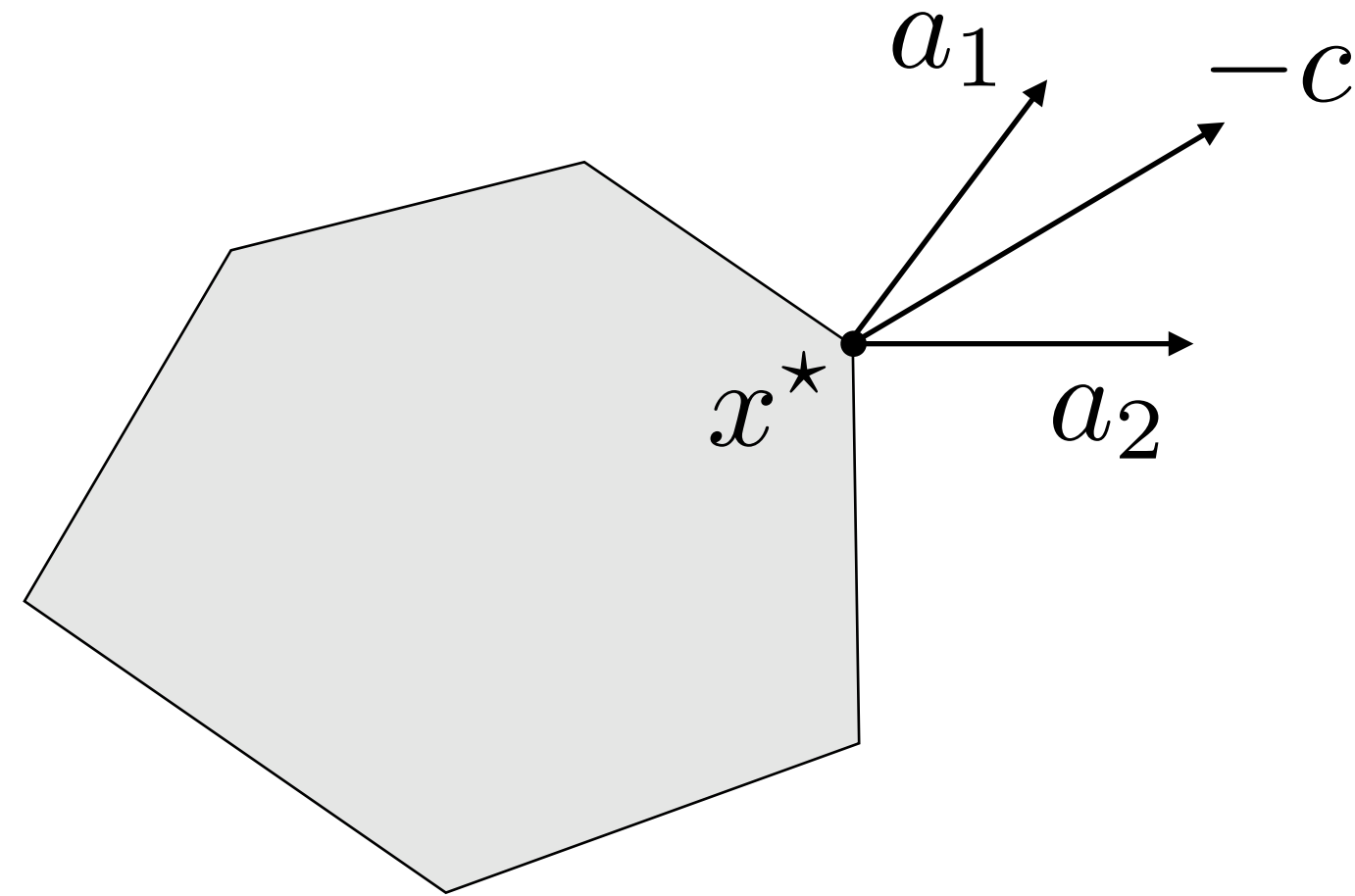
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For **feasible** x and y **complementary slackness = zero duality gap**

Geometric interpretation

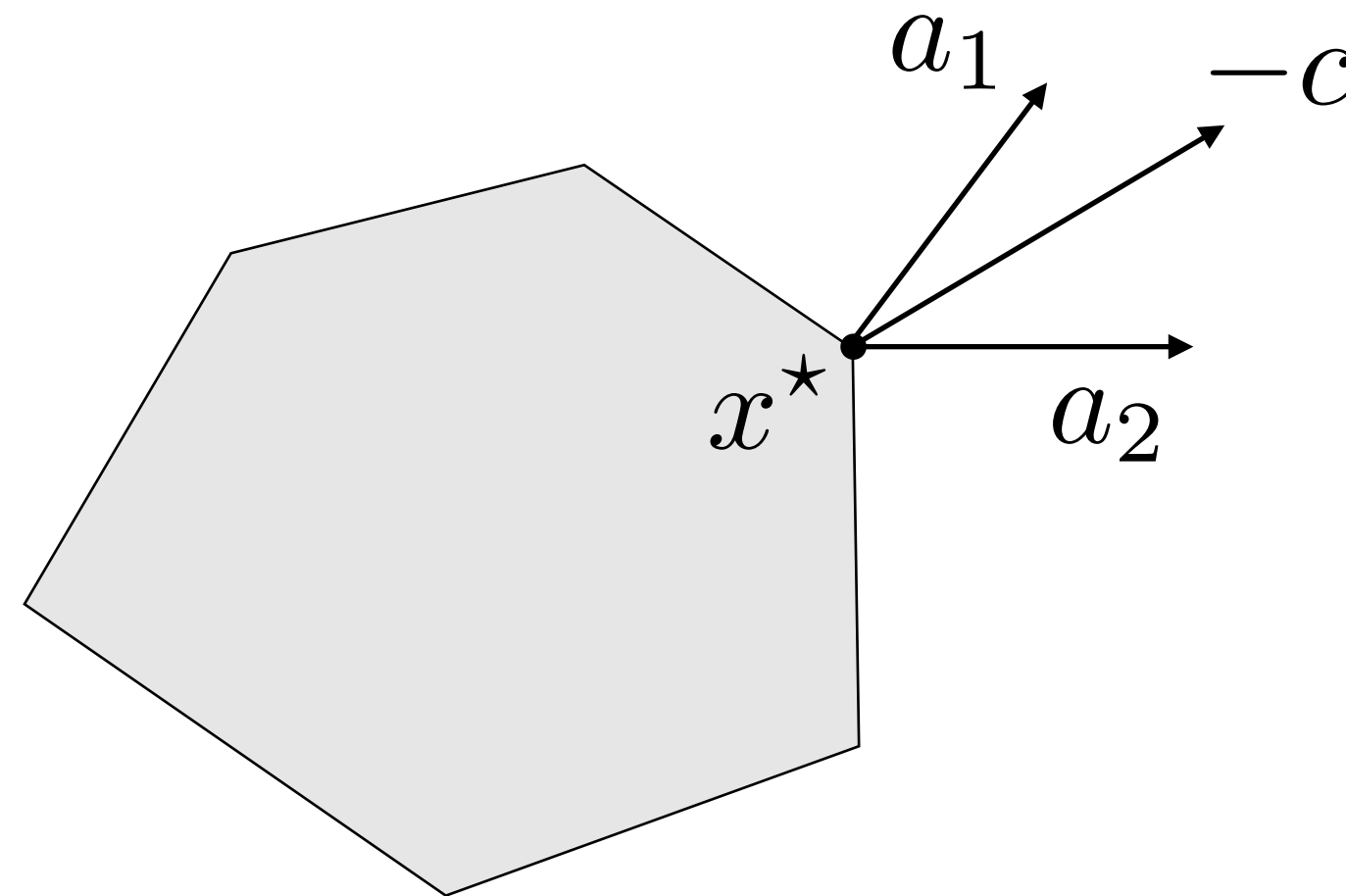
Example in \mathbb{R}^2



Two active constraints at optimum: $a_1^T x^* = b_1$, $a_2^T x^* = b_2$

Geometric interpretation

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Optimal dual solution y satisfies:

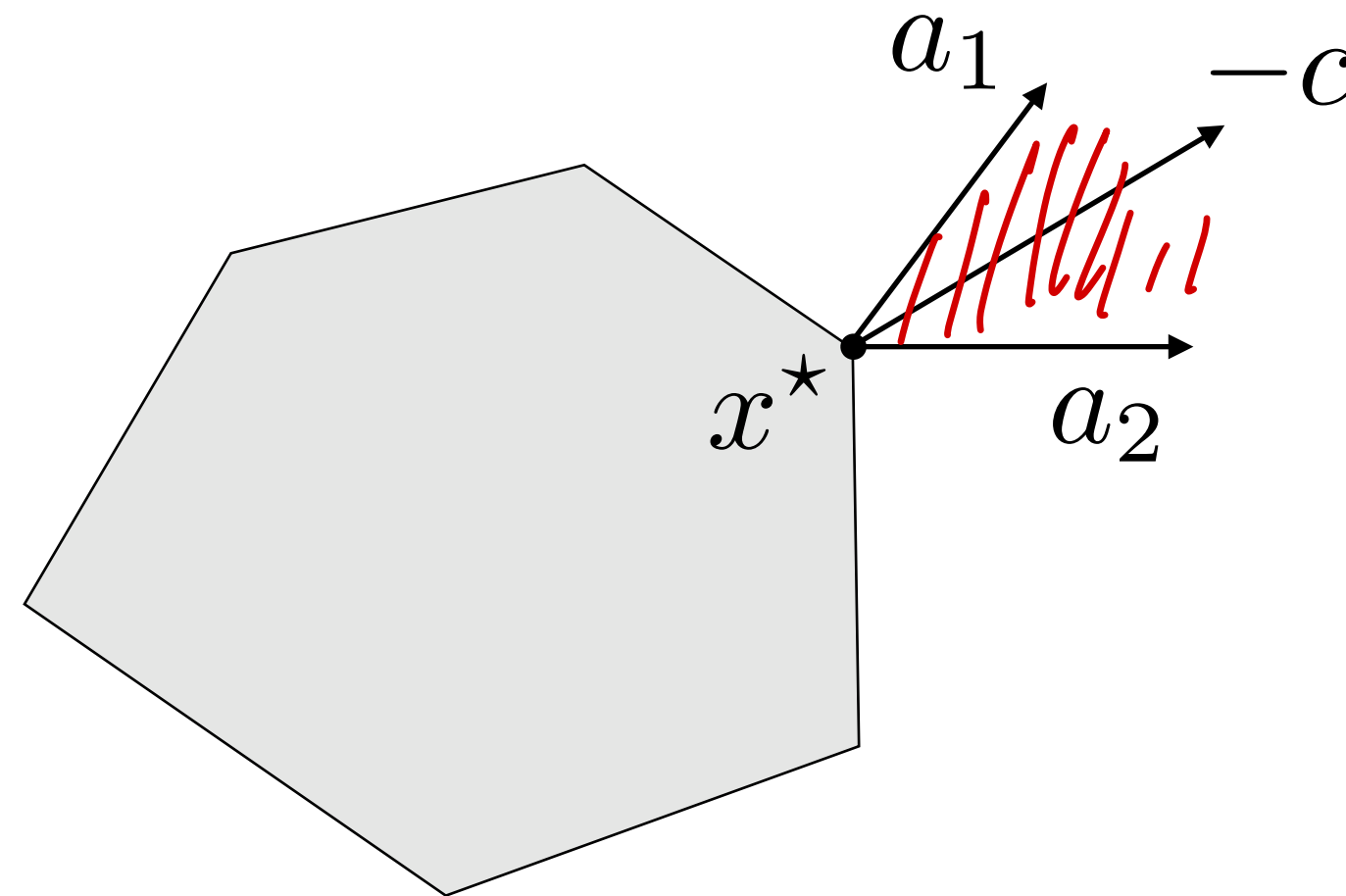
DUAL FEAS \rightarrow

$$A^T y + c = 0, \quad y \geq 0, \quad y_i = 0 \text{ for } i \neq \{1, 2\}$$

In other words, $-c = a_1 y_1 + a_2 y_2$ with $y_1, y_2 \geq 0$

Geometric interpretation

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Optimal dual solution y satisfies:

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In other words, $-c = a_1 y_1 + a_2 y_2$ with $y_1, y_2 \geq 0$

Geometric interpretation: $-c$ lies in the cone generated by a_1 and a_2

Example

$$\begin{array}{ll} \text{minimize} & -4x_1 - 5x_2 \\ \text{subject to} & \begin{bmatrix} -1 & 0 \\ 2 & 1 \\ 0 & -1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 3 \\ 0 \\ 3 \end{bmatrix} \end{array}$$

Let's **show** that feasible $x = (1, 1)$ is optimal

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Let's **show** that feasible $x = (1, 1)$ is optimal

Second and fourth constraints are active at $x \longrightarrow y = (0, y_2, 0, y_4)$

$$A^T y = -c \quad \Rightarrow \quad \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} y_2 \\ y_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 5 \end{bmatrix} \quad \text{and} \quad y_2 \geq 0, \quad y_4 \geq 0$$

Example

$$\begin{array}{ll} \text{minimize} & -4x_1 - 5x_2 \\ \text{subject to} & \begin{bmatrix} -1 & 0 \\ 2 & 1 \\ 0 & -1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 3 \\ 0 \\ 3 \end{bmatrix} \end{array}$$

Let's **show** that feasible $x = (1, 1)$ is optimal

Second and fourth constraints are active at $x \longrightarrow y = (0, y_2, 0, y_4)$

$$A^T y = -c \quad \Rightarrow \quad \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} y_2 \\ y_4 \end{bmatrix} = \begin{bmatrix} 4 \\ 5 \end{bmatrix} \quad \text{and} \quad y_2 \geq 0, \quad y_4 \geq 0$$

$y = (0, 1, 0, 2)$ satisfies these conditions and proves that x is optimal

Example

$$\begin{array}{ll} \text{minimize} & -4x_1 - 5x_2 \\ \text{subject to} & \begin{bmatrix} -1 & 0 \\ 2 & 1 \\ 0 & -1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \leq \begin{bmatrix} 0 \\ 3 \\ 0 \\ 3 \end{bmatrix} \end{array}$$

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$y = (0, 1, 0, 2)$ satisfies these conditions and proves that x is optimal

Complementary slackness is useful to recover y^* from x^*

The dual simplex

Primal and dual basic feasible solutions

Primal problem

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

Dual problem

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y + c \geq 0 \end{aligned}$$

Given a **basis** matrix A_B

Primal and dual basic feasible solutions

Primal problem

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Given a **basis** matrix A_B

$$\text{Primal feasible: } Ax = b, x \geq 0 \quad \Rightarrow \quad x_B = A_B^{-1} b \geq 0$$

Primal and dual basic feasible solutions

Primal problem

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$$\text{Primal feasible: } Ax = b, x \geq 0 \quad \Rightarrow \quad x_B = A_B^{-1} b \geq 0$$

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Primal and dual basic feasible solutions

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Given a **basis** matrix A_B

$$\text{Primal feasible: } Ax = b, x \geq 0 \quad \Rightarrow \quad x_B = A_B^{-1} b \geq 0$$

$$\text{Dual feasible: } A^T y + c \geq 0. \quad \text{If } y = -A_B^{-T} c_B \quad \Rightarrow \quad c - A^T A_B^{-T} c_B \geq 0$$

Primal and dual basic feasible solutions

Primal problem

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

Dual problem

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Given a **basis** matrix A_B

$$\text{Primal feasible: } Ax = b, x \geq 0 \quad \Rightarrow \quad x_B = A_B^{-1} b \geq 0$$

$$\text{Dual feasible: } A^T y + c \geq 0. \quad \text{If } y = -A_B^{-T} c_B \quad \Rightarrow \quad c - A^T A_B^{-T} c_B \geq 0$$

Reduced costs



Primal and dual basic feasible solutions

Primal problem

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

Dual problem

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y + c \geq 0 \end{aligned}$$

Given a **basis** matrix A_B

Primal feasible: $Ax = b, x \geq 0 \Rightarrow x_B = A_B^{-1} b \geq 0$

Reduced costs

Dual feasible: $A^T y + c \geq 0.$ If $y = -A_B^{-T} c_B \Rightarrow c - A^T A_B^{-T} c_B \geq 0$

Zero duality gap: $c^T x + b^T y = c_B^T x_B - b^T A_B^{-T} c_B = c_B^T x_B - c_B^T \underbrace{A_B^{-1} b}_{x_B} = 0$

Primal and dual basic feasible solutions

Primal problem

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

Dual problem

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y + c \geq 0 \end{aligned}$$

Given a **basis** matrix A_B

Primal feasible: $Ax = b, x \geq 0 \Rightarrow x_B = A_B^{-1} b \geq 0$

Dual feasible: $A^T y + c \geq 0$. If $y = -A_B^{-T} c_B \Rightarrow c - A^T A_B^{-T} c_B \geq 0$

Zero duality gap: $c^T x + b^T y = c_B x_B - b^T A_B^{-T} c_B = c_B x_B - c_B^T A_B^{-1} b = 0$

(by construction)

Reduced costs

The primal (dual) simplex method

Primal problem

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

Primal simplex

- Primal feasibility
- Zero duality gap



Dual feasibility

Dual problem

$$\begin{aligned} &\text{maximize} && -b^T y \\ &\text{subject to} && A^T y + c \geq 0 \end{aligned}$$

Dual simplex

- Dual feasibility
- Zero duality gap



Primal feasibility

Feasible dual directions

Conditions

$$P = \{y \mid A^T y + c \geq 0\}$$

Given a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots & A_{B(m)} \end{bmatrix}$
we have dual feasible solution y :

$$\bar{c} = A^T y + c \geq 0$$

Feasible dual directions

Conditions

$$P = \{y \mid A^T y + c \geq 0\}$$

Given a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots & A_{B(m)} \end{bmatrix}$
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$$\bar{c} = A^T y + c \geq 0$$

Feasible direction d

$$y + \theta d$$

Feasible dual directions

Conditions

$$P = \{y \mid A^T y + c \geq 0\}$$

Given a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots & A_{B(m)} \end{bmatrix}$
we have dual feasible solution y :

$$\bar{c} = A^T y + c \geq 0$$

Feasible direction d

$$y + \theta d$$

Reduced cost change

$$c + A^T (y + \theta d) \geq 0 \quad \Rightarrow \quad \bar{c} + \theta z \geq 0$$

$$A^T d = z \quad (\text{subspace restriction})$$

Feasible directions

Computation

Subspace restriction

$$A^T d = z \quad \longrightarrow \quad \begin{aligned} A_B^T d &= z_B \\ A_N^T d &= z_N \end{aligned}$$

$$N = \{z \mid z \in B\}$$

Feasible directions

Computation

Subspace restriction

$$A^T d = z \longrightarrow \begin{array}{l} A_B^T d = z_B \\ A_N^T d = z_N \end{array}$$

Basic indices

$z_B = e_i \longrightarrow B(\ell) = i$ **exits the basis**

Get d by solving $A_B^T d = z_N$

Feasible directions

Computation

Subspace restriction

$$A^T d = z \longrightarrow \begin{aligned} A_B^T d &= z_B \\ A_N^T d &= z_N \end{aligned}$$

Basic indices

$z_B = e_i \longrightarrow B(\ell) = i$ **exits the basis**

Get d by solving $A_B^T d = z$

Nonbasic indices

$$z_N = A_N^T d = A_N^T A_B^{-T} e_i$$

Feasible directions

Computation

Subspace restriction

$$A^T d = z \longrightarrow \begin{cases} A_B^T d = z_B \\ A_N^T d = z_N \end{cases}$$

Basic indices

$z_B = e_i \longrightarrow B(\ell) = i$ **exits the basis**

Get d by solving $A_B^T d = z_B$

Nonbasic indices

$$z_N = A_N^T d = A_N^T A_B^{-T} e_i$$

Non-negativity of reduced costs (non-degenerate assumption)

- Basic variables: $\bar{c}_B = 0$. Nonnegative direction $z_B \geq 0$.
- Nonbasic variables: $\bar{c}_N > 0$. Therefore $\exists \theta > 0$ such that $\bar{c}_N + \theta z_N \geq 0$

Stepsize

How far can we go?

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } \bar{c} + \theta z \geq 0\}$$

Stepsize

How far can we go?

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } \bar{c} + \theta z \geq 0\}$$

Unbounded

If $z \geq 0$, then $\theta^* = \infty$. The dual problem is unbounded (primal infeasible).

Stepsize

How far can we go?

$$\theta^* = \max\{\theta \mid \theta \geq 0 \text{ and } \bar{c} + \theta z \geq 0\}$$

Unbounded

If $z \geq 0$, then $\theta^* = \infty$. The dual problem is unbounded (primal infeasible).

Bounded

If $z_j < 0$ for some j , then

$$\theta^* = \min_{\{j \mid z_j < 0\}} \left(-\frac{\bar{c}_j}{z_j} \right) = \min_{\{j \in N \mid z_j < 0\}} \left(-\frac{\bar{c}_j}{z_j} \right)$$

(Since $z_j \geq 0$, $j \in B$)

Moving to a new basis

Next reduced cost

$$\bar{c} + \theta^* z$$

Let $j \notin \{B(1), \dots, B(m)\}$ be the index such that $\theta^* = -\frac{\bar{c}_j}{z_j}$. Then,

$$\bar{c}_j + \theta^* z_j = 0$$

Moving to a new basis

Next reduced cost

$$\bar{c} + \theta^* z$$

Let $j \notin \{B(1), \dots, B(m)\}$ be the index such that $\theta^* = -\frac{\bar{c}_j}{z_j}$. Then,

$$\bar{c}_j + \theta^* z_j = 0$$

New basis

$$A_{\bar{B}} = \left[A_{B(1)} \quad \dots \quad A_{B(\ell-1)} \quad A_j \quad A_{B(\ell+1)} \quad \dots \quad A_{B(m)} \right]$$

Moving to a new basis

Next reduced cost

$$\bar{c} + \theta^* z$$

Let $j \notin \{B(1), \dots, B(m)\}$ be the index such that $\theta^* = -\frac{\bar{c}_j}{z_j}$. Then,

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New basis

$$A_{\bar{B}} = \left[A_{B(1)} \quad \dots \quad A_{B(\ell-1)} \quad A_j \quad A_{B(\ell+1)} \quad \dots \quad A_{B(m)} \right]$$

New solution

$$A_{\bar{B}} x_{\bar{B}} = b$$

An iteration of the dual simplex method

Initialization

- a basic dual feasible solution y , i.e. $A^T y + c \geq 0$
- a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots, & A_{B(m)} \end{bmatrix}$

An iteration of the dual simplex method

Initialization

- a basic dual feasible solution y , i.e. $A^T y + c \geq 0$
- a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots, & A_{B(m)} \end{bmatrix}$

Iteration steps

1. Get x
 - Solve $A_B x_B = b$ ($O(m^2)$)
 - Set $x_i = 0$ if $i \notin B$
2. If $x \geq 0$, x **feasible. break**
3. Choose i such that $x_i < 0$
4. Compute each direction z with $z_i = 1$, $A_B^T d = e_i$ and $z_N = A_N^T d$ ($O(m^2)$)
5. If $z_N \geq 0$, the dual problem is **unbounded** and the optimal value is $+\infty$. **break**
6. Compute step length $\theta^* = \min_{\{j \in N \mid z_j < 0\}} \left(-\frac{\bar{c}_j}{z_j} \right)$
7. Compute new point $y + \theta^* d$
8. Get new basis $A_{\bar{B}} = A_B + (A_j - A_i)e_\ell^T$
perform rank-1 factor update
(j enters, i exists) $O(m^2)$

An iteration of the dual simplex method

Initialization

- a basic dual feasible solution y , i.e. $A^T y + c \geq 0$
- a basis matrix $A_B = \begin{bmatrix} A_{B(1)} & \dots, & A_{B(m)} \end{bmatrix}$

Remark

Reduced costs nonnegative



objective non-decreasing

Iteration steps

1. Get x
 - Solve $A_B x_B = b$ ($O(m^2)$)
 - Set $x_i = 0$ if $i \notin B$
2. If $x \geq 0$, x **feasible. break**
3. Choose i such that $x_i < 0$
4. Compute each direction z with $z_i = 1$, $A_B^T d = e_i$ and $z_N = A_N^T d$ ($O(m^2)$)
5. If $z_N \geq 0$, the dual problem is **unbounded** and the optimal value is $+\infty$. **break**
6. Compute step length $\theta^* = \min_{\{j \in N | z_j < 0\}} \left(-\frac{\bar{c}_j}{z_j} \right)$
7. Compute new point $y + \theta^* d$
8. Get new basis $A_{\bar{B}} = A_B + (A_j - A_i)e_\ell^T$
perform rank-1 factor update
(j enters, i exists) $O(m^2)$

Example

From lecture 6

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b \\ & x \geq 0 \end{array}$$

Dual problem

$$\begin{array}{ll} \text{maximize} & -b^T y \\ \text{subject to} & A^T y + c \geq 0 \end{array}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Initialize

$$y = (10, 0, 0) \quad B = \{1, 5, 6\}$$

$$c + A^T y = (0, 8, 8, 10, 0, 0) \geq 0$$

Example

Iteration 1

$$y = (10, 0, 0)$$

$$-b^T y = -200$$

$$c + A^T y = (0, 8, 8, 10, 0, 0)$$

$$B = \{1, 5, 6\}$$

$$A_B = \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Example

Iteration 1

$$\begin{aligned}y &= (10, 0, 0) \\ -b^T y &= -200 \\ c + A^T y &= (0, 8, 8, 10, 0, 0) \\ B &= \{1, 5, 6\} \\ A_B &= \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}\end{aligned}$$

$$\begin{aligned}c &= (-10, -12, -12, 0, 0, 0) \\ A &= \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix} \\ b &= (20, 20, 20)\end{aligned}$$

Primal solution $x = (20, 0, 0, 0, -20, -20)$

Solve $Ax_B = b \Rightarrow x_B = (20, -20, -20)$

Example

Iteration 1

$$\begin{aligned}y &= (10, 0, 0) \\ -b^T y &= -200 \\ c + A^T y &= (0, 8, 8, 10, 0, 0) \\ B &= \{1, 5, 6\} \\ A_B &= \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}\end{aligned}$$

$$\begin{aligned}c &= (-10, -12, -12, 0, 0, 0) \\ A &= \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix} \\ b &= (20, 20, 20)\end{aligned}$$

Primal solution $x = (20, 0, 0, 0, -20, -20)$

Solve $Ax_B = b \Rightarrow x_B = (20, -20, -20)$

Direction $z = (0, -3, -2, -2, 1, 0), \quad i = 5$

Solve $A_B^T d = e_i \Rightarrow d = (-2, 1, 0)$

Get $z_N = A_N^T d = (-3, -2, -2)$

Example

Iteration 1

$$\begin{aligned}y &= (10, 0, 0) \\ -b^T y &= -200 \\ c + A^T y &= (0, 8, 8, 10, 0, 0) \\ B &= \{1, 5, 6\} \\ A_B &= \begin{bmatrix} 1 & 0 & 0 \\ 2 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix}\end{aligned}$$

$$\begin{aligned}c &= (-10, -12, -12, 0, 0, 0) \\ A &= \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix} \\ b &= (20, 20, 20)\end{aligned}$$

Primal solution $x = (20, 0, 0, 0, -20, -20)$

Solve $Ax_B = b \Rightarrow x_B = (20, -20, -20)$

Direction $z = (0, -3, -2, -2, 1, 0), \quad i = 5$

Solve $A_B^T d = e_i \Rightarrow d = (-2, 1, 0)$

Get $z_N = A_N^T d = (-3, -2, -2)$

Step $\theta^* = 2.66, \quad j = 2$

$$\theta^* = \min_{\{j|z_j < 0\}} (-\bar{c}_j / z_j) = \{2.66, 4, 5\}$$

New $y \leftarrow y + \theta^* d = (4.66, 2.66, 0)$

Example

Iteration 2

$$y = (4.66, 2.66, 0)$$

$$-b^T y = -146.66$$

$$c + A^T y = (0, 0, 2.66, 4.66, 2.66, 0)$$

$$B = \{1, 2, 6\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Example

Iteration 2

$$y = (4.66, 2.66, 0)$$

$$-b^T y = -146.66$$

$$c + A^T y = (0, 0, 2.66, 4.66, 2.66, 0)$$

$$B = \{1, 2, 6\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Primal solution $x = (6.66, 6.66, 0, 0, 0, -6.66)$

Solve $Ax_B = b \Rightarrow x_B = (6.66, 6.66, -6.66)$

Example

Iteration 2

$$y = (4.66, 2.66, 0)$$

$$-b^T y = -146.66$$

$$c + A^T y = (0, 0, 2.66, 4.66, 2.66, 0)$$

$$B = \{1, 2, 6\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Primal solution $x = (6.66, 6.66, 0, 0, 0, -6.66)$

Solve $Ax_B = b \Rightarrow x_B = (6.66, 6.66, -6.66)$

Direction $z = (0, 0, -1.66, -0.66, -0.66, 1), \quad i = 6$

Solve $A_B^T d = e_i \Rightarrow d = (-0.66, -0.66, 1)$

Get $z_N = A_N^T d = (-1.66, -0.66, -0.66)$

Example

Iteration 2

$$y = (4.66, 2.66, 0)$$

$$-b^T y = -146.66$$

$$c + A^T y = (0, 0, 2.66, 4.66, 2.66, 0)$$

$$B = \{1, 2, 6\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 0 \\ 2 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix}$$

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$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Primal solution $x = (6.66, 6.66, 0, 0, 0, -6.66)$

Solve $Ax_B = b \Rightarrow x_B = (6.66, 6.66, -6.66)$

Direction $z = (0, 0, -1.66, -0.66, -0.66, 1), \quad i = 6$

Solve $A_B^T d = e_i \Rightarrow d = (-0.66, -0.66, 1)$

Get $z_N = A_N^T d = (-1.66, -0.66, -0.66)$

Step $\theta^* = 1.6, \quad j = 3$

$$\theta^* = \min_{\{j|z_j < 0\}} (-\bar{c}_j / z_j) = \{1.6, 7, 4\}$$

New $y \leftarrow y + \theta^* d = (3.6, 1.6, 1.6)$

Example

Iteration 3

$$y = (3.6, 1.6, 1.6)$$

$$-b^T y = -136$$

$$c + A^T y = (0, 0, 0, 3.6, 1.6, 1.6)$$

$$B = \{1, 2, 3\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Example

Iteration 3

$$y = (3.6, 1.6, 1.6)$$

$$-b^T y = -136$$

$$c + A^T y = (0, 0, 0, 3.6, 1.6, 1.6)$$

$$B = \{1, 2, 3\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Primal solution $x = (4, 4, 4, 0, 0, 0)$

Solve $Ax_B = b \Rightarrow x_B = (4, 4, 4)$

Example

Iteration 3

$$y = (3.6, 1.6, 1.6)$$

$$-b^T y = -136$$

$$c + A^T y = (0, 0, 0, 3.6, 1.6, 1.6)$$

$$B = \{1, 2, 3\}$$

$$A_B = \begin{bmatrix} 1 & 2 & 2 \\ 2 & 1 & 2 \\ 2 & 2 & 1 \end{bmatrix}$$

$$c = (-10, -12, -12, 0, 0, 0)$$

$$A = \begin{bmatrix} 1 & 2 & 2 & 1 & 0 & 0 \\ 2 & 1 & 2 & 0 & 1 & 0 \\ 2 & 2 & 1 & 0 & 0 & 1 \end{bmatrix}$$

$$b = (20, 20, 20)$$

Primal solution $x = (4, 4, 4, 0, 0, 0)$

Solve $Ax_B = b \Rightarrow x_B = (4, 4, 4)$

$$x \geq 0 \quad \longrightarrow$$

Optimal solution

$$x^* = (4, 4, 4, 0, 0, 0)$$

**Same as
primal
simplex!**

Equivalence and symmetry

The dual simplex is equivalent to the primal simplex applied to the dual problem.

Dual problem

$$\begin{array}{ll} \text{maximize} & -b^T y \\ \text{subject to} & A^T y + c \geq 0 \end{array}$$



Symmetrized dual

$$\begin{array}{ll} \text{minimize} & b^T y \\ \text{subject to} & A^T y + c = w \\ & w \geq 0 \end{array}$$

$w \geq 0$ are the **reduced costs**

Dual simplex efficiency

Sequence of problems with varying feasible region
previous y still dual feasible \longrightarrow **warm-start**

Dual simplex efficiency

Sequence of problems with varying feasible region
previous y still dual feasible \longrightarrow **warm-start**

Applied in many different contexts, for example:

1. **sequential decision-making**
2. **mixed-integer optimization to solve subproblems**

(more later in the course...)

Linear optimization duality

Today, we learned to:

- **Interpret** linear optimization duality using game theory
- **Prove** Farkas lemma using duality
- **Geometrically link** primal and dual solutions with complementary slackness
- **Implement** the dual simplex method

Next lecture

- Sensitivity analysis