

## CHAP 5. Eigenvalues and eigenvectors

For a square matrix  $A$ , we set the equation

$$Ax = \lambda x$$

↑      ↑  
eigenvalue    eigenvector ( $\neq 0$ )

\* When  $x$  is mapped to  $y$  by  $A$ ,  
an eigenvector

its direction is invariant.

\* Solving the eigenvalue problem

$$(A - \lambda I)x = 0.$$

1. Compute  $\det(A - \lambda I)$ , which is a polynomial of degree  $n$  in  $\lambda$ .
2. Find the roots of the polynomial. The  $n$  roots are the eigenvalues.
3. For each eigen value  $\lambda$ , solve the equation

$$(A - \lambda I)x = 0.$$

These solutions are the eigenvectors

Ex)  $A = \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix}$

$$A - \lambda I = \begin{bmatrix} 4 - \lambda & -5 \\ 2 & -3 - \lambda \end{bmatrix}$$

$$\begin{aligned} \det(A - \lambda I) &= \lambda^2 - \lambda - 12 + 10 \\ &= \lambda^2 - \lambda - 2 \\ &= (\lambda - 2)(\lambda + 1) \end{aligned}$$

①  $\lambda_1 = 2$

$$(A - 2I)x = \begin{bmatrix} 2 & -5 \\ 2 & -5 \end{bmatrix}x = 0$$

$$x_1 = \begin{bmatrix} 5 \\ 2 \end{bmatrix}$$

②  $\lambda_2 = -1$

$$(A + I)x = \begin{bmatrix} 5 & -5 \\ 2 & -2 \end{bmatrix}$$

$$x_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$A^k$  ?

$$A = \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix}$$

$$A^2 = \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix} \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix} = \begin{bmatrix} 6 & -5 \\ 2 & -1 \end{bmatrix}$$

$$A^3 = \begin{bmatrix} 6 & -5 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} 4 & -5 \\ 2 & -3 \end{bmatrix} = \begin{bmatrix} 14 & -15 \\ 6 & -7 \end{bmatrix}$$

$A^{100}$  ?

Note that

$$A \begin{bmatrix} 5 \\ 2 \end{bmatrix} = 2 \begin{bmatrix} 5 \\ 2 \end{bmatrix}$$

$$A \begin{bmatrix} 1 \\ 1 \end{bmatrix} = -1 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$A \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & -1 \end{bmatrix}$$

$$A = \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix}^{-1}$$

$$A^{100} = \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 2^{100} & 0 \\ 0 & (-1)^{100} \end{bmatrix} \begin{bmatrix} 5 & 1 \\ 2 & 1 \end{bmatrix}^{-1}$$

Ex 2) Diagonal matrix

$$A = \begin{bmatrix} 3 & \\ & 2 \end{bmatrix}$$

$$\lambda_1 = 3, x_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\lambda_2 = 2, x_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Ex 3) Projection matrix

$$P = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

$$\det(P - \lambda I) = \det \begin{bmatrix} \frac{1}{2} - \lambda & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} - \lambda \end{bmatrix} = \lambda^2 - \lambda = \lambda(\lambda - 1)$$

$$\lambda_1 = 0, x_1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

the points on the perpendicular line is mapped to 0.

$$\lambda_2 = 1, x_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

the points on  $y=x$  is not changed.

Projection onto the line  $y=x$ .

Ex 4) Another projection matrix

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\lambda_0 = 1 \quad x_0 = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad x_1 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

Both  $x_0$  and  $x_1 \in \mathcal{R}(P)$

$$\lambda_1 = 0 \quad x_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \quad x_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

Both  $x_2$  and  $x_3 \in \mathcal{N}(P)$ .

Ex 5) Triangular matrix

$$A = \begin{bmatrix} 1 & 4 & 5 \\ & \frac{3}{4} & 6 \\ & & \frac{1}{2} \end{bmatrix}$$

$$\det(A - \lambda I) = (1 - \lambda) \left(\frac{3}{4} - \lambda\right) \left(\frac{1}{2} - \lambda\right)$$

$\therefore \lambda = 1, \frac{3}{4}, \frac{1}{2}$  // diagonal elements

Properties of eigenvalues.

①  $\lambda_1 + \lambda_2 + \dots + \lambda_n = a_{11} + a_{22} + \dots + a_{nn} = \text{trace}(A)$

$$f(\lambda) = \det(A - \lambda I) = \det \begin{bmatrix} a_{11} - \lambda & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} - \lambda & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} - \lambda \end{bmatrix}$$

$$f(\lambda) = (a_{11} - \lambda)(a_{22} - \lambda) \dots (a_{nn} - \lambda) + \underbrace{g(\lambda)}_{\text{order less than } n-1}$$

$$= (-\lambda)^n + (a_{11} + a_{22} + \dots + a_{nn})(-\lambda)^{n-1} + \underbrace{h(\lambda)}_{\text{order less than } n-2} + \dots \textcircled{1}$$

Also

$$f(\lambda) = (\lambda_1 - \lambda)(\lambda_2 - \lambda) \dots (\lambda_n - \lambda)$$

$$= (-\lambda)^n + (\lambda_1 + \lambda_2 + \dots + \lambda_n)(-\lambda)^{n-1} + \underbrace{k(\lambda)}_{\text{order less than } n-2} + \dots \textcircled{2}$$

Since  $\textcircled{1} = \textcircled{2}$

$$a_{11} + \dots + a_{nn} = \lambda_1 + \dots + \lambda_n$$

②  $\lambda_1 \lambda_2 \dots \lambda_n = \det A$

$$\det(A - \lambda I) = (\lambda_1 - \lambda)(\lambda_2 - \lambda) \dots (\lambda_n - \lambda)$$

$$\Rightarrow \det A = \lambda_1 \lambda_2 \dots \lambda_n$$

## The diagonal form of a matrix

Assume that an  $n \times n$  matrix  $A$  has  $n$  linearly independent eigenvectors.

$$A x_i = \lambda_i x_i \quad (1 \leq i \leq n) \quad \text{and } x_i\text{'s are independent.}$$

$$A \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} = \begin{bmatrix} \lambda_1 x_1 & \lambda_2 x_2 & \dots & \lambda_n x_n \end{bmatrix}$$

$$= \underbrace{\begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix}}_S \underbrace{\begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \dots & \\ & & & \lambda_n \end{bmatrix}}_\Lambda$$

$$\# \quad A S = S \Lambda$$

$$\text{or } A = S \Lambda S^{-1}$$

Theorem. A matrix with distinct eigenvalues can be diagonalized, i.e.,  $x_1, \dots, x_n$  are independent.

Proof) Assume that  $c_1 x_1 + c_2 x_2 + \dots + c_n x_n = 0$

Then

$$\lambda_1 c_1 x_1 + \lambda_2 c_2 x_2 + \dots + \lambda_n c_n x_n = 0$$

$$\lambda_1^2 c_1 x_1 + \lambda_2^2 c_2 x_2 + \dots + \lambda_n^2 c_n x_n = 0$$

$\vdots$

$$\begin{bmatrix} c_1 x_1 & c_2 x_2 & \dots & c_n x_n \end{bmatrix} \begin{bmatrix} 1 & \lambda_1 & \dots & \lambda_1^{n-1} \\ 1 & \lambda_2 & \dots & \lambda_2^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \lambda_n & \dots & \lambda_n^{n-1} \end{bmatrix} = 0$$

Vandermonde's matrix

It is invertible if  $\lambda_i \neq \lambda_j$  when  $i \neq j$

By definition  $x_i$ 's are nonzero vectors.

Thus,  $c_1 = c_2 = \dots = c_n = 0$

and  $x_i$ 's are independent.

\* Suppose that Vandermonde's matrix is not invertible

$$\text{Then } \exists \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \neq 0 \text{ such that } \begin{bmatrix} 1 & \lambda_1 & \dots & \lambda_1^{n-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \lambda_n & \dots & \lambda_n^{n-1} \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} = 0$$

This implies that

$f(x) = c_1 + c_2 x + \dots + c_n x^{n-1}$  has  $n$  distinct solutions, which is a contradiction.

† Not all matrices are diagonalizable.

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

$$\lambda = 0 \quad z = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$\lambda = 0$  is a double eigenvalue, but we have only one eigenvector.

$$B = \begin{bmatrix} 3 & 1 \\ 0 & 3 \end{bmatrix}$$

$\lambda = 3$  but we have only one eigenvector.

$$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Ex 1)

$$A = \begin{bmatrix} \pm & \pm \\ \pm & \pm \end{bmatrix}$$

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

Ex 2)

$$K = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

No real eigenvalues and eigenvectors.

∴ The direction of a nonzero vector is changed by the rotation matrix.

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

$$\lambda = \pm i$$

$$\textcircled{1} \quad \lambda_1 = i \quad \begin{bmatrix} -i & -1 \\ 1 & -i \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = 0$$

$$z_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$$

$$\textcircled{2} \quad \lambda_2 = -i \quad \begin{bmatrix} i & -1 \\ 1 & i \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = 0$$

$$z_2 = \begin{bmatrix} 1 \\ i \end{bmatrix}$$

$$\therefore A \begin{bmatrix} 1 & 1 \\ -i & i \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -i & i \end{bmatrix} \begin{bmatrix} i & -i \\ -i & i \end{bmatrix}$$

**Thm.** If  $A$  has eigenvalues  $\lambda_1, \dots, \lambda_n$ , the eigenvalues of  $A^2$  are exactly  $\lambda_1^2, \dots, \lambda_n^2$ . Also, if  $x$  is an eigenvector of  $A$ , it is also an eigenvector of  $A^2$ .

Proof)  $A x_i = \lambda_i x_i$

$\Rightarrow A^2 x_i = \lambda_i^2 x_i$

**Thm.** If  $A = S \Lambda S^{-1}$ ,

$A^k = S \Lambda^k S^{-1}$ .

**Thm.** If  $A$  is invertible,  $\lambda_i$ 's are nonzero, and  $A^{-1}$  has eigenvalues  $\frac{1}{\lambda_i}$ .

$A x_i = \lambda_i x_i \Rightarrow \frac{1}{\lambda_i} x_i = A^{-1} x_i$

Ex)

$K = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$      $\lambda_1 = i$      $x_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$   
 $\lambda_2 = -i$      $x_2 = \begin{bmatrix} 1 \\ i \end{bmatrix}$

$K^2 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$

$\lambda_1 = -1$  (double root)

$x_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$      $x_2 = \begin{bmatrix} 1 \\ i \end{bmatrix}$

$K^{-1} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$

$\lambda_1 = \frac{1}{-i} = i$      $x_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$

$\lambda_2 = \frac{1}{i} = -i$      $x_2 = \begin{bmatrix} 1 \\ i \end{bmatrix}$

## Difference Equations

① Fibonacci sequence

0, 1, 1, 2, 3, 5, 8, ...

$$F_{k+2} = F_{k+1} + F_k, \quad F_0 = 0, \quad F_1 = 1.$$

$$u_k = \begin{bmatrix} F_{k+1} \\ F_k \end{bmatrix}$$

$$u_{k+1} = \begin{bmatrix} F_{k+2} \\ F_{k+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} F_{k+1} \\ F_k \end{bmatrix} \\ = A u_k$$

$$u_0 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$u_1 = A u_0$$

$$u_2 = A u_1 = A^2 u_0$$

⋮

$$u_k = A^k u_0$$

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

$$\det \begin{bmatrix} 1-\lambda & 1 \\ 1 & -\lambda \end{bmatrix} = \lambda^2 - \lambda - 1 = 0$$

$$\lambda = \frac{1 \pm \sqrt{5}}{2} \quad \lambda_1 \lambda_2 = -1$$

$$\lambda_1 = \frac{1 + \sqrt{5}}{2}$$

$$\lambda_2 = \frac{1 - \sqrt{5}}{2}$$

$$\begin{bmatrix} \frac{1-\sqrt{5}}{2} & 1 \\ 1 & -\frac{1-\sqrt{5}}{2} \end{bmatrix}$$

$$\begin{bmatrix} \frac{1+\sqrt{5}}{2} & 1 \\ 1 & -\frac{1+\sqrt{5}}{2} \end{bmatrix}$$

$$x_1 = \begin{bmatrix} \frac{1+\sqrt{5}}{2} \\ 1 \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ 1 \end{bmatrix}$$

$$x_2 = \begin{bmatrix} \frac{1-\sqrt{5}}{2} \\ 1 \end{bmatrix} = \begin{bmatrix} \lambda_2 \\ 1 \end{bmatrix}$$

$$\therefore A \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix}$$

$$A = \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1 & \\ & \lambda_2 \end{bmatrix} \frac{1}{\lambda_1 - \lambda_2} \begin{bmatrix} 1 - \lambda_2 & \\ -1 & \lambda_1 \end{bmatrix}$$

$$A^k = \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1^k & \\ & \lambda_2^k \end{bmatrix} \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix}^{-1}$$



$$\begin{aligned} \therefore u_k &= \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1^k & \\ & \lambda_2^k \end{bmatrix} \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1^k & \\ & \lambda_2^k \end{bmatrix} \frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \\ &= \frac{1}{\sqrt{5}} \begin{bmatrix} \lambda_1 & \lambda_2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} \lambda_1^k \\ -\lambda_2^k \end{bmatrix} \end{aligned}$$

$$\begin{aligned} \therefore F_k &= \frac{1}{\sqrt{5}} [\lambda_1^k - \lambda_2^k] \\ &= \frac{1}{\sqrt{5}} \left[ \left( \frac{1+\sqrt{5}}{2} \right)^k - \left( \frac{1-\sqrt{5}}{2} \right)^k \right] \end{aligned}$$

$$\begin{aligned} \text{Golden ratio} &= \lim_{k \rightarrow \infty} \frac{F_{k+1}}{F_k} = \frac{1+\sqrt{5}}{2} \\ &\doteq 1.618. \end{aligned}$$

In general, (if  $A$  is diagonalizable?)

$$\begin{cases} u_k = A^k u_0 \\ A^k = S \Lambda^k S^{-1} \end{cases}$$

Therefore,

$$u_k = S \Lambda^k S^{-1} u_0$$

$$\text{let } S^{-1} u_0 \doteq \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} = c \quad \dots (b)$$

$$\begin{aligned} \text{Then } u_k &= \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} \begin{bmatrix} \lambda_1^k & & \\ & \ddots & \\ & & \lambda_n^k \end{bmatrix} \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \\ &= \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} \begin{bmatrix} \lambda_1^k c_1 \\ \vdots \\ \lambda_n^k c_n \end{bmatrix} \\ &= c_1 \lambda_1^k x_1 + c_2 \lambda_2^k x_2 + \dots + c_n \lambda_n^k x_n \quad \dots (a) \end{aligned}$$

Another interpretation of (a)

From (b),

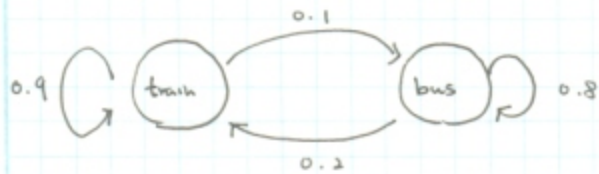
$$\begin{aligned} u_0 &= S c \\ &= c_1 x_1 + \dots + c_n x_n \end{aligned}$$

Then

$$\begin{aligned} A^k u_0 &= c_1 A^k x_1 + \dots + c_n A^k x_n \\ &= c_1 \lambda_1^k x_1 + \dots + c_n \lambda_n^k x_n \end{aligned}$$

stability.

## ② Markov Process



$y_k$  # of train users on day  $k$

$z_k$  # of bus users on day  $k$ .

$$\begin{bmatrix} y_k \\ z_k \end{bmatrix} = \begin{bmatrix} 0.9 & 0.2 \\ 0.1 & 0.8 \end{bmatrix} \begin{bmatrix} y_{k-1} \\ z_{k-1} \end{bmatrix}$$

$I=1 \quad I=1$

All entries are nonnegative.

$$\begin{bmatrix} y_k \\ z_k \end{bmatrix} = A^k \begin{bmatrix} y_0 \\ z_0 \end{bmatrix}$$

where  $A = \begin{bmatrix} 0.9 & 0.2 \\ 0.1 & 0.8 \end{bmatrix}$

## Diagonalization of $A$

Characteristic polynomial

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

$$= (0.9 - \lambda)(0.8 - \lambda) - 0.02$$

$$= \lambda^2 - 1.7\lambda + 0.7$$

$$= (\lambda - 1)(\lambda - 0.7)$$

$$\lambda_1 = 1 \quad A - \lambda_1 I = \begin{bmatrix} -0.1 & 0.2 \\ 0.1 & -0.2 \end{bmatrix}$$

$$\therefore z_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$\lambda_2 = 0.7 \quad A - \lambda_2 I = \begin{bmatrix} 0.2 & 0.2 \\ 0.1 & 0.1 \end{bmatrix}$$

$$z_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

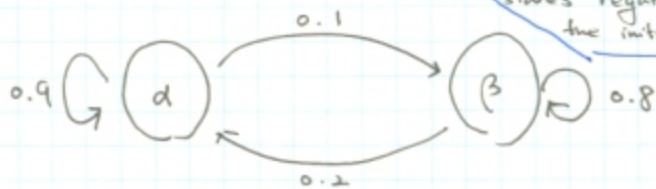
$$\therefore A \begin{bmatrix} 2 & 1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0.7 \end{bmatrix}$$

$$A = S \begin{bmatrix} 1 & \\ & 0.7 \end{bmatrix} S^{-1}$$

$$\begin{aligned}
 \begin{bmatrix} y_k \\ z_k \end{bmatrix} &= S \begin{bmatrix} 1 \\ (0.7)^k \end{bmatrix} S^{-1} \begin{bmatrix} y_0 \\ z_0 \end{bmatrix} \\
 &= S \begin{bmatrix} 1 \\ (0.7)^k \end{bmatrix} \cdot \frac{1}{3} \begin{bmatrix} -1 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} y_0 \\ z_0 \end{bmatrix} \\
 &= \frac{1}{3} S \begin{bmatrix} 1 \\ (0.7)^k \end{bmatrix} \begin{bmatrix} y_0 + z_0 \\ y_0 - 2z_0 \end{bmatrix} \\
 &= \frac{1}{3} S \begin{bmatrix} y_0 + z_0 \\ (0.7)^k (y_0 - 2z_0) \end{bmatrix} \\
 &= \frac{1}{3} \begin{bmatrix} 2 \\ 1 \end{bmatrix} (y_0 + z_0) + \frac{1}{3} \begin{bmatrix} 1 \\ -1 \end{bmatrix} (0.7)^k (y_0 - 2z_0)
 \end{aligned}$$

$$\Rightarrow \begin{bmatrix} \frac{2(y_0 + z_0)}{3} \\ \frac{(y_0 + z_0)}{3} \end{bmatrix} \text{ as } k \rightarrow \infty.$$

It goes to the steady states regardless of the initial conditions.



$$\alpha + \beta = y_0 + z_0$$

$$\alpha \cdot 0.1 = \beta \cdot 0.2$$

$$\therefore \alpha = \frac{2(y_0 + z_0)}{3} \quad \beta = \frac{y_0 + z_0}{3}$$

\* General properties of Markov processes

(a)  $\lambda_1 = 1$  is an eigenvalue

(b) Its eigenvector  $x_1$  is nonnegative and it is a steady state since  $Ax_1 = z_1$ .

(c) The other eigenvalues satisfy  $|\lambda_i| \leq 1$ .

(d) If any power of  $A$  has all positive entries, these other  $|\lambda_i|$  are strictly less than 1. The solution  $A^k u_0$  approaches a multiple of  $z_1$ .

beyond the scope of this course.

Extension from  $\mathbb{R}^n$  to  $\mathbb{C}^n$

\* Length of  $x = (1, i)$  ?

$$x^T x = 1^2 + i^2 = 0 \quad ?$$

\*  $x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$

$$\|x\|^2 = |x_1|^2 + |x_2|^2 + |x_3|^2 + \dots + |x_n|^2 \dots ①$$
$$= \bar{x}^T x$$

where  $\bar{x}$  denotes the complex conjugate of  $x$ , i.e.

$$\bar{x} = \begin{bmatrix} \bar{x}_1 \\ \vdots \\ \bar{x}_n \end{bmatrix}$$

For example.

If  $x = \begin{bmatrix} 1 \\ i \end{bmatrix}$

$$\|x\|^2 = \bar{x}^T x$$
$$= \begin{bmatrix} 1 \\ -i \end{bmatrix}^T \begin{bmatrix} 1 \\ i \end{bmatrix}$$
$$= 1 - i^2 = 2$$

\* Inner product between  $x$  and  $y$

$$\bar{x}^T y = \bar{x}_1 y_1 + \bar{x}_2 y_2 + \dots + \bar{x}_n y_n \dots ②$$

This is consistent with our definition of length

$$\|x\|^2 = \text{the inner product of } x \text{ with itself.}$$

Also, if both  $x$  and  $y$  are real

$$\bar{x}^T y = x^T y$$

Thus, it is consistent with our definition of inner product in  $\mathbb{R}^n$ .

\*  $x$  and  $y$  are orthogonal (perpendicular) if

$$\bar{x}^T y = 0$$

Ex)  $x = (1+i, 3i)$      $y = (4, 2-i)$

$$\bar{x}^T y = (1-i)4 - 3i(2-i)$$
$$= 1 - 10i$$

$x$  and  $y$  are not orthogonal.

In both ① and ②, we see

$\bar{x}^T$ , i.e., the combined operation of conjugate and transpose.

Thus, we define, for any matrix  $A$ ,

$$A^H = \bar{A}^T$$

which is called "A conjugate transpose."

As a rule of thumb, the transpose in  $\mathbb{R}^n$  is converted to the conjugate transpose in  $\mathbb{C}^n$

① Length  $x^T x \rightarrow x^H x$

② Innerproduct  $x^T y \rightarrow x^H y$

Ex)

$$A = \begin{bmatrix} 2+i & 3i \\ 4-i & 5 \\ 0 & 0 \end{bmatrix}$$

$$A^H = \begin{bmatrix} 2-i & 4+i & 0 \\ -3i & 5 & 0 \end{bmatrix}$$

Also, note that

$$(AB)^H = B^H A^H$$

$$\begin{aligned} \therefore (AB)^H &= (\overline{AB})^T = (\bar{A}\bar{B})^T \\ &= \bar{B}^T \bar{A}^T = B^H A^H. \end{aligned}$$

## Hermitian Matrices

$$A^H = A$$

$$\text{Ex)} \quad A = \begin{bmatrix} 2 & 3-3i \\ 3+3i & 5 \end{bmatrix}$$

Properties:

- ① Diagonal elements are real.
- ② A real symmetric matrix is Hermitian.

$$[\because A^H = \bar{A}^T = A^T = A.]$$

- ③ For all complex vectors  $x$ ,  
 $x^H A x$  is real.

$$\begin{aligned} \text{ex)} \quad & [\bar{u} \quad \bar{v}] \begin{bmatrix} 2 & 3-3i \\ 3+3i & 5 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \\ & = \frac{2\bar{u}u}{\text{real}} + \underbrace{\bar{u}(3-3i)v + \bar{v}(3+3i)u}_{\text{complex conjugate}} + \frac{5\bar{v}v}{\text{real}} \end{aligned}$$

In general,

$$\begin{aligned} y &= x^H A x = y^H = x^H A^H x \\ \therefore y &= \bar{y} \quad y \text{ is real.} \end{aligned}$$

- ④ Every eigenvalue is real.

$\therefore$  Suppose  $Ax = \lambda x$

$$x^H A x = x^H \lambda x = \lambda \|x\|^2$$

$$\lambda = \frac{x^H A x}{\|x\|^2} \text{ is real.}$$

$$\begin{aligned} \text{ex)} \quad \det \begin{bmatrix} 2-\lambda & 3-3i \\ 3+3i & 5-\lambda \end{bmatrix} &= \lambda^2 - 7\lambda + 10 - 18 \\ &= (\lambda-8)(\lambda+1) \end{aligned}$$

$$\lambda = 8 \text{ or } -1$$

- ⑤ A has an orthonormal set of eigenvectors.

Proof) For simplicity, assume that all eigenvalues are distinct.

$$Ax_1 = \lambda_1 x_1, \quad Ax_2 = \lambda_2 x_2$$

$$x_2^H A x_1 = \lambda_1 x_2^H x_1$$

$$x_1^H A x_2 = \lambda_2 x_1^H x_2$$

$$x_2^H A x_1 = \lambda_2 x_2^H x_1$$

$$\therefore (\lambda_1 - \lambda_2) x_2^H x_1 = 0$$

$$\therefore x_2^H x_1 = 0.$$

They are orthogonal, and we can normalize them by

$$\frac{x_1}{\|x_1\|}, \frac{x_2}{\|x_2\|}, \dots$$

ex)  $A = \begin{bmatrix} 2 & 3-3i \\ 3+3i & 5 \end{bmatrix}$

$\lambda_1 = 8$

$A - \lambda_1 I = \begin{bmatrix} -6 & 3-3i \\ 3+3i & -3 \end{bmatrix}$

$x_1 = \begin{bmatrix} 1 \\ 1+i \end{bmatrix}$  or  $\frac{1}{\sqrt{5}} \begin{bmatrix} 1 \\ 1+i \end{bmatrix}$

$\lambda_2 = -1$

$A - \lambda_2 I = \begin{bmatrix} 3 & 3-3i \\ 3+3i & 6 \end{bmatrix}$

$x_2 = \begin{bmatrix} 1-i \\ -1 \end{bmatrix}$  or  $\frac{1}{\sqrt{2}} \begin{bmatrix} 1-i \\ -1 \end{bmatrix}$

$x_1^H x_2 = 1-i - (1-i) = 0$ .

⑥  $A \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} = \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$

where  $x_i^H x_j = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{if } i \neq j \end{cases}$

$\mathcal{U}$  = unitary matrix  
 $A \mathcal{U} = \mathcal{U} \Lambda$

$A = \mathcal{U} \Lambda \mathcal{U}^H$   
 $= \mathcal{U} \Lambda \mathcal{U}^H$

$\mathcal{U}^H \mathcal{U} = \begin{bmatrix} x_1^H & & \\ & \ddots & \\ & & x_n^H \end{bmatrix} \begin{bmatrix} x_1 & \dots & x_n \end{bmatrix} = I$

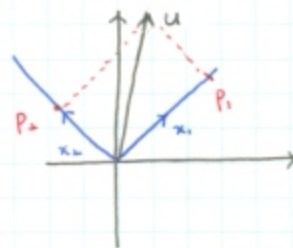
⑦ If  $A$  is real and symmetric, the eigenvectors are also real.

( $\because$  They are solutions of  $(A - \lambda I)x = 0$  real.)

Then  $A = \mathcal{U} \Lambda \mathcal{U}^H$   
 $= \mathcal{Q} \Lambda \mathcal{Q}^T \dots (i)$   
 orthogonal matrix.

$A = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & & \\ & \ddots & & \\ & & \lambda_n & \\ & & & \ddots \end{bmatrix} \begin{bmatrix} x_1^T \\ \vdots \\ x_n^T \end{bmatrix}$   
 $= \lambda_1 (x_1 x_1^T) + \dots + \lambda_n x_n x_n^T$   
 projection onto  $x_i$ -axis

For example,



$Au = \lambda_1 x_1 x_1^T u + \lambda_2 x_2 x_2^T u$   
 $= \lambda_1 P_1 + \lambda_2 P_2$

Considering  $x_1$  and  $x_2$  as new coordinate axes,  $A$  scales <sup>the</sup> input  $u$  by a factor of  $\lambda_1$  along  $x_1$  axis,  $\lambda_2$  along  $x_2$  axis.

(i) is called also as principal axis theorem

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

$$\det \begin{bmatrix} 2-\lambda & -1 \\ -1 & 2-\lambda \end{bmatrix} = \lambda^2 - 4\lambda + 3 = (\lambda-1)(\lambda-3)$$

$$\lambda_1 = 1 \quad x_1 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\lambda_2 = 3 \quad x_2 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} \end{bmatrix}$$

$$A \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & \\ & 3 \end{bmatrix}$$

$$\begin{aligned} A &= \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 1 & \\ & 3 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \\ &= 1 \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix} + 3 \begin{bmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} \end{bmatrix} \end{aligned}$$

To summarize, a Hermitian matrix has real eigenvalues and orthonormal set of eigenvectors.

It is diagonalizable

$$A = U \Lambda U^H$$

$U$  unitary matrix

$$= Q \Lambda Q^H$$

$Q$  orthogonal matrix  
(when  $A$  is real and symmetric)



## Unitary Matrices

$$U^H U = I.$$

Properties:

$$\textcircled{1} (Ux)^H Uy = x^H y$$

(angle and length are preserved)

$\textcircled{2}$  Every eigenvalue has absolute value  $|\lambda| = 1$

$$\therefore Ux = \lambda x$$

$$\|Ux\| = \|x\| = |\lambda| \|x\|$$

$$\Rightarrow |\lambda| = 1$$

$\textcircled{3}$  Eigenvectors, corresponding to different eigenvalues, are orthogonal.

$$\text{Let } Ux_1 = \lambda_1 x_1, \quad Ux_2 = \lambda_2 x_2$$

$$\begin{aligned} (Ux_1)^H (Ux_2) &= x_1^H x_2 \\ &= \bar{\lambda}_1 \lambda_2 x_1^H x_2 \end{aligned}$$

$$\therefore (\bar{\lambda}_1 \lambda_2 - 1) x_1^H x_2 = 0$$

$$(e^{-i\theta_1} e^{i\theta_2} - 1) x_1^H x_2 = 0$$

$$\therefore x_1^H x_2 = 0 \quad (\because \theta_2 - \theta_1 \neq 2\pi n)$$

Ex)

$$U = \begin{bmatrix} \cos t & -\sin t \\ \sin t & \cos t \end{bmatrix}$$

$$\begin{aligned} \det(U - \lambda I) &= (\lambda - \cos t)^2 + \sin^2 t \\ &= \lambda^2 - 2\cos t \lambda + 1 \end{aligned}$$

$$\lambda = \cos t \pm \sqrt{\cos^2 t - 1} = \cos t \pm i \sin t = e^{\pm it}$$

$$\lambda_1 = e^{it} \quad x_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ i \end{bmatrix}$$

$$\lambda_2 = e^{-it} \quad x_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -i \end{bmatrix}$$

$$\therefore U = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ i & -i \end{bmatrix} \begin{bmatrix} e^{it} & \\ & e^{-it} \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix}$$

$$\text{Note that } x_1^H x_2 = \frac{1}{2} (1 - 1) = 0.$$

$$|\lambda_1| = |\lambda_2| = 1.$$