

Optimization  
Màster de Fonaments de Ciència de Dades

**PART 2. Analysis**

**Chapter 3. Unconstrained and  
constrained optimization with equalities.  
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# Chapter 4

Constrained optimization  
with  
inequalities.

Optimality conditions

## The problem

Let  $D \subset \mathbb{R}^n$  be an open set and let

$$\begin{aligned} f &: D \rightarrow \mathbb{R}, \\ g_j &: D \rightarrow \mathbb{R}, \quad j = 1, \dots, m, \text{ and} \\ h_j &: D \rightarrow \mathbb{R}, \quad j = 1, \dots, p, \end{aligned} \tag{1}$$

with  $m \ll n$ , be  $\mathcal{C}^1$ -functions defined in  $D$ .

**Problem.** The **constrained optimization problem** ( $\mathcal{P}$ ) is defined by

$$\begin{aligned} & \min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}) \\ \text{subject to: } & g_j(\mathbf{x}) = 0, \quad i = 1, \dots, m \\ & h_j(\mathbf{x}) \geq 0, \quad j = 1, \dots, p. \end{aligned} \tag{2}$$

## Constructing an equality constrained problem

**Remark.** Problem  $\mathcal{P}$  may be written as an equality constrained problem by enlarging the number of variables.

$$\begin{aligned} & \min_{\mathbf{x} \in \mathbb{R}^n} f(\mathbf{x}) \\ \text{subject to: } & g_i(\mathbf{x}) = 0, & i = 1, \dots, m \\ & h_j(\mathbf{x}) - z_j^2 = 0, & j = 1, \dots, p. \end{aligned} \tag{3}$$

## Solutions of $\mathcal{P}$ . Feasible set and points and directions

**Definition.** The set of points  $\mathcal{X} \subset D$  satisfying conditions (12) are called **feasible points** and  $\mathcal{X}$  is called the **feasible set** for the constrained optimization problem.

**Definition.** A point  $\mathbf{x}^* \in \mathcal{X}$  is called a **local solution (minimum) of problem  $\mathcal{P}$**  if there exists  $\varepsilon$  such that  $f(\mathbf{x}) \geq f(\mathbf{x}^*)$  for all  $\mathbf{x} \in \mathcal{X} \cap \mathbf{B}(\mathbf{x}^*, \varepsilon)$ .

**Definition.** A point  $\mathbf{x}^* \in \mathcal{X}$  is called a **global solution (minimum) of problem  $\mathcal{P}$**  if  $f(\mathbf{x}) \geq f(\mathbf{x}^*)$  for all  $\mathbf{x} \in \mathcal{X}$ .

**Definition.** Let  $\mathbf{x} \in \mathcal{X}$ . A unitary vector  $\mathbf{z}$  is called a **feasible direction from  $\mathbf{x}$**  if for small enough  $\delta > 0$  we have that if  $|\theta| < \delta$  then

$$\{\mathbf{y} \in \mathbb{R}^n \mid \mathbf{y} = \mathbf{x} + \theta \mathbf{z}\} \subset \mathcal{X}$$

## Active inequality constrains

**Remark.** The previous notion of **local solution of  $\mathcal{P}$**  writes as

$$f(\mathbf{x}^* + \theta \mathbf{z}) \geq f(\mathbf{x}^*), \text{ for } |\theta| < \delta,$$

with  $\mathbf{z}$  being a feasible direction.

**Definition.** We introduce the following set.

$$\mathcal{I}(\mathbf{x}^*) := \{j : h_j(\mathbf{x}^*) = 0\}.$$

For those  $j \in \mathcal{I}(\mathbf{x}^*)$  we say that the inequality constrains  $h_j$ 's are **saturated** or **active** at the solution  $\mathbf{x}^*$ .

## Feasible set and points and directions

**Lemma.** Let  $\mathbf{x}^*$  a local solution of  $\mathcal{P}$ . Suppose  $k \in \mathcal{I}(\mathbf{x}^*)$ . Let  $z$  a feasible direction from  $\mathbf{x}^*$ . Then  $z^T \nabla h_k(\mathbf{x}^*) \geq 0$ .

**Proof.** Assume  $z^T \nabla h_k(\mathbf{x}^*) < 0$  We have that

$$h_k(\mathbf{x}^* + \theta z) = h_k(\mathbf{x}^*) + \theta \nabla h_k(\mathbf{x}^*)^T z + \varepsilon_k(\theta)$$

where  $\varepsilon_k(\theta) \rightarrow 0$  as  $\theta \rightarrow 0$ . Hence for  $\theta$  small enough  $\theta \nabla h_k(\mathbf{x}^*)^T z + \varepsilon_k(\theta) < 0$  and so  $h_k(\mathbf{x}^* + \theta z) < h_k(\mathbf{x}^*)$ , a contradiction with  $z$  a feasible direction.

**Lemma.** Let  $\mathbf{x}^*$  a local solution of  $\mathcal{P}$ . Let  $z$  a feasible direction from  $\mathbf{x}^*$ . Then  $z^T \nabla g_j(\mathbf{x}^*) = 0$  for all  $j = 1, \dots, m$ .

## The linearizing cone $\mathcal{Z}^1(\mathbf{x}^*)$

**Definition.** Assume previous notation. We define the **linearizing cone of  $\mathcal{X}$  at  $\mathbf{x}^*$**  as

$$\mathcal{Z}^1(\mathbf{x}^*) := \left\{ z \mid \begin{array}{l} z^T \nabla h_k(\mathbf{x}^*) \geq 0 \text{ if } k \in \mathcal{I}(\mathbf{x}^*), \text{ and} \\ z^T \nabla g_j(\mathbf{x}^*) = 0 \text{ } j = 1, \dots, m \end{array} \right\}$$

**Lemma.** If  $z$  is a feasible direction from  $\mathbf{x}^* \in \mathcal{X}$  (that is,  $(\mathbf{x}^* + \theta z) \in \mathcal{X}$  for  $\theta$  small), then  $z \in \mathcal{Z}^1(\mathbf{x}^*)$ .

**Proof.** We argue by contradiction. If  $z \notin \mathcal{Z}^1(\mathbf{x}^*)$  then either  $z^T \nabla h_k(\mathbf{x}^*) < 0$  for  $k \in \mathcal{I}(\mathbf{x}^*)$ , or  $z^T \nabla g_j(\mathbf{x}^*) \neq 0$ . Using linear expansion of  $h_k$ ,  $k \in \mathcal{I}(\mathbf{x}^*)$  and  $g_j$ ,  $j = 1, \dots, m$  these imply that either  $h_k(\mathbf{x}^* + \theta z) < 0$ ,  $k \in \mathcal{I}(\mathbf{x}^*)$  or  $g_j(\mathbf{x}^* + \theta z) \neq 0$ ,  $j = 1, \dots, m$ , for  $\theta$  small enough, respectively.



The set  $\mathcal{Z}^2(\mathbf{x}^*)$

**Definition.** Assume previous notation. We define the set

$$\mathcal{Z}^2(\mathbf{x}^*) := \{z \mid z^T \nabla f(\mathbf{x}^*) < 0\}$$

**Lemma.** If  $z \in \mathcal{Z}^2(\mathbf{x}^*)$  then  $f(\mathbf{x}^* + \theta z) < f(\mathbf{x}^*)$ ,  $\theta$  small enough.

## The (generalized) Lagrangian associated to $\mathcal{P}$

**Definition.** Assume previous notation. We define the **generalized Lagrangian associated to  $\mathcal{P}$**  as the function

$$L(x, \lambda, \mu) = f(x) - \sum_{j=1}^m \lambda_j g_j(x) - \sum_{j=1}^p \mu_j h_j(x).$$

**Definition.** A solution point  $x^*$  is called **regular** if the equality constraints and the active inequality constraints at  $x^*$  have linearly independent gradient vectors.

**Remark.** This definition generalize the previous technical condition of the Jacobian matrix  $D(g)(x^*)$  having rank  $m$ .

## Necessary conditions for minimum

**Theorem (Karush-Kuhn-Tucker conditions).** Assume previous notation. Let  $\mathbf{x}^*$  be a regular local minimum for  $\mathcal{P}$ . Then, there exist (unique) Lagrange multiplier vectors  $\boldsymbol{\lambda}^* = (\lambda_1^*, \dots, \lambda_m^*)$  and  $\boldsymbol{\mu}^* = (\mu_1^*, \dots, \mu_p^*)$  such that

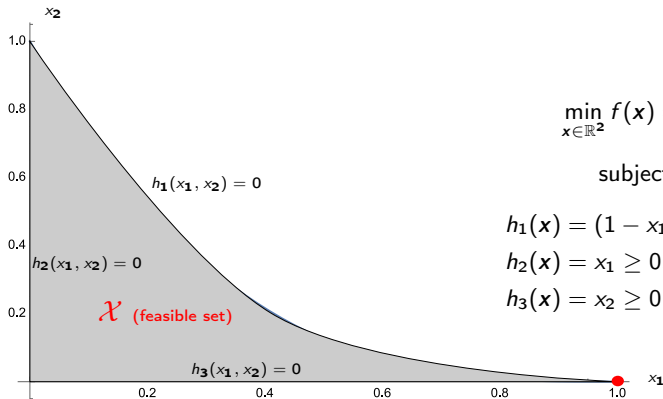
$$\nabla_{\mathbf{x}} L(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\mu}^*) = \nabla f(\mathbf{x}^*) - \sum_{j=1}^m \lambda_j \nabla g_j(\mathbf{x}^*) - \sum_{j=1}^p \mu_j \nabla h_j(\mathbf{x}^*) = 0.$$

Moreover,  $\mu_j \geq 0$  and  $\mu_j h_j(\mathbf{x}^*) = 0$ ,  $j = 1, \dots, p$ . If  $f, g_j$  and  $h_j$  are  $\mathcal{C}^2$ -functions then

$$\mathbf{y}^T H_{\mathbf{x}}(L)(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\mu}^*) \mathbf{y} \geq 0$$

for all  $\mathbf{y} \in \mathbb{R}^n$  such that  $(\nabla g_j(\mathbf{x}^*))^T \mathbf{y} = 0$ ,  $j = 1, \dots, m$  and  $(\nabla h_k(\mathbf{x}^*))^T \mathbf{y} = 0$ ,  $k \in \mathcal{I}(\mathbf{x}^*)$ .

## An example: non-regular local minimums



$$\min_{x \in \mathbb{R}^2} f(x) = -x_1$$

subject to

$$h_1(x) = (1 - x_1)^3 - x_2 \geq 0$$

$$h_2(x) = x_1 \geq 0,$$

$$h_3(x) = x_2 \geq 0$$

## An exemple: non-regular local minimums

**Solution.** Easily we can see that the point  $\mathbf{x}^* = (1, 0)$  is a local minimum of  $f$  under the constrains. However

$$\nabla h_1(\mathbf{x}) = (-3(1 - x_1)^2, -1), \quad \nabla h_2(\mathbf{x}) = (1, 0), \quad \nabla h_3(\mathbf{x}) = (0, 1),$$

and so, observe that  $\nabla h_1(\mathbf{x}) = (0, -1)$  and  $\nabla h_3(\mathbf{x}) = (0, 1)$  are not linearly independent. Moreover,

$$\nabla f(\mathbf{x}^*) = (1, 0) \neq \mu_1(0, -1) + \mu_3(0, 1),$$

and so  $\mathbf{x}^*$  does not satisfies the necessary conditions.

**Exercise.** Prove that  $\mathcal{Z}^1(\mathbf{x}^*) \cup \mathcal{Z}^2(\mathbf{x}^*) \neq \emptyset$ . Indeed, this is the condition that characterizes non regular candidates.

## Turning to sufficient conditions

**Theorem.** Assume previous notation and assume that all functions are of class  $\mathcal{C}^2$ . Assume that  $\mathbf{x}^* \in \mathbb{R}^n$ ,  $\boldsymbol{\lambda}^* \in \mathbb{R}^m$  and  $\boldsymbol{\mu}^* \in \mathbb{R}^p$  satisfy  $g_j(\mathbf{x}^*) = 0$ ,  $j = 1, \dots, m$ ,  $h_j(\mathbf{x}^*) \geq 0$ ,  $j = 1, \dots, p$ ,

$$\nabla_{\mathbf{x}} L(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\mu}^*) = 0, \quad \mu_j \geq 0, \quad \mu_j h_j(\mathbf{x}^*) = 0, \quad j = 1, \dots, m,$$

and

$$\mathbf{y}^T H_{\mathbf{x}}(L)(\mathbf{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{\mu}^*) \mathbf{y} \geq 0$$

for all  $\mathbf{y} \in \mathbb{R}^n$  such that  $(\nabla g_j(\mathbf{x}^*))^T \mathbf{y} = 0$ ,  $j = 1, \dots, m$  and  $(\nabla h_k(\mathbf{x}^*))^T \mathbf{y} = 0$ ,  $k \in \mathcal{I}(\mathbf{x}^*)$ . Assume also that  $\mu_k^* > 0$  for all  $k \in \mathcal{I}(\mathbf{x}^*)$ .

Then,  $\mathbf{x}^*$  is a strict local minimum of  $f$  subject to the constraints given by  $\mathcal{P}$ .

## An interesting example

**Exercise.** Discuss the following optimization problem in terms of the parameter  $\beta > 0$ .

$$\min_{\mathbf{x} \in \mathbb{R}^2} f(\mathbf{x}) = (x_1 - 1)^2 + x_2^2$$

subject to

$$h(x_1, x_2) = -x_1 + \beta x_2^2 \geq 0$$

Interpret the solutions geometrically in terms of the level curves and the restriction.

## Saddlepoints of the Lagrangian

**Definition.** Let  $\mathbf{x} \in E_x \subset \mathbb{R}^n$  and  $\mathbf{y} \in E_y \subset \mathbb{R}^m$ . Let  $\varphi$  a (continuous) function  $\varphi : E_x \times E_y \rightarrow \mathbb{R}$ . We say that a point  $(\hat{\mathbf{x}}, \hat{\mathbf{y}}) \in E_x \times E_y$  is a **saddlepoint** of  $\varphi$  if

$$\varphi(\hat{\mathbf{x}}, \mathbf{y}) \leq \varphi(\hat{\mathbf{x}}, \hat{\mathbf{y}}) \leq \varphi(\mathbf{x}, \hat{\mathbf{y}}).$$

**Definition.** We define the **problem (S)** as follows. Find a saddlepoint  $\hat{\mathbf{x}} \in \mathbb{R}^n$ ,  $\hat{\boldsymbol{\lambda}} \in \mathbb{R}^m$  and  $\hat{\boldsymbol{\mu}} \in \mathbb{R}^p$  with  $\boldsymbol{\mu} \geq 0$  for the Lagrangian. That is

$$L(\hat{\mathbf{x}}, \boldsymbol{\lambda}, \boldsymbol{\mu}) \leq L(\hat{\mathbf{x}}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}}) \leq L(\mathbf{x}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}}) \quad (4)$$

for every  $\mathbf{x} \in \mathbb{R}^n$ ,  $\boldsymbol{\lambda} \in \mathbb{R}^m$  and  $\boldsymbol{\mu} \in \mathbb{R}^p$  with  $\boldsymbol{\mu} \geq 0$ .



## Connecting $(\mathcal{P})$ with $(\mathcal{S})$

**Theorem.** If  $(\hat{\mathbf{x}}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}})$  is a solution of  $(\mathcal{S})$  then  $\hat{\mathbf{x}}$  is a solution of  $(\mathcal{P})$ .

**Proof.** Assume  $(\hat{\mathbf{x}}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}})$  is a solution of  $(\mathcal{S})$ . Then from (4) we have

$$\sum_{j=1}^m (\hat{\lambda}_j - \lambda_j) g_j(\hat{\mathbf{x}}) + \sum_{j=1}^p (\hat{\mu}_j - \mu_j) h_j(\hat{\mathbf{x}}) \leq 0 \quad (\text{a})$$

$$f(\hat{\mathbf{x}}) \leq f(\mathbf{x}) + \sum_{j=1}^m \hat{\lambda}_j (g_j(\hat{\mathbf{x}}) - g_j(\mathbf{x})) + \sum_{j=1}^p \hat{\mu}_j (h_j(\hat{\mathbf{x}}) - h_j(\mathbf{x})) \quad (\text{b})$$

After some computations we conclude that

$$g_j(\hat{\mathbf{x}}) = 0, \quad j = 1, \dots, m \quad \text{and} \quad \hat{\mu}_j h_j(\hat{\mathbf{x}}) = 0, \quad j = 1, \dots, p.$$

Hence

$$f(\hat{\mathbf{x}}) \leq f(\mathbf{x}) - \sum_{j=1}^m \hat{\lambda}_j g_j(\mathbf{x}) - \sum_{j=1}^p \hat{\mu}_j h_j(\mathbf{x}).$$

## Connecting $(\mathcal{P})$ with $(\mathcal{S})$

**Theorem.** Suppose all functions are differentiable and suppose that  $(\hat{\mathbf{x}}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}})$  is a solution of  $(\mathcal{S})$ . Then  $\mathcal{Z}^1(\hat{\mathbf{x}}) \cup \mathcal{Z}^2(\hat{\mathbf{x}}) \neq \emptyset$  and

$$\nabla_{\mathbf{x}} L(\hat{\mathbf{x}}, \hat{\boldsymbol{\lambda}}, \hat{\boldsymbol{\mu}}) = 0 \quad \hat{\mu}_j h_j(\hat{\mathbf{x}}) = 0, \quad j = 1, \dots, p,$$

with  $\hat{\boldsymbol{\mu}} \geq 0$ .

These were conditions for minimum of  $f$  under general inequality constraints.