

Exercise

$$f(x) = 3x_1^2 + x_2^2 - 2x_1x_2 + x_1 + x_2 + 1$$

write in the quadratic form A, b, c

Comedion:

$$\nabla f(x) = \begin{pmatrix} 6x_1 - 2x_2 + 1 \\ 2x_2 - 2x_1 + 1 \end{pmatrix} \quad Hf(x) = \begin{pmatrix} 6 & -2 \\ -2 & 2 \end{pmatrix} = A$$

$$\begin{aligned} f(x) &= f(0) + \langle \nabla f(0), x \rangle + \frac{1}{2} \langle Hf(0)x, x \rangle + 0 \\ &= \underbrace{1}_c + \langle x, \underbrace{\begin{pmatrix} 1 \\ 1 \end{pmatrix}}_b \rangle + \frac{1}{2} \langle Ax, x \rangle \end{aligned}$$

$$\det(A - \lambda I) = (6 - \lambda)(2 - \lambda) - 4 = \lambda^2 - 8\lambda + 8 = 0$$

$$\Delta = 64 - 32 = 32 = (\sqrt{2} \cdot 4)^2$$

$$\lambda = \frac{8 \pm 4\sqrt{2}}{2} > 0$$

$$A \in S_{++}^n \Rightarrow Ax^* + b = 0$$

has a unique solution

which is the global minimum of f : $\left(-\frac{1}{2}, -1\right) = x^*$

Exercice

$$f: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$f(x_1, x_2) = 4(x_1^2 + x_2^2) - (x_1^2 + x_2^2)^2 \quad X = (x_1, x_2)$$

1) Compute $\nabla f(x)$ and $Hf(x)$

2) Compute the set of points $\{\nabla f(x) = 0\} = S$

3) Say if $X \in S$ is minimum or maximum or what?

$$\nabla f(x) = \begin{pmatrix} 8x_1 - 4x_1(x_1^2 + x_2^2) \\ 8x_2 - 4x_2(x_1^2 + x_2^2) \end{pmatrix} \quad Hf(x) = \begin{pmatrix} 8 - 12x_1^2 - 4x_2^2 & -8x_1x_2 \\ -8x_1x_2 & 8 - 12x_2^2 - 4x_1^2 \end{pmatrix}$$

$$\begin{pmatrix} 2x_1 = x_1(x_1^2 + x_2^2) \\ 2x_2 = x_2(x_1^2 + x_2^2) \end{pmatrix} \Leftrightarrow S = \{(0,0)\} \cup \left\{ \begin{array}{l} x_1^2 + x_2^2 = 2 \\ \text{circle of center } (0,0) \\ \text{radius } \sqrt{2} \end{array} \right\}$$

question 3 for tomorrow

$$z = \|x\|^2, \quad f(x) = 4z - z^2$$

Outline

Course goals and terms

Introduction to Optimization

Reminders : Differential calculus

Convexity

- Convex sets

- Convex functions

Unconstrained optimisation

- Optimality conditions in the unconstrained case

- Solving systems of non linear equations

- Descent methods

Non-linear least squares

Optimisation with constraints

- Duality

- Algorithms for constrained optimization

Canonical problem

$$\begin{cases} \text{inf} & f(x) \\ \text{s.c.} & c^E(x) = 0 \\ \text{i.c.} & c^I(x) \leq 0 \\ & x \in \mathbb{R}^n \end{cases}$$

equality constraints
inequality constraints

with

$$\begin{aligned} f &: \mathbb{R}^n \longrightarrow \mathbb{R}, \\ c^E &: \mathbb{R}^n \longrightarrow \mathbb{R}^m, \\ c^I &: \mathbb{R}^n \longrightarrow \mathbb{R}^p, \\ f, c & \text{ smooth.} \end{aligned}$$

m eq. constraints
 p ineq. const.

admissible domain

$$D_a = \{x \in \mathbb{R}^n, c^E(x) = 0, c^I(x) \leq 0\}$$

General existence theorem

$$\inf_{x \in D_a} f(x)$$

if $D_a = C$, f continuous

We consider f continuous from $C \subset \mathbb{R}^n$ into \mathbb{R} with C closed. If one of the following hypotheses is satisfied

- ▶ C bounded
- ▶ C not bounded and f coercive

then f has a minimum on C

$$\begin{array}{l} f(x) \longrightarrow +\infty \\ \|x\| \longrightarrow +\infty \\ \text{example } f(x) = \|x\|^2 \end{array}$$

$$c^E: \mathbb{R}^n \rightarrow \mathbb{Q}^m$$

$$c^I: \mathbb{R}^n \rightarrow \mathbb{R}^p$$

$$c^E = (c_i^E)_{i=1, \dots, m} \quad c_i^E: \mathbb{R}^n \rightarrow \mathbb{R}$$

Notations for the gradient and the hessian of the i^{th} constraint

$$a_i^E(x) = \nabla c_i^E(x) \quad H_i^E(x) = \text{Hess } c_i^E(x),$$

$$a_i^I(x) = \nabla c_i^I(x) \quad H_i^I(x) = \text{Hess } c_i^I(x).$$

Jacobian Matrices of the constraints :

$$A^E(x) = \nabla c^E(x) = \begin{pmatrix} a_1^E(x)^T \\ \vdots \\ a_m^E(x)^T \end{pmatrix}, \quad A^I(x) = \nabla c^I(x) = \begin{pmatrix} a_1^I(x)^T \\ \vdots \\ a_p^I(x)^T \end{pmatrix}$$

Lagrangian and Lagrange multipliers

(P) direct or primal problem

$\left(\begin{array}{l} \text{inf } f(x) \\ c^E(x) = 0 \\ c^I(x) \leq 0 \end{array} \right) \text{ (P)}$

Let y a vector of \mathbb{R}^m , z a vector of \mathbb{R}^p , **Lagrange multipliers**.

The Lagrangian is defined by

$$l: \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$$

$$l(x, y, z) = f(x) + \langle y, c^E(x) \rangle + \langle z, c^I(x) \rangle$$

$+ \sum_{i=1}^m y_i c_i^E(x) + \sum_{j=1}^p z_j c_j^I(x)$

The gradient and the hessian of the Lagrangian with respect to x are

$$\sum y_i \nabla c_i^E(x) + \sum z_j \nabla c_j^I(x)$$

$$g(x, y, z) = \nabla_x l(x, y, z) = \nabla f(x) + \sum_{i=1}^m y_i a_i^E(x) + \sum_{i=1}^p z_i a_i^I(x)$$

$$H(x, y, z) = \text{Hess}_x l(x, y, z) = Hf(x) + \sum_{i=1}^m y_i H_i^E(x) + \sum_{i=1}^p z_i H_i^I(x)$$

Example 1: $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ $f(x) = x_1 + x_2$, $\inf_{x_1^2 + x_2^2 = 2} f(x)$

$$c^E: \mathbb{R}^2 \rightarrow \mathbb{R} \quad m=1, p=0$$

$$c^E(x) = x_1^2 + x_2^2 - 2 \quad C^E(x) = 0$$

$$l: \mathbb{R}^2 \times \mathbb{R} \rightarrow \mathbb{R}$$

$$l(x, y) = f(x) + y c^E(x) = x_1 + x_2 + y(x_1^2 + x_2^2 - 2)$$

$$\nabla_x l(x, y) = \begin{pmatrix} 1 \\ 1 \end{pmatrix} + y \begin{pmatrix} 2x_1 \\ 2x_2 \end{pmatrix} = \begin{pmatrix} 1 + 2yx_1 \\ 1 + 2yx_2 \end{pmatrix}$$

$$H_x l(x, y) \in \mathcal{M}_{2 \times 2}(\mathbb{R}); H_x l(x, y) = \begin{pmatrix} 2y & 0 \\ 0 & 2y \end{pmatrix}$$

Example 2: $f: \mathbb{R}^n \rightarrow \mathbb{R}$ *only inequality constraints* $f(x) = \|x\|^2$, $\inf_{\substack{x_{i+1} - x_i \leq 2 \\ i=1, \dots, n-1}} f(x)$

$m=0, p=n-1$

$l: \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}$

$l(x, z) = f(x) + \langle z, C^I(x) \rangle$

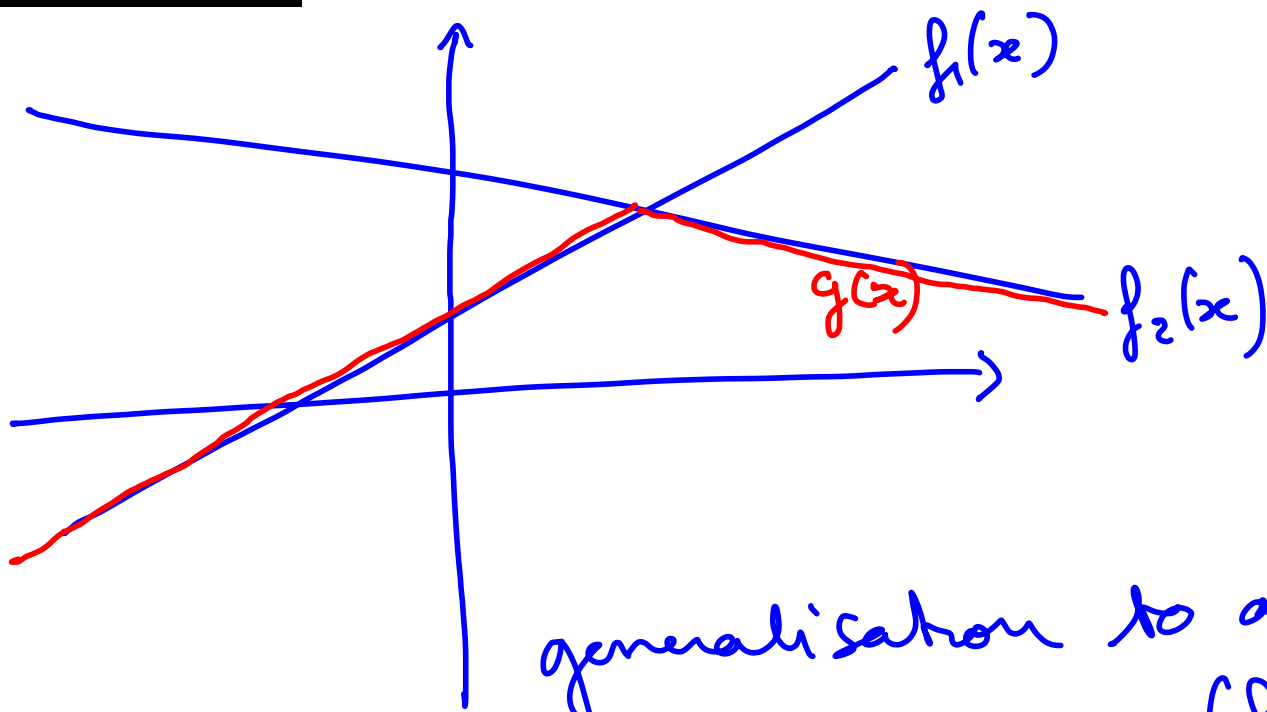
$= \|x\|^2 + \sum_{j=1}^{n-1} z_j (x_{j+1} - x_j - 2) = \|x\|^2$

$C^I: \mathbb{R}^n \rightarrow \mathbb{R}^p = \mathbb{R}^{n-1}$

$x \mapsto \begin{pmatrix} x_2 - x_1 - 2 \\ \vdots \\ x_n - x_{n-1} - 2 \end{pmatrix}$

$\nabla_x l(x, z) = 2x + \begin{pmatrix} -z_1 \\ +z_1 - z_2 \\ \vdots \\ +z_{n-2} - z_{n-1} \\ +z_{n-1} \end{pmatrix} + \begin{pmatrix} z_1(x_2 - x_1 - 2) \\ z_2(x_3 - x_2 - 2) \\ \vdots \\ z_{n-2}(x_{n-1} - x_{n-2} - 2) \\ z_{n-1}(x_n - x_{n-1} - 2) \end{pmatrix}$

$H_x l(x, z) = 2I_{n \times n} + 0$



each f_i is concave
 $f(\lambda x + (1-\lambda)y) \geq \lambda f(x) + (1-\lambda)f(y)$

$$g(x) = \min_{i=1,2} f_i(x)$$

g is concave

generalisation to any family of
 $(f_i(x))_{i \in I}$ f_i concave for n

generalize to any uncountable family
 $(f(x, p))_{p \in C}$ when $f(x, p)$ is concave for each p

then $g(x) = \min_{p \in C} f(x, p)$ is concave

Actives Constraints / Contraintes actives *in the case of inequality constraints*

Let x^* a minimizer of f .

The i^{th} inequality constraint is **active** if $c_i^I(x^*) = 0$.

$$\begin{aligned} \inf f(x) &= f(x^*) \\ c^I(x) &\leq 0 \\ \text{and, possibly, } c^E(x) &= 0 \\ c_j^I(x^*) &\leq 0 \\ c_j^I(x^*) &= 0 \text{ or } < 0 \\ &\downarrow \\ c_j^I &\text{ active at } x^* \end{aligned}$$

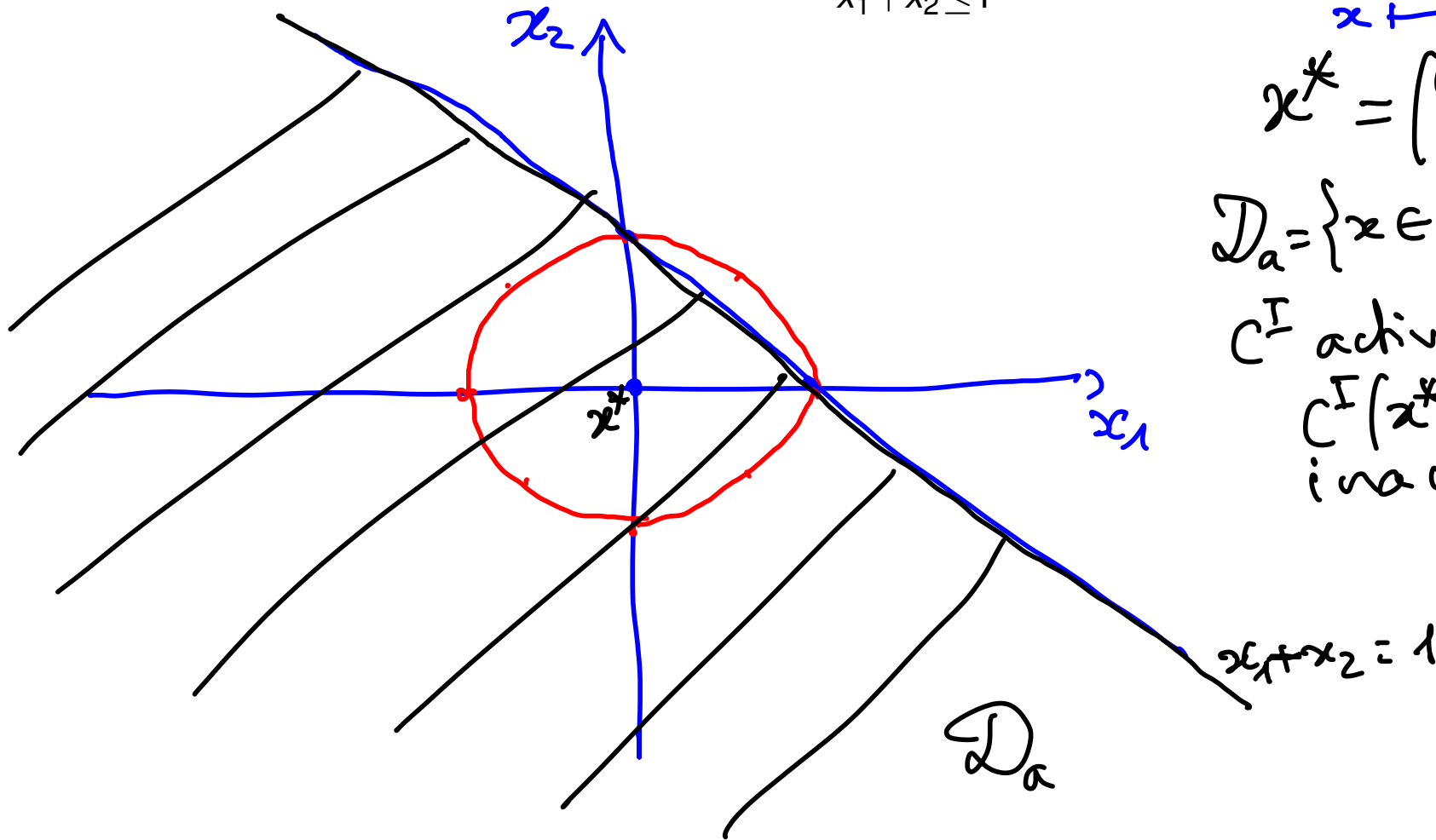
$$\begin{aligned} x^* \in D_a &= \{ c^E(x)=0, c_j^I(x) \leq 0 \} \\ \Rightarrow c^E(x^*) &= 0 \quad \underbrace{c^I(x^*) \leq 0} \\ j &= 1, \dots, p \\ c_j^I(x^*) &< 0 \quad j = 1, \dots, p \\ &\downarrow \\ c_j^I &\text{ is inactive at } x^* \end{aligned}$$

Actives Constraints / Contraintes actives

Let x^* a minimizer of f .

The i^{th} inequality constraint is **active** if $c_i'(x^*) = 0$.

1. $f: \mathbb{R}^2 \rightarrow \mathbb{R}$ $f(x) = \|x\|^2$, $\inf_{x_1+x_2 \leq 1} f(x)$



$f'(0) = \{0,0\}$
 $f^{-1}(x) = \text{circle}$

$C^I: \mathbb{R}^2 \rightarrow \mathbb{R}$
 $x \mapsto x_1 + x_2 - 1$
 $x^* = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \in \mathcal{D}_a$
 $\mathcal{D}_a = \{x \in \mathbb{R}^2, C^I(x) \leq 0\}$
 C^I active or not?
 $C^I(x^*) = -1$
 inactive

In green : second example

Actives Constraints / Contraintes actives

$$C^I: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$x \mapsto \begin{pmatrix} x_1 + x_2 + 1 \\ x_2 \end{pmatrix}$$

Let x^* a minimizer of f .

The i^{th} inequality constraint is **active** if $c_i^I(x^*) = 0$.

2. $f: \mathbb{R}^2 \rightarrow \mathbb{R} \quad f(x) = \|x\|^2, \quad \inf_{\substack{x_1 + x_2 \leq -1 \\ x_2 \leq 0}} f(x)$

$$C^I: \mathbb{R}^2 \rightarrow \mathbb{R}$$

$$x \mapsto x_1 + x_2 + 1$$

$$x^* \in \mathcal{D}_a$$

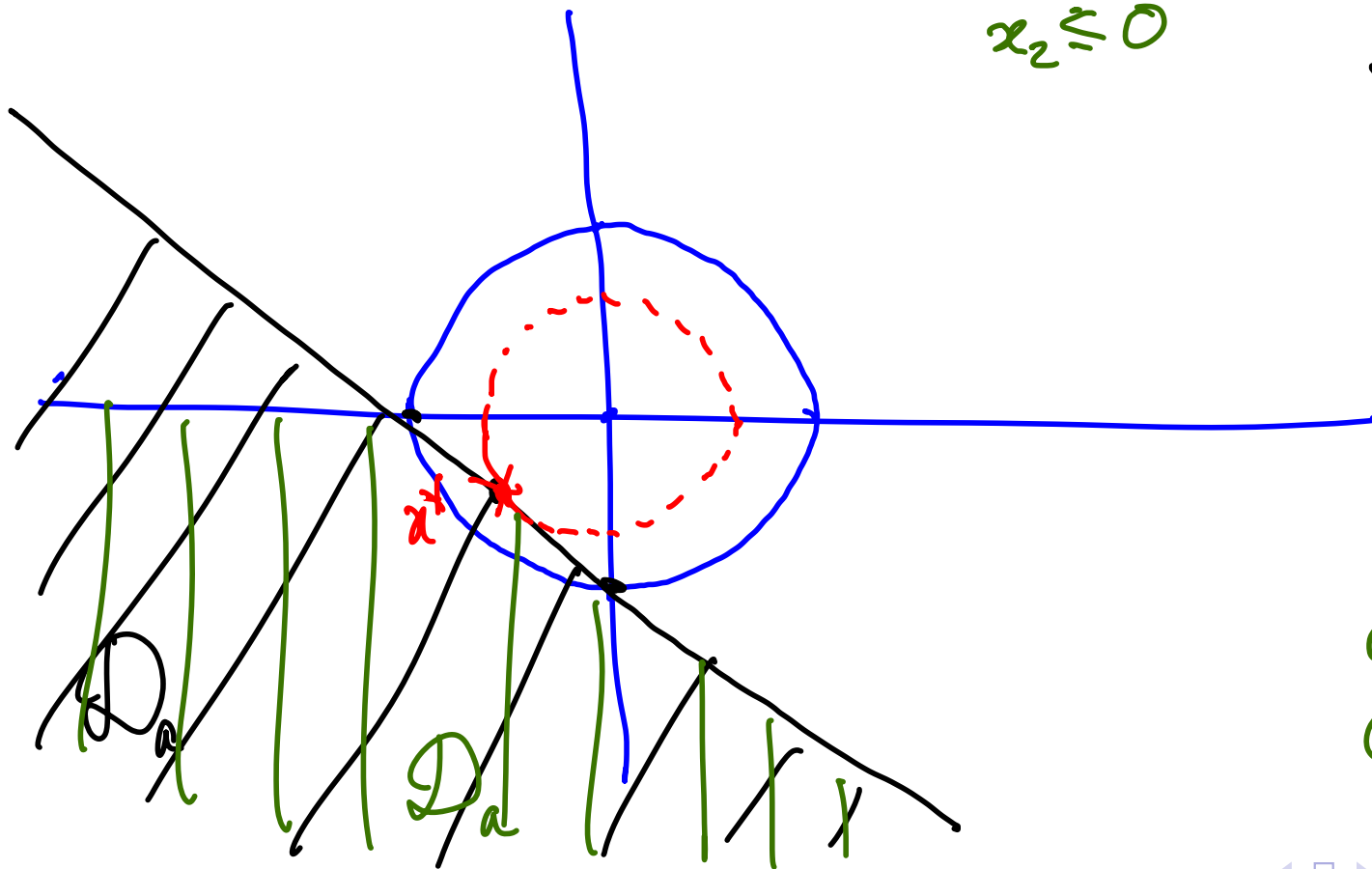
$$x^* = \begin{pmatrix} -1/2 \\ -1/2 \end{pmatrix}$$

$$C^I(x^*) = 0$$

therefore

C^I is active at x^*

C_1^I is active
 C_2^I is not active



Lagrange dual function

x primal variable
 y, z dual variable
 $\inf_{x \in D_a} f(x)$ — primal problem

proof:
$$l(x^*, y, z) = f(x^*) + \langle z, c^I(x^*) \rangle \leq p^*$$

$$c^I(x^*) \leq 0$$

$$g : \mathbb{R}^m \times \mathbb{R}^p \rightarrow \mathbb{R}$$

$$g(y, z) = \inf_{x \in D_a} l(x, y, z) \leq l(x^*, y, z) \leq p^*$$

$$= \inf_{x \in D_a} \left(f(x) + \sum_{i=1}^m y_i c_i^E(x) + \sum_{i=1}^p z_i c_i^I(x) \right)$$

g is concave (can be unbounded for some y, z)

Property : inferior bound:

If $z \geq 0$ then $g(y, z) \leq p^* = \inf_{x \in D_a} f(x) = f(x^*)$

→ an affine function is both convex and concave
 → for fixed x $(y, z) \mapsto f(x) + \langle y, c^E(x) \rangle + \langle z, c^I(x) \rangle$
 concave in y, z

Exemple : solution of a linear system with minimal norm

Solve

$$p^* = \inf_{Ax=b} x^T x$$

- ▶ Lagrangian : $\ell(x, y) = x^T x + y^T (Ax - b)$
- ▶ In order to minimize $\ell(x, y)$ with respect to x we seek gradient zeros

$$\nabla_x \ell(x, y) = 2x + A^T y = 0 \Leftrightarrow x = -A^T y / 2$$

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- ▶ Inject in the definition of the dual function

$$g(y) = \ell(-A^T y / 2, y) = -\frac{1}{4} y^T A A^T y - b^T y$$

concave in y

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- ▶ Inject in the definition of the dual function

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concave in y

- ▶ Inferior bound property

$$p^* \geq -\frac{1}{4} y^T A A^T y - b^T y \quad \forall y$$

Resolution of the dual problem

since $g(y, z) \leq p^*$ for all y, z
 $d^* = \sup_{y, z \geq 0} g(y, z) \leq p^*$

Solve

$$d^* = \sup_{y \in \mathbb{R}^m, z \in \mathbb{R}^p, z \geq 0} g(y, z)$$

- ▶ Best inferior bound for $p^* \geq d^*$
- ▶ The dual problem is concave : existence of an optimal problem d^*

Weak duality $d^* \leq p^*$

Strong duality $d^* = p^*$

Slater qualification

many hypothesis can ensure strong duality of constraints

Qualified constraints

Slater hypothesis

- ▶ Condition for $d^* = p^*$
- ▶ We say that the constraints are **qualified** in x^* if the rank of the matrix formed by the union of the Jacobian matrix of equality constraints and the Jacobian matrix of q constraints of active inequality in x^* is equal to $m + q$, then called maximal rank.
- ▶ Particular case of a convex problem :

Solve

$$p^* = \inf_{\substack{Ax = b \\ c'(x) \leq 0}} f(x)$$

f convex CI, convex x if there exist $x \in D_a$

If $\exists x$ s.t. $c'(x) < 0$ and $Ax = b$ then $d^* = p^*$

Case of equality constraints

C qualified \Leftrightarrow

Rank $J_C(x^*) = m$
or
 C affine

$$\begin{cases} \inf & f(x) \\ \text{s.c.} & C(x) = 0 \\ & x \in \mathbb{R}^n \end{cases}$$

with

$$f : \mathbb{R}^n \longrightarrow \mathbb{R},$$

$$C : \mathbb{R}^n \longrightarrow \mathbb{R}^m,$$

f C smooth.

Théorème des extrema liés - Lagrange multipliers

Primal Pb: $x^* = \min_{x \in D_0} f(x)$
 $D_0 = \{x, C(x)=0\}$

Let f and C in C^1 , and x^* a local minimizer of f satisfying

$f: \mathbb{R}^n \rightarrow \mathbb{R}$
 $C: \mathbb{R}^n \rightarrow \mathbb{R}^m$
 $C(x^*) = 0$ primal feasibility

If the constraints are qualified, there exists a vector of Lagrange multipliers $y^* \in \mathbb{R}^m$ s. t.

$\nabla_x l(x^*, y^*) = 0_{\mathbb{R}^n}$

$\nabla f(x^*) + \sum_{i=1}^m y_i^* \nabla C_i(x^*) = 0$ dual feasibility

look for (x^*, y^*) such that

- ▶ Linear constraints special case
- ▶ $n = 2, m = 1$ special case

$C(x^*) = 0_{\mathbb{R}^m}$
 $\nabla_x l(x^*, y^*) = 0_{\mathbb{R}^n}$
 $x \in \mathbb{R}^n, y \in \mathbb{R}^m$