

Outline

Numerical methods for optimisation

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Course goals and terms

Introduction to Optimization

Reminders : Differential calculus

Convexity

Unconstrained optimisation

Optimisation with constraints

Practical issues

- ▶ Final grade : weighted sum of following grades
 - ▶ Python and math team assignments (at least 3)
 - ▶ Final written exam (2 hours 16/02)
- ▶ There will be at least 3 Python hands on sessions in place of regular classes
- ▶ Each hands on session will be followed by an evening session to complete the program before handing it in

Course objective

- ▶ Introduction to numerical methods of Optimization
- ▶ Improve programming skills
- ▶ Implementation and test of algorithms

Why Python 3.1

- ▶ Ideal for building algorithm prototypes
- ▶ Flexible interactive graphics
- ▶ Widely used in business and all scientific sectors
- ▶ Performance worse than in a compiled language of high level (C++, Fortran)

Course map

- ▶ Introduction
 - ▶ Introduction of Optimization
 - ▶ Differential calculus revisions
 - ▶ Convexity revisions
 - ▶ Numerical approximation of derivatives
- ▶ **Un-constrained** Continuous Optimization
 - ▶ Optimality conditions
 - ▶ Nonlinear equations (Fixed point, Newton and Quasi-Newton)
 - ▶ Descent/Gradient algorithms
- ▶ **Constrained** Continuous Optimization
 - ▶ Duality
 - ▶ Optimality conditions with **equality** constraints
 - ▶ SQP algorithm
 - ▶ Optimality conditions with **inequality** constraints
 - ▶ Uzawa algorithm

Course goals and terms

Introduction to Optimization

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Different categories of optimization

- ▶ Discrete optimization : variables in a discrete set
 - ▶ Combinatorial \leftrightarrow linear programming
 - ▶ "NP-complete" (nondeterministic polynomial-time complete)
 - ▶ Logistics, Economy (Traveling salesman, Knapsack, etc.)
 - ▶ Heuristic methods : Hill climbing, Simulated annealing, Ant colony, etc.
- ▶ Continuous optimization : variables within a range of values
 - ▶ Infinite dimensions : calculus of variations, shape optimization, control theory
 - ▶ Finite dimension : includes the discretization of above problems

Definition of a minimum

Def : Let $f : V \rightarrow \mathbb{R}$ with V normed vector space.

$x^* \in D_a \subset V$ **achieves**

- ▶ a **local minimum on D_a** if there exists $\varepsilon > 0$ such that

$$f(x^*) \leq f(x) \quad \text{for all } x \in D_a \quad \text{t.q. } \|x - x^*\| \leq \varepsilon.$$

- ▶ a **strict local minimum** if there exists $\varepsilon > 0$ such that

$$f(x^*) < f(x) \quad \text{for all } x \in D_a \quad \text{s. t. } x \neq x^* \quad \text{and } \|x - x^*\| \leq \varepsilon.$$

Definition of a minimum

Def : $x^* \in D_a$ **achieves**

- ▶ a **global minimum** on D_a if

$$f(x^*) \leq f(x) \quad \text{for all } x \in D_a.$$

- ▶ a **strict global minimum** if

$$f(x^*) < f(x) \quad \text{for all } x \in D_a \quad \text{s. t. } x \neq x^*.$$

It is sometimes said that x^* **is a minimum** of $f(x)$, but this is a misnomer. The exact term, if x^* **realizes** a minimum of f , is that it is a **minimizer** of f , denoted

$$x^* = \underset{x \in D_a}{\operatorname{argmin}} f(x)$$

Definition of a maximum

To find the **maximum** of f we search the minimum of $-f$.

General Optimization problem

example $f: \mathbb{R}^n \rightarrow \mathbb{R}$

$$f(x) = \|x\|^2 = \sum_{i=1}^n x_i^2$$

Definition : Let $F : V \rightarrow \mathbb{R}$ with V normed vector space. F is coercive iff $\lim_{\|x\| \rightarrow +\infty} F(x) = +\infty$.

Property : If F is continuous, F has a minimum on every compact set $\subset E$

Property : A function $F(x)$ from a finite dimensional space V into \mathbb{R} which is continuous and coercive admits at least one minimum

Optimization applied to differential problems : Calculus of Variations

Let $V_0 = \{u \in C^2([0, 1]), u(0) = u(1) = 0\}$ and $g : \mathbb{R}^3 \rightarrow \mathbb{R}$, $g \in C^1$.

$$\mathcal{J}(u) = \int_0^1 g(x, u(x), u'(x)) dx, \quad u \in V_0.$$

$$D\mathcal{J}(u)(v) = \left\langle -\frac{d}{dx} \frac{\partial g}{\partial u'}(x, u, u') + \frac{\partial g}{\partial u}(x, u, u'), v \right\rangle_{L^2([0,1])}.$$

Euler-Lagrange Theorem: An extremum of \mathcal{J} satisfies

$$-\frac{d}{dx} \frac{\partial g}{\partial u'}(x, u, u') + \frac{\partial g}{\partial u}(x, u, u') = 0$$

Infinite dimension example

Let $V_0 = \{u \in C^2([0, 1]), u(0) = u(1) = 0\}$, $f \in C^1([0, 1])$ and $g : \mathbb{R}^3 \rightarrow \mathbb{R}$, $g \in C^1$.

$$\mathcal{J}(u) = \int_0^1 \frac{1}{2} u'(x)^2 + \frac{1}{2} u(x)^2 - f(x)u(x) dx, \quad u \in V_0.$$

$$g(x, u, u') = \frac{1}{2} u'^2 + \frac{1}{2} u^2 - f(x)u.$$

$$\begin{aligned} D\mathcal{J}(u)(v) &= \left\langle -\frac{d}{dx} \frac{\partial g}{\partial u'}(x, u, u') + \frac{\partial g}{\partial u}(x, u, u'), v \right\rangle \\ &= \int_0^1 (-u'' + u - f)v dx. \end{aligned}$$

$$\mathcal{J}(\bar{u}) = \min \mathcal{J}(u) \text{ iff } \left\{ \begin{array}{l} -u'' + u = f \\ u(0) = u(1) = 0 \end{array} \right\} \quad \text{Boundary value problem}$$

Canonical Continuous Optimization problem on \mathbb{R}^n

Find the extrema of a function $f(x)$ defined on \mathbb{R}^n (or part of \mathbb{R}^n in the case of a optimization with constraints).

Find

$$\inf_{x \in \mathbb{R}^n} f(x),$$

under constraints

$$C^E(x) = 0,$$

$$C^I(x) \preceq 0 \quad (\Leftrightarrow C^I_i(x) \leq 0, i = 1, \dots, p)$$

with

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

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

$$C^E : \mathbb{R}^n \longrightarrow \mathbb{R}^m, \quad f, C^I, C^E, \text{ smooth}$$

Admissible domain

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

Example 1: linear programming

Lagrange multiplier

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ linear
 $f(x) = c^T x = \langle c, x \rangle = \sum_{i=1}^n c_i x_i$

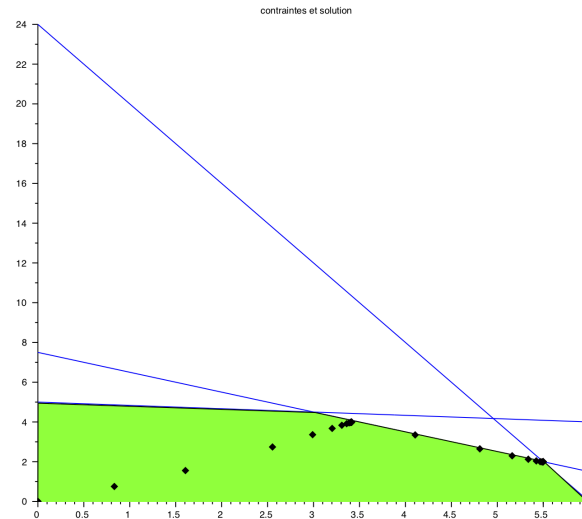
Generic problem

$$(P) \left\{ \begin{array}{l} \text{Minimize} \\ \text{under constraints} \end{array} \right. \begin{array}{l} c^T x \\ Ax \preceq b \\ x \succeq 0 \end{array} \quad \text{with} \quad \begin{array}{l} c \text{ and } x \in \mathbb{R}^n, \\ b \in \mathbb{R}^m, \\ A \in \mathcal{M}_{m \times n}(\mathbb{R}) \end{array}$$

Example and admissible domain

$$A = \begin{pmatrix} 1 & 6 \\ 2 & 2 \\ 4 & 1 \end{pmatrix}, \quad b = \begin{pmatrix} 30 \\ 15 \\ 24 \end{pmatrix}$$

$$c = \begin{pmatrix} -2 \\ -1 \end{pmatrix}$$



Rewrite example 1 in canonical form

$\inf_{x \in \mathbb{R}^n} f(x)$ under constraints $\begin{cases} \cancel{C^E(x) = 0} \\ C^I(x) \preceq 0 \end{cases}$

$$\begin{cases} Ax \leq b \\ x \geq 0 \end{cases}$$

- ▶ $f : \mathbb{R}^n \rightarrow \mathbb{R} \quad f(x) = c^T x$
- ▶ ~~$C^E = \mathbb{R}^n$~~
- ▶ $C^I = \mathbb{R}^n \rightarrow \mathbb{R}^{m+n}$
- ▶ D_a , def, nature

$$C^I(x) = \begin{pmatrix} Ax - b & m \leq \\ -x & n \leq \end{pmatrix}$$

Solve with the Python toolbox linprog

```
scipy.optimize.linprog (c, A_ub=None,  
B_ub=None, A_eq=None, B_eq=None, bounds=None,  
method='interior-point', callback=None,  
options=None, x0=None)
```

The problem must be written in the form expected by the program

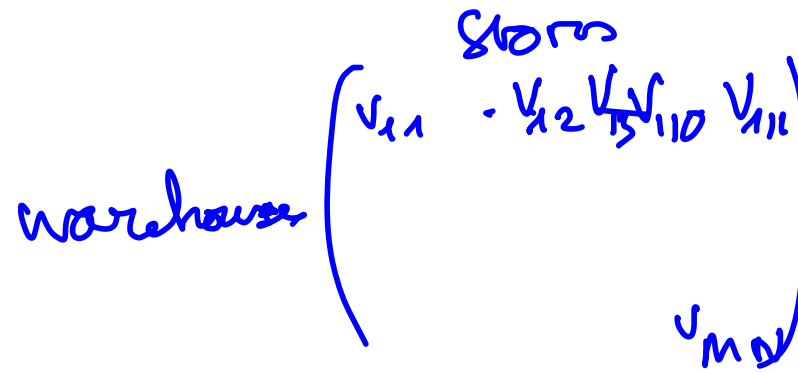
$$\begin{aligned} \min_x \quad & c^T x \\ \text{such that} \quad & A_{ub}x \preceq B_{ub} \\ & A_{eq}x = B_{eq} \\ & l \preceq x \preceq u \end{aligned}$$

lower *upper*

Solve with the Python toolbox linprog

```
c = [-2, -1]
Aub = [[1, 6], [2, 2], [4, 1]]
Bub = [30, 15, 24]
lu = (0., None)
bounds=2*[lu]
res = scipy.optimize.linprog(c, A_ub=Aub,
b_ub=Bub, bounds=bounds)
```


Mathematical modelling



Let us denote

- ▶ $v_{i,j}$ the quantity of merchandise shipped from warehouse i to store j
- ▶ $Q = \sum_{i=1}^M q_i$ the total quantity of goods available in the warehouses
- ▶ $R = \sum_{j=1}^N r_j$ the total quantity of goods ordered by the stores, assuming $Q \geq R$
- ▶ $D_{i,j}$ the cost of unit transport from the warehouse i to the store j , directly proportional to the distance between the store and the warehouse.

Rewriting as a linear programming problem

The problem (whose unknowns are the $v_{i,j}$) is therefore to minimize

$$f(v) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} D_{i,j} v_{i,j} \quad \text{linear}$$

with respect to v , under the constraints

- (i) $v_{i,j} \geq 0$ we do not return goods from a store to a warehouse
- (ii) $\sum_{j=0}^{N-1} v_{i,j} \leq q_i$ a warehouse cannot supply more than its stock
- (iii) $\sum_{i=0}^{M-1} v_{i,j} = r_j$ each store must receive the requested quantity

Solve with the Python toolbox linprog

```
scipy.optimize.linprog (c, A_ub=None,  
B_ub=None, A_eq=None, B_eq=None, bounds=None,  
method='interior-point', callback=None,  
options=None, x0=None)
```

The problem must be written in the form expected by the program

$$\begin{aligned} \min_x \quad & c^T x \\ \text{such that} \quad & A_{ub}x \preceq B_{ub} \\ & A_{eq}x = B_{eq} \\ & \underline{l} \preceq x \preceq \underline{u} \end{aligned}$$

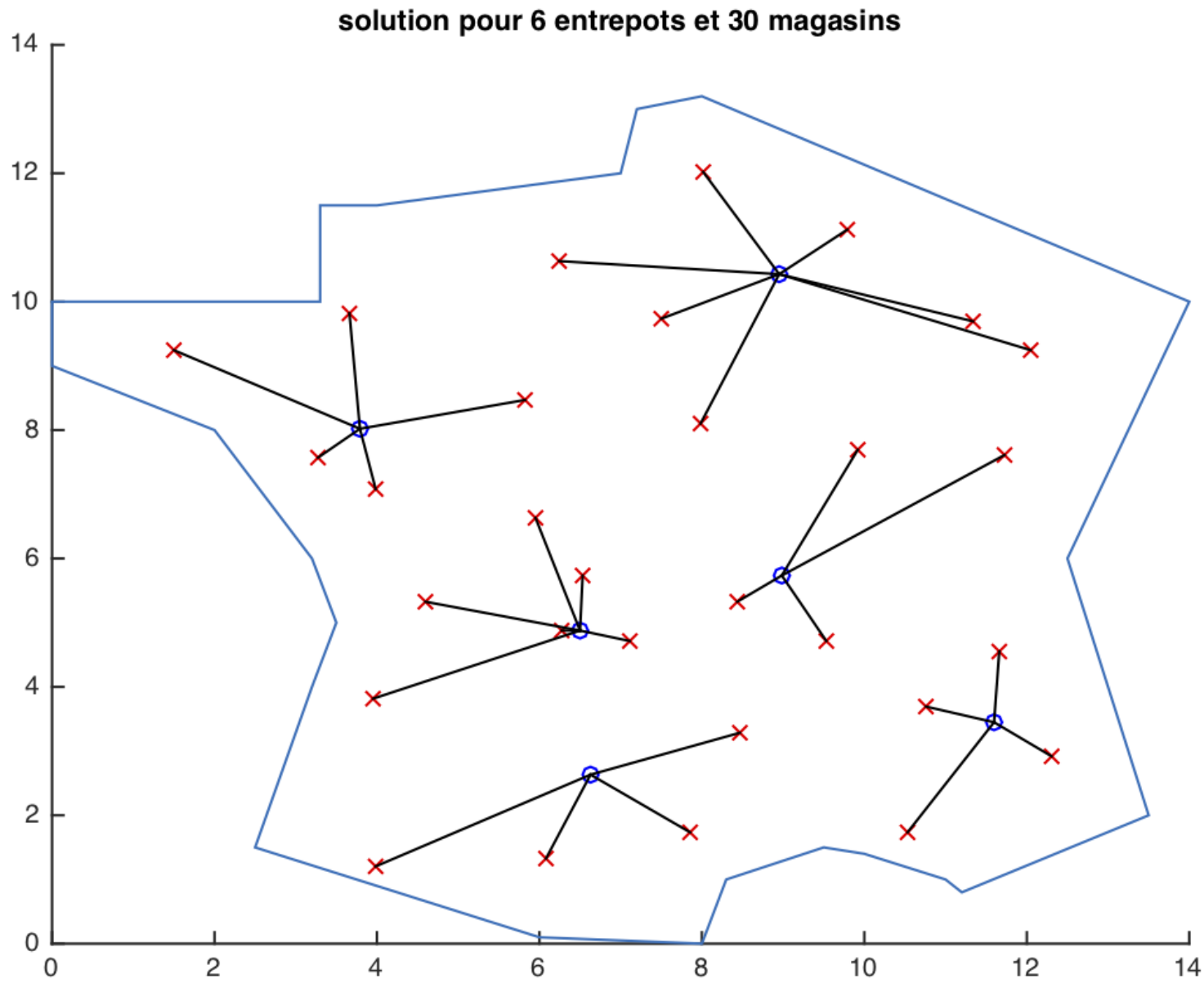
c, x, B_{ub}, b_{eq} are 1-D arrays or lists, A_{ub}, A_{eq} are 2-D arrays or lists. $bounds$ is a list of 2 1-D lists

Solve with the Python toolbox linprog

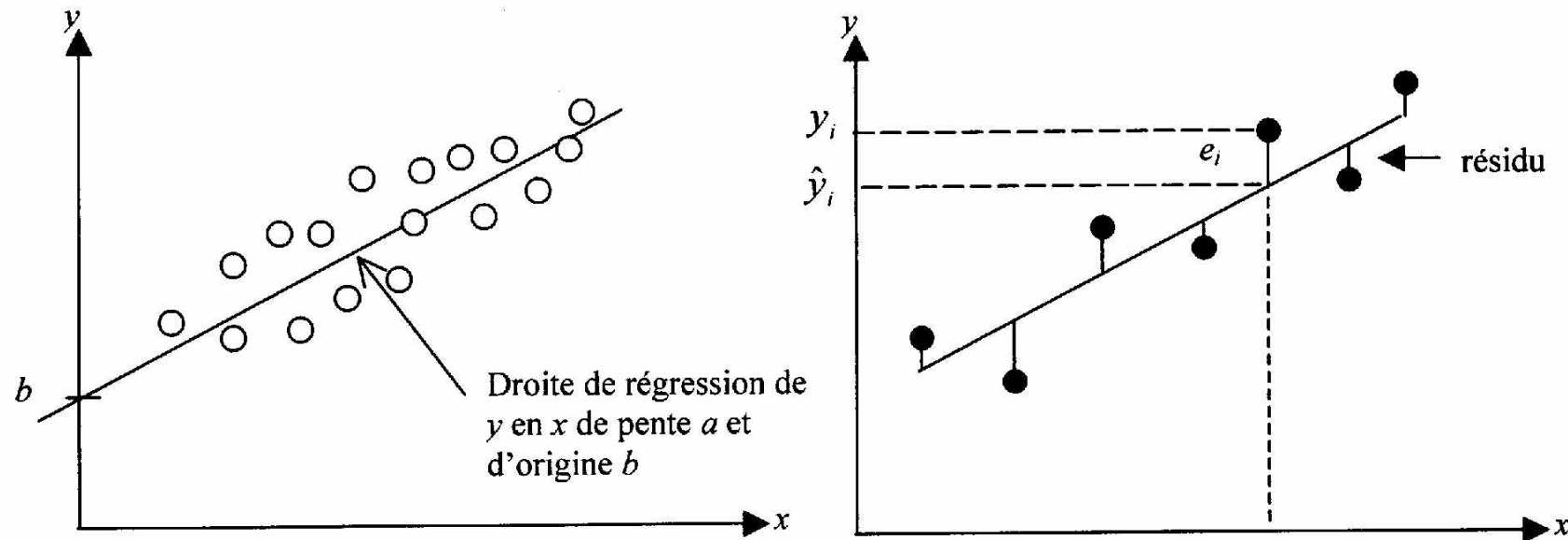
We must therefore define Python structures

- ▶ $x \in \mathbb{R}^{NM \times 1}$ contains the solution matrix v unrolled in columns
- ▶ $c \in \mathbb{R}^{NM \times 1}$ contains the matrix D unrolled in columns
- ▶ $Aub \in \mathcal{M}_{M, MN}(\mathbb{R})$ contains 1s in the right places so that $(Aub x)_i = \sum_{j=0}^{N-1} v_{i,j}$ for $i = 0, \dots, M - 1$
- ▶ $Bub \in \mathbb{R}^M$ contains q (the warehouse stocks)
- ▶ $Aeq \in \mathcal{M}_{N, MN}(\mathbb{R})$ contains 1s in the right places so that $(Aeq x)_j = \sum_{i=0}^{M-1} v_{i,j}$ for $j = 0, \dots, N - 1$
- ▶ $Beq \in \mathbb{R}^N$ contains r (the store orders)
- ▶ $\ell \in \mathbb{R}^{NM \times 1} = 0$

Solution Matlab du problème d'optimisation linéaire



Example 2 : Least Squares

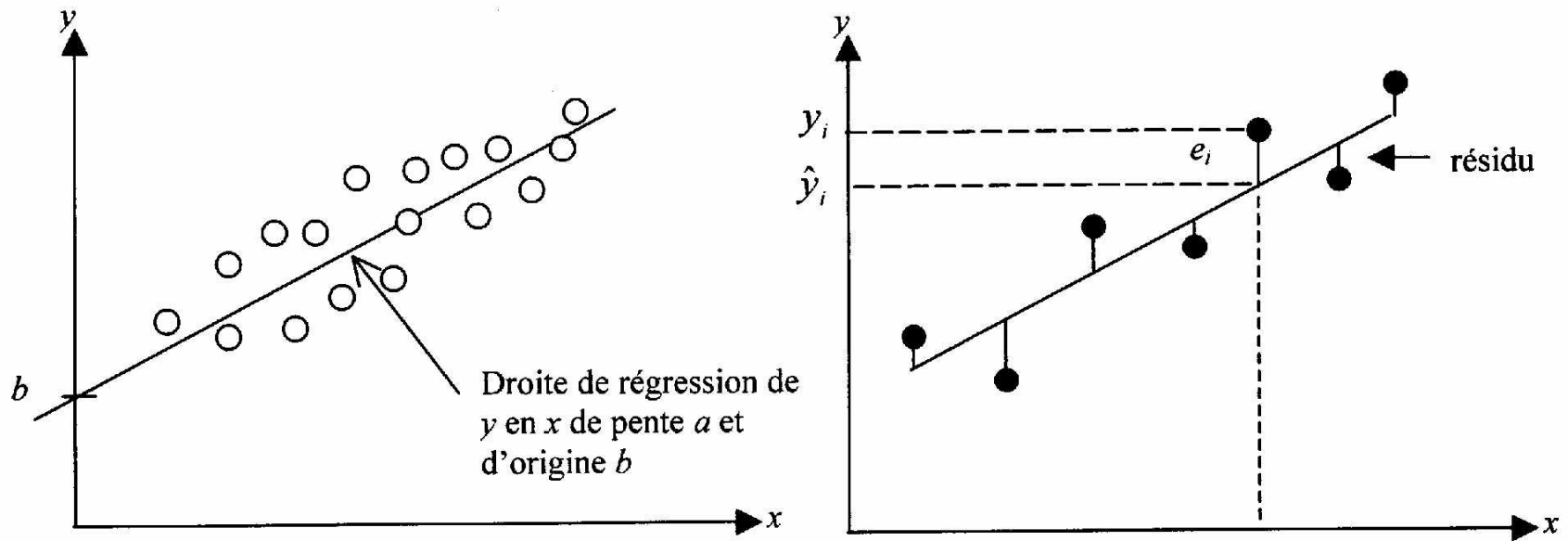


Data $x_i, y_i, i = 1, \dots, n$

Linear model $y = ax + b$

Minimize $\sum_{i=1}^n (ax_i + b - y_i)^2$ with respect to $(a, b) \in \mathbb{R}^2$

Example 2 : Least Squares - vector formulation



Data $x_i, y_i, i = 1, \dots, n$
Linear model $y = ax + b$

$$\sum (ax_i + b - y_i)^2 = f(a, b)$$

$$X = \begin{pmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{pmatrix}, \quad Y = \begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix}, \quad P = \begin{pmatrix} a \\ b \end{pmatrix}$$

Minimize $\|Y - XP\|_2^2$ with respect to $P \in \mathbb{R}^2$

Rewrite Least Square problem in canonical form

$$\inf_{x \in \mathbb{R}^n} f(x) \text{ under constraints } \begin{cases} C^E(x) = 0, \\ C^I(x) \preceq 0 \end{cases}$$

X and Y are parameters

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

▶ ~~C^E~~

▶ ~~C^I~~

▶ D_a , def, nature

$$f(P) = \|XP - Y\|^2$$

$$\mathbb{D}_a = \mathbb{R}^2$$

Example 3 : Non differentiable convex Optimization

Parsimonious Least Squares Lasso (least absolute shrinkage and selection operator)

- ▶ Sociological models (e.g. explanation of academic success as a function of social, family, medical factors, etc.)
- ▶ Data $Y = (y_i)_{i=1,\dots,n}$, $X = (x_{i,j})_{i=1,\dots,n,j=1,\dots,p}$
- ▶ Linear model $\tilde{Y} = XP$, with $P \in \mathbb{R}^p$, using as few factors as possible

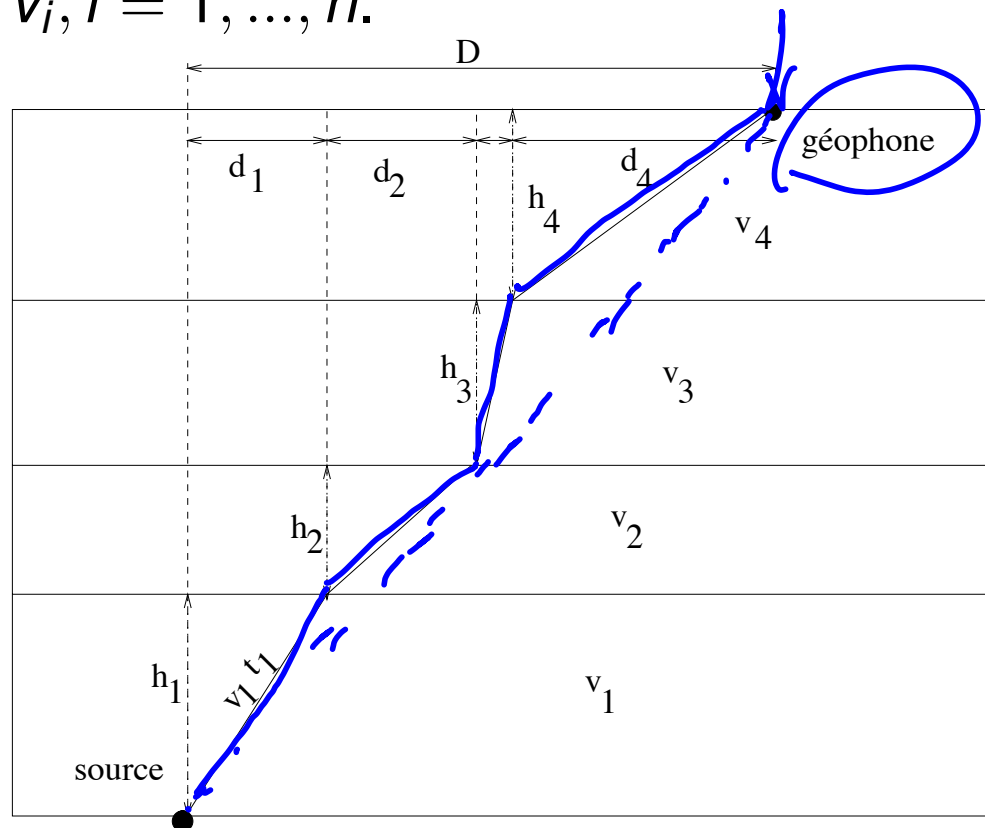
- ▶ Minimize $\|Y - XP\|_2^2 + \alpha \|P\|_1$

$$\|P\|_1 = \sum |P_i|$$

Example 5: Wave propagation in a stratified medium by "ray tracing"

n parallel layers of thickness $h_i, i = 1, \dots, n$.

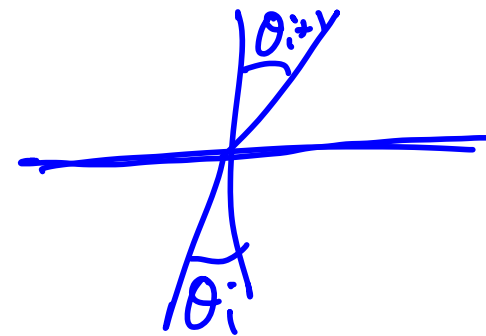
In each layer the speed of propagation is constant and equals $v_i, i = 1, \dots, n$.



(h_i, v_i) = parameters of the problem
unknowns: (d_i)



Optimization problem



Path followed by the seismic wave from the source to a geophone on the surface, at distance D from the vertical of the epicenter.

Descartes' law

Snell's law

$$\frac{\sin(\theta_i)}{v_i} = \text{constant}$$

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

Find the minimum travel time $\sum_i t_i$ under constraints

$$D = \sum_{i=1}^n d_i$$

$$d_i^2 + h_i^2 = v_i^2 t_i^2$$

$$d_i = \sqrt{v_i^2 t_i^2 - h_i^2}$$

$$f(x) = \sum_{i=1}^n t_i$$

$$C^E(x) = \sum \sqrt{v_i^2 t_i^2 - h_i^2} - D$$

Canonical form of the optimization problem

$$\inf_{x \in \mathbb{R}^n} f(x) \text{ under constraints } \begin{cases} C^E(x) = 0, \\ C^I(x) \preceq 0 \end{cases}$$

- ▶ f
- ▶ C^E
- ▶ C^I
- ▶ D_a , def, nature


Canonical form of the optimization problem

Choice of unknowns: $(t_i)_{i=1,\dots,n}$ or $(d_i)_{i=1,\dots,n}$

▶ If $X = (t_i)_{i=1,\dots,n}$

$$f(X) = \sum_{i=1}^n x_i \text{ and } C^E(x) = \sum_{i=1}^n \sqrt{v_i^2 x_i^2 - h_i^2} - D$$

▶ If $X = (d_i)_{i=1,\dots,n}$

$$f(X) = \sum_{i=1}^n \frac{\sqrt{x_i^2 + h_i^2}}{v_i} \text{ and } C^E(x) = \sum_{i=1}^n x_i - D$$


Equality or inequality constraints

$$C^E(x) = \sum_{i=1}^n x_i - D = 0 \quad \Leftrightarrow \quad \left\{ \begin{array}{l} C_1^I(x) = \sum_{i=1}^n x_i - D \leq 0 \\ C_2^I(x) = D - \sum_{i=1}^n x_i \leq 0 \end{array} \right.$$

Special case of absolute values

$$\inf_{x \in \mathbb{R}^n} f(x) \text{ under constraints } |g(x)| \preceq b \quad |g_i(x)| \leq b_i$$

with $g : \mathbb{R}^n \rightarrow \mathbb{R}^d$ and $b \in \mathbb{R}_+^d$ $i = 1, \dots, d$

Define C'

$$|g_i(x)| \leq b_i \Leftrightarrow -b_i \leq g_i(x) \leq b_i$$

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

$$x \mapsto C^I(x) = \begin{pmatrix} g(x) - b \\ -b - g(x) \end{pmatrix}$$

$\Leftrightarrow \begin{cases} g_i(x) - b_i \leq 0 \\ \text{and} \\ -b_i - g_i(x) \leq 0 \end{cases}$
 \leftarrow bloc of d components
 \leftarrow bloc of d components

Example 6: Epidemiy model

give 6 values for P
solve the ODE problem
for $[0, 2.5]$

SIRC model

- ▶ $S(t)$, proportion of *susceptibles* persons
- ▶ $I(t)$, proportion of *infected* persons
- ▶ $R(t)$, proportion of *recovered* persons
- ▶ $C(t)$, proportion of *cross immuned* persons

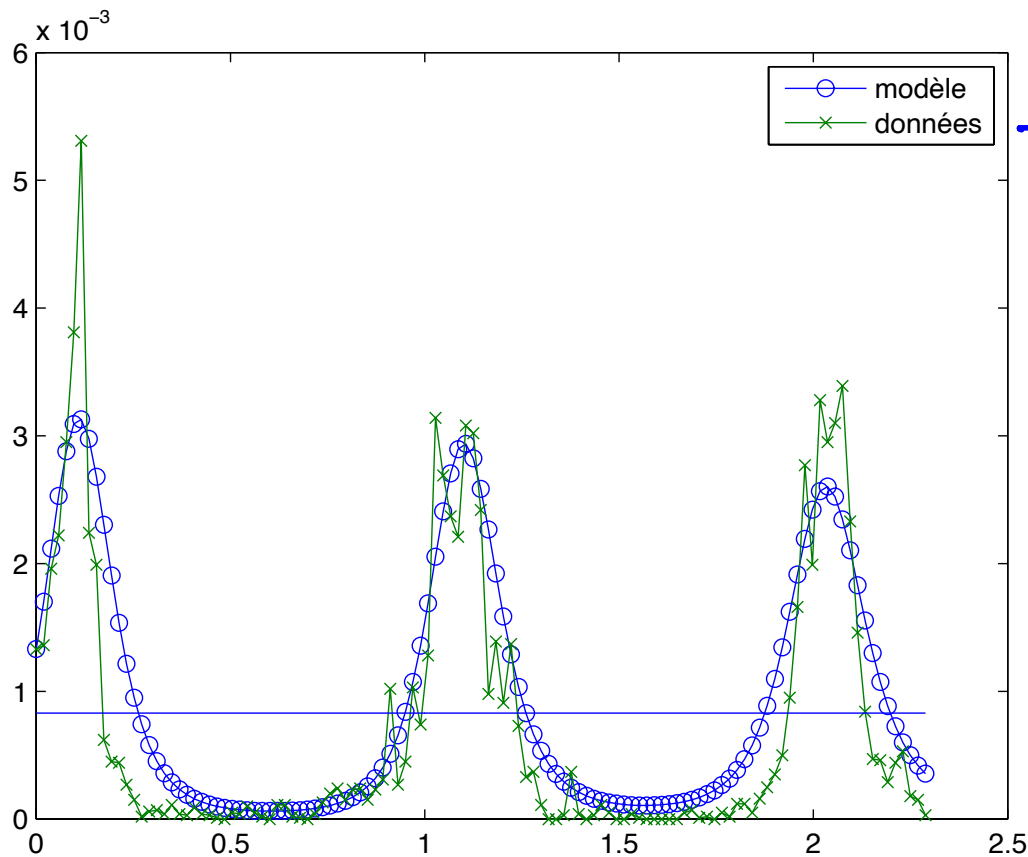
$$\frac{d(S,I)}{dt} = \begin{cases} \dot{S}(t) &= \mu(1 - S) - \beta SI + \gamma C, \\ \dot{I}(t) &= \beta SI + \sigma\beta CI - (\mu + \alpha)I, \\ \dot{R}(t) &= (1 - \sigma)\beta CI + \alpha I - (\mu + \delta)R, \\ \dot{C}(t) &= \delta R - \beta CI - (\mu + \gamma)C, \end{cases} \quad (1)$$

Parameters $P = (\mu, \alpha, \beta, \gamma, \delta, \sigma)$ ($M = 6$)

Adequation of model with data

Data $(\tilde{I}_j)_{j=1,\dots,d}$ to be compared with values predicted by the model $(I(t_j))_{j=1,\dots,d}$ *green points*

Proportion of flu in Paris region between Jan 2007 and April 2009 (source : "Reseau Sentinelle")



*→ nb of people who have
flu
~ I(t)*

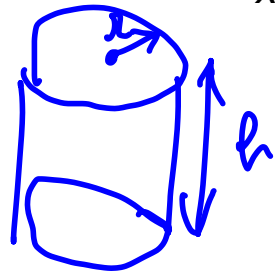
Rewrite Epidemic problem in canonical form

$$\inf_{x \in \mathbb{R}^n} f(x) \text{ under constraints } \begin{cases} C^E(x) = 0, \\ C^I(x) \preceq 0 \end{cases}$$

- ▶ f
- ▶ C^E
- ▶ C^I
- ▶ D_a , def, nature

Exercise

A cylindrical container should hold $20\pi m^3$. The price of the material constituting the bottom and the cover is 10 euros / m^2 , that of the material constituting the sides is 8 euros / m^2 . Write the optimisation problem to find the dimensions (radius r and height h) of the most economical container.



$$\inf_{x \in \mathbb{R}^n} f(x) \text{ under constraints } \begin{cases} C^E(x) = 0, \\ C^I(x) \leq 0 \end{cases}$$

$$S_c = \pi r^2 \rightarrow \text{top and bottom}$$

$$S_{\text{side}} = 2\pi r h$$

$$\text{Constraint: Volume} = 20\pi m^3 = \pi r^2 h$$

$$\blacktriangleright f(r, h) = 10 \times S_{\text{bot}} + 8 \times S_{\text{side}} = 20\pi r^2 + 16\pi r h$$

$$\blacktriangleright C^E(r, h) = r^2 h - 20$$

$$\blacktriangleright C^I: \mathbb{R}^2 \rightarrow \mathbb{R}^2 \quad r, h \geq 0 \quad C^F(r, h) = \begin{pmatrix} -r \\ -h \end{pmatrix}$$

$\blacktriangleright D_a$, def, nature

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Optimality conditions in the unconstrained case

Solving systems of non linear equations

Descent methods

Optimisation with constraints

Duality

Algorithms for constrained optimization

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1st order differentiability

a function $f(h)$ is a $o(\|h\|)$ if $\frac{f(h)}{\|h\|} \xrightarrow{h \rightarrow 0} 0$ little o of $\|h\|$
a $O(\|h\|)$ if $\exists C > 0$ s.t. $f(h) \leq C\|h\|$ for h small enough

Definition : Let E and F be two normed vector spaces. Let f be an application of E in F . We say that f is differentiable in the sense of Fréchet at x if there exists a continuous linear map L from E into F such that for all $h \in E$

$$f(x + h) = f(x) + L(h) + \underline{o}(\|h\|),$$

and we note $Df(x) = Df_x = L$, the differential of f at the point x .

$$f(x+h) = f(x) + \begin{matrix} Df(x)(h) \\ Df_x(h) \end{matrix} + o(\|h\|)$$

Directional derivatives

Definition : We say that f is differentiable in the sense of Gâteaux at x if for all $h \in E$, the function $g(t) = f(x + th)$ is differentiable. We denote by $Df(x)$ the differential map of f in x which applies to $h \in E$

$$Df(x)h = \left. \frac{df(x + th)}{dt} \right|_{t=0}.$$

and $Df(x)h$ is the directional derivative at x according to the vector h .

Property : If a function is differentiable (in the sense of Fréchet) then its differential in the sense of Gâteaux exists (the converse not always being true).

Partial derivatives

$$\mathbb{R}^n \quad e_i = \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \quad i^{\text{th}} \text{ row}$$

E finite dimension

$(e_i)_{i=1, \dots, n}$ basis of E

$$x = \sum_{i=1}^n x_i e_i$$

Partial derivative

$$\frac{\partial f(x)}{\partial x_i} = Df(x) e_i$$

Examples

1. $f : \mathbb{R} \rightarrow \mathbb{R}$, differentiable on \mathbb{R}
2. $L : E \rightarrow F$, linear with E and F nvs
3. $A : E \rightarrow F$, affine: $A(x) = L(x) + b$ with linear L and $b \in F$
4. $f(X) = \|X\|_2^2$, with $X \in \mathbb{R}^n$
5. $f : \mathbb{R}^2 \rightarrow \mathbb{R} : (x_1, x_2) \mapsto \begin{cases} 0 & \text{if } (x_1, x_2) = (0, 0) \\ \frac{x_1 x_2}{x_1^2 + x_2^2} & \text{else} \end{cases}$
6. $f : \mathbb{R}^2 \rightarrow \mathbb{R} : (x_1, x_2) \mapsto \begin{cases} 0 & \text{if } (x_1, x_2) = (0, 0) \\ \frac{(x_2^2 - x_1)^2}{x_1^2 + x_2^4} & \text{else} \end{cases}$
7. $f : \mathbb{R}^2 \rightarrow \mathbb{R} : (x_1, x_2) \mapsto \begin{cases} 0 & \text{if } (x_1, x_2) = (0, 0) \\ \frac{x_1^2 x_2}{x_1^2 + x_2^2} & \text{else} \end{cases}$

$f : \mathbb{R} \rightarrow \mathbb{R}$, differentiable on \mathbb{R}

link between $df(x)$ and $f'(x)$

$$f(x+h) = f(x) + h f'(x) + o(|h|)$$
$$f(x+h) = f(x) + Df(x)(h) + o(|h|)$$

$Df(x) : \mathbb{R} \rightarrow \mathbb{R}$ linear function

$$h \mapsto Df(x)(h) = f'(x)h$$