

Inverse Matrices, cont'd

Def: An $n \times n$ (square!) matrix A is invertible if there exists another $n \times n$ matrix B such that $AB = I_n = BA$.

Remark: Since $AB \neq BA$ in general, you have to require $AB = I_n = BA$. But:

Fact: If A and B are $n \times n$ matrices and $AB = I_n$ or $BA = I_n$, then $B = A^{-1}$.

So the definition above is a bit pedantic...

Remark: A non-square matrix does not admit both a left- and right-inverse, so not invertible. (Can't solve $AB = I_m$ and $CA = I_n$ unless A is square.) This is why we only treat invertibility of square matrices.

Fact: $(A^{-1})^{-1} = A$

because $AB = I_n$ means $B = A^{-1}$ and $A = B^{-1}$

Fact: If A & B are invertible, then so is AB , and $(AB)^{-1} = \cancel{A^{-1}B^{-1}} B^{-1}A^{-1}$.

Check: $(AB)(B^{-1}A^{-1}) = A(BB^{-1})A^{-1} = A(I_n)A^{-1} = AA^{-1} = I_n$ ✓

Thm: Let A be an $n \times n$ matrix. either all are true or all are false
The following are equivalent: (TFAE)

(1) A is invertible

(2) The RREF of A is I_n

(3) A has a pivot in every row/every column.

We'll see why a bit later.

Eg: $A = \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I_2$ invertible
● = pivots

Eg: $A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$ is in RREF, $\neq I_2$ singular

How do you compute the inverse?

Algorithm (Matrix Inversion):

Input: A square matrix.

Output: The inverse matrix, or "singular"

Procedure:

(a) Form the augmented matrix $[A | I_n]$

(b) Run Gauss-Jordan on $[A | I_n]$.

(c) If the output is $[I_n | B]$ then $B = A^{-1}$.

Otherwise A is singular. → why does this work? See below.

Eg: Compute $\begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix}^{-1}$.

$$\left[\begin{array}{cc|cc} 2 & 3 & 1 & 0 \\ 1 & 2 & 0 & 1 \end{array} \right] \xrightarrow{R_2 \leftrightarrow R_1} \left[\begin{array}{cc|cc} 1 & 2 & 0 & 1 \\ 2 & 3 & 1 & 0 \end{array} \right]$$

$$\xrightarrow{R_2 \times = 2} \left[\begin{array}{cc|cc} 1 & 2 & 0 & 1 \\ 0 & 1 & -1 & 2 \end{array} \right]$$

$$\xrightarrow{R_1 - 2R_2} \left[\begin{array}{cc|cc} 1 & 0 & 2 & -3 \\ 0 & 1 & -1 & 2 \end{array} \right]$$

$$\xrightarrow{R_1 \div 2} \left[\begin{array}{cc|cc} 1/2 & 0 & 1 & -3/2 \\ 0 & 1 & -1 & 2 \end{array} \right]$$

This has the form $\left[I_2 \mid \begin{matrix} 2 & -3 \\ -1 & 2 \end{matrix} \right]$

$$\text{So } \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix}^{-1} = \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix}.$$

Eg: Compute $\begin{bmatrix} 1 & 3 \\ -1 & -3 \end{bmatrix}^{-1}$.

$$\left[\begin{array}{cc|cc} 1 & 3 & 1 & 0 \\ -1 & -3 & 0 & 1 \end{array} \right] \xrightarrow{R_2 + R_1} \left[\begin{array}{cc|cc} 1 & 3 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{array} \right]$$

$$\xrightarrow{R_1 - R_2} \left[\begin{array}{cc|cc} 1 & 3 & 0 & -1 \\ 0 & 0 & 1 & 1 \end{array} \right]$$

But this is in RREF and it does not have the form $[I_2 \mid B] \Rightarrow$ singular.

NB: We knew this after the first step: no pivot in the second column.

Actually there's a **shortcut** for **2x2** matrices:

Fact: $\begin{bmatrix} a & b \\ c & d \end{bmatrix}$ is invertible $\iff ad-bc \neq 0$,
in which case

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

Eg: $\begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix}^{-1} = \frac{1}{2 \cdot 2 - 3 \cdot 1} \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix}$

Check: $\frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix}$
 $= \frac{1}{ad-bc} \begin{bmatrix} ad-bc & bd-bd \\ ac-ac & ad-bc \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ ✓

What is this good for?

Suppose A is invertible. Let's solve $Ax=b$.

$$Ax=b \iff A^{-1}(Ax) = A^{-1}b$$

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

$$\iff x = A^{-1}b$$

For invertible A :

$$Ax=b \iff x=A^{-1}b$$

In particular, $Ax=b$ has ^{exactly} one solution for any b , and we have an expression for b in terms of x .

Eg: Solve
$$\begin{aligned} 2x_1 + 3x_2 &= b_1 \\ x_1 + 2x_2 &= b_2. \end{aligned}$$

$$A = \begin{bmatrix} 2 & 3 \\ 1 & 2 \end{bmatrix} \quad A^{-1} = \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix}$$

$$A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \iff \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = A^{-1} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} 2 & -3 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

$$\iff \begin{aligned} x_1 &= 2b_1 - 3b_2 \\ x_2 &= -b_1 + 2b_2 \end{aligned}$$

So if you want to solve
$$\begin{aligned} 2x_1 + 3x_2 &= 3 \\ x_1 + 2x_2 &= 4 \end{aligned}$$

$$\Rightarrow x_1 = 2(3) - 3(4) = -6$$

$$x_2 = -(3) + 2(4) = 5$$

Elementary Matrices

These give a way to do row operations by matrix multiplication!

Def: An elementary matrix is a matrix obtained from I_n by doing one row operation.

Eg: • $R_1 \leftarrow R_1 + 2R_2$ $\begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

• $R_2 \leftarrow 2R_2$ $\begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

• $R_1 \leftrightarrow R_2$ $\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

Fact: If E is an $m \times m$ elementary matrix and A is an $m \times n$ matrix, then

$E \cdot A =$ (what you get by performing that row operation on A .)

(row operations) \equiv (left-multiplication by elementary matrices)

$$\text{Eg: } \begin{bmatrix} -2 & -3 & 0 & -7 \\ 1 & 2 & 3 & 4 \\ 0 & 1 & 0 & 1 \end{bmatrix} \xrightarrow{R_1 \leftrightarrow R_2} \begin{bmatrix} 0 & 1 & 6 & 1 \\ 1 & 2 & 3 & 4 \\ 0 & 1 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow{R_1 \leftrightarrow R_2} \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{same!}$$

$$\begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} -2 & -3 & 0 & -7 \\ 1 & 2 & 3 & 4 \\ 0 & 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 6 & 1 \\ 1 & 2 & 3 & 4 \\ 0 & 1 & 0 & 1 \end{bmatrix}$$

Left-multiplication by $\begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ does $R_1 \leftrightarrow R_2$.

Fact: An elementary matrix is invertible. Its inverse corresponds to the elementary matrix that un-does the row operation.

Why? $E_1 = (\text{matrix for } R_1 \leftrightarrow R_2) = \begin{bmatrix} 1 & 2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

$$E_2 = (\text{matrix for } R_1 \leftrightarrow R_2) = \begin{bmatrix} 1 & -2 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$E_1 E_2 = E_1 E_2 I_n = E_1 (\text{do } R_1 \leftrightarrow R_2 \text{ to } I_n)$$

$$= \left(\begin{array}{l} \text{first do } R_1 \leftrightarrow R_2 \text{ to } I_n, \\ \text{then do } R_1 \leftrightarrow R_2 \text{ to } I_n \end{array} \right) = I_n.$$

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

What if you do multiple row operations?

Consider these row operations & their elementary matrices:

$$E_1: R_1 \leftarrow R_1 + 2R_2 \quad E_2: R_2 \leftarrow R_2 \times 2 \quad E_3: R_2 \leftrightarrow R_3$$

Apply in order to A

$$A \xrightarrow{R_1 \leftarrow R_1 + 2R_2} E_1 A \xrightarrow{R_2 \leftarrow R_2 \times 2} E_2(E_1 A) \xrightarrow{R_2 \leftrightarrow R_3} E_3(E_2(E_1 A)) \\ = (E_3 E_2 E_1) A$$

The elementary matrices ended up in the **opposite order!** Why?

$$E_3 E_2 E_1 A = E_3 E_2 (E_1 A): \text{first multiply by } E_1$$

Application to Invertibility:

Suppose $\text{RREF}(A) = I_n$.

So there are some number of row ops to transform $A \rightsquigarrow I_n$.

Let E_1, \dots, E_r be their elementary matrices.

$$I_n = (E_r E_{r-1} \dots E_1) A$$

$$\Rightarrow A^{-1} = E_r E_{r-1} \dots E_1$$

In particular, A is **invertible**: justifies (part of) the **Thm** above (p.2).

This also justifies the algorithm for computing A^{-1} :

$$[A \mid I_n] \xrightarrow{\text{row ops}} [I_n \mid B]$$

$$\text{Then } [I_n \mid B] = (E_r \cdots E_1)[A \mid I_n]$$

$$= [(E_r \cdots E_1)A \mid (E_r \cdots E_1)]$$

column \sim 1st
matrix
multiplication

$$\Rightarrow B = E_r \cdots E_1 = A^{-1}$$

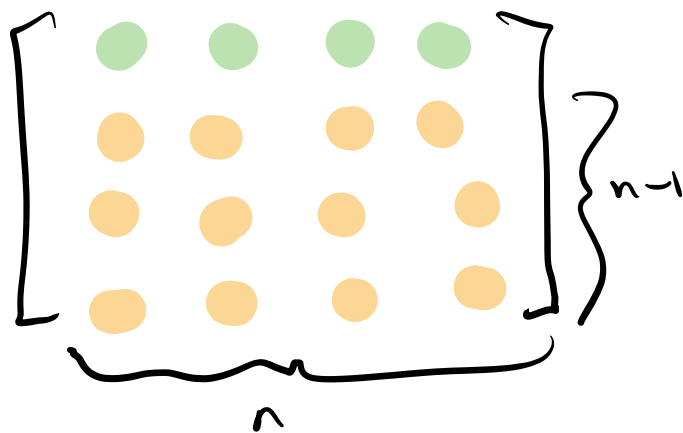
$$\Downarrow$$

$$C[AB] = [CA \mid CB]$$

LU Decomposition

How much computer time does Gauss-Jordan take?
(computational complexity)

Gaussian Elimination on an $n \times n$ matrix takes:

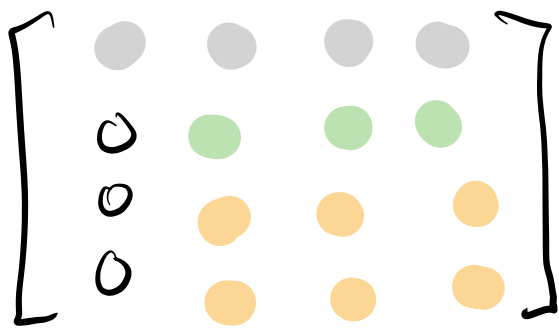


Step 1: Each row replacement requires $n-1$ multiplications & $n-1$ additions. (no computation in 1st col: just write "0")
Do for $n-1$ lower rows:

$$(n-1)(n-1) \quad \text{mult}$$

$$(n-1)(n-1) \quad \text{add}$$

$$\underline{2(n-1)^2} \quad \text{flops} \leftarrow (\text{floating point operations})$$



Step 2: Each row replacement requires $n-2$ multiplications & $n-2$ additions. Must do this for $n-2$ remaining rows

$$\begin{aligned} & (n-2)(n-2) \text{ mult} \\ & + (n-2)(n-2) \text{ add} \\ & \hline & 2(n-2)^2 \text{ flops} \\ & \text{etc.} \end{aligned}$$

Total: $2 \left[\overbrace{(n-1)^2 + (n-2)^2 + \dots + 1^2}^{\text{pyramidal number}} \right]$

$$= 2 \cdot \frac{n(n-1)(2n-1)}{6} \approx \frac{2}{3} n^3 \text{ flops}$$

Back-Substitution

$$\text{green dot } x_n = \text{brown dot}$$

$$1 \text{ mult} = 1 \text{ flop}$$

$$\text{purple dot } x_{n-1} + \text{green dot } x_n = \text{brown dot}$$

$$2 \text{ mult, } 1 \text{ add} = 3 \text{ flops}$$

(substitute $x_n \times \text{green dot}$, subtract, $\div \text{purple dot}$)

$$\text{red dot } x_{n-2} + \text{purple dot } x_{n-1} + \text{green dot } x_n = \text{brown dot}$$

$$3 \text{ mult, } 2 \text{ add} = 5 \text{ flops}$$

(substitute x_n & x_{n-1} , $\times \text{green dot}$, $\times \text{purple dot}$, subtract, $\div \text{red dot}$)

$$\text{blue dot } x_1 + \dots + \text{green dot } x_n = \text{brown dot}$$

$$n \text{ mult, } (n-1) \text{ add} = 2n-1 \text{ flops}$$

Total: $1+3+5+\dots+(2n-1) = n^2 \text{ flops}$

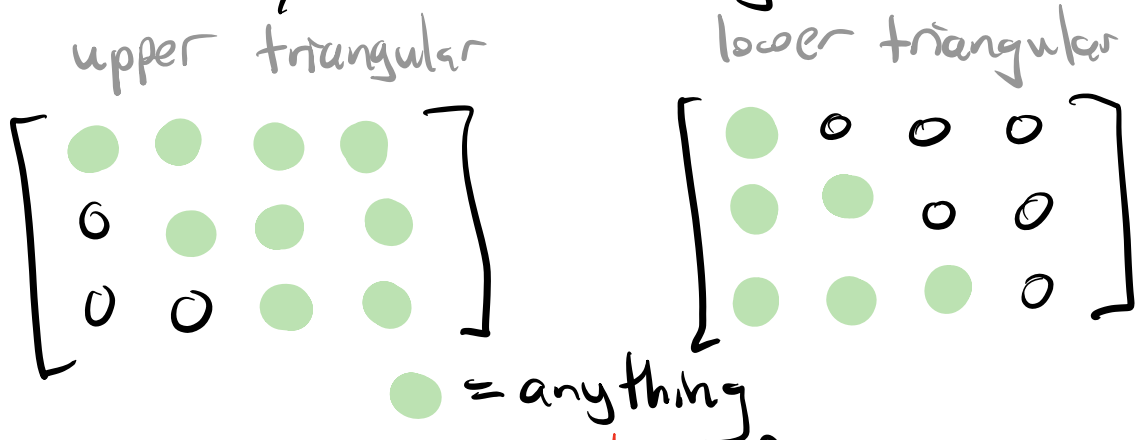
NB: $\frac{2}{3}n^3$ is a lot more than n^2 !

For a 1000×1000 matrix, $\frac{2}{3}n^3 \approx \frac{2}{3}$ gigaflops but $n^2 = 1$ megaflop. If we want to solve $Ax=b$ for 1000 values of b , doing elimination each time takes $\frac{2}{3}$ teraflops!

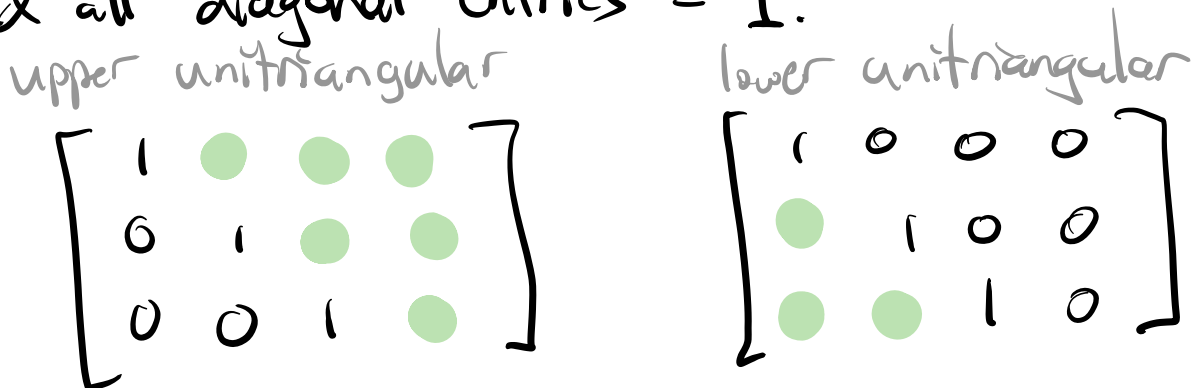
Upshot: We want to do elimination **only once!**

This is what LU decomposition does.

Def: A matrix is **upper/lower triangular** if all entries below/above the diagonal are zero.



A matrix is **unitriangular** if it is triangular and all diagonal entries = 1.



Eg: A matrix in REF is upper-triangular

Eg: If E is the elementary matrix for $R_i \leftarrow c \cdot R_j$ for $i > j$ (add a higher row to a lower row) then E is lower-triangular.

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \xrightarrow{R_3 \leftarrow 2R_1} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 2 & 0 & 1 \end{bmatrix} = E$$

Fact: Products & inverses of square upper/lower (uni) triangular matrices are again upper/lower (uni) triangular.

Suppose A can be reduced to REF (using the Gaussian elimination algorithm) without doing any row swaps. Then the only row operations necessary are $R_i \leftarrow c R_j$ for $i > j$.

U = output of Gaussian elimination (in REF)

$$U = \underbrace{E_r \cdots E_1}_{\text{lower-triangular}} A \Rightarrow A = \underbrace{(E_r \cdots E_1)^{-1}}_{\text{lower-triangular}} U = LU$$

So we've shown:

Fact: If Gaussian elimination on A requires no row swaps, then

$$A = LU$$

for L lower-unitriangular and U in REF.