

④

Applications of LU

(1) Solve linear equations. How?

$$PA = LU \quad \leadsto \quad \Leftrightarrow PAx = Pb$$

$$\Leftrightarrow \underbrace{LU}_y x = Pb$$

(1) Solve $Ly = Pb$

(2) Solve $Ux = y$

Isn't this complicated or expensive?

(No: The factorization itself is cheap--and reusable.)

(2) Solve a matrix equation. How?

Given: $Ax = B$

known
↙ ↘

↑
unknown

Simplifying assumption:

A, X, B are square and have same size.

We can solve this column-by-column:

$$\left(A \right) \left(\begin{array}{c} (x_1) \\ \vdots \\ (x_n) \end{array} \right) = \left(\begin{array}{c} (b_1) \\ \vdots \\ (b_n) \end{array} \right)$$

No different than solving lots of linear systems with the same A and lots of different right-hand side vectors b. Can reuse L and U.

Example: $Ax = I$ (I is the identity matrix.)

→ Solved by $X = A^{-1}$.

→ Can find inverse A^{-1} using LU

Computational Cost: $\overbrace{O(n^3)}^{LU} + n \cdot \overbrace{O(n^2)}^{BW+FW \text{ subst}} = O(n^3)$

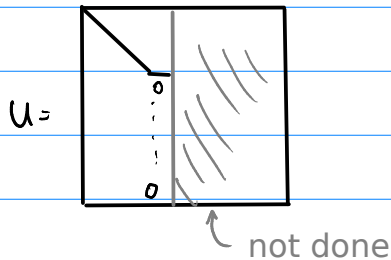
(3) Find row echelon form



The factor U in pivoted LU looks like it is in upper echelon form, and most of the time it is... but this is not guaranteed.

For example, U can contain linearly dependent rows.

Demo: LU and upper echelon form, Part I



If you hit a column of all zeros, then to achieve echelon form, you would need to "move right" (and just keep eliminating in the same row).

Then our pivot/elimination split trick no longer works, and L is no longer lower triangular!

(Pivoting is the problem here!)

If you are wondering:
The details of why this breaks will not be on the exam.

But: We can still use the same process as pivoted LU to compute an invertible matrix M so that

$$MA = U$$

so that U is in upper echelon form. But M cannot easily be factored into elimination and permutation matrices--and thus not easily inverted!

Nonetheless, we can obtain the "echelon factorization":

$$A = M^{-1}U$$

Demo: LU and upper echelon form, Part II

(4) Find the basis of a span. How?

Given: $\vec{x}_1, \dots, \vec{x}_n$ linearly dependent

Want: $\vec{y}_1, \dots, \vec{y}_k \in \text{span}\{\vec{x}_1, \dots, \vec{x}_n\} = V$
linearly independent

Define $A = \begin{pmatrix} \text{---} x_1 \text{---} \\ \text{---} x_n \text{---} \end{pmatrix}$

Obtain $MA = U$ in echelon form

Non-zero rows of U form a basis of V .

(5) Find the determinant of a matrix. How?

$$PA = LU$$

$$\rightarrow \det(P) \det(A) = \det(L) \det(U)$$

↙

± 1

↓

1

↘

product of diagonal
entries

(5) We'd like to find the rank* of a matrix. Is that possible using a computer?

Two randomly vectors almost surely do not point in the same direction.

Two random vectors are almost surely not linearly dependent.

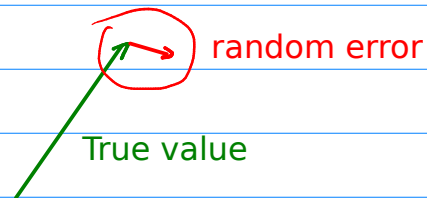
Computers do not represent numbers exactly. (in floating point)

Every floating point number:

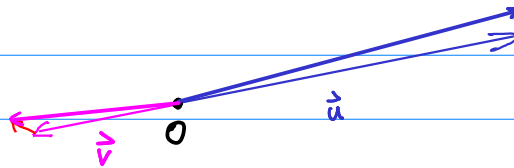
3.14159 777777
good digits junk

Model that as: True value + (small?) "random" error

In a vector:



Suppose we would like to test two inexact vectors for linear dependence.



True: $\vec{u} = \alpha \vec{v}$ (linearly dependent)

Computed: $\vec{u} \neq \alpha \vec{v}$ (not linearly dependent)

Lesson: We cannot hope for exact equality on a computer. Instead, we must define some sort of tolerance.

*rank: Number of linearly independent rows/columns

Suppose we take that into account. How would we compute the rank?

Just compute echelon form. In exact arithmetic,
"missing" row rank would appear as rows of zeros.

On a computer, we cannot hope for exact zeros.

Demo: Computing the Rank

Lesson: To find the rank computationally, we must specify
a threshold on (for example) the minimum norm of
an echelon form row.

(6) Finding the nullspace of a matrix A

Echelon factorization of A is not much help:

$$A = M^{-1} U = M^{-1} \begin{array}{|c|} \hline \text{---} \\ \hline 0 \\ \hline \end{array}$$

↑ nullspace not obvious

Idea: Start with echelon factorization of A^T :

$$A^T = M^{-1} U \quad \Leftrightarrow \quad A = U^T M^{-T}$$

$(M^{-1})^T = (M^T)^{-1}$

echelon form

$$N(U^T) = ? \quad U^T = \begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix}^T = \begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix}$$

$$\leadsto N(U^T) = \left\{ \begin{array}{l} [0, 0, 0, \dots, 0, 1, 0, \dots, 0], \\ \vdots \\ [0, 0, 0, \dots, 0, 0, \dots, 0, 1] \end{array} \right\}$$

because these vectors "hit" the zero columns in U^T .

So we know a few vectors \vec{x} so that $U^T \vec{x} = \vec{0}$.

$$\text{But } A = U^T M^{-T}$$

We're looking for \vec{y} so that $M^{-T} \vec{y} = \vec{x}$. (for each of our \vec{x})

$$\text{Easy: } \vec{y} = M^T \vec{x}.$$

$$\leadsto N(A) = M^T N(U^T)$$

Demo: Computing the Nullspace