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# LINMA2415 Quantitative Energy Economics

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<https://github.com/SimonDesmidt/Syntheses>

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UCLouvain

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# Reminder about optimization

## 1.1 Formulations

**Definition 1.1.** The primal problem is the original optimization problem that we want to solve. It is formulated as:

$$\begin{aligned} \max_x \quad & c^T x \\ \text{s.t.} \quad & Ax \leq b \\ & x \geq 0 \end{aligned} \tag{1.1}$$

**Definition 1.2.** The dual problem is derived from the primal problem. It is formulated as:

$$\begin{aligned} \min_y \quad & b^T y \\ \text{s.t.} \quad & A^T y \geq c \\ & y \geq 0 \end{aligned} \tag{1.2}$$

Another way to look at the dual problem is by using the Lagrangian function. Consider now the primal under the form:

$$\begin{aligned} p^* = \min \quad & f_0(x) \\ \text{s.t.} \quad & f_i(x) \leq 0, \quad i = 1, \dots, m \\ & h_j(x) = 0, \quad j = 1, \dots, p \end{aligned} \tag{1.3}$$

**Definition 1.3.** The Lagrangian function is defined as:

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{j=1}^p \nu_j h_j(x) \tag{1.4}$$

**Definition 1.4.** The Lagrange dual function is defined as:

$$g(\lambda, \nu) = \inf_x L(x, \lambda, \nu) \tag{1.5}$$

**Definition 1.5.** The Lagrange dual problem is defined as:

$$\begin{aligned} d^* = \max \quad & g(\lambda, \nu) \\ \text{s.t.} \quad & \lambda \geq 0 \end{aligned} \tag{1.6}$$

## 1.2 Optimality conditions

**Definition 1.6.** Weak duality is when  $d^* \leq p^*$ , it always holds and can be used to find bounds on the optimal value of the primal problem.

**Definition 1.7.** Strong duality is when  $d^* = p^*$ , does not holds in general, but usually holds for convex problems.

**Definition 1.8.** Complementary slackness is a condition that holds at optimality, it states that for each constraint, either the constraint is active (i.e.  $f_i(x) = 0$ ) or the corresponding dual variable is zero (i.e.  $\lambda_i = 0$ ).

$$0 \leq \lambda_i^* \perp f_i(x^*) \leq 0 \quad (1.7)$$

**Definition 1.9.** The KKT conditions are a set of necessary conditions for optimality. Consider this problem:

$$\begin{aligned} \max & f(x, y) \\ \text{s.t.} & Ax + By \leq b \quad (\lambda) \\ & Cx + Dy = d \quad (\mu) \\ & x \geq 0 \quad (\lambda_2) \end{aligned} \quad (1.8)$$

The KKT conditions are:

$$\begin{aligned} & Cx + Dy - d = 0 \\ & 0 \leq \lambda \perp Ax + By - b \leq 0 \\ & 0 \leq x \perp \lambda^T A + \mu^T C - \nabla_x f(x, y)^T \geq 0 \\ & \lambda^T B + \mu^T D - \nabla_y f(x, y)^T = 0 \end{aligned} \quad (1.9)$$

And the Lagrangian function can be written as:

$$L(x, y, \lambda, \mu) = f(x, y) + \lambda^T (b - Ax - By) + \mu^T (d - Cx - Dy) + \lambda_2^T x \quad (1.10)$$