

Lecture 20: How to find eigenvectors

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Admin:

Reading: Meyer Ch. 6, 7.1-7.4
Strang Chs. 4-5

Recall:

eigenvalue
 $A\vec{v} = \lambda\vec{v}$
eigenvector

A is diagonalizable $\Leftrightarrow A = UDU^{-1}$

diagonal matrix
 $\begin{pmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \ddots \\ & & & \lambda_n \end{pmatrix}$

columns of U are eigenvectors
 $A\vec{u}_i = \lambda_i \vec{u}_i$

there is a basis of eigenvectors of A

Example: $\begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} = \begin{pmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{pmatrix} \begin{pmatrix} e^{-i\theta} & 0 \\ 0 & e^{i\theta} \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{pmatrix}$

vector (pointing to $\frac{1}{\sqrt{2}}$) e-value (pointing to $e^{-i\theta}$)

Example: $A = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$ is not diagonalizable.
 $A\vec{e}_1 = 0 \cdot \vec{e}_1$, but that's it!

Today: Every matrix has an eigenvector.
How to find eigenvalues and eigenvectors
- in theory (using determinants)
- in practice (using the "power method")

Application: Systems of differential equations

Problem: Solve

$$\frac{d}{dt} \vec{v}(t) = A \vec{v}(t)$$

subject to $\vec{v}(t=0) = \vec{v}_0$ initial conditions

Answer:

① In terms of eigenvalues/eigenvectors:

• Say $A\vec{u}_1 = \lambda_1\vec{u}_1$
and $\vec{v}_0 = \vec{u}_1$

$\Rightarrow \vec{v}(t)$ is always proportional to \vec{u}_1

$$\vec{v}(t) = e^{\lambda_1 t} \vec{u}_1$$

(so the time derivative is $e^{\lambda_1 t} \cdot \lambda_1 \vec{u}_1 = A \cdot \vec{v}(t)$ ✓)

$$\vec{v}(t) = e^{\lambda t} \vec{u}_1$$

(so the time derivative is $e^{\lambda t} \cdot \lambda \vec{u}_1 = A \cdot \vec{v}(t)$ ✓)

• Say $A \vec{u}_1 = \lambda_1 \vec{u}_1$
 $A \vec{u}_2 = \lambda_2 \vec{u}_2$
 and $\vec{v}_0 = \vec{u}_1 - 2\vec{u}_2$
 $\Rightarrow \vec{v}(t) = e^{\lambda_1 t} \vec{u}_1 - e^{\lambda_2 t} \cdot 2\vec{u}_2$

by linearity:
 if $\frac{d}{dt} \vec{w}(t) = A \vec{w}(t)$
 and $\frac{d}{dt} \vec{x}(t) = A \vec{x}(t)$,
 then $\frac{d}{dt} (\vec{w}(t) + \vec{x}(t)) = A (\vec{w}(t) + \vec{x}(t))$

• If A is diagonalizable, then its eigenvectors form a basis, so any \vec{v}_0 can be expressed as a linear combination of eigenvectors — and then they evolve independently

$$\vec{v}(t) = \alpha_1 e^{\lambda_1 t} \vec{u}_1 + \dots + \alpha_n e^{\lambda_n t} \vec{u}_n$$

② In terms of matrices:

$$\begin{aligned} \vec{v}(t) &= e^{At} \vec{v}_0 \\ &\stackrel{||}{=} \mathbf{I} + At + \frac{(At)^2}{2} + \frac{(At)^3}{6} + \dots \\ &= \sum_{j=0}^{\infty} \frac{1}{j!} (At)^j \end{aligned}$$

Proof:

• $\vec{v}(0) = e^{A \cdot 0} \vec{v}_0 = \mathbf{I} \vec{v}_0 = \vec{v}_0$ ✓

• $\frac{d}{dt} (e^{At} \vec{v}_0) = \left(\frac{d}{dt} e^{At} \right) \vec{v}_0$
 $= \left(\sum_{j=0}^{\infty} \frac{1}{j!} \cdot \frac{d}{dt} (A^j t^j) \right) \vec{v}_0$
 $= \left(\sum_{j=1}^{\infty} \frac{1}{(j-1)!} A^j t^{j-1} \right) \vec{v}_0$
 $= A \left(\sum_{j=0}^{\infty} \frac{1}{j!} (At)^j \right) \vec{v}_0$
 $= A \vec{v}(t)$ ✓

Extension: Higher-order differential equations with constant coefficients.

To solve a 2nd-order diff. eq. like

$$\begin{aligned} \ddot{x} &= -\dot{y} + 2x \\ \ddot{y} &= \dot{x} + \dot{y} - 3y \end{aligned}$$

use the same trick we used for solving the Fibonacci sequence recursion:

$$\frac{d}{dt} \begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix} = \begin{pmatrix} 0 & -1 & 2 & 0 \\ 1 & 1 & 0 & -3 \\ 1 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

use the same trick we used for solving the fibonacci sequence recursion:

$$\frac{d}{dt} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0 & -1 & 2 & 0 \\ 1 & 1 & 0 & -3 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

Then continue as before.

WHAT MATRICES HAVE AN EIGENVECTOR?

Theorem: Every (real or complex) square matrix has at least one eigenvector (over \mathbb{C} !).

Proof: Let A be an $n \times n$ matrix, real or complex.

Goal: Prove that there exists a vector $\vec{x} \neq \vec{0}$ such that $A\vec{x} = \lambda\vec{x}$ for some λ .

Step 1. Let \vec{v} be any nonzero vector.

Consider the vectors

$$\vec{v}, A\vec{v}, A^2\vec{v}, \dots, A^n\vec{v}$$

Since there are $n+1$ vectors in an n -dimensional space, they must be linearly dependent.

(Note: This argument only works in finite dimensions.)

Say

$$\alpha_0 \vec{v} + \alpha_1 A\vec{v} + \alpha_2 A^2\vec{v} + \dots + \alpha_n A^n\vec{v} = \vec{0}$$

with not all α_j 's 0.

Step 2. Thus

$$\left(\sum_{j=0}^n \alpha_j A^j \right) \vec{v} = \vec{0}$$

Factor the polynomial

$$p(x) = \sum_j \alpha_j x^j = \prod_j (x - \lambda_j)$$

$$\Rightarrow \left[\prod_j (A - \lambda_j I) \right] \vec{v} = \vec{0}$$

Step 3.

\Rightarrow at least one of the matrix terms $A - \lambda_j I$

must be singular

(the product of two nonsingular matrices is nonsingular!)

✓ Done. \square

Note: The first step can be "justified" by noticing that $\lim_{k \rightarrow \infty} \frac{A^k \vec{v}}{\|A^k \vec{v}\|}$ converges to an eigenvector with largest magnitude eigenvalue (though I don't want to prove this). So it makes sense to look at successive powers $A^k \vec{v}$.

DETERMINANTS (in brief)

Definition: The determinant of an $n \times n$ square matrix A is

$$\sum_{\sigma \in S_n} \text{sign}(\sigma) \cdot \prod_{i=1}^n A_{i, \sigma(i)}$$

\sum : n-element permutations σ
 $\text{sign}(\sigma)$: $(-1)^{\# \text{ of transpositions required to get to } \sigma}$

Examples:

• $n=1$: $A = (A_{11})$
 $\det(A) = A_{11}$

• $n=2$: $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$

Permutations Sign
 $1 \mapsto 1, 2 \mapsto 2$ $+1$ (0 transpositions)
 $1 \leftrightarrow 2$ -1

$$\Rightarrow \det A = ((+1) \cdot a_{11} a_{22}) + ((-1) \cdot a_{12} a_{21})$$

$$= a_{11} a_{22} - a_{12} a_{21}$$

• $n=3$:

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}$$

Permutation σ	Sign(σ)	$\prod_{i=1}^3 a_{i, \sigma(i)}$	
identity	$+1$	$a_{11} a_{22} a_{33}$	
$2 \leftrightarrow 3$	-1	$a_{11} a_{23} a_{32}$	
$1 \leftrightarrow 2$	-1	$a_{12} a_{21} a_{33}$	
$\begin{matrix} 1 \rightarrow 2 \\ 2 \rightarrow 3 \\ 3 \rightarrow 1 \end{matrix}$	$+1$	$a_{12} a_{23} a_{31}$	
$\begin{matrix} 1 \rightarrow 3 \\ 2 \rightarrow 1 \\ 3 \rightarrow 2 \end{matrix}$	$+1$	$a_{13} a_{21} a_{32}$	
$1 \leftrightarrow 3$	-1	$a_{13} a_{22} a_{31}$	

↑ since $\begin{matrix} 1 \rightarrow 2 \\ 2 \rightarrow 3 \\ 3 \rightarrow 1 \end{matrix} = 1 \leftrightarrow 2$ followed by $1 \leftrightarrow 3$ (two transpositions)

add these up to get the determinant!

Observe: $\det(A) = a_{11} \cdot \det \begin{pmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{pmatrix}$
 $- a_{12} \cdot \det \begin{pmatrix} a_{21} & a_{23} \\ a_{31} & a_{33} \end{pmatrix}$
 $+ a_{13} \cdot \det \begin{pmatrix} a_{21} & a_{22} \\ a_{31} & a_{32} \end{pmatrix}$

• General n : the same recursion works

$a_{11} \cdot \det(n-1 \times n-1 \text{ submatrix missing } 1^{\text{st}} \text{ row, } 1^{\text{st}} \text{ col})$
 $- a_{12} \cdot \det(n-1 \times n-1 \text{ submatrix missing } 1^{\text{st}} \text{ row, } 2^{\text{nd}} \text{ col})$
 $+ a_{13} \cdot \dots$
 \vdots

$+(-1)^n a_{1n} \cdot \det(\text{submatrix missing row 1, col } n)$
 [You can actually do this across any row or down any column; note that $\det(A) = \det(A^T)$.]

Problem: There are $n! \approx (\frac{n}{e})^n$ permutations of n elements; although

$$\det(A) = \sum_{\substack{\text{n-element} \\ \text{permutations } \sigma}} \text{sign}(\sigma) \cdot \prod_{i=1}^n A_{i, \sigma(i)}$$

defines the determinant, that's not how it is actually computed!

Compare: The permanent of a square matrix A is

$$\text{perm}(A) = \sum_{\substack{\text{n-element} \\ \text{permutations } \sigma}} \prod_{i=1}^n A_{i, \sigma(i)}$$

without the sign! Computing the permanent is NP-hard.

More examples:

• $\text{Det} \begin{pmatrix} a & & & \\ & b & & \\ & & c & \\ & & & d \end{pmatrix} = abcd$
 diagonal matrix
 product of diagonal entries

• $\text{Det} \begin{pmatrix} a & e & f & g \\ 0 & b & h & i \\ 0 & 0 & c & j \\ 0 & 0 & 0 & d \end{pmatrix} = abcd$
 upper triangular matrix
 still!

↖ true for permanent, too

↙ false for permanent!

Cool fact (that I won't prove or use):

$$\text{Det}(AB) = \text{Det}(A) \cdot \text{Det}(B)$$

Example:

```
>> n = 50;
>> A = randn(n,n);
>> B = randn(n,n);
>> det(A*B)
```

ans =

3.1827e+61

```
>> det(A) * det(B)
```

ans =

3.1827e+61

Note: `>> factorial(50)` — how did Matlab compute $\det(A)$, $\det(B)$?

ans =

3.0414e+64

Answer: It takes the LU decomposition:

Answer: It takes the LU decomposition:

$$A = P \cdot \begin{pmatrix} \text{lower triangular} & \text{upper triangular} \\ \text{permutation matrix} & \end{pmatrix} \cdot \begin{pmatrix} \text{upper triangular} \\ \text{lower triangular} \end{pmatrix}$$

$\Rightarrow \det(A) = \det(P) \cdot \det(L) \cdot \det(U)$.

More on this later...

Corollary: If A is diagonalizable,

$$A = U \begin{pmatrix} \lambda_1 & & 0 \\ & \lambda_2 & \\ 0 & & \lambda_n \end{pmatrix} U^{-1},$$

then $\det(A) = \lambda_1 \cdot \lambda_2 \cdot \dots \cdot \lambda_n$.
product of the eigenvalues

Proof:

$$\begin{aligned} \det(A) &= \det(U D U^{-1}) \\ &= \det(U) \cdot \det(D) \cdot \det(U^{-1}) \end{aligned}$$

$$\text{But } U \cdot U^{-1} = I$$

$$\Rightarrow \det(U) \cdot \det(U^{-1}) = \det(I) = 1$$

$$\Rightarrow \det(A) = \det(D) = \lambda_1 \dots \lambda_n \quad \checkmark \square$$

Key fact (that we will prove):

$$\det(A) \neq 0 \iff A \text{ is invertible}$$

- ~ "nonsingular"
- ~ inverse exists
- ~ $\text{rank}(A) = n$

$$\det(A) = 0 \iff A \text{ is not invertible}$$

- ~ $\text{rank}(A) < n$

COROLLARY: HOW TO FIND EIGENVECTORS:

Observe: λ is an eigenvalue of A



$$A\vec{v} = \lambda\vec{v} \text{ for a nonzero vector } \vec{v}$$



$$(A - \lambda I)\vec{v} = 0 \text{ for } \vec{v} \neq 0$$



$$N(A - \lambda I) \neq \{0\}.$$



$$A - \lambda I \text{ is singular!}$$



$$\det(A - \lambda I) = 0$$

$$\det(A - \lambda I) = 0 \iff \lambda \text{ is an eigenvalue of } A$$

- Recipe:
1. Compute $\det(A - \lambda I)$
 2. Find all roots, $\det(A - \lambda I) = 0$
 3. For each λ , corresponding eigenspace is $N(A - \lambda I)$ — find it with Gaussian elimination!

Problem: Calculate the eigenvalues and eigenvectors of

$$\begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix}$$

Answer: A

$$\begin{aligned} \det(A - \lambda I) &= \det \begin{pmatrix} 3 - \lambda & 1 \\ 1 & 3 - \lambda \end{pmatrix} \\ &= (3 - \lambda)(3 - \lambda) - 1 \\ &= \lambda^2 - 6\lambda + 8 \\ &= (\lambda - 4)(\lambda - 2) = 0 \end{aligned}$$

\Rightarrow Two eigenvalues, $\lambda_1 = 4$ and $\lambda_2 = 2$

Note: In general, if A is an $n \times n$ matrix, $\det(A - \lambda I)$ will be a degree- n polynomial in λ . Why?

Note: $\det A = \delta = \lambda_1 \cdot \lambda_2$
 — this is generally true!
 $\text{trace}(A) = \text{sum of diagonal elements}$
 $= 6$
 $= \lambda_1 + \lambda_2$
 — also generally true!

For 2×2 matrices, these two equations are enough to solve for λ_1 and λ_2 .

Next, the eigenspaces:

$$\begin{aligned} \bullet N(A - \lambda_1 I) &= N \left(\begin{pmatrix} -1 & 1 \\ 1 & -1 \end{pmatrix} \right) \\ &= \text{Span} \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\} \\ A \begin{pmatrix} 1 \\ 1 \end{pmatrix} &= 4 \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} \checkmark \end{aligned}$$

$$\begin{aligned} \bullet N(A - \lambda_2 I) &= N \left(\begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \right) \\ &= \text{Span} \left\{ \begin{pmatrix} -1 \\ 1 \end{pmatrix} \right\} \\ A \begin{pmatrix} -1 \\ 1 \end{pmatrix} &= \begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} -1 \\ 1 \end{pmatrix} = 2 \cdot \begin{pmatrix} -1 \\ 1 \end{pmatrix} \checkmark \end{aligned}$$

Done: $A = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}^{-1}$

↑ ↑ e-vectors ↑ e-values
Observe: The eigenvectors of $\begin{pmatrix} 3 & 1 \\ 1 & 3 \end{pmatrix}$ are the same as those for $\begin{pmatrix} 3 & 1 \\ 0 & 3 \end{pmatrix}$.

$$\text{If } B\vec{v} = \lambda\vec{v}, (B+3I)\vec{v} = (\lambda+3)\vec{v}$$

— But the eigenvalues of the sum of two matrices will not generally be the sum of the eigenvalues, unless they have the same eigenvectors.

Problem: Calculate the eigenvalues and eigenvectors of $\begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}$

Answer: First, give it a name (always a good idea!).

$$\text{Let } A = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}.$$

Now we solve for λ in

$$\begin{aligned} 0 &= \det(A - \lambda I) \\ &= \det \begin{pmatrix} -\lambda & -1 \\ 1 & -\lambda \end{pmatrix} \\ &= \lambda^2 + 1 \end{aligned}$$

$$\Rightarrow \lambda \in \{i, -i\}$$

↑ They add to 0 since $\text{Trace}(A) = 0$
 Their product is $1 = \det(A)$. ✓

To calculate the respective eigenvectors, we could solve for $N(A \pm iI)$. But it is easier just to go directly:

$$\begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ y \end{pmatrix} = i \begin{pmatrix} 1 \\ y \end{pmatrix}$$

$$\begin{pmatrix} -y \\ 1 \end{pmatrix} \Rightarrow y = -i \checkmark$$

Similarly,

$$\begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ i \end{pmatrix} = -i \begin{pmatrix} 1 \\ i \end{pmatrix}$$

Problem: What are the eigenvalues and eigenvectors of $\begin{pmatrix} 3 & 1 \\ 0 & 3 \end{pmatrix}$?

Answer: A''

$$A - \lambda I = \begin{pmatrix} 3-\lambda & 1 \\ 0 & 3-\lambda \end{pmatrix} \text{ is upper triangular}$$

⇒ determinant is product of diagonal entries
 ⇒ eigenvalue 3 (with multiplicity 2)

Eigenvectors: Solve

$$0 = (A - 3I)x = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$\Rightarrow x_2 = 0$$

and we may scale so $x_1 = 1$

⇒ eigenvector (δ')

is the only eigenvector!
(The matrix is not diagonalizable)

Problem: What are the eigenvalues of

$$\begin{pmatrix} 3 & 5 & 8 & 13 \\ & 2 & 3 & 5 \\ 0 & & 1 & 2 \\ & & & 1 \end{pmatrix} ?$$

Answer: Just as above, since the matrix is upper triangular, its eigenvalues are the diagonal elements: 3, 2 and 1 (with multiplicity 2). ✓

Moral: Triangular matrices are easy!

Question: Why does an $n \times n$ matrix have at most n distinct eigenvalues?

Answer 1:

Because $\det(A - \lambda I)$ is a degree n polynomial in λ , it always has ≥ 1 and $\leq n$ roots.

Answer 2:

Assume there are $n+1$ different eigenvalues:

$$A\vec{v}_1 = \lambda_1\vec{v}_1$$

$$\vdots$$

$$A\vec{v}_n = \lambda_n\vec{v}_n$$

$$A\vec{v}_{n+1} = \lambda_{n+1}\vec{v}_{n+1}$$

⇒ e-vectors cannot be linearly independent

If, say, the first n are lin. indep., then

$$\vec{v}_{n+1} = \alpha_1\vec{v}_1 + \alpha_2\vec{v}_2 + \dots + \alpha_n\vec{v}_n$$

for some constants $\alpha_1, \dots, \alpha_n$

Apply A to both sides

$$A\vec{v}_{n+1} = \lambda_{n+1}\vec{v}_{n+1}$$

$$\alpha_1\lambda_1\vec{v}_1 + \dots + \alpha_n\lambda_n\vec{v}_n \quad \alpha_1\lambda_{n+1}\vec{v}_1 + \dots + \alpha_n\lambda_{n+1}\vec{v}_n$$

$$\Rightarrow \sum_{j=1}^n \underbrace{\alpha_j(\lambda_j - \lambda_{n+1})}_{\text{nonzero!}} \vec{v}_j = 0$$

⇒ contradicts that $\{\vec{v}_1, \dots, \vec{v}_n\}$ are linearly independent.

Note: Dotting the i 's, this argument actually proves

Lemma: Any set of eigenvectors for a matrix, corresponding to distinct eigenvalues, is linearly independent.

Recall : λ is an eigenvalue of A



$$A\vec{v} = \lambda\vec{v} \text{ for a nonzero vector } \vec{v}$$



$$(A - \lambda I)\vec{v} = 0 \text{ for } \vec{v} \neq 0$$



$$N(A - \lambda I) \neq \{0\}.$$



we still need to prove this step!

$A - \lambda I$ is singular!



$$\det(A - \lambda I) = 0$$

Proof that $\det(A) \neq 0 \iff A$ is nonsingular:

① This is true in the case that A is upper triangular.

$$A = \begin{pmatrix} \text{[scribble]} \\ \text{[scribble]} \\ \text{[scribble]} \\ 0 \end{pmatrix}$$

A is nonsingular $\iff \text{rank}(A) = n$
 \iff all diagonal entries are nonzero
 $\iff \det A$ (product of diagonal entries) nonzero

② To reduce to the upper-triangular case, use Gaussian elimination! (Sorry.)
 Gaussian elimination has one basic operation:
 Add a multiple of one row to another row.
 How does this affect the determinant?

Lemma 1: If a row is repeated $\implies \det(A) = 0$.

Example: $\det \begin{pmatrix} a & b \\ a & b \end{pmatrix} = ab - ba = 0$ ✓

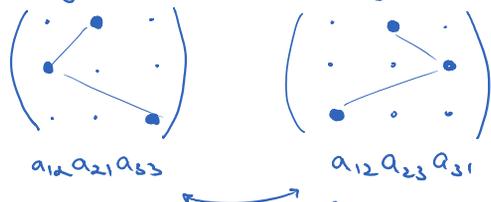
```
>> n = 10;
>> A = randn(n-1, n);
>> A = [A; A(5, :)];
>> det(A)
```

```
ans =
-1.6929e-14
```

Why?

$$\det(A) = \sum_{\text{permutations } \sigma} \text{sign}(\sigma) \cdot \prod_{i=1}^n A_{i, \sigma(i)}$$

If rows j and k are the same, then every term appears twice!



$$\begin{array}{c} | \cdot \cdot \cdot | \\ a_{12} a_{21} a_{33} \end{array} \quad \begin{array}{c} | \cdot \cdot \cdot | \\ a_{12} a_{23} a_{31} \end{array}$$

↔ the same if row 2 = row 3

But the permutations for matching terms differ by one transposition — so have opposite signs, and cancel out. ✓ □

Observation 2: The determinant function is definitely not linear, eg., $\det(10 \cdot A) = 10^n \cdot \det(A)$.

But each summand in

$$\det(A) = \sum_{\text{permutations } \sigma} \text{sign}(\sigma) \cdot \prod_{i=1}^n A_{i, \sigma(i)}$$

involves exactly one entry from any given row of A .

$$\Rightarrow \det \begin{pmatrix} 5a_{11} & 5a_{12} \\ a_{21} & a_{22} \end{pmatrix} = 5 \cdot \det \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix},$$

and, more importantly,

$$\det \begin{pmatrix} \text{--- row 1 ---} \\ \text{--- row 2 ---} \\ \vdots \\ \text{--- row n ---} \end{pmatrix} + \det \begin{pmatrix} \text{--- a different row 1 ---} \\ \text{--- row 2 ---} \\ \vdots \\ \text{--- row n ---} \end{pmatrix} \\ = \det \begin{pmatrix} \text{row 1 + different row 1} \\ \text{--- row 2 ---} \\ \vdots \\ \text{--- row n ---} \end{pmatrix}$$

Corollary: Adding one row to another does not change the determinant (by Obs. 2 and Lemma 1).

$$\det \begin{pmatrix} \text{row 1 + row 5} \\ \text{--- row 2 ---} \\ \vdots \\ \text{--- row n ---} \end{pmatrix} = \det \begin{pmatrix} \text{row 1} \\ \text{--- row 2 ---} \\ \vdots \\ \text{--- row n ---} \end{pmatrix} + \det \begin{pmatrix} \text{row 5} \\ \text{--- row 2 ---} \\ \text{row 3} \\ \vdots \\ \text{--- row n ---} \end{pmatrix}$$

= 0 since row 5 is repeated

⇒ Applying Gaussian elimination to A does not change whether $\det A = 0$ or $\det A \neq 0$.

After Gaussian elimination, $\det A' = 0 \Leftrightarrow \text{rank}(A') < n$.
Hence, before Gaussian elimination, $\det A = 0 \Leftrightarrow \text{rank}(A) < n$.

✓ □

SUMMARY OF EIGENVALUES ≠ EIGENVECTORS

To find the eigenvalues of an $n \times n$ matrix A , find the roots λ where $\det(A - \lambda I) = 0$.

$\det(A - \lambda I)$ is a polynomial in λ of degree n

⇒ it can be factored

$$\det(A - \lambda I) = (\lambda - \lambda_1)^{\alpha_1} \cdot (\lambda - \lambda_2)^{\alpha_2} \cdots (\lambda - \lambda_k)^{\alpha_k}$$

with $\alpha_1 + \alpha_2 + \cdots + \alpha_k = n$.

(hence $k \leq n$)

The eigenvalues of A are $\lambda_1, \lambda_2, \dots, \lambda_k$.

For each distinct eigenvalue λ_i ,

$$\dim N(A - \lambda_i I) \geq 1 \quad (\text{since it is an eigenvalue})$$

$$\text{and } \dim N(A - \lambda_i I) \leq \alpha_i$$

\Rightarrow There are at least k independent eigenvectors.

There are n independent eigenvectors

(i.e., A is diagonalizable)

if and only if

$$\dim N(A - \lambda_i I) = \alpha_i \quad \text{for every } i=1, \dots, k$$

Why is $\dim N(A - \lambda_i I) \leq \alpha_i$?

Proof: We want to show that $\text{rank}(A - \lambda_i I) \geq n - \alpha_i$;

the claim $\dim N(A - \lambda_i I) \leq \alpha_i$ then follows by the

Rank-Nullity Theorem.

Useful claim: If U is invertible, then the eigenvalues of A are the same as those of $U A U^{-1}$.

Proof: If $A \vec{v} = \lambda \vec{v}$, then

$$\begin{aligned} (U A U^{-1})(U \vec{v}) &= U A \vec{v} \\ &= \lambda (U \vec{v}) \quad \checkmark \end{aligned}$$

Now apply Gaussian elimination to A ; assuming no row interchanges are required, this gives

$$A = \begin{pmatrix} \boxed{L} \end{pmatrix} \begin{pmatrix} \boxed{U} \end{pmatrix}$$

where L has 1s along the diagonal and U has each λ_i on its diagonal α_i times. (Think about it....)

Thus we can also write

$$A = L U^{-1} L^{-1};$$

this means applying the same operations to the columns of U as were done to the rows of A in Gaussian elimination.

U^{-1} leaves the diagonal entries unchanged.

But then

$$\text{rank}(A - \lambda_i I) = \text{rank}(U^{-1} - \lambda_i I)$$

\geq # of nonzero entries along the diagonal, since $U^{-1} - \lambda_i I$ is upper triangular

$$= n - \alpha_i. \quad \checkmark \quad \square$$

Note: The recipe

- ① Compute $p(\lambda) = \det(A - \lambda I)$
- ② Find its factors $\lambda_1, \dots, \lambda_k \Rightarrow$ eigenvalues of A
- ③ Compute nullspaces $N(A - \lambda_i I) \Rightarrow$ eigenspaces

- (2) Find its factors $\lambda_1, \dots, \lambda_k \Rightarrow$ eigenvalues of A
 (3) Compute nullspaces $N(A - \lambda_i I) \Rightarrow$ eigenspaces

works in theory, and for 2×2 , 3×3 matrices.

But it quickly becomes impractical. Writing down $p(\lambda)$, and then finding its roots, is very time-consuming.

Next time we'll learn a faster way...

In fact, a common way of solving for the roots of a polynomial

$$p(\lambda) = \lambda^n + a_{n-1}\lambda^{n-1} + \dots + a_1\lambda + a_0$$

is to compute the eigenvalues of a matrix!

For

$$A = \begin{pmatrix} 0 & 0 & \dots & 0 & -a_0 \\ 1 & 0 & \dots & 0 & -a_1 \\ 0 & 1 & \dots & 0 & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & 0 & 1 & -a_{n-1} \end{pmatrix},$$

$$\det(A - \lambda I) = p(\lambda).$$

$$\begin{vmatrix} \lambda & a_0 \\ -1 & \lambda + a_1 \end{vmatrix} = \lambda^2 + \lambda a_1 + a_0$$

$$\begin{vmatrix} \lambda & 0 & a_0 \\ -1 & \lambda & a_1 \\ 0 & -1 & \lambda + a_2 \end{vmatrix} = \lambda^3 + \lambda^2 a_2 + \lambda a_1 + a_0$$

$$\begin{vmatrix} \lambda & 0 & 0 & a_0 \\ -1 & \lambda & 0 & a_1 \\ 0 & -1 & \lambda & a_2 \\ 0 & \dots & -1 & \lambda + a_3 \end{vmatrix} = \lambda^4 + \lambda^3 a_3 + \lambda^2 a_2 + \lambda a_1 + a_0$$

⋮