

# LECTURE 9

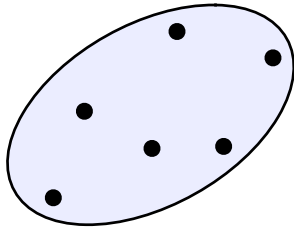
## LECTURE OUTLINE

- Min common/max crossing duality
- Weak duality
- Special Cases
- Constrained optimization and minimax
- Strong duality

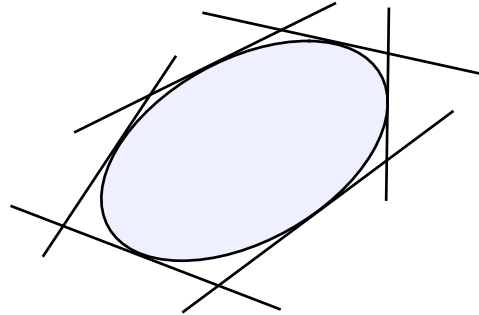
**Reading:** Sections 4.1,4.2, 3.4

# EXTENDING DUALITY CONCEPTS

- From dual descriptions of sets

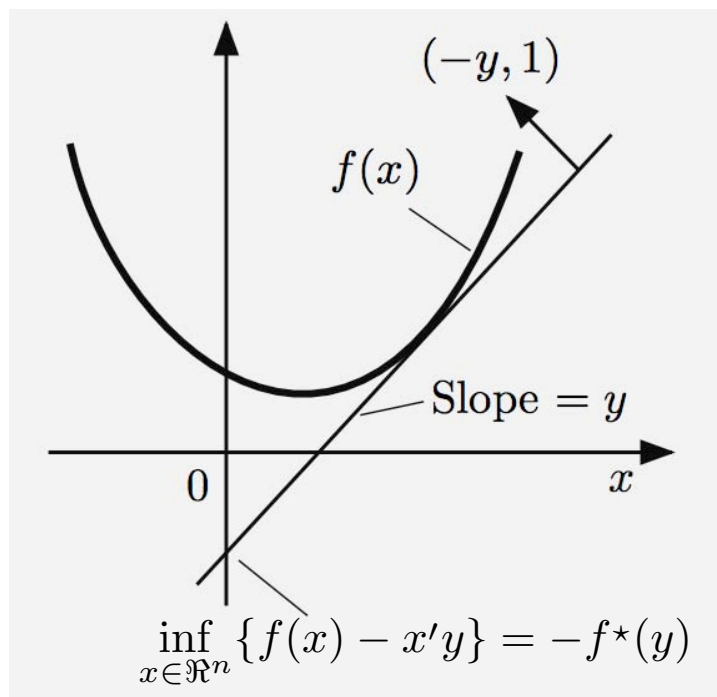


A union of points



An intersection of halfspaces

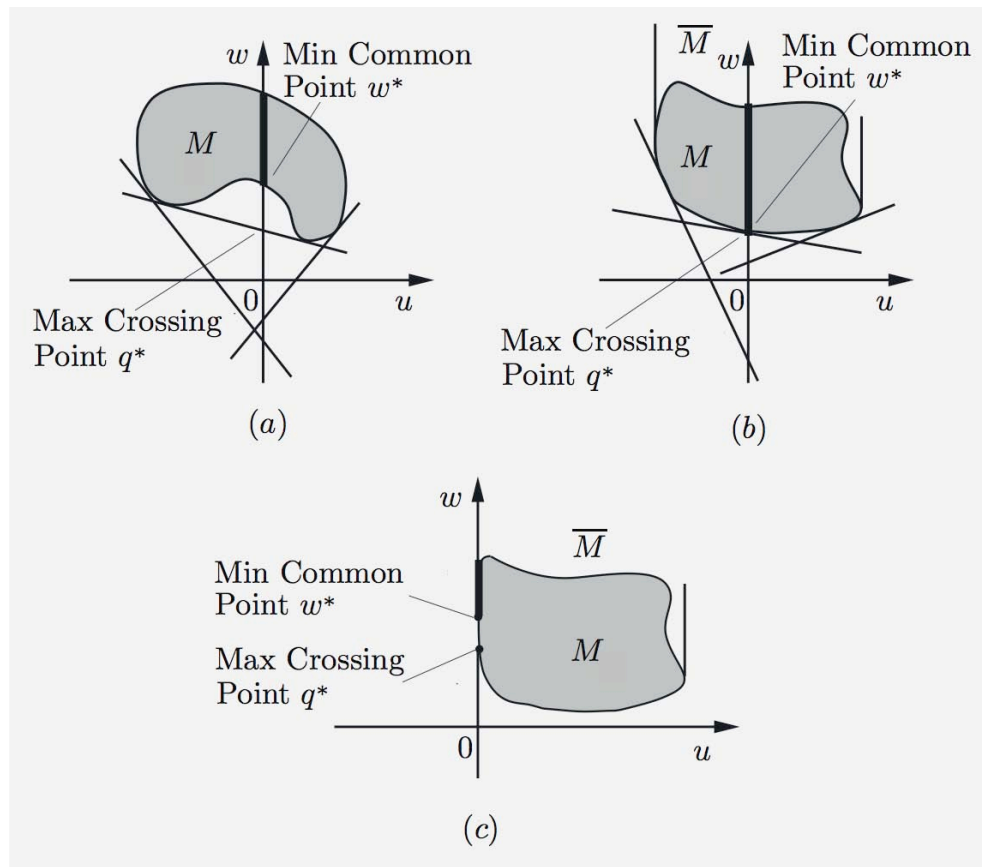
- To dual descriptions of functions (applying set duality to epigraphs)



- We now go to **dual descriptions of problems**, by applying conjugacy constructions to a simple generic geometric optimization problem

# MIN COMMON / MAX CROSSING PROBLEMS

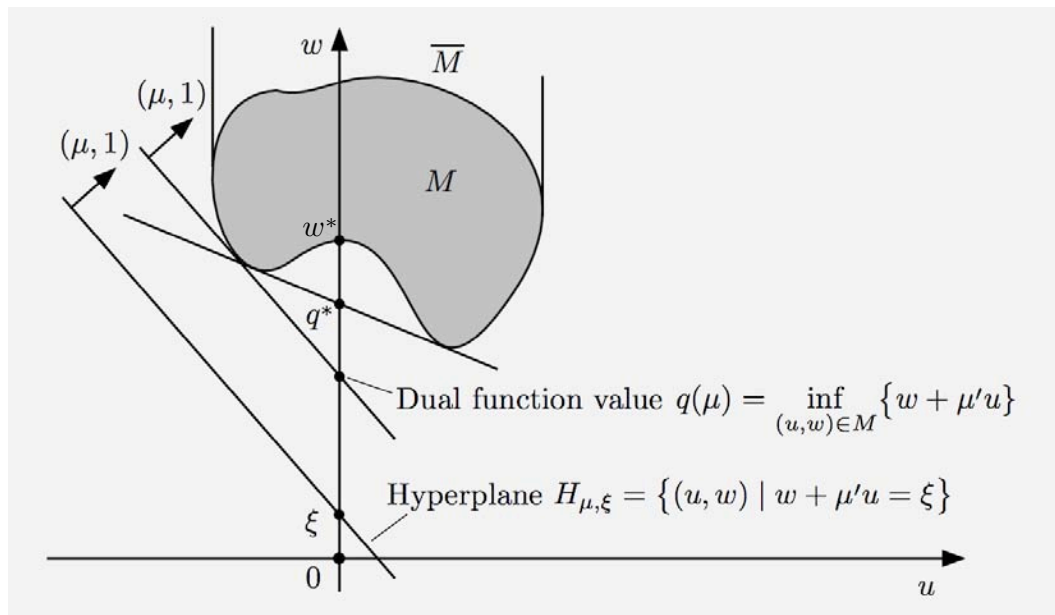
- We introduce a pair of fundamental problems:
- Let  $M$  be a nonempty subset of  $\mathfrak{R}^{n+1}$ 
  - (a) *Min Common Point Problem*: Consider all vectors that are common to  $M$  and the  $(n + 1)$ st axis. Find one whose  $(n + 1)$ st component is minimum.
  - (b) *Max Crossing Point Problem*: Consider non-vertical hyperplanes that contain  $M$  in their “upper” closed halfspace. Find one whose crossing point of the  $(n + 1)$ st axis is maximum.



# MATHEMATICAL FORMULATIONS

- **Optimal value of the min common problem:**

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



- **Math formulation of the max crossing problem:** Focus on hyperplanes with normals  $(\mu, 1)$  whose crossing point  $\xi$  satisfies

$$\xi \leq w + \mu'u, \quad \forall (u, w) \in M$$

Max crossing problem is to maximize  $\xi$  subject to  $\xi \leq \inf_{(u,w) \in M} \{w + \mu'u\}$ ,  $\mu \in \mathbb{R}^n$ , or

$$\text{maximize } q(\mu) \triangleq \inf_{(u,w) \in M} \{w + \mu'u\}$$

subject to  $\mu \in \mathbb{R}^n$ .

# GENERIC PROPERTIES – WEAK DUALITY

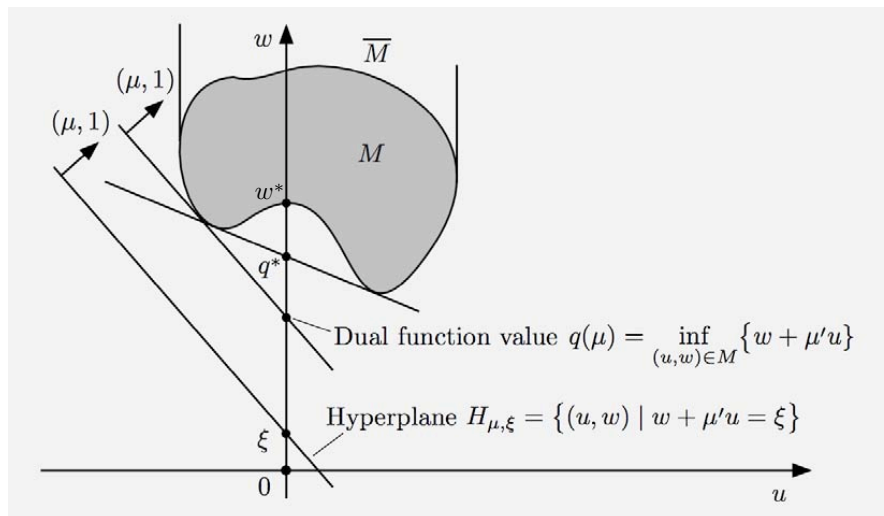
- Min common problem

$$\inf_{(0,w) \in M} w$$

- Max crossing problem

$$\text{maximize } q(\mu) \triangleq \inf_{(u,w) \in M} \{w + \mu'u\}$$

subject to  $\mu \in \mathfrak{R}^n$ .



- Note that  $q$  is concave and upper-semicontinuous (inf of linear functions).

- **Weak Duality:** For all  $\mu \in \mathfrak{R}^n$

$$q(\mu) = \inf_{(u,w) \in M} \{w + \mu'u\} \leq \inf_{(0,w) \in M} w = w^*,$$

so maximizing over  $\mu \in \mathfrak{R}^n$ , we obtain  $q^* \leq w^*$ .

- We say that **strong duality** holds if  $q^* = w^*$ .

# CONNECTION TO CONJUGACY

- An important special case:

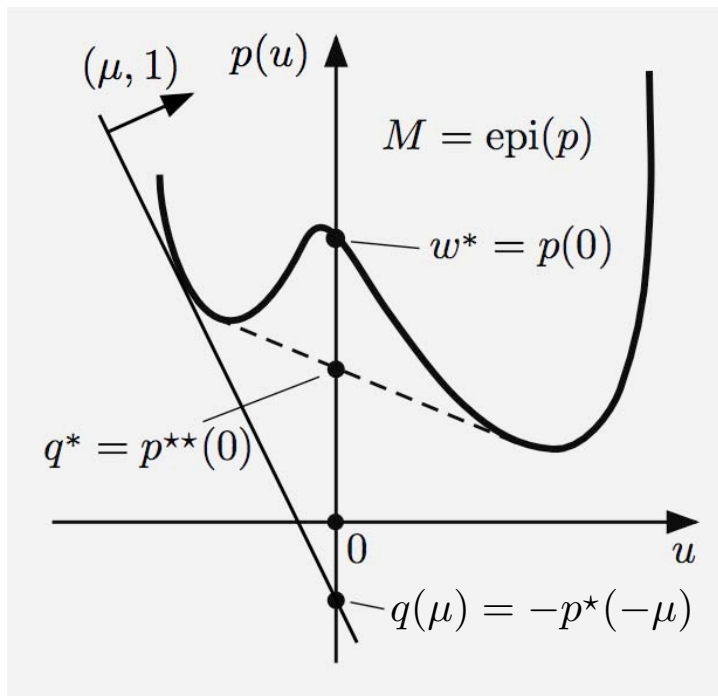
$$M = \text{epi}(p)$$

where  $p : \mathfrak{R}^n \mapsto [-\infty, \infty]$ . Then  $w^* = p(0)$ , and

$$q(\mu) = \inf_{(u,w) \in \text{epi}(p)} \{w + \mu'u\} = \inf_{\{(u,w) | p(u) \leq w\}} \{w + \mu'u\},$$

and finally

$$q(\mu) = \inf_{u \in \mathfrak{R}^m} \{p(u) + \mu'u\}$$



- Thus,  $q(\mu) = -p^*(-\mu)$  and

$$q^* = \sup_{\mu \in \mathfrak{R}^n} q(\mu) = \sup_{\mu \in \mathfrak{R}^n} \{0 \cdot (-\mu) - p^*(-\mu)\} = p^{**}(0)$$

# GENERAL OPTIMIZATION DUALITY

- Consider minimizing a function  $f : \mathfrak{R}^n \mapsto [-\infty, \infty]$ .
- Let  $F : \mathfrak{R}^{n+r} \mapsto [-\infty, \infty]$  be a function with

$$f(x) = F(x, 0), \quad \forall x \in \mathfrak{R}^n$$

- Consider the *perturbation function*

$$p(u) = \inf_{x \in \mathfrak{R}^n} F(x, u)$$

and the MC/MC framework with  $M = \text{epi}(p)$

- The min common value  $w^*$  is

$$w^* = p(0) = \inf_{x \in \mathfrak{R}^n} F(x, 0) = \inf_{x \in \mathfrak{R}^n} f(x)$$

- The dual function is

$$q(\mu) = \inf_{u \in \mathfrak{R}^r} \{p(u) + \mu' u\} = \inf_{(x, u) \in \mathfrak{R}^{n+r}} \{F(x, u) + \mu' u\}$$

so  $q(\mu) = -F^*(0, -\mu)$ , where  $F^*$  is the conjugate of  $F$ , viewed as a function of  $(x, u)$

- Since

$$q^* = \sup_{\mu \in \mathfrak{R}^r} q(\mu) = - \inf_{\mu \in \mathfrak{R}^r} F^*(0, -\mu) = - \inf_{\mu \in \mathfrak{R}^r} F^*(0, \mu),$$

we have

$$w^* = \inf_{x \in \mathfrak{R}^n} F(x, 0) \geq - \inf_{\mu \in \mathfrak{R}^r} F^*(0, \mu) = q^*$$

# CONSTRAINED OPTIMIZATION

- Minimize  $f : \mathfrak{R}^n \mapsto \mathfrak{R}$  over the set

$$C = \{x \in X \mid g(x) \leq 0\},$$

where  $X \subset \mathfrak{R}^n$  and  $g : \mathfrak{R}^n \mapsto \mathfrak{R}^r$ .

- Introduce a “perturbed constraint set”

$$C_u = \{x \in X \mid g(x) \leq u\}, \quad u \in \mathfrak{R}^r,$$

and the function

$$F(x, u) = \begin{cases} f(x) & \text{if } x \in C_u, \\ \infty & \text{otherwise,} \end{cases}$$

which satisfies  $F(x, 0) = f(x)$  for all  $x \in C$ .

- Consider *perturbation function*

$$p(u) = \inf_{x \in \mathfrak{R}^n} F(x, u) = \inf_{x \in X, g(x) \leq u} f(x),$$

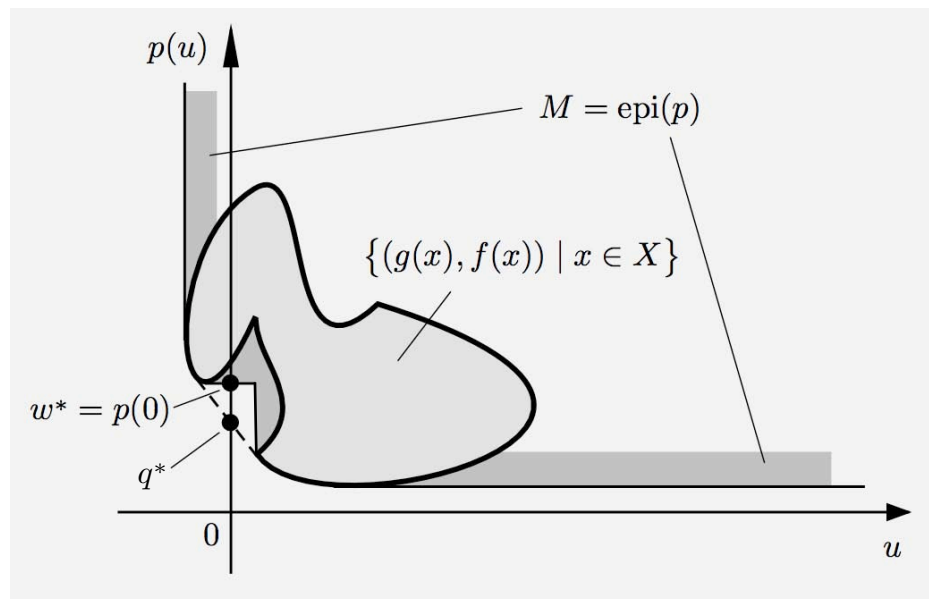
and the MC/MC framework with  $M = \text{epi}(p)$ .



# CONSTR. OPT. - PRIMAL AND DUAL FNS

- Perturbation function (or *primal function*)

$$p(u) = \inf_{x \in \mathfrak{R}^n} F(x, u) = \inf_{x \in X, g(x) \leq u} f(x),$$



- Introduce  $L(x, \mu) = f(x) + \mu'g(x)$ . Then

$$\begin{aligned} q(\mu) &= \inf_{u \in \mathfrak{R}^r} \{p(u) + \mu'u\} \\ &= \inf_{u \in \mathfrak{R}^r, x \in X, g(x) \leq u} \{f(x) + \mu'u\} \\ &= \begin{cases} \inf_{x \in X} L(x, \mu) & \text{if } \mu \geq 0, \\ -\infty & \text{otherwise.} \end{cases} \end{aligned}$$

# LINEAR PROGRAMMING DUALITY

- Consider the linear program

$$\begin{aligned} & \text{minimize } c'x \\ & \text{subject to } a'_j x \geq b_j, \quad j = 1, \dots, r, \end{aligned}$$

where  $c \in \mathfrak{R}^n$ ,  $a_j \in \mathfrak{R}^n$ , and  $b_j \in \mathfrak{R}$ ,  $j = 1, \dots, r$ .

- For  $\mu \geq 0$ , the dual function has the form

$$\begin{aligned} q(\mu) &= \inf_{x \in \mathfrak{R}^n} L(x, \mu) \\ &= \inf_{x \in \mathfrak{R}^n} \left\{ c'x + \sum_{j=1}^r \mu_j (b_j - a'_j x) \right\} \\ &= \begin{cases} b'\mu & \text{if } \sum_{j=1}^r a_j \mu_j = c, \\ -\infty & \text{otherwise} \end{cases} \end{aligned}$$

- Thus the dual problem is

$$\begin{aligned} & \text{maximize } b'\mu \\ & \text{subject to } \sum_{j=1}^r a_j \mu_j = c, \quad \mu \geq 0. \end{aligned}$$

# MINIMAX PROBLEMS

Given  $\phi : X \times Z \mapsto \mathfrak{R}$ , where  $X \subset \mathfrak{R}^n$ ,  $Z \subset \mathfrak{R}^m$   
consider

$$\begin{aligned} & \text{minimize} && \sup_{z \in Z} \phi(x, z) \\ & \text{subject to} && x \in X \end{aligned}$$

or

$$\begin{aligned} & \text{maximize} && \inf_{x \in X} \phi(x, z) \\ & \text{subject to} && z \in Z. \end{aligned}$$

- Some important contexts:
  - Constrained optimization duality theory
  - Zero sum game theory
- We always have

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

- **Key question:** When does equality hold?

# CONSTRAINED OPTIMIZATION DUALITY

- For the problem

$$\begin{aligned} & \text{minimize } f(x) \\ & \text{subject to } x \in X, \quad g(x) \leq 0 \end{aligned}$$

introduce the Lagrangian function

$$L(x, \mu) = f(x) + \mu'g(x)$$

- Primal problem (equivalent to the original)

$$\min_{x \in X} \sup_{\mu \geq 0} L(x, \mu) = \begin{cases} f(x) & \text{if } g(x) \leq 0, \\ \infty & \text{otherwise,} \end{cases}$$

- Dual problem

$$\max_{\mu \geq 0} \inf_{x \in X} L(x, \mu)$$

- Key duality question: Is it true that

$$\inf_{x \in \mathfrak{R}^n} \sup_{\mu \geq 0} L(x, \mu) = w^* \stackrel{?}{=} q^* = \sup_{\mu \geq 0} \inf_{x \in \mathfrak{R}^n} L(x, \mu)$$

## ZERO SUM GAMES

- Two players: 1st chooses  $i \in \{1, \dots, n\}$ , 2nd chooses  $j \in \{1, \dots, m\}$ .
- If  $i$  and  $j$  are selected, the 1st player gives  $a_{ij}$  to the 2nd.
- Mixed strategies are allowed: The two players select probability distributions

$$x = (x_1, \dots, x_n), \quad z = (z_1, \dots, z_m)$$

over their possible choices.

- Probability of  $(i, j)$  is  $x_i z_j$ , so the expected amount to be paid by the 1st player

$$x'Az = \sum_{i,j} a_{ij} x_i z_j$$

where  $A$  is the  $n \times m$  matrix with elements  $a_{ij}$ .

- Each player optimizes his choice against the worst possible selection by the other player. So
  - 1st player minimizes  $\max_z x'Az$
  - 2nd player maximizes  $\min_x x'Az$

# SADDLE POINTS

**Definition:**  $(x^*, z^*)$  is called a *saddle point* of  $\phi$  if

$$\phi(x^*, z) \leq \phi(x^*, z^*) \leq \phi(x, z^*), \quad \forall x \in X, \forall z \in Z$$

**Proposition:**  $(x^*, z^*)$  is a saddle point if and only if the minimax equality holds and

$$x^* \in \arg \min_{x \in X} \sup_{z \in Z} \phi(x, z), \quad z^* \in \arg \max_{z \in Z} \inf_{x \in X} \phi(x, z) \quad (*)$$

**Proof:** If  $(x^*, z^*)$  is a saddle point, then

$$\begin{aligned} \inf_{x \in X} \sup_{z \in Z} \phi(x, z) &\leq \sup_{z \in Z} \phi(x^*, z) = \phi(x^*, z^*) \\ &= \inf_{x \in X} \phi(x, z^*) \leq \sup_{z \in Z} \inf_{x \in X} \phi(x, z) \end{aligned}$$

By the minimax inequality, the above holds as an equality throughout, so the minimax equality and Eq. (\*) hold.

Conversely, if Eq. (\*) holds, then

$$\begin{aligned} \sup_{z \in Z} \inf_{x \in X} \phi(x, z) &= \inf_{x \in X} \phi(x, z^*) \leq \phi(x^*, z^*) \\ &\leq \sup_{z \in Z} \phi(x^*, z) = \inf_{x \in X} \sup_{z \in Z} \phi(x, z) \end{aligned}$$

Using the minimax equ.,  $(x^*, z^*)$  is a saddle point.

# MINIMAX MC/MC FRAMEWORK

- Introduce perturbation function  $p : \mathfrak{R}^m \mapsto [-\infty, \infty]$

$$p(u) = \inf_{x \in X} \sup_{z \in Z} \{ \phi(x, z) - u'z \}, \quad u \in \mathfrak{R}^m$$

- Apply the MC/MC framework with  $M = \text{epi}(p)$
- Introduce  $\hat{\text{cl}} f$ , the *concave closure of  $f$*
- We have

$$\sup_{z \in Z} \phi(x, z) = \sup_{z \in \mathfrak{R}^m} (\hat{\text{cl}} \phi)(x, z),$$

so

$$w^* = p(0) = \inf_{x \in X} \sup_{z \in \mathfrak{R}^m} (\hat{\text{cl}} \phi)(x, z).$$

- The dual function can be shown to be

$$q(\mu) = \inf_{x \in X} (\hat{\text{cl}} \phi)(x, \mu), \quad \forall \mu \in \mathfrak{R}^m$$

so if  $\phi(x, \cdot)$  is concave and closed,

$$w^* = \inf_{x \in X} \sup_{z \in \mathfrak{R}^m} \phi(x, z), \quad q^* = \sup_{z \in \mathfrak{R}^m} \inf_{x \in X} \phi(x, z)$$

# PROOF OF FORM OF DUAL FUNCTION

- Write  $p(u) = \inf_{x \in X} p_x(u)$ , where

$$p_x(u) = \sup_{z \in Z} \{ \phi(x, z) - u'z \}, \quad x \in X,$$

and note that

$$\inf_{u \in \mathfrak{R}^m} \{ p_x(u) + u' \mu \} = - \sup_{u \in \mathfrak{R}^m} \{ u'(-\mu) - p_x(u) \} = -p_x^*(-\mu)$$

Except for a sign change,  $p_x$  is the conjugate of  $(-\phi)(x, \cdot)$  [assuming  $(-\hat{\text{cl}} \phi)(x, \cdot)$  is proper], so

$$p_x^*(-\mu) = -(\hat{\text{cl}} \phi)(x, \mu).$$

Hence, for all  $\mu \in \mathfrak{R}^m$ ,

$$\begin{aligned} q(\mu) &= \inf_{u \in \mathfrak{R}^m} \{ p(u) + u' \mu \} \\ &= \inf_{u \in \mathfrak{R}^m} \inf_{x \in X} \{ p_x(u) + u' \mu \} \\ &= \inf_{x \in X} \inf_{u \in \mathfrak{R}^m} \{ p_x(u) + u' \mu \} \\ &= \inf_{x \in X} \{ -p_x^*(-\mu) \} \\ &= \inf_{x \in X} (\hat{\text{cl}} \phi)(x, \mu) \end{aligned}$$



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