Equivalence of  $LP_S$  and  $LP_K$ 

Theorem:  $LP_S$  and  $LP_K$  are equivalent problems.

Proof:

Let  $P_1, c^1$  and  $P_2, c^2$  be instances of any optimization problem.

(Refer to Lecture 2, Slide 31 for a definition of optimization problems. Note that we are minimizing).

Lemma: Assume that  $\forall x^1 \in P_1 \exists x^2 \in P_2$  with  $c^{2^T}x^2 \leq c^{1^T}x^1$  and  $\forall x^2 \in P_2 \exists x^1 \in P_1$  with  $c^{1^T}x^1 \leq c^{2^T}x^2$ Then if  $x^2 \in P^2$  is optimal, then the analogous  $x^1 \in P^1$  is optimal, and they have the same objective function value.

*Proof:* Let  $y^1$  be any element of  $P^1$ . Let  $y^2$  be an element of  $P^2$  with  $c^{2^T}y^2 \leq c^{1^T}y^1$ 

( as in the supposition). Then:

$$c^{1^{T}}x^{1} \le c^{2^{T}}x^{2} \le c^{2^{T}}y^{2} \le c^{1^{T}}y^{1}.$$

Therefore  $x^1$  is optimal.  $\Box$ 

1. Let  $LP_K$ :

$$\min c^T x \ s.t. \ x \ge 0 \ , \ Ax \ge b$$

be given. Then with

$$\tilde{A} := (A, -I), \tilde{b} := b, \tilde{c} := \begin{pmatrix} c \\ 0 \end{pmatrix}, \tilde{x} := \begin{pmatrix} x \\ x^s \end{pmatrix}$$

we can describe an optimization problem in standard form  $(LP_S)$  by:

$$\min \tilde{c}^T \tilde{x} \ s.t. \ \tilde{x} \ge 0 \ , \ \tilde{A} \tilde{x} = \tilde{b}$$

Let  $\tilde{x}$  be a solution of  $LP_S$ . Then x is a solution of  $LP_K$  with

$$\tilde{c}^T \tilde{x} = (c^T, 0^T) \cdot \begin{pmatrix} x \\ x^s \end{pmatrix} = c^T x + 0^T \cdot x^s = c^T x$$

Now let x be a solution of  $LP_K$  and let  $\tilde{x} := \begin{pmatrix} x \\ Ax-b \end{pmatrix}$ . Then, with  $\tilde{x} \ge 0$  since  $x \ge 0$  and  $Ax - b \ge 0$ , also

$$\tilde{A}\tilde{x} = (A, -I) \cdot \begin{pmatrix} x \\ Ax - b \end{pmatrix} = Ax - Ax + b = b$$

Therefore  $\tilde{x}$  is a solution of  $LP_S$ . For these it follows that:

$$c^{T}x = c^{T}x + 0^{T} \cdot (Ax - b) = (c^{T}, 0^{T}) \cdot \begin{pmatrix} x \\ Ax - b \end{pmatrix} = \tilde{c}^{T}\tilde{x}$$

2. Let  $LP_S$  be given as  $\min c^T x \ s.t. \ x \ge 0$ , Ax = b. Then with

$$\tilde{A} := \begin{pmatrix} A \\ -A \end{pmatrix}, \tilde{b} := \begin{pmatrix} b \\ -b \end{pmatrix}, \tilde{c} := c, \tilde{x} := x$$

we can describe an optimization problem in canonical form  $(LP_K)$  by:

$$\min \tilde{c}^T \tilde{x} \ s.t. \ \tilde{x} \ge 0 \ , \ \tilde{A} \tilde{x} \ge b$$

From these it follows: x is exactly the feasible solution for  $LP_S$  when x is a feasible solution for  $LP_K$ . Furthermore, it follows that  $c^T x = \tilde{c}^T \tilde{x}$ . The proof concerning this is similar to the first case.