

PROBLEM SET 1: UNCONSTRAINED OPTIMIZATION

6) $I(x, y) = 2x + 3y$

$$C(x, y) = x^2 - 2xy + 2y^2 + 6x - 9y + 5$$

The profit function is $P(x, y) = I(x, y) - C(x, y) = 2x + 3y - (x^2 - 2xy + 2y^2 + 6x - 9y + 5)$

$$P(x, y) = -x^2 - 2y^2 + 2xy - 4x + 12y - 5$$

The problem to solve is the following: $\begin{cases} \max_{x, y} P(x, y) \\ x \geq 0, y \geq 0 \end{cases} \quad P: \mathbb{R}_+^2 \rightarrow \mathbb{R}, P \in C^2$

The maximum can be found where

$$\nabla P(x, y) = 0, H_P(x, y) \text{ definite negative}$$

$$\frac{\partial P}{\partial x}(x, y) = -2x + 2y - 4 \quad \frac{\partial P}{\partial y}(x, y) = -4y + 2x + 12 \quad \nabla P(x, y) = \begin{bmatrix} \frac{\partial P}{\partial x} \\ \frac{\partial P}{\partial y} \end{bmatrix} = \begin{bmatrix} -2x + 2y - 4 \\ -4y + 2x + 12 \end{bmatrix}$$

$$\nabla P(x, y) = 0 \Leftrightarrow \begin{cases} -2x + 2y - 4 = 0 \rightarrow y = x + 2 \\ -4y + 2x + 12 = 0 \rightarrow -4x - 8 + 2x + 12 = 0 \rightarrow x = 2, y = 4 \end{cases}$$

$$H_P(x, y) = \begin{bmatrix} \frac{\partial^2 P}{\partial x^2} & \frac{\partial^2 P}{\partial x \partial y} \\ \frac{\partial^2 P}{\partial y \partial x} & \frac{\partial^2 P}{\partial y^2} \end{bmatrix} = \begin{bmatrix} -2 & 2 \\ 2 & -4 \end{bmatrix} \quad \det H_P = 8 - 4 = 4 = \lambda_1 \lambda_2 > 0 \\ \text{tr } H_P = -6 = \lambda_1 + \lambda_2 < 0 \quad \left. \begin{array}{l} \lambda_1 < 0, \lambda_2 < 0 \\ \Rightarrow H_P \text{ definite negative} \end{array} \right\}$$

The point $(2, 4)$ satisfies $\nabla P(2, 4) = 0$ and

$H_P(2, 4)$ definite negative, which means it is a maximum for $P(x, y)$.

Furthermore, it satisfies $x \geq 0$ and $y \geq 0$, thus it is a solution for the given problem.

For the pair $(2, 4)$ the profit is $P(2, 4) = -4 - 32 + 16 - 8 + 48 - 5 = 15$ (millions of euros)

12) Let $x \in \mathbb{R}^2, A \in \mathbb{R}^{2 \times 2}$ symmetric, $f(x) = x^T A x$ and consider the problem $\begin{cases} \max f(x) \\ \text{s.t. } x^T x = 1 \end{cases}$

Consider the Lagrangian associated to the problem given:

$$L(x, \lambda) = f(x) - \lambda g(x) = x^T A x - \lambda(x^T x - 1)$$

An optimal solution of the problem must satisfy the KKT conditions

$$\begin{aligned} \nabla_x L(x^*, \lambda^*, \mu^*) &= \nabla f(x^*) - \lambda \nabla g(x^*) = 0 \\ &= 2Ax^* - 2\lambda^* x^* = 0 \rightarrow Ax^* = \lambda^* x^* \end{aligned}$$

Thus an optimal is of the form (x^*, λ^*) : $\begin{cases} Ax^* = \lambda^* x^* \\ (x^*)^T x^* = 1 \end{cases}$

This means x^* is an eigenvector of A and

$\lambda^* \in \mathbb{R}$, since A is symmetric, is the corresponding eigenvalue.

Since $x^T x = 1$, we have $(x^*)^T A x^* = (x^*)^T \lambda^* x^* = \lambda^* \underbrace{(x^*)^T x^*}_{=1} = \lambda^*$

The given solution is a

maximum of $f(x)$ if $H_f(x^*)$ is negative definite: $H_f(x) = 2A$.

$$(x^*)^T H_f(x^*) x^* = (x^*)^T 2A x^* = 2 \underbrace{(x^*)^T A x^*}_{=\lambda^*} = 2\lambda^* \rightarrow H_f(x^*) \text{ neg. def.} \Leftrightarrow \lambda^* < 0$$

Therefore, for (x^*, λ^*) to be

a maximum λ^* needs to be a negative eigenvalue of A .

This reasoning can be extended to $n \geq 2$ dimensions under the same conditions.

13) Given $y_1, \dots, y_m, y_j \in \mathbb{R}^2, j=1, \dots, m, w_1, \dots, w_m, w_j \in \mathbb{R}_+, j=1, \dots, m$
 consider the problem $\begin{cases} \min \sum_{j=1}^m w_j \|x - y_j\| \\ \text{s.t. } x \in \mathbb{R}^2 \end{cases}$

(a) The function $f(x) = \sum_{j=1}^m w_j \|x - y_j\| = \sum_{j=1}^m w_j \sqrt{(x_1 - y_{j1})^2 + (x_2 - y_{j2})^2}$
 is minimized where the function $g(x) = \sum_{j=1}^m w_j \|x - y_j\|^2 = \sum_{j=1}^m w_j [(x_1 - y_{j1})^2 + (x_2 - y_{j2})^2]$
 is minimized.

Therefore, consider the equivalent problem $\begin{cases} \min g(x) \\ \text{s.t. } x \in \mathbb{R}^2 \end{cases}$

$$\frac{\partial g}{\partial x_1} = \sum_{j=1}^m w_j [2(x_1 - y_{j1})] = 2x_1 \sum_{j=1}^m w_j - 2 \sum_{j=1}^m w_j y_{j1}$$

$$\frac{\partial g}{\partial x_2} = \sum_{j=1}^m w_j [2(x_2 - y_{j2})] = 2x_2 \sum_{j=1}^m w_j - 2 \sum_{j=1}^m w_j y_{j2}$$

$$\Rightarrow \nabla g(x) = 2x \sum_{j=1}^m w_j - 2 \sum_{j=1}^m w_j y_j = \begin{bmatrix} 2x_1 \sum_{j=1}^m w_j - 2 \sum_{j=1}^m w_j y_{j1} \\ 2x_2 \sum_{j=1}^m w_j - 2 \sum_{j=1}^m w_j y_{j2} \end{bmatrix}$$

$$\nabla g(x) = 0 \Leftrightarrow \begin{cases} x_1 \sum_{j=1}^m w_j - \sum_{j=1}^m w_j y_{j1} = 0 \\ x_2 \sum_{j=1}^m w_j - \sum_{j=1}^m w_j y_{j2} = 0 \end{cases} \quad x^* = \begin{bmatrix} \sum_{j=1}^m w_j y_{j1} / \sum_{j=1}^m w_j \\ \sum_{j=1}^m w_j y_{j2} / \sum_{j=1}^m w_j \end{bmatrix}$$

Thus $x^* = \frac{1}{\sum_{j=1}^m w_j} \sum_{j=1}^m w_j y_j$ is such that $\nabla g(x^*) = 0$

Consider the Hessian: $H_g(x) = \begin{bmatrix} 2 \sum_{j=1}^m w_j & 0 \\ 0 & 2 \sum_{j=1}^m w_j \end{bmatrix}, \lambda = 2 \sum_{j=1}^m w_j > 0 \ (w_j > 0, j=1, \dots, m)$

$\Rightarrow H_g(x^*)$ is positive definite

$\Rightarrow x^*$ is a minimum of $g(x)$ and an optimal solution for the given problem

Notice that x^* can be seen as the central point of the network with masses w_j in positions y_j since it has the same form of a center of mass.

(b) Since the Hessian $H_g(x)$ is positive definite $\forall x \in \mathbb{R}^2$, the function is convex. This implies that the optimal solution is unique.

(c) Consider the potential energy of the mechanical system given $p = \sum_{j=1}^m w_j h_j$. The height h_j can be expressed in terms of x as follows:

$$c = d_j + \|x - y_j\|, c = \text{constant} \rightarrow d_j = c - \|x - y_j\|$$

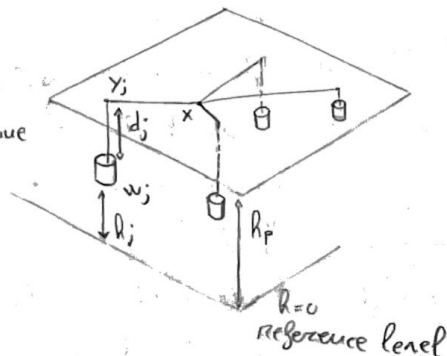
$$h_j = h_P - d_j \rightarrow h_j = h_P - (c - \|x - y_j\|), h_P: \text{height}$$

$$h_j = \underbrace{h_P - c}_k + \|x - y_j\| \quad \text{of } \mathbb{R}^2 \text{ plane}$$

$$h_j = k + \|x - y_j\|, k = \text{constant}$$

$$\text{Thus we have } p(x) = \sum_{j=1}^m w_j (k + \|x - y_j\|):$$

$$\Rightarrow p(x) = \underbrace{k \sum_{j=1}^m w_j}_{\text{constant}} + \underbrace{\sum_{j=1}^m w_j \|x - y_j\|}_{f(x)} = \text{const.} + f(x)$$



Therefore, $\min p(x) = \min [\text{const.} + f(x)] \Rightarrow (x^* \text{ min. for } f(x) \Leftrightarrow x^* \text{ min. for } p(x))$