

15.081J/6.251J Introduction to Mathematical
Programming

Lecture 11: Duality Theory IV

1 Outline

SLIDE 1

- Overview and objectives
- Weistrass Theorem
- Separating hyperplanes theorem
- Farkas lemma revisited
- Duality theorem revisited

2 Overview and objectives

SLIDE 2

- So far: Simplex \rightarrow Duality \rightarrow Farkas lemma
- Disadvantages: specialized to LP, relied on a particular algorithm
- Plan today: Separation (A Geometric property) \rightarrow Farkas lemma \rightarrow Duality
- Purely geometric, generalizes to general nonlinear problems, more fundamental

3 Closed sets

SLIDE 3

- A set $S \subset \mathfrak{R}^n$ is closed if $\mathbf{x}^1, \mathbf{x}^2, \dots$ is a sequence of elements of S that converges to some $\mathbf{x} \in \mathfrak{R}^n$, then $\mathbf{x} \in S$.
- Every polyhedron is closed.

4 Weierstrass' theorem

SLIDE 4

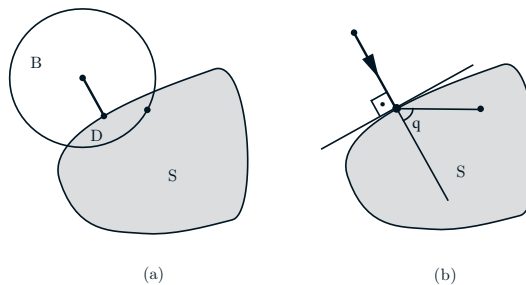
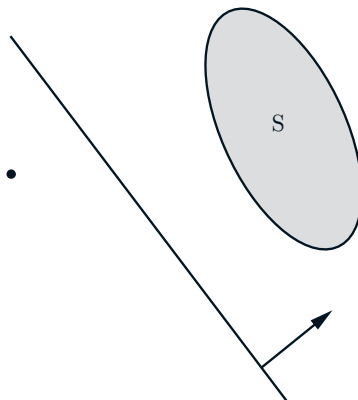
If $f : \mathfrak{R}^n \mapsto \mathfrak{R}$ is a continuous function, and if S is a nonempty, closed, and bounded subset of \mathfrak{R}^n , then there exists some $\mathbf{x}^* \in S$ such that $f(\mathbf{x}^*) \leq f(\mathbf{x})$ for all $\mathbf{x} \in S$. Similarly, there exists some $\mathbf{y}^* \in S$ such that $f(\mathbf{y}^*) \geq f(\mathbf{x})$ for all $\mathbf{x} \in S$.

Note: Weierstrass' theorem is not valid if the set S is not closed. Consider, $S = \{x \in \mathfrak{R} \mid x > 0\}$, $f(x) = x$

5 Separation

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Theorem: Let S be a nonempty closed convex subset of \mathfrak{R}^n and let $\mathbf{x}^* \in \mathfrak{R}^n$: $\mathbf{x}^* \notin S$. Then, there exists some vector $\mathbf{c} \in \mathfrak{R}^n$ such that $\mathbf{c}'\mathbf{x}^* < \mathbf{c}'\mathbf{x}$ for all $\mathbf{x} \in S$.



5.1 Proof

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- Fix $w \in S$
- $B = \{x \mid \|x - x^*\| \leq \|w - x^*\|\}$,
- $D = S \cap B$
- $D \neq \emptyset$, closed and bounded. Why?
- Consider $\min \|x - x^*\|$

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- By Weierstrass' theorem there exists some $y \in D$ such that

$$\|y - x^*\| \leq \|x - x^*\|, \quad \forall x \in D.$$

- $\forall x \in S$ and $x \notin D$, $\|x - x^*\| > \|w - x^*\| \geq \|y - x^*\|$.
- y minimizes $\|x - x^*\| \forall x \in S$.
- Let $c = y - x^*$

- $\mathbf{x} \in S$. $\forall \lambda$ satisfying $0 < \lambda \leq 1$, $\mathbf{y} + \lambda(\mathbf{x} - \mathbf{y}) \in S$ (S convex)
- $\|\mathbf{y} - \mathbf{x}^*\|^2 \leq \|\mathbf{y} + \lambda(\mathbf{x} - \mathbf{y}) - \mathbf{x}^*\|^2$

$$= \|\mathbf{y} - \mathbf{x}^*\|^2 + 2\lambda(\mathbf{y} - \mathbf{x}^*)'(\mathbf{x} - \mathbf{y}) + \lambda^2\|\mathbf{x} - \mathbf{y}\|^2$$

- $2\lambda(\mathbf{y} - \mathbf{x}^*)'(\mathbf{x} - \mathbf{y}) + \lambda^2\|\mathbf{x} - \mathbf{y}\|^2 \geq 0$.
- Divide by λ , $(\mathbf{y} - \mathbf{x}^*)'(\mathbf{x} - \mathbf{y}) \geq 0$, i.e.,

$$\begin{aligned} (\mathbf{y} - \mathbf{x}^*)'\mathbf{x} &\geq (\mathbf{y} - \mathbf{x}^*)'\mathbf{y} \\ &= (\mathbf{y} - \mathbf{x}^*)'\mathbf{x}^* + (\mathbf{y} - \mathbf{x}^*)'(\mathbf{y} - \mathbf{x}^*) \\ &> (\mathbf{y} - \mathbf{x}^*)'\mathbf{x}^*. \end{aligned}$$

- $\mathbf{c} = \mathbf{y} - \mathbf{x}^*$ proves theorem

6 Farkas' lemma

Theorem: If $\mathbf{Ax} = \mathbf{b}$, $\mathbf{x} \geq \mathbf{0}$ is infeasible, then there exists a vector \mathbf{p} such that $\mathbf{p}'\mathbf{A} \geq \mathbf{0}'$ and $\mathbf{p}'\mathbf{b} < 0$.

- $S = \{\mathbf{y} \mid \text{there exists } \mathbf{x} \text{ such that } \mathbf{y} = \mathbf{Ax}, \mathbf{x} \geq \mathbf{0}\}$ $\mathbf{b} \notin S$.
- S is convex; nonempty; closed;
 S is the projection of $\{(\mathbf{x}, \mathbf{y}) \mid \mathbf{y} = \mathbf{Ax}, \mathbf{x} \geq \mathbf{0}\}$ onto the \mathbf{y} coordinates, is itself a polyhedron and is therefore closed.
- $\mathbf{b} \notin S$: $\exists \mathbf{p}$ such that $\mathbf{p}'\mathbf{b} < \mathbf{p}'\mathbf{y}$ for every $\mathbf{y} \in S$.
- Since $\mathbf{0} \in S$, we must have $\mathbf{p}'\mathbf{b} < 0$.
- $\forall \mathbf{A}_i$ and $\forall \lambda > 0$, $\lambda\mathbf{A}_i \in S$ and $\mathbf{p}'\mathbf{b} < \lambda\mathbf{p}'\mathbf{A}_i$
- Divide by λ and then take limit as λ tends to infinity: $\mathbf{p}'\mathbf{A}_i \geq 0 \Rightarrow \mathbf{p}'\mathbf{A} \geq \mathbf{0}'$

7 Duality theorem

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

and we assume that the primal has an optimal solution \mathbf{x}^* . We will show that the dual problem also has a feasible solution with the same cost. Strong duality follows then from weak duality.

- $I = \{i \mid \mathbf{a}'_i\mathbf{x}^* = b_i\}$
- We next show: if $\mathbf{a}'_i\mathbf{d} \geq 0$ for every $i \in I$, then $\mathbf{c}'\mathbf{d} \geq 0$

- $\mathbf{a}'_i(\mathbf{x}^* + \epsilon \mathbf{d}) \geq \mathbf{a}_i \mathbf{x}^* = b_i$ for all $i \in I$.
- If $i \notin I$, $\mathbf{a}'_i \mathbf{x}^* > b_i$ hence $\mathbf{a}'_i(\mathbf{x}^* + \epsilon \mathbf{d}) > b_i$.
- $\mathbf{x}^* + \epsilon \mathbf{d}$ is feasible

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- By optimality \mathbf{x}^* , $\mathbf{c}' \mathbf{d} \geq 0$
- By Farkas' lemma

$$\mathbf{c} = \sum_{i \in I} p_i \mathbf{a}_i.$$

- For $i \notin I$, we define $p_i = 0$, so $\mathbf{p}' \mathbf{A} = \mathbf{c}'$.

•

$$\mathbf{p}' \mathbf{b} = \sum_{i \in I} p_i b_i = \sum_{i \in I} p_i \mathbf{a}'_i \mathbf{x}^* = \mathbf{c}' \mathbf{x}^*,$$

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