A Unifying Framework for Duality AND Minimax

Dimitri Bertsekas, Angelia Nedic, Asuman Ozdaglar

ELECTRICAL ENGINEERING AND COMPUTER SCIENCE DEPT.

Massachusetts Institute of Technology

November 19, 2002

Motivation

• Minimax Theory: Given $\phi: X \times Z \mapsto \Re$, where $X \subset \Re^n$, $Z \subset \Re^m$, under what conditions do we have

$$\sup_{z \in Z} \inf_{x \in X} \phi(x, z) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z) ?$$

• Optimization Duality: Consider the problem

minimize
$$f(x)$$

subject to $x \in X$, $g_j(x) \le 0$, $j = 1, ..., r$.

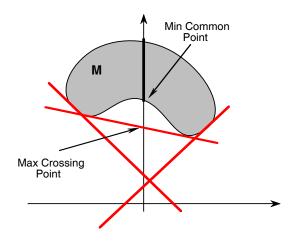
Define the Lagrangian function : $L(x, \mu) = f(x) + \sum_{j=1}^{r} \mu_j g_j(x)$.

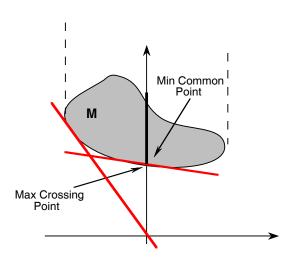
- Primal problem: $f^* = \inf_{x \in X} \sup_{\mu > 0} L(x, \mu)$
- Dual problem: $q^* = \sup_{\mu \ge 0} q(\mu)$ = $\sup_{\mu > 0} \inf_{x \in X} L(x, \mu)$
- All of (convex/concave) minimax theory and duality theory can be developed in terms of simple geometry of convex sets! (Need machinery from convex analysis)

Min Common/Max Crossing Problems

Let M be a nonempty subset of \Re^{n+1}

- Min Common Point Problem: Consider all vectors that are common to M and the (n + 1)st axis. Find one whose (n + 1)st component is minimum.
- Max Crossing Point Problem: Consider nonvertical hyperplanes that contain M in their "upper" closed halfspace. Find one whose crossing point of the (n + 1)st axis is maximum.





Weak Duality

• Optimal value of the min common problem:

$$w^* = \inf_{(0,w) \in M} w.$$

• Focus on hyperplanes with normals $(\mu, 1)$ whose crossing point ξ satisfies

$$\xi \le w + \mu' u, \qquad \forall \ (u, w) \in M.$$

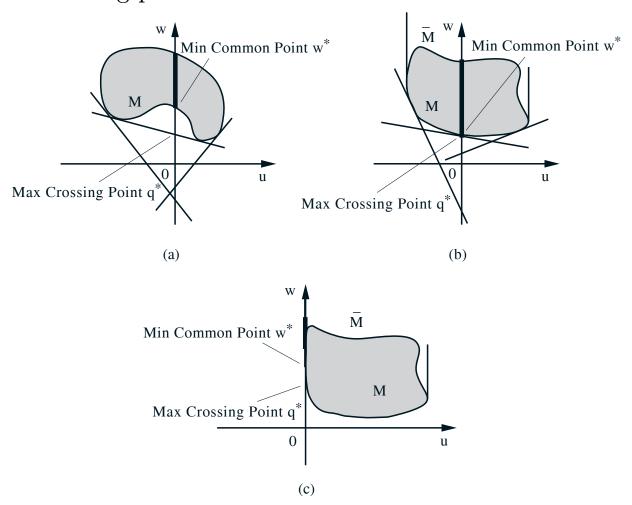
• Maximum crossing level over all hyperplanes with normal $(\mu, 1)$ is $q(\mu) = \inf_{(u,w) \in M} \{ w + \mu' u \}$

Max crossing problem: maximize $q(\mu)$ subject to $\mu \in \Re^n$.

• Note that for all $(u, w) \in M$ and $\mu \in \Re^n$, $q(\mu) = \inf_{(u, w) \in M} \{w + \mu' u\} \le \inf_{(0, w) \in M} w = w^*,$ $\sup_{\mu \ge 0} q(\mu) = q^* \le w^*.$

Strong Duality

Question: Under what conditions do we have $q^* = w^*$ and the supremum in the max crossing problem is attained?



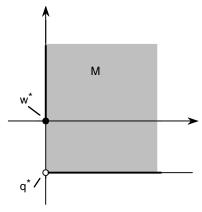
Duality Theorems

• Assume that w^* is finite and that the set

$$\bar{M} = \{(u, w) \mid \exists \ \bar{w} \text{ with } \bar{w} \leq w \text{ and } (u, \bar{w}) \in M\}$$

is convex.

• Min Common Max Crossing Theorem I: We have $q^* = w^*$ if and only if for every sequence $\{(u_k, w_k)\} \subset M$ with $u_k \to 0$, we have $w^* \leq \liminf_{k \to \infty} w_k$.



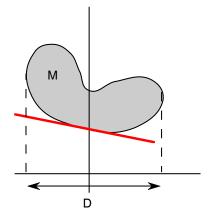
Attainment of Optimum in Max Crossing Problem

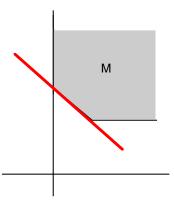
• Min Common Max Crossing Theorem II: Assume that the set

$$D = \{u \mid \text{there exists } w \in \Re \text{ with } (u, w) \in \bar{M} \}$$

contains the origin in its relative interior. Then $q^* = w^*$ and there exists a vector $\mu \in \mathbb{R}^n$ such that $q(\mu) = q^*$.

• Min Common Max Crossing Theorem III: Involves polyhedral assumptions and guarantees $q^* = w^*$ as well as attainment of the optimum of the max crossing problem.



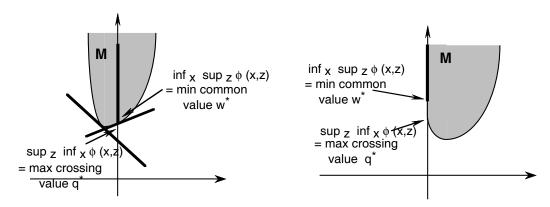


Minimax Problems

• Given $\phi: X \times Z \mapsto \Re$, where $X \subset \Re^n$, $Z \subset \Re^m$, under what conditions do we have

$$\sup_{z \in Z} \inf_{x \in X} \phi(x, z) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z) ?$$

- Introduce the perturbation function $p: \mathbb{R}^m \mapsto [-\infty, \infty]$ $p(u) = \inf_{x \in X} \sup_{z \in Z} \{\phi(x, z) - u'z\}, \qquad u \in \mathbb{R}^m.$
- Apply min common/max crossing framework with M = epi(p).



- Note that $w^* = \inf_{x \in X} \sup_{z \in Z} \phi(x, z)$.
 - Convexity in x implies M is a convex set.
 - Concavity/semicont. in z implies $q^* = \sup_{z \in Z} \inf_{x \in X} \phi(x, z)$.

Minimax Theorems

- Assume that:
 - X and Z are convex and $p(0) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z)$ is finite.
 - For each $z \in \mathbb{Z}$, the function $\phi(\cdot, z)$ is convex.
 - For each $x \in X$, the function $-\phi(x,\cdot)$ is closed and convex.
- Minimax Thm. I: The minimax equality holds iff the function p is lower semicontinuous at u = 0.
- Minimax Thm. II: If 0 lies in the relative interior of dom(p), then the minimax equality holds and the supremum in $\sup_{z\in Z}\inf_{x\in X}\phi(x,z)$ is attained by some $z\in Z$.
 - Proofs by applying min common max crossing theorems to the set

$$M = \operatorname{epi}(p).$$

Conditions for Attaining the Minimum

• Assume that:

- 1. X and Z are convex and $p(0) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z) < \infty$.
- 2. For each $x \in X$, the function $r_x(z) = -\phi(x, z)$ if $z \in Z$, and ∞ otherwise, is closed and convex.
- 3. For each $z \in Z$, the function $t_z(x) = \phi(x, z)$ if $x \in X$, and ∞ otherwise, is closed and convex.
- 4. The set of common directions of recession of all the functions t_z , $z \in \mathbb{Z}$, consists of the zero vector only.
- Then, the minimax equality holds, and the infimum over X is attained at a compact set of points.
- Special cases of Condition 4:
 - -X is compact.
 - \exists a scalar γ and $\bar{z} \in Z$ s.t. the level set $\{x \in X \mid \phi(x,\bar{z}) \leq \gamma\}$ is nonempty and compact.

Saddle Point Theorem

• Assume that:

- 1. X and Z are convex and either $-\infty < \sup_{z \in Z} \inf_{x \in X} \phi(x, z)$, or $\inf_{x \in X} \sup_{z \in Z} \phi(x, z) < \infty$.
- 2. For each $x \in X$, the function $r_x(z)$ is closed and convex, and the set of common directions of recession of all the functions r_x , $x \in X$, consists of the zero vector only.
- 3. For each $z \in Z$, the function $t_z(x)$ is closed and convex, and the set of common directions of recession of all the functions t_z , $z \in Z$, consists of the zero vector only.
- Then, the minimax equality holds, and the set of saddle points of ϕ is nonempty and compact.

• Special cases:

- -X and Z are compact.
- Z is compact, and \exists a scalar γ and $\bar{z} \in Z$ such that the level set $\{x \in X \mid \phi(x,\bar{z}) \leq \gamma\}$ is nonempty and compact.

Optimization Duality

• Consider the primal problem (optimal value f^*)

minimize
$$f(x)$$

subject to $x \in C$, $g_j(x) \le 0$, $j = 1, ..., r$,

where C is a convex set, f and g_j are convex over C.

• Consider also the dual problem (optimal value q^*)

maximize
$$q(\mu) = \inf_{x \in C} \left\{ f(x) + \sum_{j=1}^{r} \mu_j g_j(x) \right\}$$

subject to $\mu \ge 0$.

• Main Question: Under what conditions do we have

$$f^* = q^* = q(\mu^*)$$
?

• Question can be addressed using min common max crossing framework.

Nonlinear Farkas' Lemma

• Let C be convex, and f and the g_j be convex functions. Assume that

$$f(x) \ge 0, \qquad \forall \ x \in F = \{x \in C \mid g(x) \le 0\},\$$

and one of the following conditions holds:

1. 0 is in the relative interior of the set

$$D = \{ u \mid g(x) \le u \text{ for some } x \in C \}.$$

- 2. The functions g_j , j = 1, ..., r are affine, and $F \cap ri(C) \neq \emptyset$.
- Then, there exist scalars $\mu_j^* \geq 0$, $j = 1, \ldots, r$, such that

$$f(x) + \sum_{j=1}^{r} \mu_j^* g_j(x^*) \ge 0, \quad \forall x \in C.$$

- Reduces to Farkas' Lemma if $C = \Re^n$, and f, g_j linear.
- Proofs by applying min common max crossing theorems to

$$M = \{(u, w) \mid \text{there is } x \in C \text{ s.t. } g(x) \le u, \ f(x) \le w\}.$$

Application to Convex Programming

• Consider the problem (optimal value f^* , assumed finite)

minimize
$$f(x)$$

subject to $x \in C$, $g_j(x) \le 0$, $j = 1, ..., r$,

where C is convex, f and g_j are convex over C.

• Apply Farkas' Lemma. There exist $\mu_i^* \geq 0$ such that

$$f^* \le f(x) + \sum_{j=1}^r \mu_j^* g_j(x), \qquad \forall \ x \in C.$$

Since $F \subset C$ and $\mu_j^* g_j(x) \leq 0$ for all $x \in F$,

$$f^* \le \inf_{x \in F} \left\{ f(x) + \sum_{j=1}^r \mu_j^* g_j(x) \right\} \le \inf_{x \in F} f(x) = f^*.$$

Thus equality holds throughout above, and we have

$$f^* = \inf_{x \in C} \{ f(x) + \mu^{*'} g(x) \} = q(\mu^*).$$

Reference

Convex Analysis and Optimization,
Dimitri Bertsekas, with Angelia Nedic and Asuman Ozdaglar.

- To be published January 2003.
- http://web.mit.edu/6.291/www-old
 - Min Common/Max Crossing Duality
 - Existence of Solutions and Strong Duality
 - Pseudonormality and Lagrange Multipliers
 - Incremental Subgradient Methods