

# LECTURE 10

## STRONG DUALITY

$$P_* := \underset{x \in \mathbb{R}^n}{\text{minimize}} \quad f(x)$$

$c_j(x) = 0 \quad j \in E$   
 $c_j(x) \geq 0 \quad j \in I$

↓  
 see  
 previous  
 lecture

 PRIMAL  
PROBLEM

$$d_* := \underset{M \in \mathbb{R}^m, \lambda \in \mathbb{R}^p}{\text{maximize}} \quad g(M, \lambda)$$

$\lambda \geq 0$

↓  
 see  
 previous  
 lecture

 DUAL  
PROBLEM

where

$$g(M, \lambda) := \inf_{x \in D} L(x; M, \lambda)$$

and

$$L(x; M, \lambda) := f(x) - \sum_{j \in E} M_j c_j(x) - \sum_{j \in I} \lambda_j c_j(x)$$

$$D := \left\{ \bigcap_{j \in I \cup E} \text{dom } c_j(x) \right\} \cap \text{dom } f(x)$$

We always have the weak duality

$$P_* \geq d_*$$

Strong duality is said to hold if

$$P_* = d_*$$

# Convex optimization problems

(Convex programs)

minimize  $f(x)$

$$x \in \mathbb{R}^n$$

$$c_j(x) \geq 0 \quad j \in I$$

$$Ax = b$$

where

$f$  is convex

$-c_j$  is convex  $\forall j \in I$

## Remark

Above defn is equivalent to  $f(x)$  is convex, and the feasible region  $F$  is a convex set.

$$F = \{x \mid c_j(x) \geq 0 \text{ and } Ax = b\}$$

In particular the dual problem

$$\begin{array}{l} \text{maximize} \\ \mu \in \mathbb{R}^m, \lambda \in \mathbb{R}^p \\ \lambda \geq 0 \end{array} g(\mu, \lambda) \quad \left( \begin{array}{l} \equiv \text{minimize } -g(\mu, \lambda) \\ \mu, \lambda \\ \lambda \geq 0 \end{array} \right)$$

is convex, since  $-g(\mu, \lambda)$  is convex.

# Geometric View for Strong / Weak Duality

$$G := \{ (c_{j_1}(x), \dots, c_{j_m}(x), c_{k_1}(x), \dots, c_{k_p}(x), f(x)) \mid x \in D \}$$

Above,

$$E = \{j_1, \dots, j_m\} \text{ and } I = \{k_1, \dots, k_p\}$$

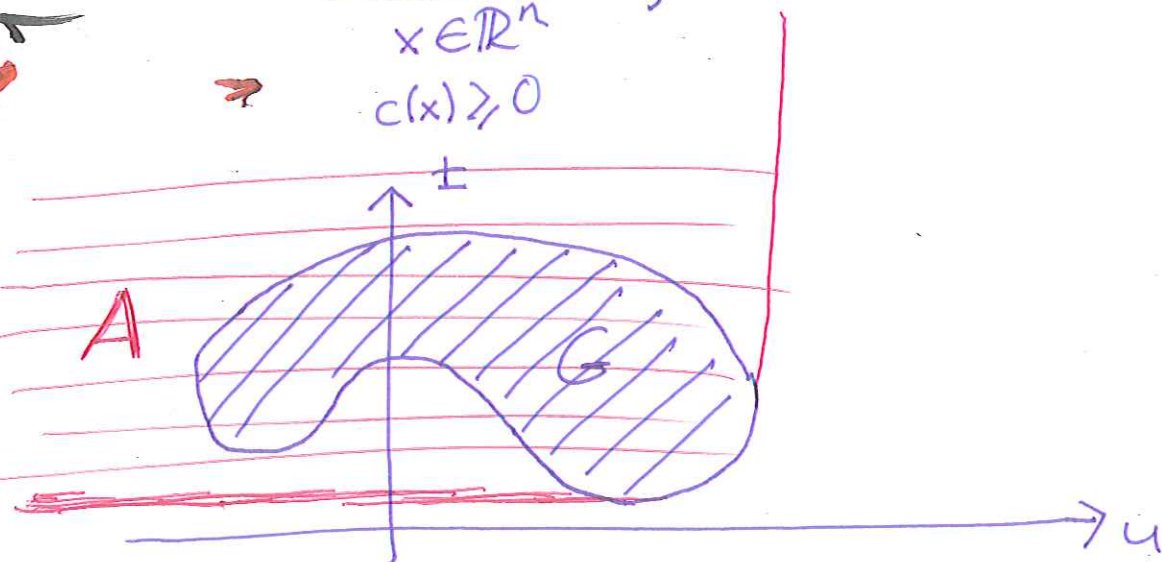
$$A := \{ (v, u, t) \mid v \in \mathbb{R}^m, u \in \mathbb{R}^p, t \in \mathbb{R} \text{ such that } \exists x \in D \\ f(x) \leq t, c_{j_l}(x) = v_l \quad l=1, \dots, m, c_{k_l} \geq u_l \quad l=1, \dots, p \}$$

Illustration (one inequality case)

minimize  $f(x)$   
 $x \in \mathbb{R}^n$

$$c(x) \geq 0$$

$t$



Primal problem

$$P^* = \inf \{ t \mid (0, 0, t) \in A \} \\ = \inf \{ t \mid \exists (v, u) \text{ s.t. } (v, u, t) \in G, u \geq 0, v = 0 \}$$

(3)

Lagrange dual function

$$g(\mu, \lambda) = \inf \left\{ \underbrace{(-\mu, -\lambda, 1)^T (v, u, t)}_{-\mu^T v - \lambda^T u + t} \mid (v, u, t) \in G \right\}$$

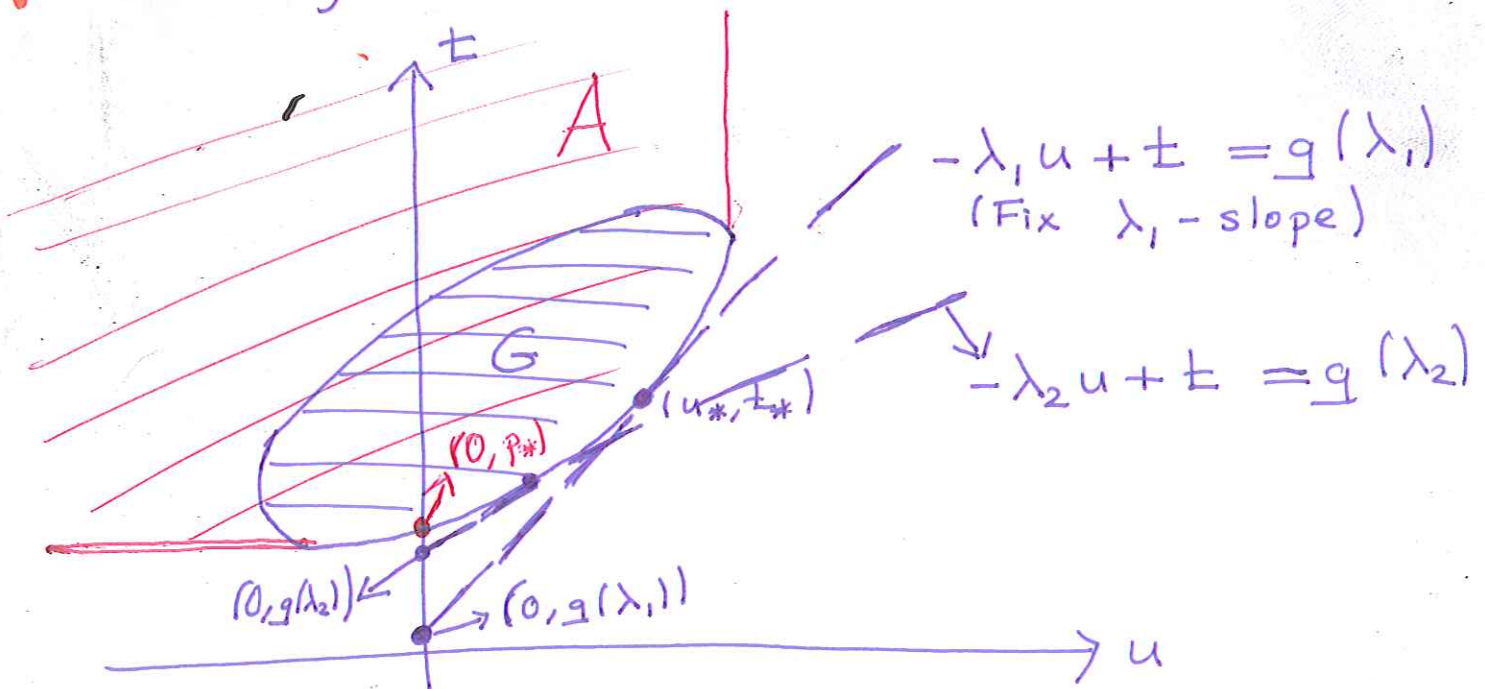
If infimum is attained

$$(i) \underbrace{(-\mu, -\lambda, 1)^T (v, u, t)}_{-\mu^T v - \lambda^T u + t} \geq g(\mu, \lambda) \quad \forall (v, u, t) \in G$$

$$(ii) \underbrace{(-\mu, -\lambda, 1)^T (v_*, u_*, t_*)}_{-\mu^T v_* - \lambda^T u_* + t_*} = g(\mu, \lambda) \quad \exists (v_*, u_*, t_*) \in G$$

Illustration

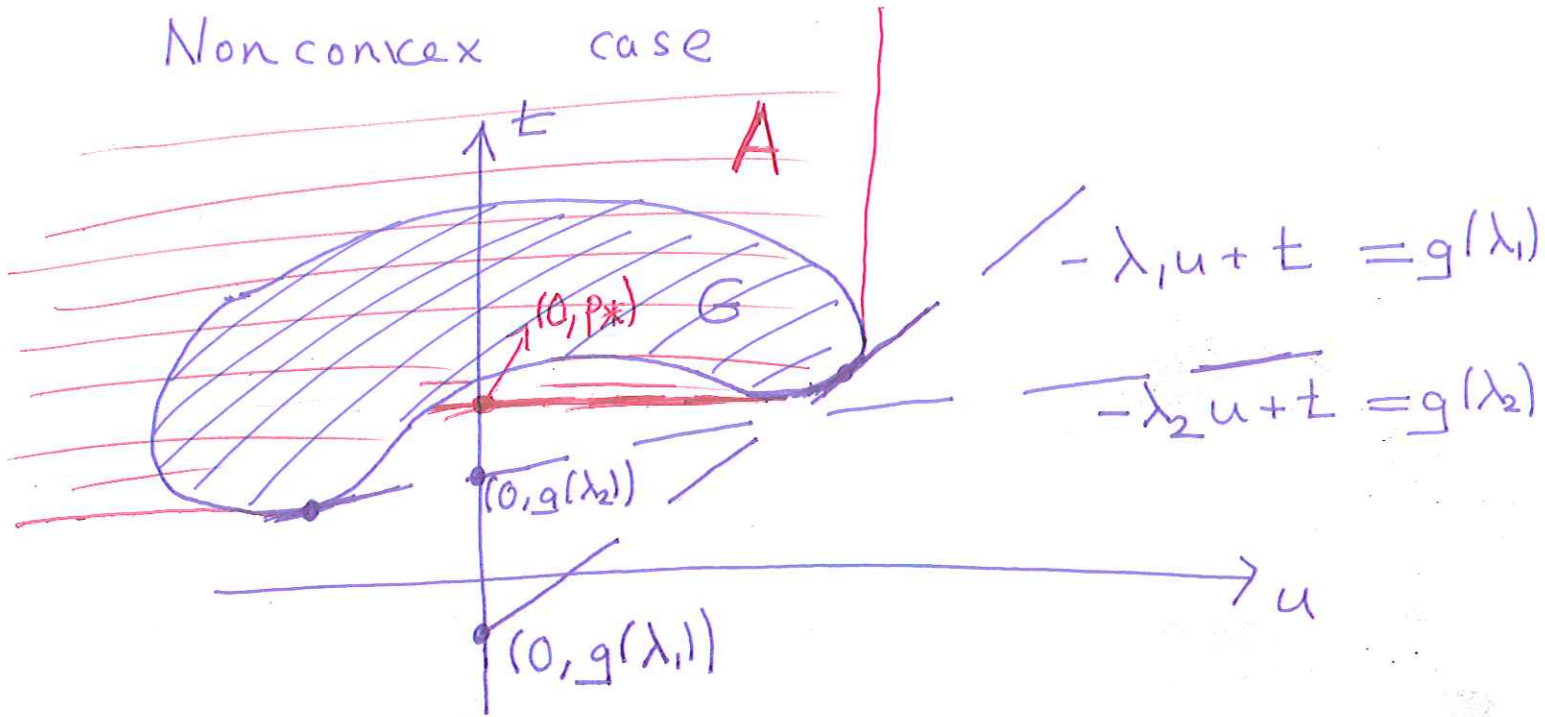
Convex case (A has to be convex, but for simplicity suppose G is also)



$$\left[ d_* = \sup_{\lambda \geq 0} g(\lambda) \right] = P_*$$



Non convex case



$$[d_* = \sup_{\lambda \geq 0} g(\lambda)] \neq p_*$$

Suppose the infimum

$$p_* = \inf \{t \mid (0, 0, t) \in A\}$$

is attained.

For each  $(M, \lambda) \in \text{dom } g$  s.t.  $\lambda \geq 0$

$$p_* = (-M, -\lambda, 1)^T \cdot (0, 0, p_*)$$

$$\geq g(M, \lambda)$$

intuitively  $-\lambda^T u - M^T v + t = g(M, \lambda)$   
 (tangent to G at  $(0, 0, p)$ )

Strong duality holds



Above holds with equality  $\exists (M, \lambda) \in \text{dom } g$  s.t.  $\lambda \geq 0$ . (5)

## Interior

Let  $D$  be a given set.

$x_* \in \text{int}(D)$  if  $\exists \delta > 0$  such that

$$\cancel{B(x_*, \delta)} \quad B(x_*, \delta) \subseteq D.$$

## Relative interior

$x_* \in \text{relint}(D)$  if  $\exists \delta > 0$  such that

$$B(x_*, \delta) \cap \text{Aff}(D) \subseteq D.$$

$$\text{Aff}(D) := \left\{ \theta_1 x_1 + \dots + \theta_K x_K \mid \begin{array}{l} K \in \mathbb{Z}^+, x_1, \dots, x_K \in D, \\ \theta_1, \dots, \theta_K \in \mathbb{R} \text{ s.t. } \sum_{j=1}^K \theta_j = 1 \end{array} \right\}$$

$$\begin{aligned} \text{e.g. } \text{Aff} \left( \left\{ \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\} \right) &= \left\{ t(1,0) + (1-t)(0,1) \mid t \in \mathbb{R} \right\} \\ &= \left\{ (0,1) + t(1,-1) \mid t \in \mathbb{R} \right\} \\ &\text{line through } (1,0) \text{ and } (0,1) \end{aligned}$$

## Ex

$$D := \{ (x, 0) \mid x \in [0, 1] \}$$

$$\text{int } D = \emptyset$$

$$\text{Aff } D = \{ (x, 0) \mid x \in \mathbb{R} \}$$

$$\text{relint } D = \{ (x, 0) \mid x \in (0, 1) \}$$

## THM (Slater Condition)

Suppose that the primal problem is convex,  
and that there exists  $x_* \in \text{Relint}(D)$   
such that

$$(i) Ax_* = b \quad \text{and} \quad (ii) c_j(x_*) > 0 \quad \forall j \in I.$$

Then  $p_* = d_*$ .

## Remark

If  $\exists S \subseteq I$  such that for each  $j \in S$

$$c_j(x) = a_j^T x + b_j$$

for some  $a_j, b_j \in \mathbb{R}$ , then condition (ii)

above can be replaced by

$$c_j(x_*) > 0 \quad \forall j \in I \setminus S \quad \text{and} \quad c_j(x_*) \geq 0 \quad \forall j \in S.$$

## Ex

$$\text{minimize}_{x \in \mathbb{R}^n} \quad \frac{1}{2} x^T H x + g^T x$$

$$Ax = b$$

$$x \geq 0$$

$H$  -  $n \times n$  symmetric PD

$A$  -  $m \times n$

$g \in \mathbb{R}^n, b \in \mathbb{R}^m$

$$L(x; \mu, \lambda) = \frac{1}{2} x^T H x + g^T x - \mu^T (Ax - b) - \lambda^T x$$

$$\begin{aligned} g(\mu, \lambda) &= \inf_{x \in \mathbb{R}^n} \frac{1}{2} x^T H x + g^T x - \mu^T (Ax - b) - \lambda^T x \\ &= \mu^T b + \inf_{x \in \mathbb{R}^n} \frac{1}{2} x^T H x + (g - A^T \mu - \lambda)^T x \end{aligned}$$

Optimal  $x_*$  for the minimization problem

$$x_* = H^{-1} (A^T \mu + \lambda - g)$$

so

$$g(\mu, \lambda) = \mu^T b - \frac{1}{2} (A^T \mu + \lambda - g)^T H^{-1} (A^T \mu + \lambda - g)$$

Dual problem

$$\begin{aligned} &\text{maximize } \mu^T b - \frac{1}{2} (A^T \mu + \lambda - g)^T H^{-1} (A^T \mu + \lambda - g) \\ &\mu \in \mathbb{R}^m, \lambda \in \mathbb{R}^n \\ &\lambda \geq 0 \end{aligned}$$

If there exists an  $x$  such that

$$Ax = b \quad \text{and} \quad x \geq 0$$

the primal and dual problems have the same optimal value.



## Ex (Matrix games)

P1 makes a choice from  $\{1, 2, \dots, n\}$

P2 makes a choice from  $\{1, 2, \dots, m\}$

P -  $n \times m$  matrix,  $p_{kl}$  corresponds to the payment P1 makes to P2 when P1 chooses  $k$  and P2 chooses  $l$ .

$u, v$  - (discrete) probability distribution associated with choices of P1, P2

$$\sum_{i=1}^n u_i = \sum_{i=1}^m v_i = 1 \quad \text{and} \quad u_i, v_i \geq 0.$$

Expected payment

$$\sum_{k=1}^n \sum_{l=1}^m u_k v_l p_{kl} = u^T P v$$

P2 aims to maximize by choosing  $v$

P1 aims to minimize by choosing  $u$

Suppose P2 plays the best possible (given u-play of P1)

$$\underset{v}{\text{maximize}} \quad u^T P v = \max_{j=1, \dots, m} (P^T u)_j$$

The best P1 can do

$$\underset{u}{\text{minimize}} \quad \underset{v}{\text{maximize}} \quad u^T P v$$

$$= \underset{u}{\text{minimize}} \left\{ \max_{j=1, \dots, m} (P^T u)_j \right\}$$

that is

$$P^* := \underset{u \in \mathbb{R}^n, t \in \mathbb{R}}{\text{minimize}} \quad t$$

(PI)  $e^T \cdot u = 1$   
 $u \geq 0$   
 $P^T u \leq t e$

Conversely, suppose P1 plays the best possible (given v-play of P2)

$$\underset{u}{\text{minimize}} \quad u^T P v = \min_{j=1, \dots, n} (P v)_j$$

The best P2 can do

$$\text{maximize}_v \left\{ \min_{j=1, \dots, n} (Pv)_j \right\}$$

that is

$$d_* := \text{maximize}_v \quad t$$

$v \in \mathbb{R}^m, t \in \mathbb{R}$

$$\textcircled{P2} \quad \begin{aligned} e^T \cdot v &= 1 \\ v &\geq 0 \\ P \cdot v &\geq t \cdot e \end{aligned}$$

$\textcircled{P1}$  and  $\textcircled{P2}$  are primal dual problems (i.e.,  $\textcircled{P2}$  is the dual of  $\textcircled{P1}$ ) - Verification exercise.

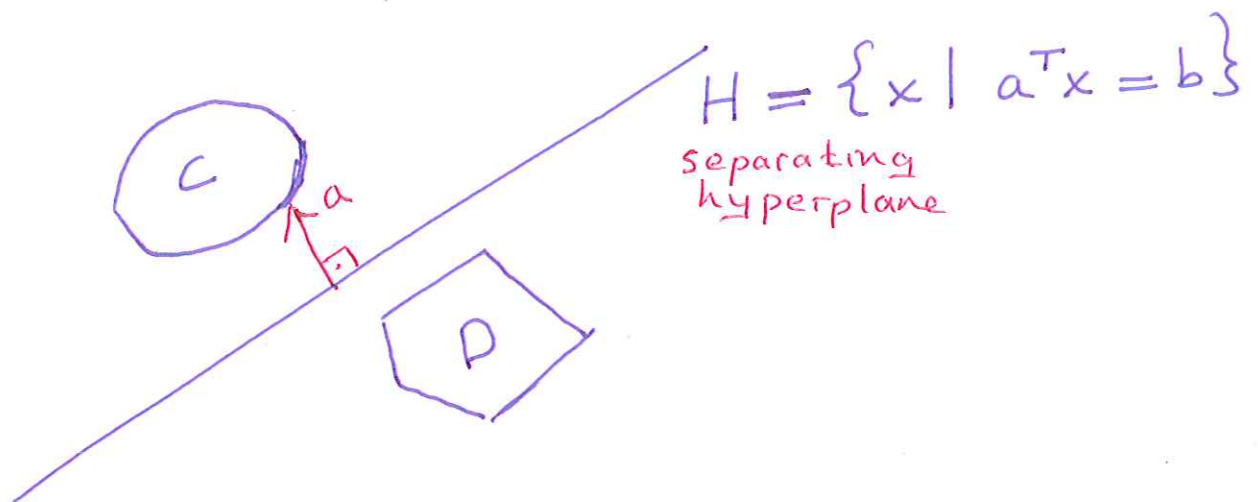
Slater conditions guarantee  $p_* = d_*$ .

## LEMMA (Separating Hyperplane)

Let  $C$  and  $D$  be nonempty convex sets  $\nearrow$  in  $\mathbb{R}^n$  such that  $C \cap D = \emptyset$ . There exists a nonzero  $a \in \mathbb{R}^n$  and  $b \in \mathbb{R}$  s.t.

$$(i) \quad a^T x \geq b \quad \forall x \in C, \text{ and}$$

$$(ii) \quad a^T x \leq b \quad \forall x \in D$$



PROOF OF THM (Slater Conditions)  
Assuming -  $\text{Relint}(D) = \text{Int}(D)$  and  $\text{Rank}(A) = m$

Consider the set

$$B := \{(0, 0, s) \in \mathbb{R}^m \times \mathbb{R}^p \times \mathbb{R} \mid s < p_*\}$$

Without loss of generality, we assume  $p_*$  is finite, i.e.,  $p_* \neq \infty$  is excluded since  $\exists$  feasible points by assumption, if  $p_* = -\infty$ , then  $d_* = -\infty$  by weak duality.

Notice that  $A \cap B \neq \emptyset$ : Assume  $(\overset{v}{x}, \overset{u}{x}, t) \in A \cap B$ , then  $u = v = 0$  and  $t < p_*$ . Furthermore, since  $(v, u, t) \in A$ , we have  $c_{j_l}(x) = 0 \quad l = 1, \dots, m$   
 $c_{k_l}(x) \geq 0 \quad l = 1, \dots, p$  and  $f(x) \leq t < p_* \exists x \in D$ , which is a contradiction. (12)



Due to assumption  $f(x)$  is convex,  $c_{k_0}(x)$   $k=1, \dots, p$  are convex, the set  $A$  is convex. Thus by the lemma above  $\exists (\lambda, \mu, n) \neq 0$  such that

$$(+) \quad (-\mu, -\lambda, n)^T (v, u, t) \geq \alpha \quad \forall (v, u, t) \in A$$

$$(+++) \quad (-\mu, -\lambda, n)^T (v, u, t) \leq \alpha \quad \forall (v, u, t) \in B$$

Now  $\lambda, n \geq 0$ ; because otherwise if  $(v, u, t) \in A$ , so does  $(v, \tilde{u}, \tilde{t}) \in A$  for every  $\tilde{u} \geq u$  and  $\tilde{t} \leq t$  implying  $-\mu^T v - \lambda^T \tilde{u} + n\tilde{t}$  is unbounded below over  $A$  contradicting (+).

Moreover, due to (+++)

$$ns \leq \alpha \quad \forall s \text{ s.t. } s < p_*$$

$$\implies np_* \leq \alpha.$$

Now exploiting (+), for each  $x \in D$ , we have

$$(+++) \quad -\sum_{j \in E} \mu_j c_j(x) - \sum_{j \in I} \lambda_j c_j(x) + nt \geq \alpha \geq np_*$$

First assume  $n \neq 0$ . But then

$$L(x; \frac{\mu}{n}, \frac{\lambda}{n}) \geq p_* \quad \text{with } \lambda, n \geq 0 \text{ (i.e., } \lambda, n \geq 0)$$

for every  $x \in D$  implying

$$g(\frac{\mu}{n}, \frac{\lambda}{n}) \geq p_* \implies d_* \geq p_*$$

Combining this with weak duality yields  $d_* = p_*$  as desired.

Now assume  $n = 0$ . There exists  $\bar{x} \in \text{Int}(D)$  such that  $c_j(\bar{x}) > 0$  and  $A\bar{x} = b$  by assumption.

But then from  $(+++)$

$$-\sum_{j \in E} M_j c_j(\bar{x}) - \sum_{j \in I} \lambda_j c_j(\bar{x}) \geq 0$$

$$\implies -\sum_{j \in I} \lambda_j c_j(\bar{x}) \geq 0$$

$$\implies \lambda = 0.$$

Consequently,  $M \neq 0$ . From  $(+++)$  for each  $x \in D$

$$(++++) \quad -\sum_{j \in E} M_j c_j(x) \geq 0.$$

But  $\bar{x} \in \text{Int} D$  such that  $A\bar{x} = b$ .

Due to assumption  $\text{Rank}(A) = m$ , there exists  $p$  such that  $A_p = M$ . For each  $\alpha > 0$  small enough  $\bar{x} + \alpha p \in \text{Int} D$  and

$$-\underbrace{M^T (A(\bar{x} + \alpha p) - b)}_{\sum_{j \in E} M_j c_j(\bar{x} + \alpha p)} = -\alpha M^T A_p = -\alpha \|M\|^2 < 0.$$

This contradicts  $(++++)$ . Thus  $n \neq 0$ .

