

Summary of last time:

DETERMINANT

definition: A function Δ eating n vectors in \mathbb{R}^n & gives out a real # $\Delta(\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n) \in \mathbb{R}$ which satisfies

① $\Delta(\vec{e}_1, \dots, \vec{e}_n) = 1;$

② Δ is multilinear;

③ Δ is alternating.

is called a determinant.

We had shown that such a Δ satisfies automatically

④ $\Delta(\dots, \vec{u}, \dots, \vec{u}, \dots) = 0.$

⑤ $\Delta(\vec{u}, a\vec{u} + \vec{v}, \dots) = \Delta(\vec{u}, \vec{v}, \dots).$

⑥ $\Delta(\dots, \vec{0}, \dots) = 0.$

⑦ $\Delta(\text{diag}(a_1, \dots, a_n)) = a_1 \cdot \dots \cdot a_n.$

⑧ $\Delta(\text{lower}) = \text{product of diagonal entries}$
 $\Delta(\text{upper}) =$

⑨ $\Delta(\text{permutation}) = (-1)^k$ where k is the # of row exchanges in pairs needed to turn the matrix into I .

(10) Given A invertible & $PA = LDU$,

$$\Delta(A) = (-1)^k \Delta(D) \xrightarrow{\text{by (7)}} \Delta(D) \xrightarrow{\text{by (9)}}$$

So these prove the following
thm: Given $A_{n \times n}$, if rows of A is
linearly dependent then by (5) & (6)
 $\Delta(A) = 0$. Otherwise given P , there is
unique $PA = LDU$ and
 $\Delta(A) = (-1)^k \cdot D_{11} \cdots D_{nn}$.

So a fnc that satisfies (1)-(3) is unique.

From this point on we denote this unique
function by \det . It takes in n vectors and
gives out a real #. When we write
 $\det(A)$, this means it eats the rows of A .

Now several more properties for \det :

$$(11) \det(A \cdot B) \stackrel{(*)}{=} \det(A) \cdot \det(B) \quad (A, B \text{ square})$$

$n \times n \quad n \times n$

proof: If any of A & B is singular then
so is $A \cdot B$. In that case both sides are 0
by the thm above. Equality $(*)$ holds.

Now assume A & B are invertible.
Define a fnc on rows of invertible matrices:

$$f(A) = \frac{\det(A \cdot B)}{\det(B)}.$$

If we can show that this f satisfies
①, ②, ③ then f must be \det by the
theorem above. So that proves:

$$\det(A) = \frac{\det(AB)}{\det B}.$$

This is nothing but Equality (*).

Ok then let's show that f satisfies

① - ③:

f satisfies ①: $f(I) = f(e_1, \dots, e_n)$
 $= \frac{\det(I \cdot B)}{\det(B)} = 1.$

This is exactly property ①.

f satisfies (2): For $\vec{u}, \vec{v}, \vec{u}_2, \dots$ row vectors.

Observe
$$\begin{pmatrix} a\vec{u} + b\vec{v} \\ \vec{u}_2 \\ \vdots \end{pmatrix} B = \begin{pmatrix} a\vec{u}B + b\vec{v}B \\ \vec{u}_2B \\ \vec{u}_3B \\ \vdots \end{pmatrix}$$

So


$$f \begin{pmatrix} a\vec{u} + b\vec{v} \\ \vec{u}_2 \\ \vdots \end{pmatrix} = \frac{1}{\det B} \cdot \det \begin{pmatrix} a\vec{u}B + b\vec{v}B \\ \vec{u}_2B \\ \vec{u}_3B \\ \vdots \end{pmatrix}$$
$$= \frac{1}{\det B} \left(a \cdot \det \begin{pmatrix} \vec{u}B \\ \vec{u}_2B \\ \vdots \end{pmatrix} + b \cdot \det \begin{pmatrix} \vec{v}B \\ \vec{u}_2B \\ \vdots \end{pmatrix} \right)$$

$$= a \cdot f \begin{pmatrix} \vec{u} \\ \vec{u}_2 \\ \vdots \end{pmatrix} + b \cdot f \begin{pmatrix} \vec{v} \\ \vec{u}_2 \\ \vdots \end{pmatrix}$$

This shows that f satisfies property (2) too.

f satisfies (3):

$$\begin{aligned} f \begin{pmatrix} -u_2 - \\ -u_1 - \\ -u_3 - \\ \vdots \end{pmatrix} &= \frac{1}{\det B} \det \begin{pmatrix} \vec{u}_2 B \\ \vec{u}_1 B \\ \vec{u}_3 B \\ \vdots \end{pmatrix} \\ &= \frac{-1}{\det B} \det \begin{pmatrix} \vec{u}_1 B \\ \vec{u}_2 B \\ \vec{u}_3 B \\ \vdots \end{pmatrix} = (-1) \cdot f \begin{pmatrix} -u_1 - \\ -u_2 - \\ -u_3 - \\ \vdots \end{pmatrix} \end{aligned}$$

[& this is nothing but property (3). ]

Last property:

$$(12) \det(A^T) = \det(A).$$

This shows that instead of det eating rows of A , it may eat the columns of A & gives out the same number.

Here is a proof for (12):

If A is singular so is A^T and for both $\det = 0$.

Otherwise let $PA = LDU$. Then

$$\det(A) = \det D / \det P.$$

Meanwhile $A^T P^T = U^T D L^T$ and

$$\det(A^T) = \det D / \det P^T.$$

Therefore if we make sure that
 $\det P^T = \det P$ then we're done.

Recall $P = P_1 \cdots P_k$ where each P_j
swaps two rows and $P_j^T = P_j$. So
 $P^T = P_k^T \cdots P_1^T = P_k \cdots P_1$.

Hence $\det P^T = (-1)^k = \det P$. \blacksquare

Thanks to (12), when we write $\det(A)$
we may equally let \det eat the columns
of A too.

Moreover whatever we've said for \det
about rows of A is also true for columns
of A .

We sometimes write $|A|$ for $\det(A)$.

Computing det.

We know how to compute det using LDU decomp. Here are some other methods.

ex: Consider $A = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix}$. Observe $(a \ b \ c) = a \cdot (1 \ 0 \ 0) + b \cdot (0 \ 1 \ 0) + c \cdot (0 \ 0 \ 1)$

Then by multilinearity

$$\det A = a \cdot \det \begin{pmatrix} 1 & 0 & 0 \\ d & e & f \\ g & h & i \end{pmatrix} + b \cdot \det \begin{pmatrix} 0 & 1 & 0 \\ d & e & f \\ g & h & i \end{pmatrix} + c \cdot \det \begin{pmatrix} 0 & 0 & 1 \\ d & e & f \\ g & h & i \end{pmatrix}$$

\downarrow
linearity wrt 2nd rows

$$= a \cdot \left[d \cdot \begin{vmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ g & h & i \end{vmatrix} + e \cdot \begin{vmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ g & h & i \end{vmatrix} + f \cdot \begin{vmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ g & h & i \end{vmatrix} \right] + \dots$$

\downarrow Let us pause. In the first term the det is zero, a & d brought $(1 \ 0 \ 0)$ because they're both at the same (1st) column of A.

Let's use this observation again & again:

$$\det A = \underset{\substack{\uparrow \\ \text{1st column}}}{ae} \cdot \underset{\substack{\uparrow \\ \text{2nd column}}}{i} \cdot \underset{\substack{\uparrow \\ \text{3rd}}}{\begin{vmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix}} + \underset{\substack{\uparrow \\ \text{1st}}}{af} \cdot \underset{\substack{\uparrow \\ \text{3rd}}}{h} \cdot \underset{\substack{\uparrow \\ \text{2nd}}}{\begin{vmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{vmatrix}}$$

$$+ \underset{\substack{\uparrow \\ \text{2nd}}}{b} \cdot \underset{\substack{\uparrow \\ \text{1st}}}{d} \cdot \underset{\substack{\uparrow \\ \text{3rd}}}{i} \cdot \begin{vmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{vmatrix} + \underset{\substack{\uparrow \\ \text{3rd}}}{f} \cdot \underset{\substack{\uparrow \\ \text{1st}}}{g} \cdot \begin{vmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{vmatrix}$$

$$+ \underset{\substack{\uparrow \\ \text{3rd}}}{c} \cdot \underset{\substack{\uparrow \\ \text{1st}}}{d} \cdot \underset{\substack{\uparrow \\ \text{2nd}}}{h} \cdot \begin{vmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{vmatrix} + \underset{\substack{\uparrow \\ \text{2nd}}}{e} \cdot \underset{\substack{\uparrow \\ \text{1st}}}{g} \cdot \begin{vmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{vmatrix}$$

See that we chose one entry from each row so that they also belong to different columns, because if any two came from the same column the corresponding matrix has $\det = 0$.

Now all the remaining matrices are permutations.

$$\det A = ae i - af h + bfg - bdi + cdh - ceg$$

In general we've a similar picture.
First some new words.

Let $P_{n \times n}$ be a permutation matrix. It shuffles the n rows. Thus it corresponds a shuffling (a permutation) σ of the #s $\{1, \dots, n\}$. $\forall i$ $\sigma(i)$ is a # in $\{1, \dots, n\}$.

Define $\text{sign}(\sigma) \doteq \det P$.

Now we're ready to tell the computation.
thm. \det of $A_{n \times n} = (a_{ij})$ is computed as follows. For each permutation σ of numbers $\{1, \dots, n\}$,

$$a_{1\sigma(1)}, a_{2\sigma(2)}, \dots, a_{n\sigma(n)}$$

are n entries of A , which are on different rows & on different columns of A . Then

$$\det A = \sum_{\text{all permutations } \sigma} \text{sign}(\sigma) \cdot a_{1\sigma(1)} \cdot \dots \cdot a_{n\sigma(n)}$$

ex: $\begin{vmatrix} a & b \\ c & d \end{vmatrix} = a \cdot d \cdot \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} + b \cdot c \cdot \begin{vmatrix} 0 & 1 \\ 1 & 0 \end{vmatrix}$
 $= ad - bc.$

ex: $\begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} = aei - afh - bdi + bfg + cdh - ceg$ (\square)

$= a(ei - fh) - b(di - fg) + c(dh - eg)$

$= a \cdot \begin{vmatrix} e & f \\ h & i \end{vmatrix} - b \cdot \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c \cdot \begin{vmatrix} d & e \\ g & h \end{vmatrix}$ (*)

i.e. on the first row pick the j th entry a_{1j} . Delete 1st row & j th column

Denote by M_{1j} the $(n-1) \times (n-1)$ matrix that remains & set

$$C_{1j} = (-1)^{1+j} \det M_{1j}.$$

In this notation

(*) $= a \cdot C_{11} + b \cdot C_{12} + c \cdot C_{13}$

Going back to (\square) :

$$\det M = \underbrace{-bdi + cdh + aei - ceg - afh + bfg}_{= -d \cdot \begin{vmatrix} b & c \\ h & i \end{vmatrix} + e \cdot \begin{vmatrix} a & c \\ g & i \end{vmatrix} - f \cdot \begin{vmatrix} a & b \\ g & h \end{vmatrix}}$$

$$= d \cdot C_{21} + e \cdot C_{22} + f \cdot C_{23}.$$

This computes $\det A$ "with respect to the second row".

These examples convince us about:

thm. For $A_{n \times n} = (a_{ij})$, fix a row k .

$$\det A = a_{k1} \cdot C_{k1} + \dots + a_{kn} C_{kn}$$

where

$$C_{kj} = (-1)^{k+j} \times \det \left(\begin{array}{c} \text{submatrix of } A \\ \text{obtained by} \\ \text{deleting its } k\text{th} \\ \text{row \& } j\text{th column} \end{array} \right)$$

↳ called the

k - j cofactor of A

Similarly for some fixed l^{th} column
of A :

$$\det A = a_{1l} C_{1l} + a_{2l} C_{2l} + \dots + a_{nl} C_{nl}$$