

With Gauss choice du pivot (de gauche / premier / 10101,
Gauss Jordan. Au lieu d'éliminer la variable dans le ligne
qui suit seulement, on l'élimine dans toutes
les lignes pour avoir une matrice
(on fait le m même trm à I_n jusqu'à ce que $A \rightarrow I_n$)
alors $I_n \rightarrow A^{-1}$

$\frac{2n^3}{3}$ $O(n^3)$

For LU:
 $M_k = A$ after $(k-1)$ iterations, pour les k -première colonne, les
val au dessous de diag sont nulle
hyp: $(M_k)_{k,k} \neq 0$ (c'est lui qui va jouer de pivot) k -colonne

$$(M_k)_{i,k} = \begin{pmatrix} a_{11} & \dots & a_{1k} \\ \vdots & \ddots & \vdots \\ a_{k-1,1} & \dots & a_{k-1,k} \\ a_{k+1,1} & \dots & a_{k+1,k} \\ \vdots & \ddots & \vdots \\ a_{nn} & \dots & a_{nk} \end{pmatrix} \Rightarrow E_k = \begin{pmatrix} 1 & & & & (0) \\ & \ddots & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 & & (0) \\ & & & & & \ddots & \\ & & & & & & 1 & & (0) \\ & & & & & & & \ddots & \\ & & & & & & & & 1 & & (0) \end{pmatrix}$$

$$E_{k+1} = \begin{pmatrix} 1 & & & & (0) \\ & \ddots & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 & & (0) \\ & & & & & \ddots & \\ & & & & & & 1 & & (0) \\ & & & & & & & \ddots & \\ & & & & & & & & 1 & & (0) \end{pmatrix} \quad L_{k+1,k} = \frac{a_{i,k}}{a_{k,k}} \quad L_{k+1,k} = \frac{a_{i,k}}{a_{k,k}}$$

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^n |a_{i,j}|$$

$$L = \begin{pmatrix} 1 & & & (0) \\ & \ddots & & \\ & & 1 & \\ & & & \ddots & \\ & & & & 1 & & (0) \\ & & & & & \ddots & \\ & & & & & & 1 & & (0) \end{pmatrix} \Rightarrow A = L U \quad U \text{ (upper)}$$

Cholesky:
A sym def positive. $B = \begin{pmatrix} b_{11} & & (0) \\ & \ddots & \\ & & b_{nn} \end{pmatrix}$
alors $A = B B^T$
→ 1ère colonne: $b_{11} = \sqrt{a_{11}} \quad b_{i1} = \frac{a_{i1}}{b_{11}} \quad 2 \leq i \leq n$
→ $2 \leq j \leq n$: $b_{jj} = \sqrt{a_{jj} - \sum_{k=1}^{j-1} b_{jk}^2}$
 $b_{ij} = \frac{a_{ij} - \sum_{k=1}^{j-1} b_{ik} b_{jk}}{b_{jj}} \quad i \in \{j+1, \dots, n\}$

$n^o \text{ d'op} \approx \frac{n^3}{3}$ $O(n^3)$

Jacobi: $J_p(0) = \begin{pmatrix} 1 & & & & (0) \\ & \ddots & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 & & (0) \\ & & & & & \ddots & \\ & & & & & & 1 & & (0) \end{pmatrix}$
← p row
← q row

Alg Jpq: $n) \text{ set } t_0 = \min \left| \frac{a_{pp} - a_{qq}}{2 a_{pq}} \pm \sqrt{\left(\frac{a_{pp} - a_{qq}}{2 a_{pq}} \right)^2 + 1} \right|$ fullfil (smaller one)
2) $c_0 = \frac{n}{\sqrt{n+t_0}}$, $s_0 = c_0 t_0$
3) Return J_{pq}

Alg Jacobi: $k=0 \quad A_0 = A$
while $\|A_k\| > \epsilon$ do:
choose p, q s.t. $|a_{p,q}| = \max_{i \neq j} |a_{i,j}|$
ii) get J_{pq}
iii) set $A_{k+1} = J_{pq}^T A_k J_{pq}$ set $k = k+1$
return A_n .

$$B = J_{pq}^T A J_{pq} \Leftrightarrow \begin{cases} i \notin \{p, q\} \wedge j \notin \{p, q\} & b_{ij} = b_{ij} \quad i = a_{ij} \\ i \notin \{p, q\} & b_{pi} = b_{ip} = c a_{pi} - s a_{qi} \\ i \notin \{p, q\} & b_{qi} = b_{iq} = s a_{pi} + c a_{qi} \\ b_{pp} = a_{pp} - t a_{pq} \\ b_{qq} = a_{qq} + t a_{pq} \\ b_{pq} = b_{qp} = 0 \end{cases}$$

LP: $\max_{x \in \mathbb{R}^n} C^T x$
 $Ax \leq b$
 $x \geq 0$

Lin Prog / Simplex
 $C \in \mathbb{R}^n, A \in \mathbb{R}^{m \times n}, b \in \mathbb{R}^m$

feasible region: $P = \{x \in \mathbb{R}^n : Ax \leq b, x \geq 0\}$
In one (exactly) of the following holds:
i) $P = \emptyset$ infeasible
ii) \exists sequence $x^{(m)} \in P$ s.t. $\lim_{m \rightarrow \infty} C^T x^{(m)} = +\infty$
iii) max achieved at some vertex of P

Simplex alg: Dictionary:
each any variable
 $x_{n+1} = b_1 - \sum_{i=1}^n a_{1,i} x_i$
 $x_{n+2} = b_2 - \sum_{i=1}^n a_{2,i} x_i$
 \vdots
 $x_{n+m} = b_m - \sum_{i=1}^n a_{m,i} x_i$
 $z = \sum_{j=1}^n c_j x_j$
end when $c_j \leq 0 \quad \forall j$
obligation: $\forall i \in \{1, \dots, n+m\}: x_i \geq 0$

Any n-tuple $x = (x_1, \dots, x_n)$ satisfying the constraints $Ax \leq b$ and $x \geq 0$ is called feasible.
A solution $x^* = (x_1^*, \dots, x_n^*)$ is feasible iff all its values are non neg. A feasible sol that max z (objective funct) is called optimal.
unbounded: z can take arbitrarily large values
basic sol, giving all non basic $x_i = 0$

who enters / leaves: n variables / m constraints: var on the entering var
 1) Dantzig's 1st rule: choose largest positive coeff in Z $O(n)$ if it has positive coeff
 2) Dantzig's 2nd rule: choose the variable that increases Z the most
 3) Bland's rule: choose the entering / leaving variables w/ the smallest index $O(mn)$ if there are more than one, we apply one of them

Dict is degenerate:

if the basic sol has some basic var that are null

If dict is degenerate, just apply Bland's rule, you are sure that you are not cycling.

Dict feasible: all var have non neg val in the basic sol

Duality:

$$\text{Primal max } c^T x \quad s.t. \quad Ax \leq b, \quad x \geq 0 \quad \rightarrow \quad \text{Dual min } y^T b \quad s.t. \quad A^T y \geq c, \quad y \geq 0$$

Th (weak duality) $x^* \in \mathbb{R}^n$ feasible to P, $y^* \in \mathbb{R}^m$ dual

then $c^T x \leq y^T b$

Th (strong duality) If either (P) or (D) is feasible then $Z_P^* = Z_D^*$ and if the final dict of (P) look like

then

$$d_i = -d_{n+i} \text{ is optimal for (D)} \quad Z = Z^* + \sum_{i=1}^m d_i \cdot x_i$$

Th (Complementary slackness)

A feasible point x^* of (P) is optimal iff

\exists a feas pt y^* of (D) s.t

$$\text{Th: max } Z = \sum_{j=1}^n c_j x_j \quad s.t. \quad \forall i \in \{1, \dots, m\} \quad \sum_{j=1}^n a_{ij} x_j \leq b_i \quad (P)$$

assume (P) not degenerate, variations δb_i of b_i

$$\Rightarrow (P_s): \text{max } Z = \sum_{j=1}^n c_j x_j \quad s.t. \quad \forall i \in \{1, \dots, m\} \quad \sum_{j=1}^n a_{ij} x_j \leq b_i + \delta b_i$$

$$\forall j \quad x_j \geq 0$$

assume δb_i small enough so that the optimal basis for (P) is still feasible for (P_s). the variation of the optimum

value of Z is: $\sum_{i=1}^m \delta b_i y_i^*$ where (y_1^*, \dots, y_m^*) opt sol for

dual prob of (P)

flux prob when one of the ineq has a neg second mem, so the initial dict is infeasible. If we want to check the feasibility of the prob, we add to that sec mem x_0 to relax the constraint, the goal of this first phase is to a max $Z' = -x_0$. we start by swapping x_0 entering, and the basic var with the most neg val in basic sol leaves. we still by swapping x_0 entering, and the basic var with the most neg val in basic sol leaves. we still by swapping x_0 entering, and the basic var with the most neg val in basic sol leaves. we still by swapping x_0 entering, and the basic var with the most neg val in basic sol leaves.

If some b_i are neg (prob infeasible) and all c_j are neg then we can use the dual

Th^m (complementary slackness)

$$1) \text{ for } i \leq n \text{ s.t. } \sum_{j=1}^n a_{ij} x_j < b_i \quad (\text{i-th constraint not tight})$$

$$2) \text{ for } i \leq m \text{ s.t. } x_j^* > 0 \text{ then } \sum_{i=1}^m y_i^* a_{ij} = c_j$$

$$3) \text{ And } y^* \text{ opt}$$

define x_{min}, x_{max} for which define step $h > 0$

1) if $f'(0) < 0$, do:

$$\rightarrow x_{min} < 0$$

$$\rightarrow \text{as long as } f'(h) < 0 \text{ do:}$$

$$* x_{min} \leftarrow h$$

$$* h \leftarrow 2h$$

$$\rightarrow x_{max} \leftarrow h$$

2) else if $f'(0) \geq 0$, do:

$$\rightarrow h \leftarrow -h$$

$$\rightarrow x_{max} < 0$$

3) as long as $f'(h) > 0$, do:

$$* x_{max} \leftarrow h$$

$$* h \leftarrow 2h$$

$$\rightarrow x_{min} \leftarrow h$$

Newton method

f class \mathbb{R}^2

$\nabla^2 f(x^k)$ def positive

$$x^{k+1} = x^k - (\nabla^2 f(x^k))^{-1} \nabla f(x^k)$$

x^0 chosen close enough sufficiently

close to x^*

($\nabla^2 f$) has quadratic convexity

A constant matrix $\nabla(u^T A) = \nabla(u^T) A$

$$\nabla(u^T v) = \nabla(u^T) v + \nabla(v^T) u$$

$$f \in \mathbb{C}^1 \text{ in } x^0 \quad f(x) = f(x^0) + (x - x^0)^T \nabla f(x^0) + \frac{1}{2} (x - x^0)^T \nabla^2 f(x^0) (x - x^0) + o(\|x - x^0\|^2)$$

$$g'(s) = \frac{d}{ds} \nabla f(x^0 + s \cdot d) \quad (g(s) = f(x^0 + s \cdot d))$$

$$f \in \mathbb{C}^1 \text{ in } x^0 \quad f(x) = f(x^0) + (x - x^0)^T \nabla f(x^0) + \frac{1}{2} (x - x^0)^T \nabla^2 f(x^0) (x - x^0) + o(\|x - x^0\|^2)$$