

Eigenvectors and diagonalization

- ▶ eigenvectors
- ▶ diagonalization

Eigenvectors and eigenvalues

$\lambda \in \mathbb{C}$ is called an **eigenvalue** of $A \in \mathbb{C}^{n \times n}$ if

$$A = \begin{bmatrix} i & 0 \\ 0 & 2i \end{bmatrix} \rightarrow \begin{cases} \lambda_1 = i \\ \lambda_2 = 2 \end{cases}$$

equivalent to:

Characteristic polynomial

- ▶ there exists nonzero $v \in \mathbb{C}^n$ s.t. $(\lambda I - A)v = 0$, i.e.,

$$Av = \lambda v$$

any such v is called an **eigenvector** of A (associated with eigenvalue λ)

- ▶ there exists nonzero $w \in \mathbb{C}^n$ s.t. $w^T(\lambda I - A) = 0$, i.e.,

$$w^T A = \lambda w^T$$

any such w is called a **left eigenvector** of A

$$\lambda I - A = \begin{bmatrix} \lambda & 1 \\ -1 & \lambda \end{bmatrix}$$

$$\det(\lambda I - A) = \lambda^2 + 1 = 0$$

$$\lambda^2 = -1$$

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

$$\lambda = \pm i$$

$$\begin{aligned} \lambda &= i \\ \lambda &= -i \end{aligned}$$

$$A^T w = \lambda w$$

if a scalar λ and a vector v exist, s.t.

$$Av = \lambda v$$

then λ is an **eigenvalue** of A and v is the corresponding **eigenvector**

Complex eigenvalues and eigenvectors

$$Av = \lambda v$$
$$A(\alpha v) = \lambda(\alpha v)$$

- ▶ if v is an eigenvector of A with eigenvalue λ , then so is αv , for any $\alpha \in \mathbb{C}$, $\alpha \neq 0$
- ▶ even when A is real, eigenvalue λ and eigenvector v can be complex
- ▶ when A and λ are real, we can always find a real eigenvector v associated with λ : if $Av = \lambda v$, with $A \in \mathbb{R}^{n \times n}$, $\lambda \in \mathbb{R}$, and $v \in \mathbb{C}^n$, then

$$A, \lambda \text{ real}$$
$$v = v_r + i v_i$$

$$A\Re v = \lambda\Re v, \quad A\Im v = \lambda\Im v$$

so $\Re v$ and $\Im v$ are real eigenvectors, if they are nonzero
(and at least one is)

- ▶ **conjugate symmetry**: if A is real and $v \in \mathbb{C}^n$ is an eigenvector associated with $\lambda \in \mathbb{C}$, then $\bar{v}$ is an eigenvector associated with $\bar{\lambda}$:

taking conjugate of $Av = \lambda v$ we get $\overline{Av} = \overline{\lambda v}$, so

$$\overline{A} \bar{v} = \bar{\lambda} \bar{v}$$

$$A \bar{v} = \bar{\lambda} \bar{v}$$

$$z \in \mathbb{R}$$

$$\updownarrow$$

$$z = \bar{z}$$

$$z = x + iy$$

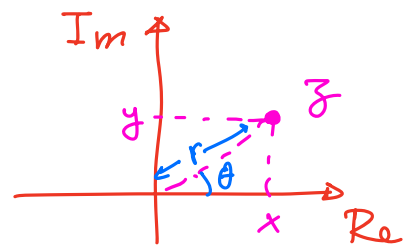
$$\bar{z} = x - iy$$

$$z \bar{z} = x^2 + y^2$$

we'll assume A is real from now on ...

$$z = x + iy$$

$\swarrow$ real $\searrow$ imaginary



$$\operatorname{Re}(z) = x$$

$$\operatorname{Im}(z) = y$$

$$i^2 = -1$$

$$\bar{z} = x - iy$$

$$z = r e^{i\theta} = r(\cos\theta + i\sin\theta)$$

$$\begin{aligned} z\bar{z} &= (x+iy)(x-iy) = x^2 - (iy)^2 \\ &= x^2 - \underbrace{(i)^2}_{-1} y^2 \\ &= x^2 + y^2 = |z|^2 \end{aligned}$$

$$z = r e^{i\theta}$$

$$r = \sqrt{x^2 + y^2}$$

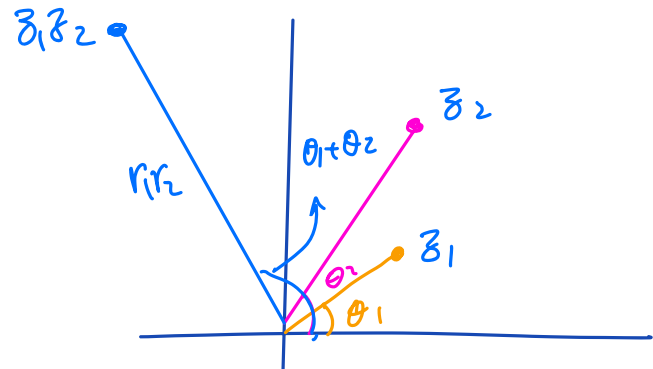
$$\theta = \tan^{-1} y/x$$

$$z_1 = x + iy$$

$$z_2 = a + ib$$

$$z_1 z_2 = (x + iy)(a + ib) = (xa - yb) + i(xb + ay)$$

$$r_1 e^{i\theta_1} \cdot r_2 e^{i\theta_2} = (r_1 r_2) e^{i(\theta_1 + \theta_2)}$$



Scaling interpretation

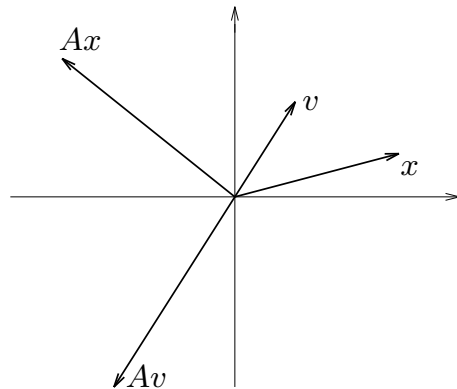
$$y = Ax$$

(assume $\lambda \in \mathbb{R}$ for now; we'll consider $\lambda \in \mathbb{C}$ later)

if v is an eigenvector, effect of A on v is very simple: scaling by λ

- ▶ $\lambda \in \mathbb{R}, \lambda > 0$: v and Av point in same direction
- ▶ $\lambda \in \mathbb{R}, \lambda < 0$: v and Av point in opposite directions
- ▶ $\lambda \in \mathbb{R}, |\lambda| < 1$: Av smaller than v
- ▶ $\lambda \in \mathbb{R}, |\lambda| > 1$: Av larger than v

(we'll see later how this relates to stability of continuous- and discrete-time systems. . .)



Diagonalization

suppose $v_1, \dots, v_n$ is a *linearly independent* set of eigenvectors of $A \in \mathbb{R}^{n \times n}$:

$$Av_i = \lambda_i v_i, \quad i = 1, \dots, n$$

express as

$$A \underbrace{\begin{bmatrix} v_1 & \cdots & v_n \end{bmatrix}}_T = \underbrace{\begin{bmatrix} v_1 & \cdots & v_n \end{bmatrix}}_T \overbrace{\begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}}^{\Lambda}$$

define $T = \begin{bmatrix} v_1 & \cdots & v_n \end{bmatrix}$ and $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$, so

$$AT = T\Lambda$$

$$T^{-1}AT = \Lambda$$

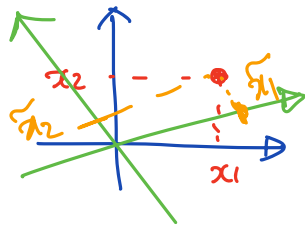
$$A = T\Lambda T^{-1}$$

holds for ANY matrix A

Diagonalization

$$T^{-1}AT = \Lambda$$

$$\begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$



- ▶ T invertible means $v_1, \dots, v_n$ linearly independent
- ▶ similarity transformation by T diagonalizes A
- ▶ existence of invertible T such that

$$T^{-1}AT = \Lambda = \mathbf{diag}(\lambda_1, \dots, \lambda_n)$$

is equivalent to existence of a linearly independent set of n eigenvectors

- ▶ we say A is diagonalizable
- ▶ if A is not diagonalizable, it is sometimes called defective

Not all matrices are diagonalizable

example: $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$

- ▶ characteristic polynomial is $\chi(s) = s^2$, so $\lambda = 0$ is only eigenvalue
- ▶ eigenvectors satisfy $Av = 0v = 0$, *i.e.*

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = 0$$

- ▶ so all eigenvectors have form $v = \begin{bmatrix} v_1 \\ 0 \end{bmatrix}$ where $v_1 \neq 0$
- ▶ thus, A cannot have two independent eigenvectors

Distinct eigenvalues

$$\begin{aligned} A = I &\rightarrow \chi(\lambda) = \det(\lambda I - A) \\ &= \det(\lambda I - I) = (\lambda - 1)^n = 0 \\ &\rightarrow \boxed{\lambda = 1} \end{aligned}$$

any $x \in \mathbb{R}^n$ is an eigenvector

if A has distinct eigenvalues then A is diagonalizable

$$\begin{aligned} T &= I \\ T^{-1} A T &= I^{-1} I I \end{aligned}$$

- ▶ distinct eigenvalues means $\lambda_i \neq \lambda_j$ for $i \neq j$
- ▶ the converse is false — A can have repeated eigenvalues but still be diagonalizable

Diagonalization and left eigenvectors

orthogonal matrix: $Q^{-1} = Q^T$

rewrite $T^{-1}AT = \Lambda$ as $T^{-1}A = \Lambda T^{-1}$, or

$$\begin{bmatrix} w_1^T \\ \vdots \\ w_n^T \end{bmatrix} A = \Lambda \begin{bmatrix} w_1^T \\ \vdots \\ w_n^T \end{bmatrix}$$

where $w_1^T, \dots, w_n^T$ are the rows of T^{-1}

thus

$$w_i^T A = \lambda_i w_i^T$$

i.e., the rows of T^{-1} are (lin. indep.) left eigenvectors, normalized so that

$$w_i^T v_j = \delta_{ij}$$

(i.e., left & right eigenvectors chosen this way are *dual bases*)

if T is orthogonal $\rightarrow T^{-1} = T^T \rightarrow w_i = v_i$

$$\begin{aligned} AT = T\Lambda &\rightarrow T^{-1}AT = \Lambda \\ &\rightarrow A = T\Lambda T^{-1} \\ &\rightarrow \boxed{T^{-1}A = \Lambda T^{-1}} \end{aligned}$$

$$\underbrace{\begin{bmatrix} w_1^T \\ \vdots \\ w_n^T \end{bmatrix}}_{T^{-1}} \underbrace{\begin{bmatrix} v_1 & \dots & v_n \end{bmatrix}}_T = I$$

$$\dots \begin{bmatrix} \dots w_i^T v_j \dots \end{bmatrix}$$

$$w_i^T v_j = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$$

Diagonalization

diagonalization simplifies many matrix expressions

powers (*i.e.*, discrete-time solution to $x(k+1) = Ax(k)$):

$$\begin{aligned} A^k &= (T\Lambda T^{-1})^k \\ &= (T\Lambda T^{-1}) \cdots (T\Lambda T^{-1}) \\ &= T\Lambda^k T^{-1} \\ &= T \mathbf{diag}(\lambda_1^k, \dots, \lambda_n^k) T^{-1} \end{aligned}$$

(for $k < 0$ only if A invertible, *i.e.*, all $\lambda_i \neq 0$)

$$\begin{aligned} A &= T\Lambda T^{-1} \\ A^2 &= T\Lambda \cancel{T^{-1}T} \Lambda T^{-1} \\ &= T\Lambda^2 T^{-1} \end{aligned}$$

$$= T \begin{bmatrix} \lambda_1^k & & \\ & \ddots & \\ & & \lambda_n^k \end{bmatrix} T^{-1}$$

Analytic function of a matrix

$$e^x = 1 + x + \frac{x^2}{2} + \frac{x^3}{3!} + \frac{x^4}{4!} + \dots$$

for any analytic function $f: \mathbb{R} \rightarrow \mathbb{R}$, i.e., given by power series

$$f(a) = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 a^3 + \dots$$

we can define $f(A)$ for $A \in \mathbb{R}^{n \times n}$ (i.e., overload f) as

$$f(A) = \beta_0 I + \beta_1 A + \beta_2 A^2 + \beta_3 A^3 + \dots$$

substituting $A = T \Lambda T^{-1}$, we have

$$\begin{aligned} f(A) &= \beta_0 I + \beta_1 A + \beta_2 A^2 + \beta_3 A^3 + \dots \\ &= \beta_0 T T^{-1} + \beta_1 T \Lambda T^{-1} + \beta_2 (T \Lambda T^{-1})^2 + \dots \\ &= T (\beta_0 I + \beta_1 \Lambda + \beta_2 \Lambda^2 + \dots) T^{-1} \\ &= T \operatorname{diag}(f(\lambda_1), \dots, f(\lambda_n)) T^{-1} \end{aligned}$$

$$x(t) = e^{At}$$

$$\beta_0 + \beta_1 \lambda_i + \beta_2 \lambda_i^2 + \dots = f(\lambda_i)$$

