



7 Eigenvalues and Eigenvectors

7.1 Definition

- For a given $n \times n$ matrix A , consider the equation :

$$(1) \quad \boxed{Ax = \lambda x} \quad \text{"eigenvalue problem"}$$

x : unknown vector

λ : unknown scalar

when (1) has a solution $x \neq 0$,

- a value of λ for which a nonzero x exists is called an eigenvalue
- the corresponding nonzero x is called an eigenvector

- How to solve an eigenvalue problem?

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

For nonzero x , we need $\det(A - \lambda I) = 0$.

\Rightarrow Compute n roots (eigenvalues)

For each λ , solve $(A - \lambda I)x = 0$ for nonzero x .

(If x is an eigenvector, so is cx .)

note Elimination does not preserve λ .

$$\text{ex) } U = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \quad A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$$

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

$$|A - \lambda I| = \begin{vmatrix} -\lambda & 1 \\ -1 & -\lambda \end{vmatrix} = \lambda^2 + 1 = 0 \quad \Rightarrow \lambda_1 = i, \quad \lambda_2 = -i$$

$$\begin{bmatrix} -i & 1 \\ -1 & -1 \end{bmatrix} x_1 = 0 \quad \Rightarrow x_1 = \begin{bmatrix} 1 \\ i \end{bmatrix}$$

$$\begin{bmatrix} i & 1 \\ -1 & 1 \end{bmatrix} x_2 = 0 \quad \Rightarrow x_2 = \begin{bmatrix} 1 \\ -i \end{bmatrix}$$

7.2 Symmetric, Skew-symmetric, and Orthogonal Matrices

- For a real matrix A
 - symmetric if $A^T = A$

- skew-symmetric if $A^T = -A$
- orthogonal if $A^T = A^{-1}$

• For a complex matrix A

- Hermitian if $\bar{A}^T = A$ $\leftarrow \bar{a}_{jj} = a_{jj}$ (real diagonal)
- skew-Hermitian if $\bar{A}^T = -A$ $\leftarrow \bar{a}_{jj} = -a_{jj}$ (pure imaginary or 0 on the diag.)
- unitary if $\bar{A}^T = A^{-1}$

Theorem [Eigenvalue]

- The eigenvalues of a Hermitian matrix (and of a symmetric matrix) are real.
- The eigenvalues of a skew-Hermitian matrix (and of a skew-symmetric matrix) are pure imaginary or 0.
- The eigenvalues of a unitary matrix (and of an orthogonal matrix) have absolute value 1.

Proof

(i) Let $\bar{A}^T = A$.

$$Ax = \lambda x \quad \Rightarrow \quad \bar{x}^T Ax = \bar{x}^T \lambda x = \lambda \underbrace{(|x_1|^2 + \dots + |x_n|^2)}_{\text{real, nonzero}} \quad (*)$$

$$(\bar{A}x) = x^T \bar{A} \bar{x} = (x^T \bar{A} \bar{x})^T = \bar{x}^T \bar{A}^T = \bar{x}^T Ax \quad (**)$$

$$\Rightarrow \bar{x}^T Ax \text{ is real.}$$

$$\therefore \lambda = \frac{\text{real}}{\text{real}} = \text{real}$$

(ii) Let $\bar{A}^T = -A$.

Then (**) becomes $\overline{(\bar{x}^T Ax)} = -\bar{x}^T Ax = \text{pure imaginary or 0}$

$$\therefore \lambda = 0$$

(iii) Let $\bar{A}^T = A^{-1}$.

$$\text{Then } \underbrace{Ax = \lambda x}_{\square} \quad \Rightarrow \quad \underbrace{(\bar{A}\bar{x})^T = (\bar{\lambda}\bar{x})^T = \bar{\lambda}\bar{x}^T}_{\blacksquare}$$

multiply \square and \blacksquare , then

$$(\bar{A}\bar{x})^T = \bar{\lambda}\bar{x}^T \lambda x = |\lambda|^2 \bar{x}^T x$$

$$|\lambda|^2 = 1.$$

7.3 Similarity and Diagonalization

Definition $n \times n$ matrices A and \hat{A} are *similar* if $\hat{A} = P^{-1}AP$ for some nonsingular matrix P .

Theorem If \hat{A} is similar to A , then \hat{A} has the same eigenvalues as A . And if x is an eigenvector of A , then $y = P^{-1}x$ is an eigenvector of \hat{A} corresponding to the same eigenvalues

Proof

$$\begin{aligned} \text{Let } Ax &= \lambda x \quad (x \neq 0) \\ P^{-1}Ax &= P^{-1} \lambda x \\ P^{-1}APP^{-1}x &= \lambda P^{-1}x \\ \hat{A} P^{-1}x & \end{aligned}$$

$\therefore P^{-1}x$ is an eigenvector of \hat{A} corresponding to eigenvalue λ

Theorem [Diagonalization] \mapsto (Strang pg. 288, Kreyzig pg.394)

Suppose the $n \times n$ matrix A has n linearly independent eigenvectors x_1, \dots, x_n .

Let $X = [x_1 \cdots x_n]$: eigenvector matrix

$$\text{Then } X^{-1}AX = \Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix} : \text{eigenvalue matrix (diagonalized!)}$$

Proof

$$\begin{aligned} AX &= A[x_1 \cdots x_n] = [Ax_1 \cdots Ax_n] = [\lambda_1 x_1 \cdots \lambda_n x_n] \\ &= [x_1 \cdots x_n] \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{bmatrix} = X\Lambda \end{aligned}$$

$\therefore X^{-1}AX = \Lambda \leftarrow$ We assumed $[x_1 \cdots x_n]$ are linearly independent.

Note Invertibility vs Diagonalizability
 whether an eigenvalue is 0 or not whether there are n linearly independent eigenvectors or not
 \Rightarrow No connection!

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

$$\det(A - \lambda I) = \begin{vmatrix} 1 - \lambda & 0 \\ 0 & 1 - \lambda \end{vmatrix} = 0 \Rightarrow \lambda_{1,2} = 1 \text{ (repeated eigenvalues)}$$

$$\text{eigenvectors satisfy } \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \mathbf{x} = 0 \Rightarrow \mathbf{x} = c \begin{bmatrix} 1 \\ 0 \end{bmatrix} \text{ (no second eigenvector)}$$

$\therefore A$ cannot be diagonalized.

Theorem Eigenvectors $x_1 \cdots x_j$ that correspond to distinct eigenvalues are linearly independent. Thus, an $n \times n$ matrix with n distinct eigenvalues is diagonalizable.

Proof

$$c_1 x_1 + \cdots + c_{j-1} x_{j-1} + c_j x_j = \mathbf{0} \quad (1)$$

$$\lambda_1 c_1 x_1 + \cdots + \lambda_{j-1} c_{j-1} x_{j-1} + \lambda_j c_j x_j = \mathbf{0} \quad (2)$$

$$\lambda_j(1) \Rightarrow \lambda_j c_1 x_1 + \cdots + \lambda_j c_{j-1} x_{j-1} + \lambda_j c_j x_j = \mathbf{0} \quad (3)$$

$$(2) - (3) \Rightarrow (\lambda_1 - \lambda_j) c_1 x_1 + \cdots + (\lambda_{j-1} - \lambda_j) c_{j-1} x_{j-1} = \mathbf{0} \quad (4)$$

$$\mathbf{A}(4) \Rightarrow (\lambda_1 - \lambda_j) c_1 x_1 + \cdots + (\lambda_{j-1} - \lambda_j) \lambda_{j-1} c_{j-1} x_{j-1} = \mathbf{0} \quad (5)$$

$$\lambda_{j-1}(4) \Rightarrow (\lambda_1 - \lambda_j) \lambda_{j-1} c_1 x_1 + \cdots + (\lambda_{j-1} - \lambda_j) \lambda_{j-1} c_{j-1} x_{j-1} = \mathbf{0} \quad (6)$$

$$(5) - (6) \Rightarrow (\lambda_1 - \lambda_j)(\lambda_1 - \lambda_{j-1}) c_1 x_1 + \cdots + (\lambda_{j-2} - \lambda_j)(\lambda_{j-2} - \lambda_{j-1}) c_{j-1} x_{j-1} = \mathbf{0} \quad (7)$$

\implies continue this process. Eventually,

$$(\lambda_1 - \lambda_j)(\lambda_1 - \lambda_{j-1} \cdots (\lambda_1 - \lambda_2) c_1 x_1) = \mathbf{0}$$

$$\Rightarrow c_1 = 0$$

\Rightarrow similarly, every $c_i = 0$

$\therefore x_1, \cdots, x_j$ are linearly independent.

when $\lambda_1, \cdots, \lambda_n$ are all different, we have linearly independent x_1, \cdots, x_n . Thus, \mathbf{A} is diagonalizable in that case.