

Gauss elimination

$$0.0003x + 1.566y = 1.569$$

$$0.3454x + 2.436y = 1.018$$

exact sol: (10, 1)

4 digits: $m = 0.3454 / 0.0003 = 1151$

$$\Rightarrow 0.3454 - 1151 \cdot 0.0003$$

etc.

$$x = 3.333 \quad y = 1.001$$

ill conditioned matrix

Fundamental eq. of NLA (KLNLA)

Swapping rows
improves results

A, b given. x is the solution. $Ax = b$

\hat{x} is a guess. $e = x - \hat{x}$ is the error

$r = b - A\hat{x}$ is the residual.

$$\boxed{A \cdot e = r}$$

if we knew e
we could get x!

$$A \cdot (x - \hat{x}) = b - A \cdot \hat{x} = r$$

Iterative improvement: (an approximate)

1. compute a solution \hat{x}

2. $r = b - A\hat{x}$

3. solve for e from $Ae = r$

4. $\hat{x} \rightarrow \hat{x} + e$

5. exit if $\|e\|$ is small enough, otherwise goto 2.

(Mixed precision methods: step 3 could use less precision.)

Works if we have at least 1 correct digit in \hat{x} , and e

Error analysis, recall induced matrix norm $\|A\| = \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|}$

$$\text{so } \|Ax\| \leq \|A\| \|x\|$$

Condition number $\text{cond}(A) = \|A^{-1}\| \cdot \|A\|$

for symmetric A

$$\|A\|_2 = \max |\lambda|$$

λ is eigenval of A

\Rightarrow

cond. number \approx

$$\frac{|\text{maximal } \lambda|}{|\text{minimal } \lambda|}$$

\hat{x} is $\underline{Ax = b}$ and we have an approximate solution $\underline{A\hat{x} + b = r}$

Then: $\frac{\|x - \hat{x}\|}{\|x\|} \leq \text{cond}(\underline{A}) \cdot \frac{\|r\|}{\|b\|}$

proof: $\underline{Ae = r} \quad \underline{e = A^{-1} \cdot r}$

$$\|e\| \leq \|A^{-1}\| \|r\|$$

$$\|b\| \leq \|A\| \|x\|$$

$$\Rightarrow \frac{\|e\|}{\|x\|} \leq \text{cond}(A) \frac{\|r\|}{\|b\|}$$

$$\|e\| \|b\| \leq \|A^{-1}\| \|A\| \|r\| \|x\|$$

QED.

More complicated theorem:

solving $Ax = b$ in finite precision w. rounding errors is equivalent to solving

$$(\underline{A} + \underline{E}) \cdot \underline{\hat{x}} = \underline{b} + \underline{f} \quad \text{exactly}$$

with $\frac{\|\underline{E}\|}{\|A\|}, \frac{\|\underline{f}\|}{\|b\|} = O(\text{machine precision})$

one can easily show if either errors are there

$$\frac{\|x - \hat{x}\|}{\|x\|} \leq \text{cond}(A) \frac{\|E\|}{\|A\|} \quad \text{or} \quad \frac{\|x - \hat{x}\|}{\|x\|} \leq \text{cond}(A) \frac{\|f\|}{\|b\|}$$

Some properties of the condition number

- $\text{cond}(A) \geq 1$ ($\|AB\| \leq \|A\| \cdot \|B\|$)
- Scaling does not matter: $\text{cond}(\alpha A) = \text{cond}(A)$ while $\det(\alpha A) = \alpha^n \det(A)$
- depends on the norm used, but usually one gets the same order of magnitude
- $\text{cond}_2(A) = |A|_{\max} / |A|_{\min}$
- $\text{cond}(A^{-1}) = \text{cond}(A)$
- eigenvalue calculations: error also governed by $\text{cond}(A)$

with some more work for both errors:

$$\frac{\|x - \hat{x}\|}{\|x\|} \leq \frac{\text{cond}(A)}{1 - \|A^{-1}\| \|E\|} \left(\frac{\|E\|}{\|A\|} + \frac{\|f\|}{\|b\|} \right)$$

LU decomposition

Suppose we can decompose A into LU

$$\underline{A} = \underline{L} \cdot \underline{U}$$

$$L = \begin{pmatrix} 1 & 0 & 0 & 0 \\ l_{21} & 1 & 0 & 0 \\ l_{31} & & 1 & \\ \vdots & & & \ddots \\ l_{n1} & & & l_{nn} & 1 \end{pmatrix}$$

$$U = \begin{pmatrix} u_{11} & u_{12} & \dots \\ 0 & u_{22} & \\ 0 & 0 & \ddots \\ 0 & 0 & 0 & u_{nn} \end{pmatrix}$$

\underline{L} is lower triangular
with 1 on the diagonal

\underline{U} is upper triangular

Now the solution is easy

$$\underline{L} \underline{U} \cdot \underline{x} = \underline{b} = \underline{L} \underline{y} \quad \underline{y} = \underline{U} \underline{x}$$

first solve $\underline{L} \underline{y} = \underline{b}$ $y_1 = b_1$

$$l_{21} y_1 + y_2 = b_2 \quad y_1 \text{ we know already}$$

$$y_i = b_i - \sum_{j=1}^{i-1} l_{ij} y_j \quad \text{Forward substitution}$$

$$\underline{U} \underline{x} = \underline{y}$$

now start with the last element

$$u_{nn} \cdot x_n = y_n$$

$$u_{n-1,n-1} \cdot x_{n-1} + u_{n-1,n} x_n = y_{n-1} \quad x_n \text{ is known.}$$

$$x_i = \frac{1}{u_{ii}} \left(y_i - \sum_{j=i+1}^n u_{ij} x_j \right) \quad \text{Backward substitution}$$

Doolittle and Crout formulas

1. $u_{ij} = a_{ij} - \sum_{k=1}^{i-1} l_{ik} u_{kj} \quad i=1 \dots j-1$

2. $l_{ij} = a_{ij} - \sum_{k=1}^{j-1} l_{ik} u_{kj} \quad i=j \dots n$

3. $u_{jj} = \delta_{jj}$

4. $l_{ij} = \frac{\delta_{ij}}{\delta_{jj}}$

$i = j+1 \dots n$
Column-wise, left looking
calculate in place
(right-looking version also exists)

Notation

$$\underline{A} = (a^1, a^2, a^3 \dots a^n) = \begin{pmatrix} a(1) \\ a(2) \\ \vdots \\ a(n) \end{pmatrix} \leftarrow \text{rows}$$

\uparrow columns

$$\left(\begin{array}{c} | \\ \underline{A} \\ | \end{array} \right) \approx \begin{pmatrix} 1 & & & \\ l_{21} & 1 & & \\ l_{31} & & \ddots & \\ & & & \ddots \end{pmatrix} \begin{pmatrix} u_{11} & & & \\ & u_{22} & & \\ & & \ddots & \\ & & & u_{nn} \end{pmatrix}$$

$$a(1) = u(1)$$

$$a(2) = u(2) + l_{21} u(1)$$

$$a(i) = l_{ik} u(k) + u(i)$$

$$a^1 = u_{11} \cdot e^1$$

$$a^2 = u_{12} e^1 + u_{22} e^2$$

$$\vdots$$
$$a^n = \sum_k u_{kn} e^k$$

solution: $u(1) = a(1)$

$$e^1 = \frac{1}{u_{11}} a^1$$

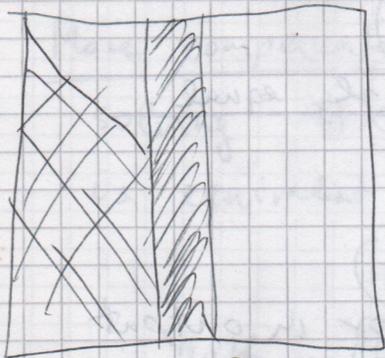
$$u(2) = a(2) - l_{21} \cdot u(1)$$

$$e^2 = (a^2 - u_{12} e^1) \frac{1}{u_{22}}$$

and ! go on.

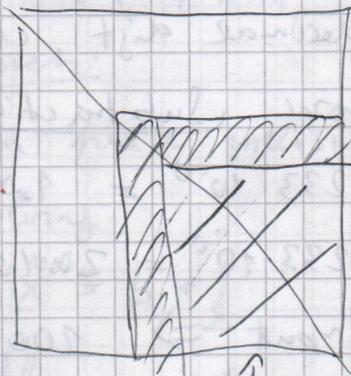
Many versions

left looking

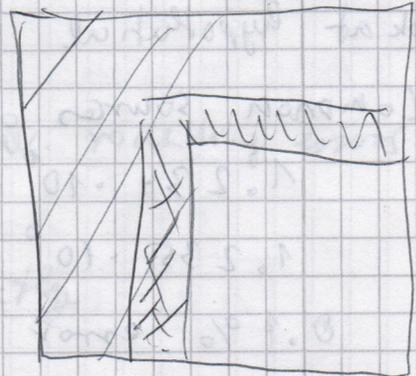


↑ read ↑ write

right looking



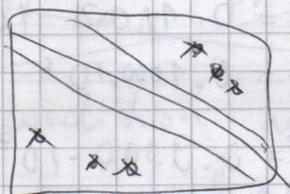
↑ read/write
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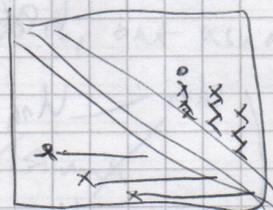
LU for sparse matrices

sparse matrix =



many zeros

↓ LU



fill in no longer zero

swap rows and columns to minimize fill in

- many algorithms, "recipes" no clear best

algorithm, depends on problem

eg.



⇒ reorder



no fill in

Cost $O(N^3)$

$$\det \underline{A} = \det \underline{LU} = \det \underline{L} \cdot \det \underline{U} = \det \underline{U}$$
$$= \prod_{i=1}^n u_{ii}$$

We also get the determinant!

Exercise 1:

$$A = \begin{pmatrix} 1 & 5 & 3 & 4 & 8 & 6 & 2 & 1 & 1 & 6 & 0 & 8 \\ 5 & 3 & 4 & 8 & 6 & 8 & 7 & 4 & 3 & 7 & 0 & 9 & 2 & 0 & 0 & 0 \\ 6 & 1 & 1 & 4 & 2 & 9 & 1 & 0 & 1 & 3 & 2 & & & & & \end{pmatrix}$$

$$x = ? \quad \|Ax - b\| = ?$$

What happens if you switch some rows?

$$b = \begin{pmatrix} 1 & 2 & 7 & 4 & 5 \\ 6 & 7 & 8 & 9 & 0 \\ 8 & 7 & 6 & 4 & 2 \end{pmatrix}$$

Pivoting

Suppose $a_{11} = 0$ $a_{11} = e_{11} \cdot u_{11} = 0 \Rightarrow e_{11} = 0$ or $u_{11} = 0$

$$\Rightarrow \det L \cdot \det U = 0 \Rightarrow \det A = 0 ?$$

In this case decomposition fails

we need to be able to swap rows $\Rightarrow A = P \cdot L \cdot U$

P, M rows of M swapped

\leftarrow permutation matrix

M, P columns of M swapped

permutation matrix

each column and row has exactly one 1 entry, others are 0

\leftarrow insert in the LU procedure above

2, 5 swap rows (1...n)

such that $|r_{jj}|$ is maximal: "partial pivoting"

~~if~~ if all r_{ij} $i = j \dots n$ is zero, matrix is singular (i.e. $\det A = 0$)

$A \cdot x = b$ unsolvable

Theorem if LU decomposition exists, it is unique
 it exists if $\det A_{1 \dots j, 1 \dots j} \neq 0$ for all j

Complex matrices

LU works with complex arithmetic
 for pivoting take abs. value

$$\underline{(A + iC)} \underline{(x + iy)} = \underline{b + id}$$

$$\begin{pmatrix} \underline{A} & \underline{-C} \\ \underline{C} & \underline{A} \end{pmatrix} \begin{pmatrix} \underline{x} \\ \underline{y} \end{pmatrix} = \begin{pmatrix} \underline{b} \\ \underline{d} \end{pmatrix}$$

real matrix of double size

$$\underline{H} = \underline{A} + i\underline{C} \quad \text{if } \underline{H} \text{ is hermitic, } \underline{M} = \begin{pmatrix} \underline{A} & \underline{-C} \\ \underline{C} & \underline{A} \end{pmatrix} \text{ is symmetric}$$

$$\underline{A}^T - i\underline{C}^T = \underline{A} + i\underline{C} \Rightarrow \underline{A} = \underline{A}^T \quad \underline{C}^T = -\underline{C}$$

Special cases

if $\underline{A} = \underline{A}^T$

$$LU = U^T L^T \quad \text{if all } u_{ii} = 1 \Rightarrow U = L^T$$

generally this isn't true

$$D = \text{diag}(u_{11}, u_{22}, \dots, u_{nn})$$

$$U = D \cdot \tilde{U} \quad \tilde{u}_{ij} = \frac{u_{ij}}{u_{ii}} \quad \text{for } j > i$$

$$\tilde{u}_{ii} = 1$$

$$A = L D \tilde{U} \quad \tilde{U}^T D^T L^T = A = L U$$

~~uniquely~~ uniqueness of LU $\Rightarrow \tilde{U}^T = L \quad A = L D L^T$

$$L D^T L^T = A = A^T = L^T D L = L D \tilde{U} = L D L^T$$

$$\Rightarrow D = D^T \quad u_{ii} \in \mathbb{R}$$

$\underline{A} = \underline{A}^T$ and positive definit

positive definit $\Leftrightarrow \underline{v}^T \underline{A} \underline{v} > 0$ for all $\underline{v} \neq 0$

$A = LDL^T$ D has real elements u_{ii}

$$\underline{v}^T \underline{A} \underline{v} = \underline{v}^T \underline{L} \underline{D} \underline{L}^T \underline{v} = \underline{w}^T \underline{D} \underline{w} > 0 \quad \underline{w} = \underline{L}^T \underline{v}$$

$$\det L^T = 1 \Rightarrow L^{T^{-1}} \text{ exists}$$

$$\Rightarrow \forall \underline{w} \quad (\underline{L}^T)^{-1} \underline{w} = \underline{v} \neq 0 \text{ exists}$$

$$\underline{w}^T \underline{D} \underline{w} > 0 \text{ for all } \underline{w} \neq 0$$

$\Rightarrow D$ is positive definit : $u_{ii} > 0$ for all i

$$D = P \cdot P \quad \text{with } P = \text{diag}(\sqrt{u_{11}}, \dots, \sqrt{u_{nn}})$$

$$\underline{A} = \underline{L} P \cdot P \cdot \underline{L}^T = \underline{L} \cdot P (\underline{L} \cdot P)^T = \underline{T} \cdot \underline{T}^T$$

with $\underline{T} = \underline{L} \cdot P$

This is called the Cholesky decomposition

Tri-diagonal matrices

LU - no pivot

$$\begin{pmatrix} b_1 & c_1 & & & \\ a_2 & b_2 & c_2 & & \\ & a_3 & & \ddots & \\ & & & & c_{n-1} \\ & & & & a_n & b_n \end{pmatrix} =$$

$$u_1 = b_1$$

$$e_j = a_j / u_{j-1} \quad u_j = b_j - e_j c_{j-1}$$

Forward subs.

$$y_1 = r_1$$

$$y_j = r_j - e_j y_{j-1}$$

Backward subs.

$$x_n = \frac{y_n}{u_n} \quad x_j = \left(\frac{y_j - c_j x_{j+1}}{u_j} \right) u_j$$

Hilbert matrix $a_{ij} = \frac{1}{i+j-1}$

cond number $\sim \frac{(1+\sqrt{2})^{4n}}{\sqrt{n}}$