MA5233 Computational Mathematics

Lecture 3: LU Factorisation

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LU factorisation

Algorithm of choice for solving dense linear systems.

Outline

- ▶ LU factorisation: why and how.
- ▶ lu() in Julia.
- ► Computational complexity of LU factorisation.
- ► Conditioning and stability of LU factorisation.

Linear system of equations

Given $A \in \mathbb{K}^{n \times n}$ and $b \in \mathbb{K}^n$, find $x \in \mathbb{K}^n$ such that Ax = b.

Observation

Problem is easy if A is triangular, i.e.

$$A(i,j) = 0$$
 for $\begin{cases} i > j \text{ (upper triangular)}, \\ i < j \text{ (lower triangular)}. \end{cases}$

$$\begin{pmatrix} 4 & 1 & -2 \\ 0 & 2 & -1 \\ 0 & 0 & 3 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} 3 \\ 4 \\ 6 \end{pmatrix}$$

Third eq.:
$$3x_3 = 6 \implies x_3 = 2$$

Second eq.: $2x_2 - x_3 = 4 \implies x_2 = 3$
First eq.: $4x_1 + x_2 - 2x_3 = 3 \implies x_1 = 1$

LU factorisation theorem

For every invertible matrix $A \in \mathbb{K}^{n \times n}$, there exist

- ▶ a permutation matrix $P \in \mathbb{K}^{n \times n}$,
- ightharpoonup a lower-triangular matrix $L \in \mathbb{K}^{n \times n}$ with unit diagonal, and
- ▶ an upper-triangular matrix $U \in \mathbb{K}^{n \times n}$

such that PA = LU.

L, U are unique for fixed P.

Why is there a P in this theorem?

Because of cases like this one:

$$\begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix}$$

$$\begin{pmatrix} 4 & 1 & -2 \\ -8 & 0 & 3 \\ 12 & 7 & -5 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 3 & 0 & 1 \end{pmatrix} \begin{pmatrix} 4 & 1 & -2 \\ 0 & 2 & -1 \\ 0 & 4 & 1 \end{pmatrix}$$
$$= \begin{pmatrix} 1 & 0 & 0 \\ -2 & 1 & 0 \\ 3 & 2 & 1 \end{pmatrix} \begin{pmatrix} 4 & 1 & -2 \\ 0 & 2 & -1 \\ 0 & 0 & 3 \end{pmatrix}$$

Column/partial pivoting

Use row with largest entry in first column to eliminate the other rows.

$$\begin{pmatrix} 4 & 1 & -2 \\ -8 & 0 & 3 \\ 12 & 7 & -5 \end{pmatrix} \rightarrow \begin{pmatrix} 12 & 7 & -5 \\ -8 & 0 & 3 \\ 4 & 1 & -2 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ -\frac{2}{3} & 1 & 0 \\ \frac{1}{3} & 0 & 1 \end{pmatrix} \begin{pmatrix} 12 & 7 & -5 \\ 0 & x & x \\ 0 & x & x \end{pmatrix}$$

Complete pivoting

Use largest overall entry (i, j) to eliminate the other entries in column j.

$$\begin{pmatrix} 1 & 4 & -2 \\ 0 & -8 & 3 \\ 7 & 12 & -5 \end{pmatrix} \rightarrow \begin{pmatrix} 12 & 7 & -5 \\ -8 & 0 & 3 \\ 4 & 1 & -2 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ -\frac{2}{3} & 1 & 0 \\ \frac{1}{3} & 0 & 1 \end{pmatrix} \begin{pmatrix} 12 & 7 & -5 \\ 0 & x & x \\ 0 & x & x \end{pmatrix}$$

Permutations

Bijective map $\pi: \{1, \ldots, n\} \rightarrow \{1, \ldots, n\}$.

Example

$$\pi(1) = 2,$$
 $\pi(2) = 4,$ $\pi(3) = 3,$ $\pi(4) = 1$

Representations

$$P = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \qquad \text{or} \qquad p = \begin{pmatrix} 2 & 4 & 3 & 1 \end{pmatrix}^T$$

Remarks on permutations

- ► PA permutes rows of A.
- ► Matrix representation is convenient, but very inefficient. Never use permutation matrices in your code!
- Applying permutation p in Julia:
 data = ["a","b","c","d"]
 p = [2,4,3,1]
 data[p] -> ["b","d","c","a"]
- ► Permutations are by definition bidirectional.

 Be careful which direction you represent in your code!

Solving Ax = b via LU factorisation

- ▶ Compute LU factorisation PA = LU.
- Permute the RHS: $\hat{b} = Pb$.
- ► Solve $y = L^{-1}\hat{b}$.
- ► Solve $x = U^{-1}y$.

Solving Ax = b in Julia

F = lu(A, pivot=Val(true)) computes "factorisation object".

- ► Access factors through F.L, F.U, F.p (vector) and F.P (matrix).
- ► F.L * F.U == A[F.p, :] == F.P * A.
- \triangleright x = F\b computes solution.
- ► A\b solves A*x = b directly.

Measuring the "required effort" of an algorithm Some ideas:

- Count the number of +,-,x,/,sqrt.
 Very tedious, and makes it hard to compare algorithms.
- Measure its runtime.
 Too dependent on input, hardware, etc.

Most common measure: big- \mathcal{O} estimate.

Examples

- Evaluating $x^T y := \sum_{k=1}^n x_i y_i$ takes
 - n multiplications, and
 - \triangleright n-1 additions.

Computing inner products takes O(n) floating-point operations.

▶ Ax for $A \in \mathbb{K}^{n \times n}$ can be computed as n inner products. Evaluating matvec takes $\mathcal{O}(n^2)$ floating-point operations.

Why is big- \mathcal{O} notation useful?

It tells us the functional dependency of runtime on problem size.

$$\mathcal{O}(n)$$
 algorithm \implies Changing $n \to 2n$ multiplies runtime by 2.

$$\mathcal{O}(n^2)$$
 algorithm \implies Changing $n \to 2n$ multiplies runtime by 4.

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Computational cost of LU factorisation

- ▶ Factorisation: $\mathcal{O}(n^3)$.
- ▶ Triangular solves: $\mathcal{O}(n^2)$.

Hence, reuse factorisation if possible.

Conditioning of linear systems

Assume

- ightharpoonup Ax = b, and
- $(A + \Delta A)(x + \Delta x) = b + \Delta b$ with $||\Delta A|| < ||A^{-1}||^{-1}$.

Then,

$$\frac{\|\Delta x\|}{\|x\|} \le \frac{\kappa(A)}{1 - \kappa(A) \frac{\|\Delta A\|}{\|A\|}} \left(\frac{\|\Delta A\|}{\|A\|} + \frac{\|\Delta b\|}{\|b\|} \right)$$

$$\approx \kappa(A) \qquad \left(\frac{\|\Delta A\|}{\|A\|} + \frac{\|\Delta b\|}{\|b\|} \right) + \mathcal{O}(\kappa(A)^2).$$

Statement to remember

Relative error in x is at most $\kappa(A)$ times relative errors in A and b up to higher-order terms.

Proof. Solving the perturbed equation for Δx yields

$$\Delta x = (A + \Delta A)^{-1} (b + \Delta b - (A + \Delta A)x)$$

= $A^{-1} (I + A^{-1} \Delta A)^{-1} (\Delta b - \Delta Ax).$

We obtain using

- ▶ the Neumann estimate $\|(1+M)^{-1}\| \le \frac{1}{1-\|M\|}$ for $\|M\| < 1$,
- $\|b\| = \|Ax\| \le \|A\| \|x\|$, and
- ▶ the monotonicity of $\frac{1}{x}$ and $\frac{1}{1-x}$

that

$$\frac{\left\|\Delta x\right\|}{\left\|x\right\|} \leq \frac{\left\|A\right\| \left\|A^{-1}\right\|}{1 - \left\|A^{-1}\right\| \left\|\Delta A\right\|} \left(\frac{\left\|\Delta b\right\|}{\left\|b\right\|} + \frac{\left\|\Delta A\right\|}{\left\|A\right\|}\right).$$

https://en.wikipedia.org/wiki/Neumann_series

Stability of solving linear systems via LU factorisation

Numerical solution \tilde{x} to Ax = b computed via LU factorisation satisfies

$$(A + \Delta A)\tilde{x} = b$$
 where $\frac{\|\Delta A\|}{\|L\| \|U\|} \approx \mathcal{O}(\varepsilon_{\mathsf{mach}}).$

Combined with condition number for linear systems, this yields

$$\frac{\|\tilde{x} - x\|}{\|x\|} \approx \kappa(A) \frac{\|L\| \|U\|}{\|A\|} \mathcal{O}(\varepsilon_{\mathsf{mach}}).$$

Error is small if

- \triangleright $\kappa(A)$ is not too large (problem is well-conditioned), and
- ▶ $\frac{\|L\| \|U\|}{\|A\|}$ is not too large (LU factorisation is stable).

Impact of pivoting

No pivoting: $||L||, ||U|| = \infty$ is possible.

- We will see special matrices which do not require pivoting.
- Do not use this algorithm unless you know what you are doing.

Partial pivoting: $||L||, ||U|| \le 2^{n-1}$ is a sharp upper bound.

- ▶ However, exponential growth of $\|L\|$, $\|U\|$ has never been observed in practice.
- Famous quote: "Anyone that unlucky has already been run over by a bus."
- ▶ This is the recommended algorithm in most applications.

Complete pivoting: probably ||L||, $||U|| = \mathcal{O}(n)$.

No one uses this algorithm.

References and further reading

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