

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

Plan

Basis of floating point arithmetic and stability analysis

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

Direct methods of factorization

Norms and other notations

$$\|A\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^n |a_{ij}|^2}$$

$$\|A\|_2 = \sigma_{\max}(A)$$

$$\|A\|_\infty = \max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|$$

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

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

Floating point arithmetic

- 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 \hat{x} , the absolute error and the relative errors are

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

- The relative error is scale independent
- Some examples, outline the difference with correct significant digits

$$x = 1.00000, \quad \hat{x} = 1.00499, \quad E_{rel}(\hat{x}) = 4.99 \times 10^{-3}$$

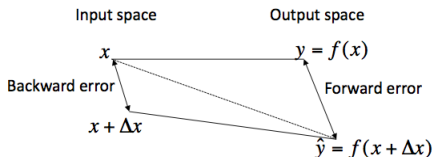
$$x = 9.00000, \quad \hat{x} = 8.99899, \quad E_{rel}(\hat{x}) = 1.12 \times 10^{-4}$$

- 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

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

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 $1 + \delta_i \equiv 1 \pm \delta$

$$\hat{s}_1 = fl(x_1 y_1) = x_1 y_1 (1 \pm \delta)$$

$$\begin{aligned}\hat{s}_2 &= fl(\hat{s}_1 + x_2 y_2) = (\hat{s}_1 + x_2 y_2 (1 \pm \delta))(1 \pm \delta) \\ &= x_1 y_1 (1 \pm \delta)^2 + x_2 y_2 (1 \pm \delta)^2\end{aligned}$$

\vdots

$$\hat{s}_n = x_1 y_1 (1 \pm \delta)^n + x_2 y_2 (1 \pm \delta)^n + x_3 y_3 (1 \pm \delta)^{n-1} + \dots + x_n y_n (1 \pm \delta)^2$$

After applying the previous lemma, we obtain

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

Inner product in FP arithmetic - error bounds

We obtain the following backward and forward errors

$$\begin{aligned}\hat{s}_n &= x_1y_1(1 + \Theta_n) + x_2y_2(1 + \Theta'_n) + \dots + x_ny_n(1 + \Theta_2) \\ fl(x^T y) &= (x + \Delta x)^T y = x^T (y + \Delta y), |\Delta x| \leq \gamma_n |x|, |\Delta y| \leq \gamma_n |y|, \\ |x^T y - fl(x^T y)| &\leq \gamma_n \sum_{i=1}^n |x_i y_i| = \gamma_n |x|^T |y|\end{aligned}$$

- High relative accuracy is obtained when computing $x^T x$
- 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

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

Algebra of the LU factorization

- We obtain

$$\begin{aligned} A &= M_1^{-1} \dots M_{n-1}^{-1} U \\ &= (I + m_1 e_1^T) \dots (I + m_{n-1} e_{n-1}^T) U \\ &= \left(I + \sum_{i=1}^{n-1} m_i e_i^T \right) U \\ &= \begin{pmatrix} 1 & & & \\ m_{21} & 1 & & \\ \vdots & \vdots & \ddots & \\ m_{n1} & m_{n2} & \dots & 1 \end{pmatrix} U = LU \end{aligned}$$

The need for pivoting

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

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

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

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

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

Existence of the LU factorization

Theorem

Given a full rank matrix A of size $m \times n$, $m \geq n$, 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 $P_1 a_{11}$ 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 .

Solving $Ax = b$ by using Gaussian elimination

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**
 - 2: Let a_{ik} be the element of maximum magnitude in $A(k : n, k)$
 - 3: Permute row i and row k
 - 4: $A(k + 1 : n, k) = A(k + 1 : n, k)/a_{kk}$
 - 5: **for** $i = k + 1 : n$ **do**
 - 6: **for** $j = k + 1 : n$ **do**
 - 7: $a_{ij} = a_{ij} - a_{ik}a_{kj}$
 - 8: **end for**
 - 9: **end for**
 - 10: **end for**

Algorithm to compute the LU factorization

- Left looking approach, pivoting ignored, A of size $m \times n$

- $\#flops = n^2 m - n^3 / 3$

```
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

$$\begin{aligned}a_{kj} &= l_{k1}u_{1j} + \dots + l_{k,k-1}u_{k-1,j} + u_{kj}, j = k : n \\a_{ik} &= l_{i1}u_{1k} + \dots + l_{ik}u_{kk}, i = k + 1 : m\end{aligned}$$

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

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

Error analysis of the LU factorization (continued)

Theorem (Theorem 9.3 in [N.J.Higham, 2002])

Let $A \in \mathbb{R}^{m \times n}$, $m \geq n$ 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,

$$\hat{L}\hat{U} = A + \Delta A, \quad |\Delta A| \leq \gamma_n |\hat{L}| |\hat{U}|.$$

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

Let $A \in \mathbb{R}^{m \times n}$, $m \geq n$ 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

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

Error analysis of $Ax = b$

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

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

Proof.

We have the following:

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

Thus

$$\begin{aligned}b &= (\hat{L} + \Delta L)(\hat{U} + \Delta U)\hat{x} = (A + \Delta A_1 + \hat{L}\Delta U + \Delta L\hat{U} + \Delta L\Delta U)\hat{x} \\ &= (A + \Delta A)\hat{x}, \text{ where} \\ |\Delta A| &\leq (3\gamma_n + \gamma_n^2)|\hat{L}||\hat{U}| \leq \gamma_{3n}|\hat{L}||\hat{U}|.\end{aligned}$$



Wilkinson's backward error stability result

Growth factor g_W defined as

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

Note that

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

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

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

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 $g(n) \leq 2^{n-1}$, 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

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

Experimental results for special matrices

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	w_b
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

Block formulation of the LU factorization

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

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

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:

$$P_1^T A = \begin{bmatrix} L_{11} & \\ L_{21} & I_{n-b} \end{bmatrix} \cdot \begin{bmatrix} I_b & \\ & A^1 \end{bmatrix} \cdot \begin{bmatrix} U_{11} & U_{12} \\ & I_{n-b} \end{bmatrix}$$

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

$$P_1 \begin{pmatrix} A_{11} \\ A_{21} \end{pmatrix} = \begin{pmatrix} L_{11} \\ L_{21} \end{pmatrix} U_{11}$$

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 .

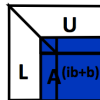
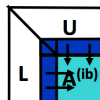
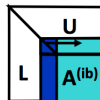
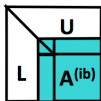
LU Factorization as in ScaLAPACK

LU factorization on a $P = P_r \times P_c$ 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



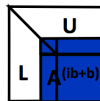
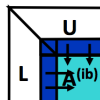
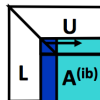
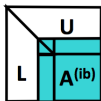
Cost of LU Factorization in ScaLAPACK

LU factorization on a $P = P_r \times P_c$ grid of processors

For $ib = 1$ to $n-1$ step b

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

1. Compute panel factorization
 - $\#messages = O(n \log_2 P_r)$
2. Apply all row permutations
 - $\#messages = O(n/b(\log_2 P_r + \log_2 P_c))$
3. Compute block row of U
 - $\#messages = O(n/b \log_2 P_c)$
4. Update trailing matrix
 - $\#messages = O(n/b(\log_2 P_r + \log_2 P_c))$



Cost of parallel block LU




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

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

Acknowledgement

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

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