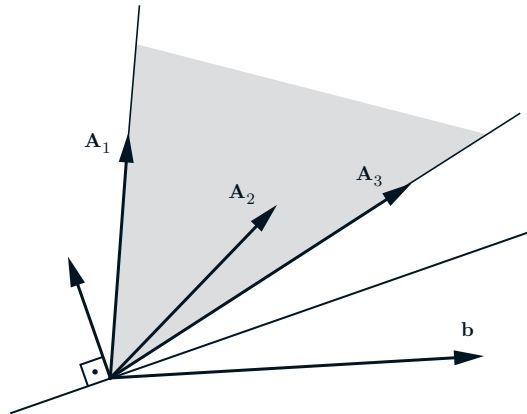


15.081J/6.251J Introduction to Mathematical
Programming

Lecture 10: Duality Theory III



1 Outline

SLIDE 1

- Farkas lemma
- Asset pricing
- Cones and extreme rays
- Representation of Polyhedra

2 Farkas lemma

SLIDE 2

Theorem:

Exactly one of the following two alternatives hold:

1. $\exists x \geq 0$ s.t. $Ax = b$.
2. $\exists p$ s.t. $p'A \geq 0'$ and $p'b < 0$.

2.1 Proof

SLIDE 3

“ \Rightarrow ” If $\exists x \geq 0$ s.t. $Ax = b$, and if $p'A \geq 0'$, then $p'b = p'Ax \geq 0$

“ \Leftarrow ” Assume there is no $x \geq 0$ s.t. $Ax = b$

$$\begin{array}{ll}
 (P) \max & 0'x \\
 \text{s.t.} & Ax = b \\
 & x \geq 0
 \end{array}
 \qquad
 \begin{array}{ll}
 (D) \min & p'b \\
 \text{s.t.} & p'A \geq 0'
 \end{array}$$

(P) infeasible \Rightarrow (D) either unbounded or infeasible

Since $p = 0$ is feasible \Rightarrow (D) unbounded

$\Rightarrow \exists p : p'A \geq 0'$ and $p'b < 0$

3 Asset Pricing

SLIDE 4

- n different assets
- m possible states of nature
- one dollar invested in some asset i , and state of nature is s , we receive a payoff of r_{si}
- $m \times n$ payoff matrix:

$$\mathbf{R} = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}$$

SLIDE 5

- x_i : amount held of asset i . A portfolio of assets is $\mathbf{x} = (x_1, \dots, x_n)$.
- A negative value of x_i indicates a “short” position in asset i : this amounts to selling $|x_i|$ units of asset i at the beginning of the period, with a promise to buy them back at the end. Hence, one must pay out $r_{si}|x_i|$ if state s occurs, which is the same as receiving a payoff of $r_{si}x_i$

SLIDE 6

- Wealth in state s from a portfolio \mathbf{x}

$$w_s = \sum_{i=1}^n r_{si}x_i.$$

- $\mathbf{w} = (w_1, \dots, w_m)$, $\mathbf{w} = \mathbf{R}\mathbf{x}$
- p_i : price of asset i , $\mathbf{p} = (p_1, \dots, p_n)$
- Cost of acquiring \mathbf{x} is $\mathbf{p}'\mathbf{x}$.

3.1 Arbitrage

SLIDE 7

- Central problem: Determine p_i
- **Absence of arbitrage:** no investor can get a guaranteed nonnegative payoff out of a negative investment. In other words, any portfolio that pays off nonnegative amounts in every state of nature, must have nonnegative cost.

if $\mathbf{R}\mathbf{x} \geq \mathbf{0}$, then $\mathbf{p}'\mathbf{x} \geq 0$.

SLIDE 8

- Theorem: The absence of arbitrage condition holds if and only if there exists a nonnegative vector $\mathbf{q} = (q_1, \dots, q_m)$, such that the price of each asset i is given by

$$p_i = \sum_{s=1}^m q_s r_{si}.$$

- Applications to options pricing

4 Cones and extreme rays

4.1 Definitions

SLIDE 9

- A set $C \subset \mathfrak{R}^n$ is a **cone** if $\lambda \mathbf{x} \in C$ for all $\lambda \geq 0$ and all $\mathbf{x} \in C$
- A polyhedron of the form $P = \{\mathbf{x} \in \mathfrak{R}^n \mid \mathbf{Ax} \geq \mathbf{0}\}$ is called a polyhedral cone

4.2 Applications

SLIDE 10

- $P = \{\mathbf{x} \in \mathfrak{R}^n \mid \mathbf{Ax} \geq \mathbf{b}\}$, $\mathbf{y} \in P$
- The recession cone at \mathbf{y}

$$RC = \{\mathbf{d} \in \mathfrak{R}^n \mid \mathbf{y} + \lambda \mathbf{d} \in P, \forall \lambda \geq 0\}$$

- It turns out that

$$RC = \{\mathbf{d} \in \mathfrak{R}^n \mid \mathbf{Ad} \geq \mathbf{0}\}$$

- RC independent of \mathbf{y}

SLIDE 11

4.3 Extreme rays

SLIDE 12

A $\mathbf{x} \neq \mathbf{0}$ of a polyhedral cone $C \subset \mathfrak{R}^n$ is called an **extreme ray** if there are $n - 1$ linearly independent constraints that are active at \mathbf{x}

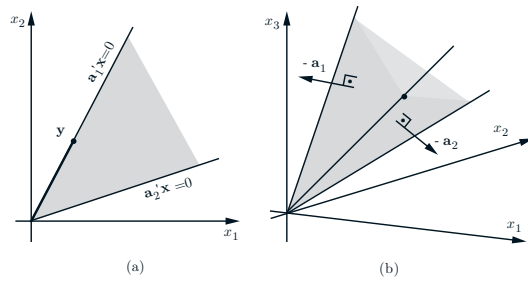
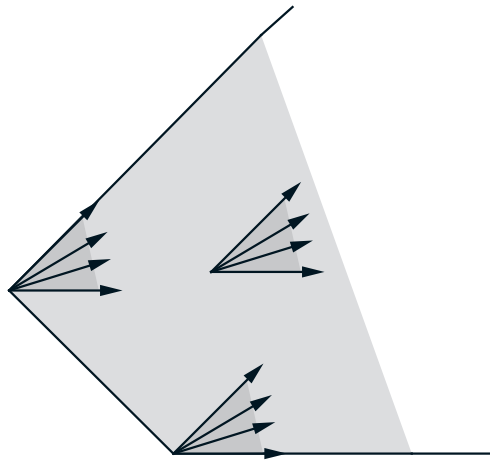
4.4 Unbounded LPs

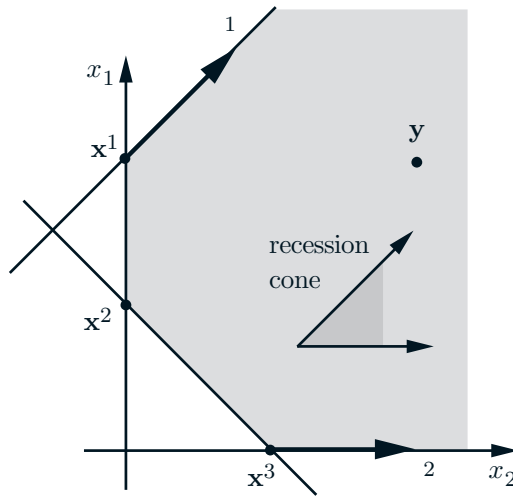
SLIDE 13

Theorem: Consider the problem of minimizing $\mathbf{c}'\mathbf{x}$ over a polyhedral cone $C = \{\mathbf{x} \in \mathfrak{R}^n \mid \mathbf{A}'_i \mathbf{x} \geq 0, i = 1, \dots, m\}$ that has zero as an extreme point. The optimal cost is equal to $-\infty$ if and only if some extreme ray \mathbf{d} of C satisfies $\mathbf{c}'\mathbf{d} < 0$. Theorem: Consider the problem of minimizing $\mathbf{c}'\mathbf{x}$ subject to $\mathbf{Ax} \geq \mathbf{b}$, and assume that the feasible set has at least one extreme point. The optimal cost is equal to $-\infty$ if and only if some extreme ray \mathbf{d} of the feasible set satisfies $\mathbf{c}'\mathbf{d} < 0$.

SLIDE 14

What happens when the simplex method detects an unbounded problem?





5 Resolution Theorem

SLIDE 15

$$P = \{ \mathbf{x} \in \mathbb{R}^n \mid \mathbf{Ax} \geq \mathbf{b} \}$$

be a nonempty polyhedron with at least one extreme point. Let $\mathbf{x}^1, \dots, \mathbf{x}^k$ be the extreme points, and let $\mathbf{w}^1, \dots, \mathbf{w}^r$ be a complete set of extreme rays of P .

$$Q = \left\{ \sum_{i=1}^k \lambda_i \mathbf{x}^i + \sum_{j=1}^r \theta_j \mathbf{w}^j \mid \lambda_i \geq 0, \theta_j \geq 0, \sum_{i=1}^k \lambda_i = 1 \right\}.$$

Then, $Q = P$.

5.1 Example

SLIDE 16

$$\begin{aligned} x_1 - x_2 &\geq -2 \\ x_1 + x_2 &\geq 1 \\ x_1, x_2 &\geq 0 \end{aligned}$$

SLIDE 17

- Extreme points: $\mathbf{x}^1 = (0, 2)$, $\mathbf{x}^2 = (0, 1)$, and $\mathbf{x}^3 = (1, 0)$.
- Extreme rays $\mathbf{w}^1 = (1, 1)$ and $\mathbf{w}^2 = (1, 0)$.

$$\mathbf{y} = \begin{bmatrix} 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \mathbf{x}^2 + \mathbf{w}^1 + \mathbf{w}^2.$$

5.2 Proof

SLIDE 18

- $Q \subset P$. Let $\mathbf{x} \in Q$:

$$\mathbf{x} = \sum_{i=1}^k \lambda_i \mathbf{x}^i + \sum_{j=1}^r \theta_j \mathbf{w}^j$$

$$\lambda_i, \theta_j \geq 0 \quad \sum_{i=1}^k \lambda_i = 1.$$

- $\mathbf{y} = \sum_{i=1}^k \lambda_i \mathbf{x}^i \in P$ and satisfies $\mathbf{A}\mathbf{y} \geq \mathbf{b}$.
- $\mathbf{A}\mathbf{w}^j \geq \mathbf{0}$ for every j : $\mathbf{z} = \sum_{j=1}^r \theta_j \mathbf{w}^j$ satisfies $\mathbf{A}\mathbf{z} \geq \mathbf{0}$.
- $\mathbf{x} = \mathbf{y} + \mathbf{z}$ satisfies $\mathbf{A}\mathbf{x} \geq \mathbf{b}$ and belongs to P .

SLIDE 19

For the reverse, assume there is a $\mathbf{z} \in P$, such that $\mathbf{z} \notin Q$.

$$\begin{aligned} \max \quad & \sum_{i=1}^k 0\lambda_i + \sum_{j=1}^r 0\theta_j \\ \text{s.t.} \quad & \sum_{i=1}^k \lambda_i \mathbf{x}^i + \sum_{j=1}^r \theta_j \mathbf{w}^j = \mathbf{z} \\ & \sum_{i=1}^k \lambda_i = 1 \\ & \lambda_i \geq 0, \quad i = 1, \dots, k, \\ & \theta_j \geq 0, \quad j = 1, \dots, r, \end{aligned}$$

Is this feasible?

SLIDE 20

- Dual

$$\begin{aligned} \min \quad & \mathbf{p}'\mathbf{z} + q \\ \text{s.t.} \quad & \mathbf{p}'\mathbf{x}^i + q \geq 0, \quad i = 1, \dots, k, \\ & \mathbf{p}'\mathbf{w}^j \geq 0, \quad j = 1, \dots, r. \end{aligned}$$

- This is unbounded. Why?
- There exists a feasible solution (\mathbf{p}, q) whose cost $\mathbf{p}'\mathbf{z} + q < 0$
- $\mathbf{p}'\mathbf{z} < \mathbf{p}'\mathbf{x}^i$ for all i and $\mathbf{p}'\mathbf{w}^j \geq 0$ for all j .

SLIDE 21

-

$$\begin{aligned} \min \quad & \mathbf{p}'\mathbf{x} \\ \text{s.t.} \quad & \mathbf{A}\mathbf{x} \geq \mathbf{b}. \end{aligned}$$

- If the optimal cost is finite, there exists an extreme point \mathbf{x}^i which is optimal. Since \mathbf{z} is a feasible solution, we obtain $\mathbf{p}'\mathbf{x}^i \leq \mathbf{p}'\mathbf{z}$, which is a contradiction.
- If the optimal cost is $-\infty$, there exists an extreme ray \mathbf{w}^j such that $\mathbf{p}'\mathbf{w}^j < 0$, which is again a contradiction

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