Dense LU factorization and its error analysis

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Basis of floating point arithmetic and stability analysis

Notation, results, proofs taken from [N.J.Higham, 2002]

Direct methods of factorization

LU factorization Error analysis of LU factorization - main results Block LU factorization

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Direct methods of factorization

Norms and other notations

$$\|A\|_{F} = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} |a_{ij}|^{2}} \\ \|A\|_{2} = \sigma_{max}(A) \\ \|A\|_{\infty} = \max_{1 \le i \le n} \sum_{j=1}^{n} |a_{ij}| \\ \|A\|_{1} = \max_{1 \le j \le n} \sum_{i=1}^{n} |a_{ij}|$$

Inequalities $|x| \le |y|$ and $|A| \le |B|$ hold componentwise.

- The machine precision or unit roundoff is *u*
 - □ The maximum relative error for a given rounding procedure
 - u is of order 10^{-8} in single precision, $2^{-53} \approx 10^{-16}$ in double precision
 - □ Another definition: the smallest number that added to one gives a result different from one
- The evaluation involving basic arithmetic operations +, -, *, / in floating point satisfies

$$fl(x \text{ op } y) = (x \text{ op } y)(1 + \delta), \quad |\delta| \leq u$$

Relative error

 Given a real number x and its approximation x̂, the absolute error and the relative errors are

$$E_{abs}(\hat{x}) = |x - \hat{x}|, \quad E_{rel}(\hat{x}) = \frac{|x - \hat{x}|}{|x|}$$
 (1)

- The relative error is scale independent
- Some examples, outline the difference with correct significant digits
 - $\begin{array}{rcl} x & = & 1.00000, & \hat{x} = 1.00499, & E_{rel}(\hat{x}) = 4.99 \times 10^{-3} \\ x & = & 9.00000, & \hat{x} = 8.99899, & E_{rel}(\hat{x}) = 1.12 \times 10^{-4} \end{array}$

When x is a vector, the componentwise relative error is

$$\max_i \frac{|x_i - \hat{x}_i|}{|x_i|}$$

Backward and Forward errors

- Consider y = f(x) a scalar function of a real scalar variable and \hat{y} its approximation.
- Ideally we would like the forward error $E_{rel}(\hat{y}) \approx u$
- Instead we focus on the backward error, "For what set of data we have solved the problem?"

that is we look for min $|\Delta x|$ such that $\hat{y} = f(x + \Delta x)$



Condition number

Assume f is twice continuously differentiable, then

$$\hat{y} - y = f(x + \Delta x) - f(x) = f'(x)\Delta x + \frac{f''(x + \tau\Delta x)}{2!}(\Delta x)^2, \quad \tau \in (0,1)$$

$$\frac{\hat{y} - y}{y} = \left(\frac{xf'(x)}{f(x)}\right)\frac{\Delta x}{x} + O((\Delta x)^2)$$

The condition number is

$$c(x) = \left| \frac{xf'(x)}{f(x)} \right|$$

Rule of thumb

When consistently defined, we have

forward error \leq condition number \times backward error

Lemma (Lemma 3.1 in [N.J.Higham, 2002]) If $|\delta_i| \leq u$ and $\rho_i = \pm 1$ for i = 1 : n, and nu < 1, then

$$\prod_{i=1}^{n} (1+\delta_i)^{\rho_i} = 1 + \Theta_n, \quad |\Theta_n| \le \frac{nu}{1-nu} = \gamma_n$$

Other notations

$$\tilde{\gamma_n} = \frac{cnu}{1 - cnu}$$

Inner product in floating point arithmetic

Consider computing $s_n = x^T y$, with an evaluation from left to right. We denote different errors as $1 + \delta_i \equiv 1 \pm \delta$

$$\begin{aligned} \hat{s}_{1} &= fl(x_{1}y_{1}) = x_{1}y_{1}(1 \pm \delta) \\ \hat{s}_{2} &= fl(\hat{s}_{1} + x_{2}y_{2}) = (\hat{s}_{1} + x_{2}y_{2}(1 \pm \delta))(1 \pm \delta) \\ &= x_{1}y_{1}(1 \pm \delta)^{2} + x_{2}y_{2}(1 \pm \delta)^{2} \\ &\vdots \\ \hat{s}_{n} &= x_{1}y_{1}(1 \pm \delta)^{n} + x_{2}y_{2}(1 \pm \delta)^{n} + x_{3}y_{3}(1 \pm \delta)^{n-1} + \ldots + x_{n}y_{n}(1 \pm \delta)^{2} \end{aligned}$$

After applying the previous lemma, we obtain

$$\hat{s}_n = x_1 y_1 (1 + \Theta_n) + x_2 y_2 (1 + \Theta'_n) + \ldots + x_n y_n (1 + \Theta_2)$$

We obtain the following backward and forward errors

$$\begin{aligned} \hat{s}_n &= x_1 y_1 (1 + \Theta_n) + x_2 y_2 (1 + \Theta'_n) + \ldots + x_n y_n (1 + \Theta_2) \\ fl(x^T y) &= (x + \Delta x)^T y = x^T (y + \Delta y), |\Delta x| \le \gamma_n |x|, |\Delta y| \le \gamma_n |y|, \\ |x^T y - fl(x^T y)| &\le \gamma_n \sum_{i=1}^n |x_i y_i| = \gamma_n |x|^T |y| \end{aligned}$$

- High relative accuracy is obtained when computing x^Tx
- No guarantee of high accuracy when $|x^T y| \ll |x|^T |y|$

Basis of floating point arithmetic and stability analysis

Direct methods of factorization

LU factorization Block LU factorization

Algebra of the LU factorization

LU factorization Compute the factorization PA = LU

Example

Given the matrix

$$A = \begin{pmatrix} 3 & 1 & 3 \\ 6 & 7 & 3 \\ 9 & 12 & 3 \end{pmatrix}$$

Let

$$M_1 = egin{pmatrix} 1 & & \ -2 & 1 & \ -3 & & 1 \end{pmatrix}, \quad M_1 A = egin{pmatrix} 3 & 1 & 3 \ 0 & 5 & -3 \ 0 & 9 & -6 \end{pmatrix}$$

Algebra of the LU factorization

In general

$$A^{(k+1)} = M_k A^{(k)} := \begin{pmatrix} I_{k-1} & & & \\ & 1 & & \\ & -m_{k+1,k} & 1 & & \\ & \dots & \ddots & \\ & -m_{n,k} & & 1 \end{pmatrix} A^{(k)}, \text{ where}$$
$$M_k = I - m_k e_k^T, \quad M_k^{-1} = I + m_k e_k^T$$

where e_k is the k-th unit vector, $e_i^T m_k = 0, \forall i \le k$ The factorization can be written as

$$M_{n-1}\ldots M_1A=A^{(n)}=U$$

Algebra of the LU factorization

We obtain

$$A = M_1^{-1} \dots M_{n-1}^{-1} U$$

= $(I + m_1 e_1^T) \dots (I + m_{n-1} e_{n-1}^T) U$
= $\left(I + \sum_{i=1}^{n-1} m_i e_i^T\right) U$
= $\begin{pmatrix} 1 \\ m_{21} & 1 \\ \vdots & \vdots & \ddots \\ m_{n1} & m_{n2} & \dots & 1 \end{pmatrix} U = LU$

The need for pivoting

- For stability, avoid division by small diagonal elements
- For example

$$A = \begin{pmatrix} 0 & 3 & 3 \\ 3 & 1 & 3 \\ 6 & 2 & 3 \end{pmatrix}$$
(2)

has an LU factorization if we permute the rows of matrix A

$$PA = \begin{pmatrix} 6 & 2 & 3 \\ 0 & 3 & 3 \\ 3 & 1 & 3 \end{pmatrix} = \begin{pmatrix} 1 & & \\ & 1 & \\ 0.5 & & 1 \end{pmatrix} \cdot \begin{pmatrix} 6 & 2 & 3 \\ & 3 & 3 \\ & & 1.5 \end{pmatrix}$$
(3)

Partial pivoting allows to bound the multipliers $m_{ik} \leq 1$ and hence $|L| \leq 1$

Theorem

Given a full rank matrix A of size $m \times n$, $m \ge n$, the matrix A can be decomposed as A = PLU where P is a permutation matrix of size $m \times m$, L is a unit lower triangular matrix of size $m \times n$ and U is a nonsingular upper triangular matrix of size $n \times n$.

Proof: simpler proof for the square case. Since A is full rank, there is a permutation P_1 such that P_1a_{11} is nonzero. Write the factorization as

$$P_1 A = \begin{pmatrix} a_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ A_{21}/a_{11} & I \end{pmatrix} \begin{pmatrix} a_{11} & A_{12} \\ 0 & A_{22} - a_{11}^{-1}A_{21}A_{12} \end{pmatrix},$$

where $S = A_{22} - a_{11}^{-1}A_{21}A_{12}$. Since $det(A) \neq 0$, then $det(S) \neq 0$. Continue the proof by induction on *S*. Composed of 4 steps

- 1. Factor A = PLU, $(2/3)n^3$ flops
- 2. Compute $P^T b$ to solve $LUx = P^T b$
- 3. Forward substitution: solve $Ly = P^T * b$, n^2 flops
- 4. Backward substitution: solve Ux = y, n^2 flops

Algorithm to compute the LU factorization

- Algorithm for computing the in place LU factorization of a matrix of size $n \times n$.
- $\# flops = 2n^3/3$
- 1: for k = 1:n-1 do Let a_{ik} be the element of maximum magnitude in A(k:n,k)2: Permute row *i* and row *k* 3: $A(k+1:n,k) = A(k+1:n,k)/a_{kk}$ 4: for i = k + 1 : n do 5: 6: for i = k + 1 : n do 7: $a_{ii} = a_{ii} - a_{ik}a_{ki}$ end for 8: end for g٠
- 10: end for

Algorithm to compute the LU factorization

• Left looking approach, pivoting ignored, A of size $m \times n$ • $\#flops = n^2m - n^3/3$ 1: for k = 1:n do 2: for j = k:n do 3: $u_{kj} = a_{kj} - \sum_{i=1}^{k-1} l_{ki}u_{ij}$ 4: end for 5: for i = k+1:m do 6: $l_{ik} = (a_{ik} - \sum_{j=1}^{k-1} l_{ij}u_{jk})/u_{kk}$ 7: end for 8: end for

Error analysis of the LU factorization

Given the first k-1 columns of L and k-1 rows of U were computed, we have

$$a_{kj} = l_{k1}u_{1j} + \ldots + l_{k,k-1}u_{k-1,j} + u_{kj}, j = k : n$$

$$a_{ik} = l_{i1}u_{1k} + \ldots + l_{ik}u_{kk}, i = k + 1 : m$$

The computed elements of \hat{L} and \hat{U} satisfy:

$$\begin{vmatrix} a_{kj} - \sum_{i=1}^{k-1} \hat{l}_{ki} \hat{u}_{ij} - \hat{u}_{kj} \end{vmatrix} \leq \gamma_k \sum_{i=1}^k |\hat{l}_{ki}| |\hat{u}_{ij}|, \quad j \ge k, \\ \begin{vmatrix} a_{ik} - \sum_{j=1}^k \hat{l}_{ij} \hat{u}_{jk} \end{vmatrix} \leq \gamma_k \sum_{j=1}^k |\hat{l}_{ij}| |\hat{u}_{jk}|, \quad i > k. \end{vmatrix}$$

Theorem (Theorem 9.3 in [N.J.Higham, 2002]) Let $A \in \mathbb{R}^{m \times n}$, $m \ge n$ and let $\hat{L} \in \mathbb{R}^{m \times n}$ and $\hat{U} \in \mathbb{R}^{n \times n}$ be its computed LU factors obtained by Gaussian elimination (suppose there was no failure during GE). Then,

$$\hat{L}\hat{U} = A + \Delta A, \qquad |\Delta A| \le \gamma_n |\hat{L}||\hat{U}|.$$

Theorem (Theorem 9.4 in [N.J.Higham, 2002])

Let $A \in \mathbb{R}^{m \times n}$, $m \ge n$ and let \hat{x} be the computed solution to Ax = b obtained by using the computed LU factors of A obtained by Gaussian elimination. Then

$$(A + \Delta A)\hat{x} = b, \qquad |\Delta A| \leq \gamma_{3n}|\hat{L}||\hat{U}|.$$

Error analysis of Ax = b

Theorem (Theorem 9.4 in [N.J.Higham, 2002] continued)

$$(A + \Delta A)\hat{x} = b, \qquad |\Delta A| \leq \gamma_{3n}|\hat{L}||\hat{U}|.$$

Proof.

We have the following:

$$\begin{split} \hat{L}\hat{U} &= A + \Delta A, \qquad |\Delta A| \leq \gamma_n |\hat{L}||\hat{U}|, \\ (\hat{L} + \Delta L)\hat{y} &= b, \qquad |\Delta L| \leq \gamma_n |\hat{L}|, \\ (\hat{U} + \Delta U)\hat{x} &= \hat{y}, \qquad |\Delta U| \leq \gamma_n |\hat{U}|. \end{split}$$

Thus

$$b = (\hat{L} + \Delta L)(\hat{U} + \Delta U)\hat{x} = (A + \Delta A_1 + \hat{L}\Delta U + \Delta L\hat{U} + \Delta L\Delta U)\hat{x}$$

= $(A + \Delta A)\hat{x}$, where
 $|\Delta A| \leq (3\gamma_n + \gamma_n^2)|\hat{L}||\hat{U}| \leq \gamma_{3n}|\hat{L}||\hat{U}|.$

Wilkinson's backward error stability result

Growth factor g_W defined as

$$g_W = rac{\max_{i,j,k} |a_{ij}^k|}{\max_{i,j} |a_{ij}|}$$

Note that

$$|u_{ij}| = |a_{ij}^i| \le g_W \max_{i,j} |a_{ij}|$$

Theorem (Wilkinson's backward error stability result, see also [N.J.Higham, 2002] for more details) Let $A \in \mathbb{R}^{n \times n}$ and let \hat{x} be the computed solution of Ax = b obtained by using GEPP. Then

$$(A + \Delta A)\hat{x} = b, \qquad \|\Delta A\|_{\infty} \leq n^2 \gamma_{3n} g_W(n) \|A\|_{\infty}.$$

The growth factor

- The LU factorization is backward stable if the growth factor is small (grows linearly with n).
- For partial pivoting, the growth factor g(n) ≤ 2ⁿ⁻¹, and this bound is attainable.
- In practice it is on the order of $n^{2/3} n^{1/2}$

Exponential growth factor for Wilkinson matrix

$$A = diag(\pm 1) \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 1 \\ -1 & 1 & 0 & \dots & 0 & 1 \\ -1 & -1 & 1 & \ddots & \vdots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 & 1 \\ -1 & -1 & \cdots & -1 & 1 & 1 \\ -1 & -1 & \cdots & -1 & -1 & 1 \end{bmatrix}$$

Several error bounds for GEPP, the normwise backward error η and the componentwise backward error w (r = b - Ax).

$$\eta = \frac{||r||_1}{||A||_1 ||x||_1 + ||b||_1},$$

$$w = \max_i \frac{|r_i|}{(|A| |x| + |b|)_i}.$$

matrix	cond(A,2)	gW	L 1	cond(U,1)	$\frac{ PA-LU _{F}}{ A _{F}}$	η	wb
hadamard	1.0E+0	4.1E+3	4.1E+3	5.3E+5	0.0E+0	3.3E-16	4.6E-15
randsvd	6.7E+7	4.7E+0	9.9E+2	1.4E+10	5.6E-15	3.4E-16	2.0E-15
chebvand	3.8E+19	2.0E+2	2.2E+3	4.8E+22	5.1E-14	3.3E-17	2.6E-16
frank	1.7E+20	1.0E+0	2.0E+0	1.9E+30	2.2E-18	4.9E-27	1.2E-23
hilb	8.0E+21	1.0E+0	3.1E+3	2.2E+22	2.2E-16	5.5E-19	2.0E-17

Partitioning of matrix A of size $n \times n$

$$A = \left[\begin{array}{cc} A_{11} & A_{12} \\ A_{21} & A_{22} \end{array} \right]$$

where A_{11} is of size $b \times b$, A_{21} is of size $(m - b) \times b$, A_{12} is of size $b \times (n - b)$ and A_{22} is of size $(m - b) \times (n - b)$.

Block LU algebra

The first iteration computes the factorization:

$$P_1^{\mathsf{T}} A = \left[\begin{array}{cc} L_{11} \\ L_{21} & I_{n-b} \end{array} \right] \cdot \left[\begin{array}{cc} I_b \\ A^1 \end{array} \right] \cdot \left[\begin{array}{cc} U_{11} & U_{12} \\ I_{n-b} \end{array} \right]$$

The algorithm continues recursively on the trailing matrix A^1 .

Block LU factorization - the algorithm

1. Compute the LU factorization with partial pivoting of the first block column

$$\mathsf{P}_1 \begin{pmatrix} \mathsf{A}_{11} \\ \mathsf{A}_{21} \end{pmatrix} = \begin{pmatrix} \mathsf{L}_{11} \\ \mathsf{L}_{21} \end{pmatrix} U_{11}$$

2. Pivot by applying the permutation matrix P_1^T on the entire matrix,

$$\bar{A} = P_1^T A$$

3. Solve the triangular system

$$L_{11}U_{12} = \bar{A}_{12}$$

4. Update the trailing matrix,

$$A^1 = \bar{A}_{22} - L_{21}U_{12}$$

5. Compute recursively the block LU factorization of A^1 .

LU Factorization as in ScaLAPACK

LU factorization on a $P = Pr \times Pc$ grid of processors For ib = 1 to n-1 step b

A(ib) = A(ib : n, ib : n)

- 1. Compute panel factorization
 - □ find pivot in each column, swap rows
- 2. Apply all row permutations
 - broadcast pivot information along the rows
 - swap rows at left and right
- 3. Compute block row of U
 - broadcast right diagonal block of L of current panel
- 4. Update trailing matrix
 - broadcast right block column of L
 - broadcast down block row of U









Cost of LU Factorization in ScaLAPACK

LU factorization on a P = Pr x Pc grid of processors For ib = 1 to n-1 step b A(ib) = A(ib : n, ib : n)1. Compute panel factorization \Box #messages = $O(n \log_2 P_r)$ 2. Apply all row permutations \Box #messages = $O(n/b(\log_2 P_r + \log_2 P_c))$ 3. Compute block row of U \Box #messages = $O(n/b \log_2 P_c)$

- $= \# messages = O(n/b \log_2 n)$
- 4. Update trailing matrix

$$= \#messages = O(n/b(\log_2 P_r + \log_2 P_c))$$









Consider that we have a $\sqrt{P} \times \sqrt{P}$ grid, block size b

$$\gamma \cdot \left(\frac{2/3n^3}{P} + \frac{n^2b}{\sqrt{P}}\right) + \beta \cdot \frac{n^2 \log P}{\sqrt{P}} + \alpha \cdot \left(1.5n \log P + \frac{3.5n}{b} \log P\right).$$

- Stability analysis results presented from [N.J.Higham, 2002]
- Some of the examples taken from [Golub and Van Loan, 1996]

References (1)

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