

# Linear Programming: The Simplex Method

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  - advanced state of the software,
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  - uncertainty in the model makes a linear model more appropriate than an overly complex non-linear model.



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- A new class of methods known as **interior-point methods** has proved to be faster for some linear programming problems.
- But the continued importance of the simplex method is assured for the foreseeable future.

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- Figure below depicts a linear program in two-dimensional space, in which the contours of the objective function are indicated by dotted lines.

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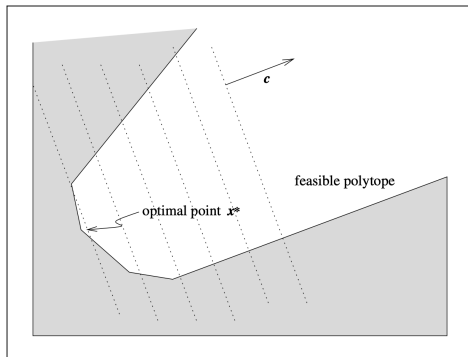
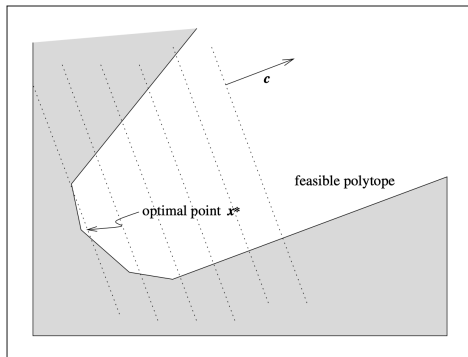


Figure: A linear program in two dimensions with solution at  $x^*$

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- The solution in this case is unique-a single vertex.

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- or if the objective function is unbounded below on the feasible region (**the unbounded case**)

# Standard Form of Linear Programs

Linear programs are usually stated and analysed in the following standard form:

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- $c$  and  $x$  are vectors in  $\mathbb{R}^n$ ,
- $b$  is a vector in  $\mathbb{R}^m$  and  $A$  is an  $m \times n$  matrix

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- Still not all variables ( $x$ ) are constrained to be non-negative as in the standard form.

# Transforming to Standard Form

- It is dealt by **splitting**  $x$  into **non-negative** and **non-positive** parts.

$$x = x^+ - x^-, \quad x^+ = \max(x, 0) \geq 0 \text{ and } x^- = \max(-x, 0)$$



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- Now the above considered problem can be written as:

$$\min \begin{bmatrix} c \\ -c \\ 0 \end{bmatrix} \begin{bmatrix} x^+ \\ x^- \\ z \end{bmatrix} \text{ s.t. } [A \quad -A \quad I] \begin{bmatrix} x^+ \\ x^- \\ z \end{bmatrix} = b, \quad \begin{bmatrix} x^+ \\ x^- \\ z \end{bmatrix} \geq 0,$$

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- The above system is now in the standard form.

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- We subtract the variables from the left hand side, they are known as **surplus variables**.
- We add the variables to the left hand side, they are known as **deficit variables**.
- By simply negating  $c$  “maximise” objective  $\max c^T x$  can be converted to “minimise” form  $\min -c^T x$ .

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- For the standard formulation, we will assume throughout that  $m < n$ .
- Otherwise, the system  $Ax = b$  contains redundant rows, or is infeasible, or defines a unique point.
- When  $m \geq n$ , factorisations such as the QR or LU factorisation can be used to transform the system  $Ax = b$  to one with a coefficient matrix of full row rank.

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- Convexity of the problem ensures that these conditions are sufficient for a global minimum.
- Do not need to refer to the second-order conditions, which are not informative because the Hessian of the Lagrangian is zero.
- The LICQ condition is not required to be enforced here as the KKT results continue to hold for dependent constraints provided they are linear, as is the case here.

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- While  $s \in \mathbb{R}^n$  is the multiplier vector for the bound constraints  $x \geq 0$ .
- Using the definition we can write the Lagrangian function:

$$\mathcal{L}(x, \lambda, s) = c^T x - \lambda^T (Ax - b) - s^T x. \quad (4)$$

# OPTIMALITY CONDITIONS

- The first-order necessary conditions for  $x^*$  to be a solution of the linear programming problem (1) are, if there exists  $\lambda$  and  $s$  such that:

$$A^T \lambda + s = c, \quad (5)$$

$$Ax = b, \quad (6)$$

$$x \geq 0, \quad (7)$$

$$s \geq 0, \quad (8)$$

$$x_i s_i = 0, \quad i = 1, 2, \dots, n. \quad (9)$$

- The last condition, which is the complementarity condition, which says that at-least either one of  $x_i$  or  $s_i$  is zero, can be wrtitten alternatively as

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- The first order KKT conditions for optimality for LPP is indeed sufficient.
- Let  $\bar{x}$  be any other feasible point, so that  $A\bar{x} = b$  and  $\bar{x} \geq 0$ .

$$\begin{aligned} c^T \bar{x} &= (A^T \lambda^* + s^*)^T \bar{x} \\ &= b^T \lambda^* + \bar{x}^T s^* \\ &\geq b^T \lambda^* = c^T x^* \end{aligned}$$

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- When  $s_i^* > 0$  then we must have  $\bar{x}_i = 0$  for all solutions  $\bar{x}$  of the LPP.