

NLA 2021-2022

Special linear systems

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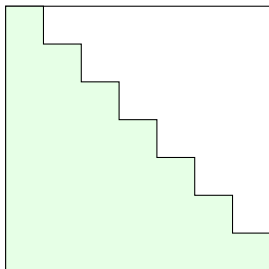
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Symmetric matrices

An $n \times n$ matrix A is *symmetric* if

$$A^T = A$$

A symmetric matrix needs *half the space* to store its entries



We should be able to solve a symmetric problem

$$Ax = b$$

with $\approx \frac{n^3}{3}$ flops instead of $\approx \frac{2n^3}{3}$

Pivoting destroys symmetry

$$\begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} a & b & c \\ b & d & e \\ c & e & f \end{bmatrix} = \begin{bmatrix} c & e & f \\ b & d & e \\ a & b & c \end{bmatrix}$$

\rightsquigarrow for a symmetric A , we just aim to compute the *LU factorization*

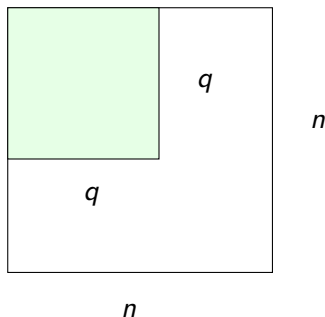
Matlab notation

For $p \leq q$ and $r \leq s$ set

$$A(p : q, r : s) = [a_{i,j}]_{p \leq i \leq q, r \leq j \leq s} \in \mathbb{R}^{(q-p+1) \times (s-r+1)}$$

For instance, the *leading $q \times q$ -principal submatrix* of A is

$$A(1 : q, 1 : q)$$



When does the LU factorization exist?

Let A be an arbitrary $n \times n$ matrix (not necessarily symmetric)

The following are equivalent (TFAE):

- 1 there are unique L unit lower triangular and U upper triangular such that $A = LU$
- 2 all leading principal submatrices of A are nonsingular

The LDLT factorization

When A is symmetric and has an LU factorization, the factors are connected:

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ \frac{c}{a} & 1 \end{bmatrix} \begin{bmatrix} a & 0 \\ 0 & d - \frac{bc}{a} \end{bmatrix} \begin{bmatrix} 1 & \frac{c}{a} \\ 0 & 1 \end{bmatrix}$$

In general symmetric case, set $d_i = u_{i,i}$ and write

$$U = D M$$

with $D = \text{diag}(d_1, \dots, d_n)$ and M unit upper triangular. Then

$$M = L^T$$

and so the LU factorization can be rewritten as

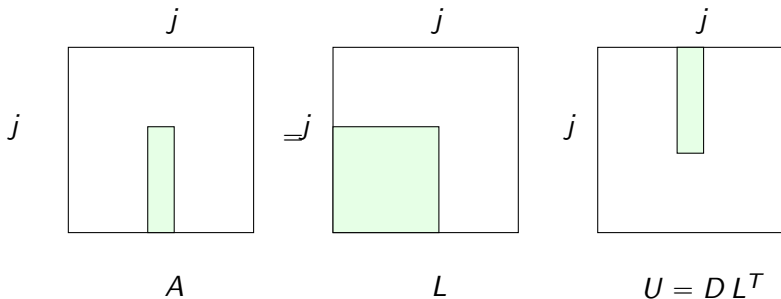
$$A = L D L^T$$

Computing the LDLT factorization

For $j = 1, \dots, n$ set $A(j : n, j) \leftarrow L(j : n, 1 : j) v(1 : j)$ with

$$v = \begin{bmatrix} d_1 l_{j,1} \\ \vdots \\ d_{j-1} l_{j,j-1} \\ d_j \end{bmatrix}$$

as in the figure



Computing the LDLT factorization (cont.)

Hence the equations

$$d_j = a_{j,j} - \sum_{k=1}^{j-1} d_k \ell_{j,k}^2$$

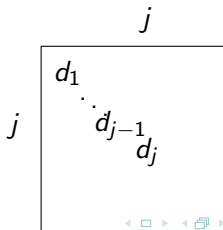
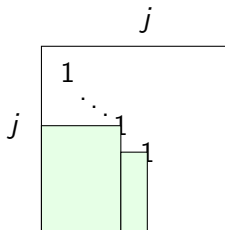
and

$$L(j+1:n, j) = \frac{1}{d_j} (A(j+1:n, j) - L(j+1:n, 1:j-1) v(1:j-1))$$

gives the j th diagonal entry and the j th column

$$d_j \quad \text{and} \quad L(j+1:n, j)$$

from the previous diagonal entries and the $(j-1)$ th column of L



The LDLT algorithm

for $j = 1, \dots, n$

 for $i = 1, \dots, j - 1$

$$v_i \leftarrow \ell_{j,i} d_i$$

 end

$$d_j \leftarrow a_{j,j} - L(j, 1 : j - 1) v(1 : j - 1)$$

$$L(j+1 : n, j) \leftarrow \frac{1}{d_j} (A(j+1 : n, j) - L(j+1, n : 1 : j - 1) v(1 : j - 1))$$

The modified LDLT algorithm

for $j = 1, \dots, n$

for $i = 1, \dots, j - 1$

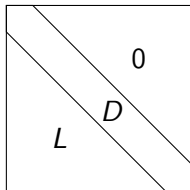
$$v_i \leftarrow \textcolor{red}{a}_{j,i} \textcolor{red}{a}_{i,i}$$

end

$$\textcolor{red}{a}_{j,j} \leftarrow a_{j,j} - \textcolor{red}{A}(j, 1 : j - 1) v(1 : j - 1)$$

$$\textcolor{red}{A}(j + 1 : n, j) \leftarrow \frac{1}{\textcolor{red}{a}_{i,i}} (A(j + 1 : n, j) - \textcolor{red}{A}(j + 1, n : 1 : j - 1) v(1 : j - 1))$$

\rightsquigarrow over-writing scheme



Example

Let

$$A = \begin{bmatrix} 1 & -1 & 2 \\ -1 & 5 & 2 \\ 2 & 2 & 17 \end{bmatrix}$$

For $j = 1$:

$$L = \begin{bmatrix} 1 & & \\ -1 & & \\ 2 & & \end{bmatrix} \quad \text{and} \quad D = \begin{bmatrix} 1 & & \\ & & \\ & & \end{bmatrix}$$

For $j = 2$:

$$[v] = -1, \quad L = \begin{bmatrix} & & \\ & & \\ & 1 & \end{bmatrix} \quad \text{and} \quad D = \begin{bmatrix} & & \\ & 4 & \\ & & \end{bmatrix}$$

coming from the operations

$$v_1 = (-1) \cdot 1 = -1, \quad d_2 = 5 - (-1) \cdot (-1) = 4, \quad \ell_{3,2} = \frac{1}{4}(2 - 2 \cdot (-1))$$

Example (cont.)

For $j = 3$:

$$v = \begin{bmatrix} 2 \\ 4 \end{bmatrix} \quad \text{and} \quad D = \begin{bmatrix} & \\ & 9 \end{bmatrix}$$

coming from

$$v_1 = 2 \cdot 1 = 1, \quad v_2 = 1 \cdot 4 = 4, \quad d_3 = 17 - (2 \cdot 2 + 1 \cdot 4) = 9$$

Hence

$$\begin{bmatrix} 1 & -1 & 2 \\ -1 & 5 & 2 \\ 2 & 2 & 17 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 9 \end{bmatrix} \begin{bmatrix} 1 & -1 & 2 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

In the machine:

$$A = \begin{bmatrix} 1 & -1 & 2 \\ -1 & 5 & 2 \\ 2 & 2 & 17 \end{bmatrix} \rightsquigarrow L \text{ \& } D = \begin{bmatrix} 1 & & \\ -1 & 4 & \\ 2 & 1 & 9 \end{bmatrix}$$

The LU factorization of a symmetric matrix can be numerically unstable:

$$A = \begin{bmatrix} \eta & 1 \\ 1 & 1 \end{bmatrix}$$

with $0 < \eta < \varepsilon$ (machine epsilon)

Symmetric positive definite systems

A symmetric A is *positive definite (SPD)* if for all $x \in \mathbb{R}^n \setminus \{0\}$

$$x^T A x > 0$$

Important fact from LA:

$$A \in \mathbb{R}^{n \times n} \text{ symmetric} \iff A = Q^T \Lambda Q$$

with Q orthogonal and Λ diagonal: A is diagonalizable over the reals through an orthogonal similarity, and

$$A \text{ is SPD} \iff \Lambda = \text{diag}(\lambda_1, \dots, \lambda_n) \text{ with } \lambda_i > 0$$

The Cholesky factorization

An SPD $n \times n$ matrix is nonsingular, and moreover all its leading principal submatrices are nonsingular

\leadsto there is unit lower triangular L and a diagonal D such that

$$A = L D L^T \quad (1)$$

We have that $d_i > 0$ for all i and so we can write (??) as

$$A = G G^T$$

with $G = L \cdot \text{diag}(\lambda_1^{1/2}, \dots, \lambda_n^{1/2})$ (*Cholesky factorization*)

Computing the Cholesky factorization

Note that

$$a_{i,j} = \sum_{k=0}^j g_{j,k} g_{i,k}$$

and so

$$g_{j,j} g_{i,j} = a_{i,j} - \sum_{k=1}^{j-1} g_{j,k} g_{i,k}$$

\rightsquigarrow we can compute the j -th column of G from the previous ones

The Cholesky algorithm

for $j = 1, \dots, n$

$$g_{j,j} \leftarrow (a_{j,j} - \sum_{k=1}^{j-1} g_{j,k}^2)^{1/2}$$

for $i = j + 1, \dots, n$

$$g_{i,j} \leftarrow \frac{1}{g_{j,j}} \left(a_{i,j} - \sum_{k=1}^{j-1} g_{i,k} g_{j,k} \right)$$

or alternatively:

for $j = 1, \dots, n$

$$a_{j,j} \leftarrow (a_{j,j} - \sum_{k=1}^{j-1} a_{j,k}^2)^{1/2}$$

for $i = j + 1, \dots, n$

$$a_{i,j} \leftarrow \frac{1}{g_{j,j}} \left(a_{i,j} - \sum_{k=1}^{j-1} a_{i,k} a_{j,k} \right)$$

Can be overwritten over A and does not need the auxiliary vector v

The example revisited

Consider again

$$A = \begin{bmatrix} 1 & -1 & 2 \\ -1 & 5 & 2 \\ 2 & 2 & 17 \end{bmatrix}$$

For $j = 1$:

$$G = \begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix}$$

and for $j = 2$:

$$G = \begin{bmatrix} 2 \\ 2 \end{bmatrix}$$

coming from the operations

$$g_{2,2} = (5 - (-1)^2)^{1/2} = 2 \quad \text{and} \quad g_{3,2} = \frac{1}{2}(2 - (-1) \cdot 2) = 2$$

The example revisited (cont.)

For $j = 3$:

$$G = \begin{bmatrix} & \\ & \\ & \\ 3 \end{bmatrix}$$

coming from $g_{3,3} = (17 - (2^2 + 2^2))^{1/2} = 3$

Hence

$$\begin{bmatrix} 1 & -1 & 2 \\ -1 & 1 & 1 \\ 2 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 2 & 0 \\ 2 & 2 & 3 \end{bmatrix} \begin{bmatrix} 1 & -1 & 2 \\ 0 & 2 & 2 \\ 0 & 0 & 3 \end{bmatrix}$$

In the machine

$$A = \begin{bmatrix} 1 & & \\ -1 & 1 & \\ 2 & 1 & 1 \end{bmatrix} \rightsquigarrow G = \begin{bmatrix} 1 & & \\ -1 & 2 & \\ 2 & 2 & 3 \end{bmatrix}$$

The complexity of this algorithm is

$$\begin{aligned}\sum_{j=1}^n \left(2j - 1 + \sum_{i=j+1}^n (2j - 1) \right) &= \sum_{j=1}^n (2j - 1) (n - j + 1) \\&= 2n \left(\sum_{j=1}^n j \right) - \sum_{j=1}^n j^2 + O(n^2) \\&= 2n \left(\frac{n^2}{2} + O(n) \right) - \frac{n^3}{3} + O(n^2) \\&= \frac{1}{3} n^3 + O(n^2)\end{aligned}$$

↪ half the complexity of the LU factorization

Numerical stability

Pivoting is not necessary for the Cholesky algorithm to be numerically stable: the same analysis of GEPP shows that the Cholesky solution \hat{x} satisfies $(A + \delta A) \hat{x} = b$ with

$$|\delta A| \leq 3 n \varepsilon |G| |G^T|$$

By the *Cauchy-Schwartz inequality*, for each i, j we have that

$$\begin{aligned} (|G| |G^T|)_{i,j} &\leq \sum_{k=1}^n |g_{i,k}| |g_{j,k}| \\ &\leq \left(\sum_{k=1}^n g_{i,k}^2 \right)^{1/2} \left(\sum_{k=1}^n g_{j,k}^2 \right)^{1/2} = a_{i,i}^{1/2} a_{j,j}^{1/2} \leq \max_{i,j} |a_{i,j}| \end{aligned}$$

Hence $\| |G| |G^T| \|_{\infty} \leq n \|A\|_{\infty}$ and so

$$\|\delta A\|_{\infty} \leq 3 n^2 \varepsilon \|A\|_{\infty}$$

\leadsto Cholesky algorithm is backward stable



Is my A an SPD matrix?

Cholesky is the cheapest way of testing is a given symmetric $n \times n$ matrix is definite positive:

it will be the case if and only if the algorithm concludes!