

Theorem (Duality theorem)

$z_P$	$z_D$	Conclusion
$\neq \phi$	$\neq \phi$	$\exists$ an optimal solution $\hat{x}$ to (P) $\exists$ an optimal solution $\hat{y}$ to (D) $c^T \hat{x} = b^T \hat{y}$ <div style="display: flex; justify-content: space-around; margin-top: 5px;"> <div style="text-align: center;"> <span style="color: red;">cost values of (D)</span>  </div> <div style="text-align: center;"> <span style="color: gray;">cost values of (P)</span>  </div> </div>
$\neq \phi$	$= \phi$	$\forall p \in \mathbb{R} \exists x \in \mathcal{F}_P \text{ s.t. } c^T x < p$ Neither (P) nor (D) have an optimal solution <div style="text-align: center; margin-top: 5px;"> <span style="color: gray;">costs of (P) not bounded below</span>  </div>
$= \phi$	$\neq \phi$	$\forall p \in \mathbb{R} \exists y \in \mathcal{F}_D \text{ s.t. } b^T y > p$ Neither (P) nor (D) have an optimal solution <div style="text-align: center; margin-top: 5px;"> <span style="color: red;">costs of (D) not bounded above</span>  </div>
$= \phi$	$= \phi$	Neither (P) nor (D) have an optimal solution.

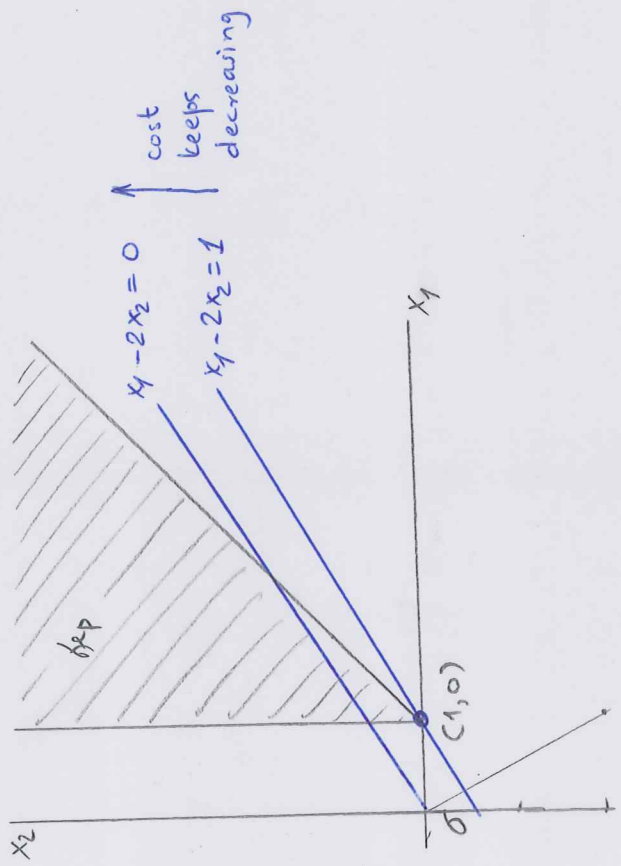
Example

$$\left\{ \begin{array}{l} \text{minimize } x_1 - 2x_2 \\ \text{s.t. } -x_1 + x_2 \geq -1 \\ x_1 \geq 1 \\ x_1 \geq 0 \\ x_2 \geq 0 \end{array} \right.$$

$$c = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

$$A = \begin{bmatrix} -1 & 1 \\ 1 & 0 \end{bmatrix}$$

$$b = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$



$$\{c^T x : x \in f.p.\}$$



(P) has no optimal solution.

$$\left\{ \begin{array}{l} \text{maximize } -y_1 + y_2 \\ \text{s.t. } -y_1 + y_2 \leq 1 \\ y_1 \leq -2 \\ y_1 \geq 0 \\ y_2 \geq 0 \end{array} \right.$$

Cannot be satisfied simultaneously

$$f_{eD} = \emptyset$$

Example (continued)


$$(D): \begin{cases} \text{maximize} & -y_1 + y_2 \\ \text{s.t.} & -y_1 + y_2 \leq 1 \\ & y_1 \leq -2 \\ & y_1 \geq 0 \\ & y_2 \geq 0 \end{cases}$$

|||

$$(\tilde{P}): \begin{cases} \text{minimize} & x_1 - x_2 \\ \text{s.t.} & x_1 - x_2 \geq -1 \\ & -x_1 \geq 2 \\ & x_1 \geq 0 \\ & x_2 \geq 0 \end{cases}$$

$\infty_{\tilde{P}} = \phi$

$c = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$   
 $A = \begin{bmatrix} 1 & -1 \\ -1 & 0 \end{bmatrix}$   
 $b = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

DUAL 

$$(\tilde{D}): \begin{cases} \text{maximize} & -y_1 + 2y_2 \\ \text{s.t.} & y_1 - y_2 \leq 1 \\ & -y_1 \leq -1 \\ & y_1 \geq 0 \\ & y_2 \geq 0 \end{cases}$$

$\infty_{\tilde{D}} \neq \phi$

possible costs of  $(\tilde{D})$



$(\tilde{D})$  has no optimal solution.

$$(P): \begin{cases} \text{minimize} & x_1 - 2x_2 \\ \text{s.t.} & -x_1 + x_2 \geq -1 \\ & x_1 \geq 1 \\ & x_1 \geq 0 \\ & x_2 \geq 0 \end{cases}$$

|||

Corollary: Let  $x \in \mathbb{R}^n$ ,  $y \in \mathbb{R}^m$

$x$ is optimal for (P) and $y$ is optimal for (D)	$\Leftrightarrow$
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$x$ is feasible for (P), $y$ is feasible for (D), and $c^T x = b^T y$
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Proof  $\Rightarrow$ :  $c^T x = c^T \hat{x} = b^T \hat{y} = b^T y$

$\Leftarrow$ : Let  $\hat{x}$  be feasible for (P).

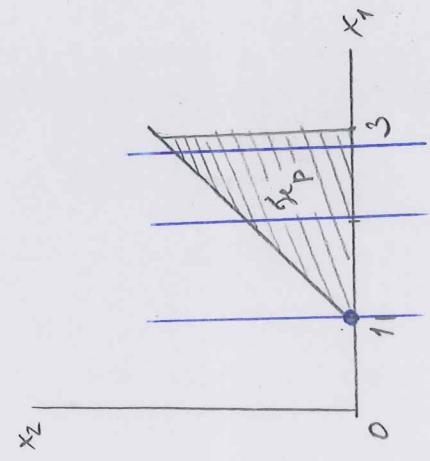
Then  $c^T \hat{x} \geq b^T \hat{y} = c^T x$ . So  $x$  is optimal for (P)

Let  $\hat{y}$  be feasible for (D)

Then  $b^T \hat{y} \leq c^T x = b^T y$ . So  $y$  is optimal for (D).  $\square$

Example

(P):  $\left\{ \begin{array}{l} \text{minimize } x_1 \\ \text{s.t. } x_1 - x_2 \geq 1 \\ -x_1 \geq -3 \\ x_1 \geq 0 \\ x_2 \geq 0 \end{array} \right.$

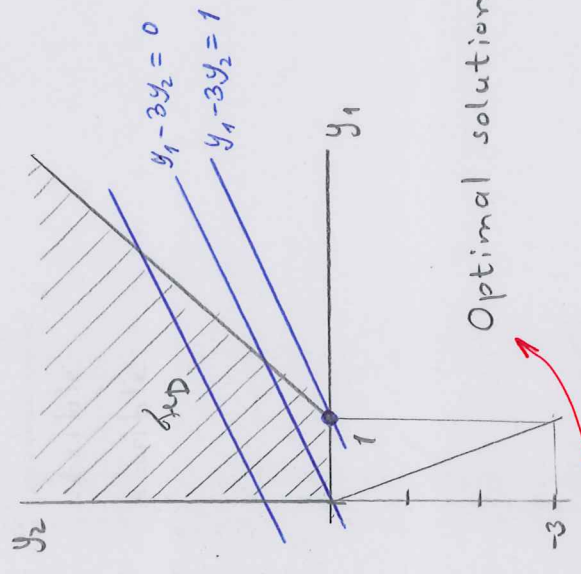


Optimal solution  $x = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

$$\begin{aligned} r &= Ax - b = \begin{bmatrix} 1 & -1 \\ -1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ -3 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ -1 \end{bmatrix} - \begin{bmatrix} 1 \\ -3 \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \end{aligned}$$

$x_1 \cdot s_1 = 1 \cdot 0 = 0$   
 $x_2 \cdot s_2 = 0 \cdot 1 = 0$

(D):  $\left\{ \begin{array}{l} \text{maximize } y_1 - 3y_2 \\ \text{s.t. } y_1 - y_2 \leq 1 \\ -y_1 \leq 0 \\ y_1 \geq 0 \\ y_2 \geq 0 \end{array} \right.$



Optimal solution  $y = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$

$$\begin{aligned} s &= c - A^T y = \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 & -1 \\ -1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} 1 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{aligned}$$

$y_1 \cdot r_1 = 1 \cdot 0 = 0$   
 $y_2 \cdot r_2 = 0 \cdot 2 = 0$

Corollary (Complementarity theorem)

Let  $x \in \mathbb{R}^n$ ,  $y \in \mathbb{R}^m$ . Define  $r := Ax - b$ ,  $s := c - A^T y$ . Then:

$x$  is optimal for (P)  
and  
 $y$  is optimal for (D)



$x_i \geq 0$                        $x_i s_i = 0$                        $i = 1, \dots, n$   
 $y_j \geq 0$                       and  
 $r_j \geq 0$                        $y_j r_j = 0$                        $j = 1, \dots, m$   
 $s_i \geq 0$

Proof  $\boxed{\Rightarrow}$ :  $x \in \mathcal{F}_P \Rightarrow x \geq 0$   
 $y \in \mathcal{F}_D \Rightarrow y \geq 0$   
 $s \geq 0$

$c^T x = b^T y$

$$\begin{aligned}
 0 &= c^T x - b^T y = x^T c - y^T b = x^T (s + A^T y) - y^T (Ax - r) \\
 &= x^T s + x^T A^T y - y^T A x + y^T r \\
 &= \sum_{i=1}^n x_i s_i + \sum_{j=1}^m \underbrace{y_j r_j}_{\geq 0}
 \end{aligned}$$

So  $x_i s_i = 0$  ( $i = 1, \dots, n$ )  
 and  
 $y_j r_j = 0$  ( $j = 1, \dots, m$ ).



$$\left. \begin{array}{l} x_i \geq 0 \\ x_j \geq 0 \end{array} \right\} \Rightarrow x \in \mathcal{X}_P$$

$$\left. \begin{array}{l} y_j \geq 0 \\ s_i \geq 0 \end{array} \right\} \Rightarrow y \in \mathcal{X}_D$$

$$\begin{aligned} 0 &= \sum_{i=1}^m x_i s_i + \sum_{j=1}^m y_j x_j = x^T s + y^T r = x^T (c - A^T y) + y^T (Ax - b) \\ &= x^T c - \cancel{x^T A^T y} + \cancel{y^T A x} - y^T b \\ &= x^T c - y^T b \\ &= c^T x - b^T y \end{aligned}$$

So  $c^T x = b^T y$ .

If  $x \in \mathcal{X}_P$ , then  $c^T x \geq b^T y = c^T x$ . So  $x$  is optimal for (P)

If  $y \in \mathcal{X}_D$ , then  $b^T y \leq c^T x = b^T y$ . So  $y$  is optimal for (D)



Dual to LP problem in general form:

Example

$$(P) \left\{ \begin{array}{l} \text{minimize} \quad 2x_1 + 3x_2 \\ \text{s.t.} \quad 4x_1 + 5x_2 \geq 6 \\ \quad \quad 7x_1 + 8x_2 = 9 \\ \quad \quad x_1 \geq 0 \end{array} \right.$$

First convert this into canonical form.

$$\left\{ \begin{array}{l} \text{minimize} \quad 2x_1 + 3x_2 \\ \text{s.t.} \quad 4x_1 + 5x_2 \geq 6 \\ \quad \quad 7x_1 + 8x_2 \geq 9 \\ \quad \quad 7x_1 + 8x_2 \leq 9 \\ \quad \quad x_1 \geq 0 \\ \quad \quad x_2 \text{ free} \end{array} \right.$$

Write  $x_2 = v_2 - v_3$ ,  $v_2 \geq 0$ ,  $v_3 \geq 0$

$$(P) \left\{ \begin{array}{l} \text{minimize} \quad 2x_1 + 3v_2 - 3v_3 \\ \text{s.t.} \quad 4x_1 + 5v_2 - 5v_3 \geq 6 \\ \quad \quad 7x_1 + 8v_2 - 8v_3 \geq 9 \\ \quad \quad -7x_1 - 8v_2 + 8v_3 \geq -9 \\ \quad \quad x_1 \geq 0 \\ \quad \quad v_2 \geq 0 \\ \quad \quad v_3 \geq 0 \end{array} \right.$$

$$c = \begin{bmatrix} 2 \\ 3 \\ -3 \end{bmatrix} \quad b = \begin{bmatrix} 6 \\ 9 \\ -9 \end{bmatrix}$$

$$A = \begin{bmatrix} 4 & 5 & -5 \\ 7 & 8 & -8 \\ -7 & -8 & 8 \end{bmatrix}$$



The dual to  $(\tilde{P})$  is:

$$(\tilde{D}): \left\{ \begin{array}{l} \text{maximize} \quad 6y_1 + 9u_2 - 9u_3 \\ \text{s.t.} \quad 4y_1 + 7u_2 - 7u_3 \leq 2 \\ 5y_1 + 8u_2 - 8u_3 \leq 3 \\ -5y_1 + 8u_2 + 8u_3 \leq -3 \\ y_1 \geq 0 \\ u_2 \geq 0 \\ u_3 \geq 0 \end{array} \right.$$

$$\text{i.e., } (D): \left\{ \begin{array}{l} \text{maximize} \quad 6y_1 + 9(u_2 - u_3) \\ \text{s.t.} \quad 4y_1 + 7(u_2 - u_3) \leq 2 \\ 5y_1 + 8(u_2 - u_3) = 3 \\ y_1 \geq 0 \\ u_2 \geq 0 \\ u_3 \geq 0 \end{array} \right.$$

This  $(D)$  is equivalent to:

$$(D): \left\{ \begin{array}{l} \text{maximize} \quad 6y_1 + 9y_2 \\ \text{s.t.} \quad 4y_1 + 7y_2 \leq 2 \\ 5y_1 + 8y_2 = 3 \\ y_1 \geq 0 \\ y_2 \text{ free} \end{array} \right.$$

In general:

$$(P) : \begin{cases} \text{minimize} & c_1^T x_1 + c_2^T x_2 \\ \text{s.t.} & A_{11} x_1 + A_{12} x_2 \geq b_1 \\ & A_{21} x_1 + A_{22} x_2 = b_2 \\ & x_1 \geq 0 \\ & x_2 \text{ free} \end{cases}$$

$x_1, x_2$  vector variables  
of sizes  $n_1, n_2$ .

First convert to canonical form:

$$\begin{cases} \text{minimize} & c_1^T x_1 + c_2^T x_2 \\ \text{s.t.} & A_{11} x_1 + A_{12} x_2 \geq b_1 \\ & A_{21} x_1 + A_{22} x_2 \geq b_2 \\ & -A_{21} x_1 - A_{22} x_2 \geq -b_2 \\ & x_1 \geq 0 \\ & x_2 \text{ free} \end{cases}$$

Write  $x_2 = v_2 - v_3, v_2 \geq 0, v_3 \geq 0$ .

$$(P') : \begin{cases} \text{minimize} & c_1^T x_1 + c_2^T v_2 - c_2^T v_3 \\ \text{s.t.} & A_{11} x_1 + A_{12} v_2 - A_{12} v_3 \geq b_1 \\ & A_{21} x_1 + A_{22} v_2 - A_{22} v_3 \geq b_2 \\ & -A_{21} x_1 - A_{22} v_2 + A_{22} v_3 \geq -b_2 \\ & x_1 \geq 0 \\ & v_2 \geq 0 \\ & v_3 \geq 0 \end{cases}$$

$$\begin{aligned}
 (\tilde{P}): \quad & \begin{cases} \text{minimize} & C^T X \\ \text{s.t.} & AX \geq B \\ & X \geq 0 \end{cases} \\
 & \text{where} \\
 & C = \begin{bmatrix} c_1 \\ c_2 \\ -c_2 \end{bmatrix} \quad X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \\
 & A = \begin{bmatrix} A_{11} & A_{12} & -A_{12} \\ A_{21} & A_{22} & -A_{22} \\ -A_{21} & -A_{22} & A_{22} \end{bmatrix} \quad B = \begin{bmatrix} b_1 \\ b_2 \\ -b_2 \end{bmatrix}
 \end{aligned}$$

The dual is:

$$\begin{aligned}
 (\tilde{D}): \quad & \begin{cases} \text{maximize} & b_1^T y_1 + b_2^T u_2 - b_2^T u_3 \\ \text{s.t.} & A_{11}^T y_1 + A_{21}^T u_2 - A_{21}^T u_3 \leq c_1 \\ & A_{12}^T y_1 + A_{22}^T u_2 - A_{22}^T u_3 \leq c_2 \\ & -A_{12}^T y_1 + A_{22}^T u_2 + A_{22}^T u_3 \leq -c_2 \end{cases} \quad \text{i.e.,} \\
 & y_1 \geq 0 \\
 & u_2 \geq 0 \\
 & u_3 \geq 0
 \end{aligned}$$

This is equivalent to:

$$\begin{aligned}
 \text{i.e., } (\tilde{D}): \quad & \begin{cases} \text{maximize} & b_1^T y_1 + b_2^T (u_2 - u_3) \\ \text{s.t.} & A_{11}^T y_1 + A_{21}^T (u_2 - u_3) \leq c_1 \\ & A_{12}^T y_1 + A_{22}^T (u_2 - u_3) = c_2 \\ & y_1 \geq 0 \\ & u_2 \geq 0 \\ & u_3 \geq 0 \end{cases} \\
 & \text{maximize} \quad b_1^T y_1 + b_2^T y_2 \\
 & \text{s.t.} \quad A_{11}^T y_1 + A_{21}^T y_2 \leq c_1 \\
 & \quad \quad A_{12}^T y_1 + A_{22}^T y_2 = c_2 \\
 & \quad \quad y_1 \geq 0 \\
 & \quad \quad y_2 \text{ free.}
 \end{aligned}$$

Thus: The dual of

$$(P): \begin{cases} \text{minimize} & c_1^T x_1 + c_2^T x_2 \\ \text{s.t.} & A_{11} x_1 + A_{12} x_2 \geq b_1 \\ & A_{21} x_1 + A_{22} x_2 = b_2 \\ & x_1 \geq 0 \\ & x_2 \text{ free} \end{cases}$$

is

$$(D): \begin{cases} \text{maximize} & b_1^T y_1 + b_2^T y_2 \\ \text{s.t.} & A_{11}^T y_1 + A_{21}^T y_2 \leq c_1 \\ & A_{12}^T y_1 + A_{22}^T y_2 = c_2 \\ & y_1 \geq 0 \\ & y_2 \text{ free} \end{cases}$$

Special case: Dual of LP problem in standard form

$$(P): \begin{cases} \text{minimize} & c^T x \\ \text{s.t.} & Ax = b \\ & x \geq 0 \end{cases}$$

$$\left. \begin{array}{l} x = x_1 \\ A_{21} = A \\ b_2 = b \\ c_1 = c \end{array} \right| \begin{array}{l} x_2 \text{ empty} \\ c_2 \\ b_1, A_{11}, A_{12} \\ A_{22} \end{array} \left. \vphantom{\begin{array}{l} x = x_1 \\ A_{21} = A \\ b_2 = b \\ c_1 = c \end{array}} \right\} \text{empty}$$

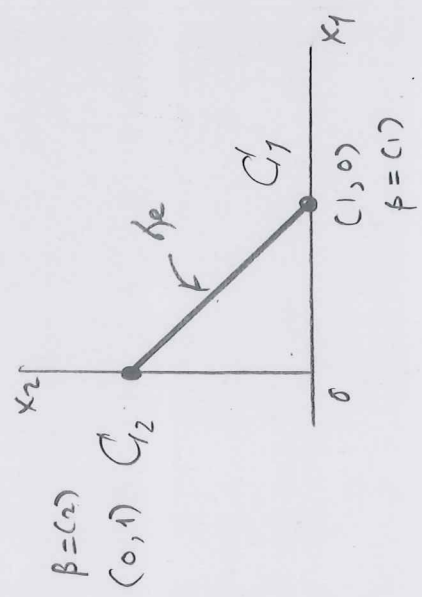
So the dual is:

$$(D): \begin{cases} \text{maximize} & b^T y \\ \text{s.t.} & A^T y \leq c \end{cases}$$

(Notice that (D) is not in standard form. This was the reason for starting with the canonical form, which is nicer.)

Example

$$(P) \begin{cases} \text{minimize} & x_1 + 2x_2 \\ \text{s.t.} & x_1 + x_2 = 1 \\ & x_1 \geq 0 \\ & x_2 \geq 0 \end{cases}$$



C1 is optimal

Simplex multipliers vector  $y$ :  $A^T y = c\beta$   
 $1 \cdot y = 1$   
 $\Rightarrow y = 1$

Reduced costs of the nonbasic variables:

$$r_2 = c_2 - A_2^T y = 2 - 1 \cdot 1 = 1 \geq 0$$

So  $C_1 = (1, 0)$  is optimal.

$$(D) \begin{cases} \text{maximize} & y \\ \text{s.t.} & \begin{bmatrix} 1 \\ 1 \end{bmatrix} y \leq \begin{bmatrix} 1 \\ 2 \end{bmatrix} \end{cases} \text{ i.e., } \begin{cases} y \leq 1 \\ y \leq 2 \end{cases}$$

$$(D) \begin{cases} \text{maximize} & y \\ \text{s.t.} & y \leq 1 \end{cases}$$

$y = 1$  is an optimal solution.

Same! (This is not a coincidence.)

Suppose we have solved the LP problem (P) in standard form using the simplex method, and that the algorithm was terminated since

$\bar{r}_2 \geq 0$  (i.e., an optimal solution is found: the last basic feasible solution  $\bar{x}$  corresponding to the basic tuple  $\beta$  is optimal.)

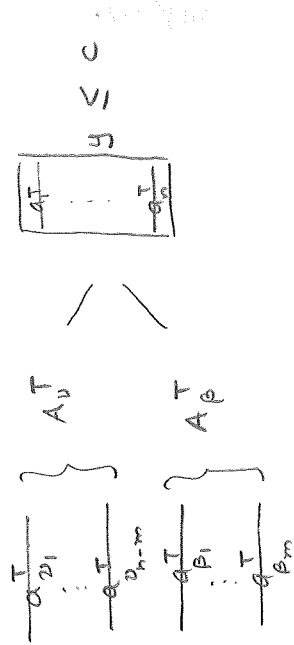
Claim. The last simplex multiplier vector  $y$  is optimal for the dual problem (D)

Proof. Recall:  $A_\beta^T y = c_\beta$   
 $c^T \bar{x} = c_\beta^T \bar{b} + c_{n-m}^T 0 \quad (\bar{b}: A_\beta \bar{b} = b)$   
 $= y^T A_\beta \bar{b}$   
 $= y^T b = b^T y.$

Question: Is  $y$  feasible for (D)? I.e., is  $A^T y \leq c$ ?

$$r_2 = c_{n-m} - A_{n-m}^T y \geq 0$$

$$\left. \begin{aligned} \text{So } A_{n-m}^T y &\leq c_{n-m} \\ A_\beta^T y &= c_\beta \end{aligned} \right\} \Rightarrow A^T y \leq c.$$



Answer: Yes.

So  $y$  is optimal for (D):

If  $y$  is feasible for (D), then

$$b^T y \leq c^T \bar{x} = b^T y.$$

□

Proof of the duality theorem uses Farkas's Lemma.

This will also be used later while deriving the necessity of KKT-conditions for nonlinear programming problems.

Farkas's lemma

$$p_1, \dots, p_m \in \mathbb{R}^n \\ q \in \mathbb{R}^n$$

Then one and exactly one of the following occurs:

- (F1)  $\exists y_1 \geq 0, \dots, y_m \geq 0$  s.t.  $q = y_1 p_1 + \dots + y_m p_m$ .  
 (F2)  $\exists x \in \mathbb{R}^n$  s.t.  $q^T x < 0$  and  $p_1^T x \geq 0, \dots, p_m^T x \geq 0$

