

Matrix multiplication (reprise)

The product of two matrices A and B is completely characterized by the rule

$$(AB)\vec{v} = A(B\vec{v}).$$

The way this works is simple: The i th column of a matrix M is $M\vec{e}_i$ (with \vec{e}_i all zero, but a 1 in entry i), so substituting $\vec{v} = \vec{e}_i$, we have $(AB)\vec{e}_i = A(B\vec{e}_i)$. That is,

column i of AB equals $A\vec{b}_i$
(with $\vec{b}_i =$ column i of B)

ex

$$\begin{pmatrix} 1 & 2 & 3 \\ 0 & 1 & 4 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 2 \end{pmatrix} = \left(\left(\begin{pmatrix} 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right) \left(\begin{pmatrix} 2 \\ 1 \end{pmatrix} + 2 \begin{pmatrix} 3 \\ 4 \end{pmatrix} \right) \right)$$

$$= \begin{pmatrix} 4 & 8 \\ 4 & 9 \end{pmatrix}.$$

or use i $\left(\begin{array}{c} \text{---} \\ | \end{array} \right) \left(\begin{array}{c} j \\ | \end{array} \right) = i$ $\left(\begin{array}{c} j \\ | \end{array} \right)$ rule :

$$\begin{pmatrix} 1 & 2 & 3 \\ 0 & 1 & 4 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 1 & 2 \end{pmatrix} = \begin{pmatrix} 1 \cdot 1 + 2 \cdot 0 + 3 \cdot 1 & 1 \cdot 0 + 2 \cdot 1 + 3 \cdot 2 \\ 0 \cdot 1 + 1 \cdot 0 + 4 \cdot 1 & 0 \cdot 0 + 1 \cdot 1 + 4 \cdot 2 \end{pmatrix}$$

The rule can also be given entrywise:

$$(AB)_{ij} = \sum_k A_{ik} B_{kj}$$

\uparrow row fixed \uparrow column fixed

Transposes

An $m \times n$ matrix A has an $n \times m$ transpose A^T which is A "flipped" over its diagonal. $(A^T)_{ij} = A_{ji}$

ex $\begin{pmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{pmatrix}^T = \begin{pmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{pmatrix}$

$$\begin{pmatrix} 1 & 2 \\ 2 & 3 \end{pmatrix}^T = \begin{pmatrix} 1 & 2 \\ 2 & 3 \end{pmatrix}$$

Properties

- $(A^T)^T = A$
- $(A+B)^T = A^T + B^T$
- $(rA)^T = rA^T \quad (r \in \mathbb{R})$
- $(AB)^T = B^T A^T \quad \leftarrow \text{reversed!}$

This last prop. is interesting. It is not too hard to show:

$$\begin{aligned} ((AB)^T)_{ij} &= (AB)_{ji} = \sum_k A_{jk} B_{ki} \\ &= \sum_k B_{ki} A_{jk} \\ &= \sum_k (B^T)_{ik} (A^T)_{kj} = (B^T A^T)_{ij} \end{aligned}$$

Corresponding entries are equal, so $(AB)^T = B^T A^T$.

Transposes will show up later in orthogonality.

Identity matrices $I_n = \begin{pmatrix} 1 & & 0 \\ & \ddots & \\ 0 & & 1 \end{pmatrix}$ ($n \times n$) have the following properties:

Say A is $m \times n$.

- $A I_n = A$
- $I_m A = A$

They are the equivalent of $1 \in \mathbb{R}$ under multiplication.

The inverse of a matrix

Like for numbers, sometimes we can multiply by a matrix to undo a previous multiplication. Unlike numbers, AB and BA might not equal, so there are two kinds of inverses.

Let A be $m \times n$ and C be $n \times m$.

- C is a left inverse if $CA = I_n$

$$\text{ex } \begin{pmatrix} 1 & 0 & 2 \\ 0 & 1 & 3 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = I_2$$

Since I_n has $\begin{cases} \text{a pivot in every row, so must } C \\ \text{a pivot in every column, so must } A \end{cases}$

- C is a right inverse if $AC = I_m$

ex same but reverse roles of matrices.

- C is an inverse if $AC = CA = I_n$ (need $n=m$)
(also two-sided inverse)

Correspondence: • A has left inverse $\Leftrightarrow \vec{x} \mapsto A\vec{x}$ is one-to-one
 • A has right inverse $\Leftrightarrow \vec{x} \mapsto A\vec{x}$ is onto
 • A has both $\Leftrightarrow \vec{x} \mapsto A\vec{x}$ is one-to-one and onto
 (bijective)

Let's just think about square A with inverse today.

If A has inverses C, D , $C = C I_n = C A D = I_n D = D$, so inverse, if it exists, is unique. Denote it by A^{-1} (if exists, otherwise singular).

1st method of computation

Since $A^{-1}A = I_n$, we have $A^{-1}A\vec{v} = \vec{v}$. If we solve $A\vec{v}_i = \vec{e}_i$, for \vec{v}_i , then $A^{-1}A\vec{v}_i = \vec{v}_i \Leftrightarrow A^{-1}\vec{e}_i = \vec{v}_i$. That is,

* column i of A^{-1} is the solution to $A\vec{x} = \vec{e}_i$.

This suggests computing solutions $[A \mid \vec{e}_i]$ repeatedly to build A^{-1} .

Do we really want to do rref n times? Observe: row operations only operate on rows! May as well compute rref of $[A \mid \vec{e}_1, \vec{e}_2, \dots, \vec{e}_n] = [A \mid I_n]$ once. Since A must have n pivots, the right side of rref will be A^{-1} , as in $[I_n \mid A^{-1}]$.

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

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

Check:
$$\begin{bmatrix} 1 & 2 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} -3 & 2 \\ 2 & -1 \end{bmatrix} = \begin{bmatrix} 1(-3) + 2(2) & 1(2) + 2(-1) \\ 2(-3) + 3(2) & 2(2) + 3(-1) \end{bmatrix} \\ = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I_2$$

ex
$$\left[\begin{array}{c|c|c} 1 & x & 1 \\ 0 & 1 & 1 \end{array} \right] \sim \left[\begin{array}{c|c|c} 1 & 0 & 1-x \\ 0 & 1 & 1 \end{array} \right]$$

so
$$\begin{bmatrix} 1 & x \\ 0 & 1 \end{bmatrix}^{-1} = \begin{bmatrix} 1 & -x \\ 0 & 1 \end{bmatrix}.$$

2nd method: A is 2x2

* For $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$, $A^{-1} = \frac{1}{ad-bc} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$

if $ad-bc \neq 0$ (the "determinant")

This is useful and easy enough to memorize ("swap major, negate minor, divide by determinant").

To prove, we need only check it's an inverse!

$$\begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} d & -b \\ -c & a \end{pmatrix} = \begin{pmatrix} ad-bc & 0 \\ 0 & ad-bc \end{pmatrix}$$

so when divided by det., $= I_2$.

ex $R_\theta = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$ is rotation θ CCW

$$R_\theta^{-1} = \frac{1}{\underbrace{\cos^2 \theta + \sin^2 \theta}} \begin{pmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{pmatrix}$$

$$= 1$$

$$\text{and } \begin{aligned} \cos \theta &= \cos(-\theta) \\ -\sin \theta &= \sin(-\theta) \end{aligned}$$

$$\text{so } = \begin{pmatrix} \cos(-\theta) & -\sin(-\theta) \\ \sin(-\theta) & \cos(-\theta) \end{pmatrix} = R_{-\theta}$$

rot. by θ CCW,

Intuitively the inverse.

If A has an inverse, $A\vec{x} = \vec{b}$ always has $\vec{x} = A^{-1}\vec{b}$ as soln, so A has a pivot in every row. A is square, so pivot in every column, too. Thus, $A^{-1}\vec{b}$ is the unique solution.

Properties

- $(A^{-1})^{-1} = A$. This is because $AA^{-1} = I_n$ and $A^{-1}A = I_n$, so A is inverse of A^{-1} (denoted $(A^{-1})^{-1}$).
 - $(AB)^{-1} = B^{-1}A^{-1}$. This is because $(B^{-1}A^{-1})AB = B^{-1}I_nB = I_n$ and $AB(B^{-1}A^{-1}) = A I_n A^{-1} = I_n$. So $B^{-1}A^{-1}$ plays role of inverse to AB .
 - $(A^T)^{-1} = (A^{-1})^T$. $(A^{-1})^T A^T = (AA^{-1})^T = I_n^T = I_n$
 $A^T (A^{-1})^T = (A^{-1}A)^T = I_n^T = I_n$
 so A^T is inverse of $(A^{-1})^T$.
- (Sometimes people write these as A^{-T} because of the rule)

Invertible matrix theorem A is $n \times n$.

The following are equivalent:

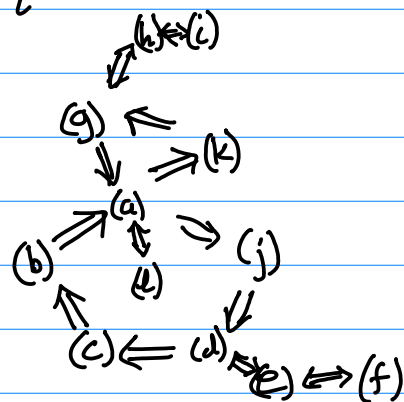
- (all true or all false)
- A is invertible
 - $A \sim I_n$
 - A has n pivots
 - $A\vec{x} = \vec{0}$ has only trivial solution
 - Columns of A are linearly independent
 - $\vec{x} \mapsto A\vec{x}$ is one-to-one
 - For each $\vec{b} \in \mathbb{R}^n$, $A\vec{x} = \vec{b}$ is solvable.
 - The columns of A span \mathbb{R}^n
 - $\vec{x} \mapsto A\vec{x}$ is onto
 - A has a left inverse.
 - A has a right inverse.
 - A^T is invertible

Caution

A is square

Pivot in every row equiv. to one group of statements
 Pivot in every col equiv. to another
 Pivotal: rows = cols in square matrix. This joins them.

Book's implications for equivalence.



ex $\begin{pmatrix} 1 & 2 & 3 \\ 1 & 2 & 3 \\ 1 & 2 & 3 \end{pmatrix}$ is not invertible.

ex $\begin{pmatrix} 1 & 2 & 3 \\ 1 & 2 \\ 1 \\ 1 \end{pmatrix}$ is invertible

ex If A, B $n \times n$ and AB is invertible,

$AB\vec{x} = \vec{b}$ is always solvable ($\vec{x} = (AB)^{-1}\vec{b}$)

so $A\vec{y} = \vec{b}$ is always solvable ($\vec{y} = B(AB)^{-1}\vec{b}$)

so A is invertible.

$(AB)^T$ is invertible, which is $B^T A^T$. By similar argument,
 B^T is invertible, so B is invertible.

Behold the power of the invertible matrix theorem!

ex If $\vec{v}_1, \dots, \vec{v}_k$ are vectors which span \mathbb{R}^n

$[\vec{v}_1 \dots \vec{v}_k]$ pivot in each row ($k \geq n$)

if indep., $[\vec{v}_1 \dots \vec{v}_k]$ pivot in each col ($k \leq n$)

if both, $k=n$, and $[\vec{v}_1 \dots \vec{v}_n]$ is invertible.