

## Eigenvalue Problems

Let  $A \in \mathbb{R}^{m \times m}$ ,  $\underline{x} \neq 0 \in \mathbb{C}^m$  ( $\mathbb{C}$  is set of complex nos.)  
then  $\underline{x}$  is an eigenvector of  $A$  and  
 $\lambda \in \mathbb{C}$  is its corresponding eigenvalue

if

$$\boxed{A\underline{x} = \lambda \underline{x}}$$

\* The set of all eigenvalues of a matrix  $A$  is called the spectrum of  $A$  denoted by  $\Lambda(A)$

## Application areas:-

- \* Insights into evolution of system
  - vibration analysis
  - study of resonance
  - stability of structures
  - fluid flows subjected to small perturbations

- \* Quantum mechanical modeling of matter  
(Solving Schrödinger equation)
- \* Principal stresses in solid mechanics
- \* PCA in data driven modeling
- \* Page rank algorithm used in search engines is an eigenvalue problem
- \* Eigenvectors of graph Laplacian matrix actually help in construction of efficient filters Graph Convolution Neural Network!

Eigenvalue decomposition!

An eigenvalue decomposition of

$\underline{A} \in \mathbb{R}^{m \times m}$  is a factorization

$$\underline{A} = \underline{X} \underline{\Lambda} \underline{X}^{-1} \text{ where}$$

$\underline{X}$  is nonsingular and  $\underline{\Lambda}$  is diagonal with  $\underline{X}$  comprising of eigenvectors of  $\underline{A}$  as columns.

Note: Such decomposition may not always exist!

$$\underline{A} \underline{X} = \underline{X} \underline{\Lambda}$$

$$[\underline{A}] \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ x_1 & x_2 & x_3 & \dots & x_m \\ \vdots & \vdots & \vdots & & \vdots \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 1 & 1 & \dots \\ x_1 & x_2 & x_3 & \dots \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix}$$

$$\underline{A} \underline{x}_j = \lambda_j \underline{x}_j$$

i.e.  $j^{\text{th}}$  column of  $\underline{X}$  is  $j^{\text{th}}$  eigenvector

and  $c_{j,j}$ ) entry of  $\Lambda$  is corresponding eigenvalue!

→ Geometric multiplicity :- The geometric multiplicity of an eigenvalue  $\lambda$  is the number of linearly independent eigenvectors associated with that eigenvalue  $\lambda$ . If  $\lambda \in \Lambda(A)$ , eigenspace  $E_\lambda$  is an invariant subspace of  $A$

$$\text{i.e } A E_\lambda \subseteq E_\lambda$$

The dimension

of  $E_\lambda$  is the geometric multiplicity of  $\lambda$  i.e maximum number of linearly

independent eigenvectors that can be found for a given  $\lambda$

$$v_1, v_2$$

$$\begin{aligned} x &= \alpha_1 v_1 + \alpha_2 v_2 \\ Ax &= A(\alpha_1 v_1 + \alpha_2 v_2) \\ &= \alpha_1 \lambda v_1 + \alpha_2 \lambda v_2 \\ &= \lambda [\alpha_1 v_1 + \alpha_2 v_2] \\ &= \lambda x \end{aligned} \quad (2)$$

## \* Characteristic Polynomial :-

The characteristic polynomial  $P_A$  of  $A \in \mathbb{R}^{m \times m}$  is the  $m^{\text{th}}$  degree monic polynomial  $\boxed{P_A(z) = \det(z\mathbb{I} - A)}$  ✓  
 (coefficient of  $z^m$  is 1 → monic polynomial)

Thm:-  $\lambda$  is eigenvalue of  $A$  if and only if  $P_A(\lambda) = 0$

Note:-  $A \in \mathbb{R}^{m \times m}$   $(A - \lambda \mathbb{I})\underline{x} = 0$   
 $\lambda$  can be complex  
 any complex  $\lambda$  must be eigenvector of  $A$  lies in the null space of  $(A - \lambda \mathbb{I})$   
 appears in complex conjugate pairs i.e.  $\lambda = a + ib$  is an eigenvalue  
 $\lambda^* = a - ib$  is an eigenvalue

## \* Algebraic multiplicity :-

Since  $p_A(z)$  is monic m-degree polynomial, it can be written as

$$p_A(z) = (z - \lambda_1)(z - \lambda_2) \dots (z - \lambda_m)$$

for some  $\lambda_j \in \mathbb{C}$  (roots of  $p_A(z)$ )

Each  $\lambda_j$  is an eigenvalue and in general may be repeated

"The multiplicity of  $\lambda$  as a root of  $p_A(z)$  is the algebraic multiplicity of an eigenvalue  $\lambda$ "

Remark:- @ If  $A \in \mathbb{R}^{m \times m}$  then A has m eigenvalues counting algebraic multiplicity. In particular if roots of  $p_A(z)$  are simple, then A has m distinct eigenvalues.

(b) The algebraic multiplicity of an eigenvalue  $\lambda$  is always at least as large as its geometric multiplicity.

\* Similarity transformation :-

If  $X \in \mathbb{R}^{m \times m}$  is non singular, then

$\underline{A} \rightarrow \underline{X}^{-1} \underline{A} \underline{X}$  is called a similarity transformation of  $\underline{A} \in \mathbb{R}^{m \times m}$

We say that two matrices  $A$  and  $B$  are similar if there is a similarity transformation of one to another

i.e. if there is a nonsingular  $X \in \mathbb{R}^{m \times m}$  such that  $\underline{B} = \underline{X}^{-1} \underline{A} \underline{X}$

then  $A$  and  $B$  are said to be similar!

Thm:- If  $\underline{x}$  is nonsingular, then  $\underline{A}$  and  $\underline{x}^{-1}\underline{A}\underline{x}$  have the same characteristic polynomial, eigenvalues and algebraic multiplicity and geometric multiplicity!

$$\begin{aligned}
 \text{Pf:- } p(z) &= \det(z\underline{I} - \underline{x}^{-1}\underline{A}\underline{x}) \\
 \underline{x}^{-1}\underline{A}\underline{x} &= \det(z\underline{x}^{-1}\underline{x} - \underline{x}^{-1}\underline{A}\underline{x}) \\
 &= \det(\underline{x}^{-1}(z\underline{I} - \underline{A})\underline{x}) \\
 &= (\det \underline{x}^{-1})(\det(z\underline{I} - \underline{A})) (\det \underline{x}) \\
 &= (\det \underline{x})^{-1} (\det(z\underline{I} - \underline{A})) (\det \underline{x}) \\
 &= \det(z\underline{I} - \underline{A}) = p_A(z)
 \end{aligned}$$

Hence  $\underline{A}$ ,  $\underline{x}^{-1}\underline{A}\underline{x}$  have the same eigenvalues (same roots of  $p_A(z)$ ) and

hence same algebraic multiplicity

Build a matrix  $E_\lambda$  whose column vectors span the eigenspace for the matrix  $A$ , corresponding to the eigen value  $\lambda$

$$\left( \underbrace{\underline{X}^{-1} A \underline{X}}_{\text{A}} \right) \left( \underbrace{\underline{X}^{-1} E_\lambda}_{\text{E}_\lambda} \right) = \underbrace{\underline{X}^{-1} A}_{\text{A}} \underbrace{\underline{E}_\lambda}_{\text{E}_\lambda}$$

$\underline{X}^{-1} E_\lambda$  is the eigenspace for  $\underline{X}^{-1} A \underline{X}$  corresponding to the eigenvalue  $\lambda$ .

Hence geometric multiplicity of

$A$  and  $\underline{X}^{-1} A \underline{X}$  are the same.

( $\because E_\lambda$  and  $\underline{X}^{-1} E_\lambda$  has the same rank)

Defective eigenvalues and matrices

\* A generic matrix need not have distinct eigenvalues i.e algebraic multiplicity need not be 1 and geometric multiplicity need not be 1 as well and need not be equal to algebraic multiplicity as well)

$$A = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}; B = \begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

Both  $A$  and  $B$  eigenvalue

$$\lambda = 2.$$

Algebraic multiplicity of  $\lambda = 2$  for  $A$ ?

$\xrightarrow{3}$  Algebraic multiplicity of  $\lambda = 2$  for  $B$ ?

$$\xrightarrow{3}$$

For  $\underline{A}$ , we can choose 3 linearly independent eigenvectors  $e_1, e_2, e_3$  and geometric multiplicity is also 3-

For  $\underline{B}$ , we can only have only linearly independent eigenvectors  $e_1$ , the geometric multiplicity of  $\underline{B}$  is 1

\* An eigenvalue whose algebraic multiplicity is greater than its geometric multiplicity is called a defective eigenvalue!

- \* A matrix that has atleast one defective eigenvalue is a defective matrix i.e it does not possess a full set of  $m$  linearly independent eigenvectors
- \* A diagonal matrix is non-defective  
 (algebraic multiplicity  
 of eigenvalue  $\lambda$   
 $=$  geometric  
 multiplicity of  $\lambda$ )

## Diagonalizability

Thm:  $A \in \mathbb{R}^{m \times m}$  is non-defective

if and only if it has eigenvalue decomposition  $\underline{A} = \underline{X} \underline{\Delta} \underline{X}^{-1}$  where

$$\underline{X} \in \mathbb{R}^{m \times n}$$

non singular matrix.

→ A non-defective matrix is diagonalizable

Proof: To show given  $\underline{A} = \underline{X} \underline{\Delta} \underline{X}^{-1}$ ,  $\underline{A}$  is non-defective!

$$\underline{A} = \underline{X} \underline{\Delta} \underline{X}^{-1} \rightarrow \underline{A} \text{ is similar to } \underline{\Delta}$$

$\underline{A}$  and  $\underline{\Delta}$  has the same eigenvalues and same multiplicities.

Since  $\underline{\Delta}$  is a diagonal matrix,

it is non-defective and thus

$\underline{A}$  is non-defective.

→ To show if  $\underline{A}$  is non-defective

then  $\underline{A} = \underline{X} \underline{\Lambda} \underline{X}^{-1}$

\* Since  $\underline{A}$  is non-defective, it must have  $m$  linearly independent eigenvectors!

If  $\underline{X} = \begin{bmatrix} \underline{x}_1 & | & \underline{x}_2 & | & \cdots & | & \underline{x}_m \end{bmatrix}$

comprises of these  $m$  linearly independent vectors,  $\underline{X}$  is full rank

$$\underline{A} \underline{X} = \underline{A} \begin{bmatrix} \underline{x}_1 & | & \underline{x}_2 & | & \cdots & | & \underline{x}_m \end{bmatrix}$$

$$= \begin{bmatrix} \underline{x}_1 & | & \underline{x}_2 & | & \cdots & | & \underline{x}_m \end{bmatrix} \begin{bmatrix} \lambda_1 & & & & \\ & \lambda_2 & & & \\ & & \ddots & & \\ & & & \lambda_m & \end{bmatrix}$$

$$= \underline{X} \underline{\Lambda}$$

$$\boxed{\begin{aligned} \underline{A} \underline{X} &= \underline{X} \underline{\Lambda} \\ \underline{A} &= \underline{X} \underline{\Lambda} \underline{X}^{-1} \end{aligned}}$$

Thm: Trace of  $\underline{A} \in \mathbb{R}^{m \times m}$

$$\text{tr}(\underline{A}) = \sum_{j=1}^m a_{jj} = \sum_{j=1}^m \lambda_j$$

Determinant of  $\underline{A} \in \mathbb{R}^{m \times m}$

$$\det(\underline{A}) = \prod_{j=1}^m \lambda_j$$

Unitary / orthogonal diagonalization:-

\*  $\underline{Q} \in \mathbb{C}^{m \times m}$  is a unitary matrix

$$\text{if } \underline{Q}^+ \underline{Q} = \underline{Q} \underline{Q}^+ = \underline{I}$$

when  $\underline{Q}^+$  is conjugate transpose of  $\underline{Q}$

\* Unitary matrix reduces to  
 orthogonal matrices if  $Q$  is  
 real i.e.  $Q^T Q = Q Q^T = I$  is  
 satisfied.

For a non-defective matrix  
 $A \in \mathbb{R}^{m \times m}$ , it is possible not only  
 to have  $m$  linearly independent  
 eigenvectors, but these vectors  
 can be orthogonal as well!

[If  $A \in \mathbb{R}^{m \times m}$  eigenvalues can be  
 complex and corresponding eigenvectors  
 have to be complex as well]

Now in general for a non-defective  
 $A \in \mathbb{R}^{m \times m}$ , we define unitary  
 diagonalizability i.e there exists

a unitary matrix  $\underline{Q}$ , such that

$$\underline{A} = \underline{Q} \Delta \underline{Q}^+$$
 where

$\underline{Q}^+$  is conjugate transpose  
of  $\underline{Q}$  and columns of  $\underline{Q}$

are eigenvectors of  $\underline{A}$

Unitary diagonalizability reduces to  
orthogonal diagonalizability if  $\underline{Q}$  is  
real matrix and  $\lambda$  are real

$$\text{i.e. } \underline{A} = \underline{Q} \Delta \underline{Q}^T$$

Eg:- A symmetric matrix  $\underline{S} \in \mathbb{R}^{m \times m}$   
Satisfies  $\underline{S} = \underline{S}^T$  & has real eigenvalues

$$\rightarrow \underline{S} \underline{x} = \lambda \underline{x}$$

Take complex  
conjugate  
both sides

$$\underline{S} \underline{x}^* = \lambda^* \underline{x}^*$$

where  $\underline{x}^*$  is  
complex conjugate of  $\underline{x}$

$$\begin{aligned} S \underline{x} = \lambda \underline{x} &\Rightarrow \underline{x}^* S \underline{x} = \lambda \underline{x}^* \underline{x} \\ &\Rightarrow \underbrace{(S \underline{x})^T}_{\text{--- (1)}} \underline{x}^* = \lambda \underline{x}^* \underline{x} \end{aligned}$$

$$\begin{aligned} S \underline{x}^* = \lambda^* \underline{x}^* &\Rightarrow \underline{x}^T S \underline{x}^* = \lambda^* \underline{x}^T \underline{x}^* \\ &\Rightarrow \underline{x}^T S^T \underline{x}^* = \lambda^* \underline{x}^T \underline{x}^* \\ &\Rightarrow \underbrace{(S \underline{x})^T}_{\text{--- (2)}} \underline{x}^* = \lambda^* \underline{x}^T \underline{x}^* \end{aligned}$$

$$\begin{aligned} \textcircled{1} - \textcircled{2} \Rightarrow \Delta &= \lambda \underline{x}^* \underline{x} - \lambda^* \underline{x}^T \underline{x}^* \\ &= (\lambda - \lambda^*) (\underline{x}^T \underline{x}^*) \end{aligned}$$

$$\begin{aligned} \text{Since } \underline{x}^T \underline{x}^* \neq 0 &\Rightarrow \lambda - \lambda^* = 0 \\ &\Rightarrow \boxed{\lambda = \lambda^*} \end{aligned}$$

Hence eigenvalues of a symmetric matrix real.

Consider the case where  $S$  is symmetric  $(\lambda_1, \underline{x}_1)$  and  $(\lambda_2, \underline{x}_2)$  are two eigenpairs of  $S$  where  $\lambda_1 \neq \lambda_2$

$$\begin{aligned} S \underline{x}_1 &= \lambda_1 \underline{x}_1, \quad S \underline{x}_2 = \lambda_2 \underline{x}_2 \\ \underline{x}_2^T S \underline{x}_1 &= \lambda_1 \underline{x}_2^T \underline{x}_1, \quad \underline{x}_1^T S \underline{x}_2 = \lambda_2 \underline{x}_1^T \underline{x}_2 \end{aligned}$$

$$\begin{array}{c}
 \underline{x}_2^T S \underline{x}_1 = \lambda_1 \underline{x}_2^T \underline{x}_1 \\
 \Rightarrow \underline{x}_2^T S^T \underline{x}_1 = \lambda_1 \underline{x}_2^T \underline{x}_1 \\
 \Rightarrow (S \underline{x}_2)^T \underline{x}_1 = \lambda_1 \underline{x}_2^T \underline{x}_1
 \end{array} \quad \left| \quad \begin{array}{l}
 \underline{x}_1^T S \underline{x}_2 = \lambda_2 \underline{x}_1^T \underline{x}_2 \\
 (S \underline{x}_2)^T \underline{x}_1 = \lambda_2 \underline{x}_1^T \underline{x}_2
 \end{array} \right. \quad - \textcircled{2}$$

- \textcircled{1}

\textcircled{1} - \textcircled{2}

$$0 = (\lambda_1 - \lambda_2) \underline{x}_1^T \underline{x}_2$$

$$\lambda_1 - \lambda_2 \neq 0 \Rightarrow \underline{x}_1^T \underline{x}_2 = 0$$

i.e. the eigenvectors  $\underline{x}_1, \underline{x}_2$   
are orthogonal to each other.

Now what happens if eigenvalues of  $S$   
are degenerate, the above proof will  
fail. Let us consider one such case  
where the geometric multiplicity of  
 $S \in \mathbb{R}^{m \times m}$  is  $r < m$  corresponding to  
an eigenvalue  $\lambda$ . We need to show  
that algebraic multiplicity of  $S$  is

also  $\sigma$ . Since we assumed geometric multiplicity of  $S \in \mathbb{R}^{m \times m}$  is  $\sigma$  for an eigenvalue  $\lambda$ , we can always find  $\sigma$  linearly independent vectors spanning the ' $\sigma$ ' dimensional eigen subspace  $V^E$  corresponding to eigenvalue  $\lambda$ .

2. This means I can choose  $\sigma$  orthogonal eigenvectors  $v_1, v_2, \dots, v_\sigma$

$V^E = \{v_1, v_2, \dots, v_\sigma\}$ . Let me now construct orthogonal vectors  $V^\perp = \{v_{\sigma+1}, v_{\sigma+2}, \dots, v_m\}$  spanning the subspace  $V^\perp$  orthogonal to  $V^E$ .

$$\text{Let } V = \begin{bmatrix} v_1 & v_2 & \dots & v_\sigma & v_{\sigma+1} & v_{\sigma+2} & \dots & v_m \end{bmatrix}$$

Now we have

$$\sum \underline{V}_i = \lambda \underline{V}_i \text{ for } i = 1 \text{ to } \sigma$$

Also

$$\sum \underline{V}_i = \sum_{j=1}^m c_{ij} \underline{v}_j$$

$$c_{ij} = \lambda s_{ij} \text{ for } i = 1 \text{ to } \sigma$$

Now we can write

$$\begin{aligned} & \sum \left[ \begin{array}{cccccc} 1 & 1 & 1 & \dots & 1 & 1 & 1 \\ \underline{V}_1 & \underline{V}_2 & \underline{V}_3 & \dots & \underline{V}_{\sigma} & \underline{V}_{\sigma+1} & \underline{V}_{\sigma+2} \dots \underline{V}_m \end{array} \right] \\ &= \left[ \begin{array}{cccccc} 1 & 1 & 1 & \dots & 1 & 1 & 1 \\ \underline{V}_1 & \underline{V}_2 & \underline{V}_3 & \dots & \underline{V}_{\sigma} & \underline{V}_{\sigma+1} & \underline{V}_{\sigma+2} \dots \underline{V}_m \end{array} \right] \left[ \begin{array}{ccc} \lambda & \lambda & \lambda \\ c_{\sigma+1,1} & c_{\sigma+1,2} & \dots & c_{\sigma+1,m} \\ c_{\sigma+2,1} & c_{\sigma+2,2} & \dots & c_{\sigma+2,m} \\ \vdots & & & \\ c_{m,1} & c_{m,2} & \dots & c_{m,m} \end{array} \right] \end{aligned}$$

$\underline{V} = \underline{V} M$

$$\Rightarrow \underline{V}^T \underline{V} = \underline{M}$$

Observe  $\underline{V}^T \underline{S} \underline{V}$  is symmetric

because  $\underline{S}$  is symmetric.

This means  $\underline{M}$  has to be

$\underline{M}$

Symmetric

i.e.  $\underline{V}^T \underline{S} \underline{V} = \begin{bmatrix} \lambda & & & & \\ & \ddots & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & C \end{bmatrix} - \textcircled{1}$

where  $C$  is a symmetric matrix of size  $(m-s) \times (m-s)$

Let us now write characteristic polynomial of LHS and RHS of  $\textcircled{1}$ , this gives  $p(z) = p_M(z)$

$\phi_{r^T S v}(z) = \phi_S(z)$  since  $V^T S V$  is similar to  $S$ . Hence

$$\begin{aligned} \phi_S(z) &= \phi_M(z) \\ \Rightarrow \det(S - z I_m) &= (\lambda - z)^m \det(C - z I_{m-s}) \quad - \textcircled{2} \\ I_m \text{ is identity matrix of} \\ \text{size } m \\ I_{m-s} \text{ is identity matrix} \\ \text{of size } m-s. \end{aligned}$$

Now our objective is to show algebraic multiplicity of  $S$  is also  $s$ . This means we need to show  $\lambda$  is not an eigenvalue of  $C$ . Let us use indirect method of proof now.

Assume  $\lambda$  can be an eigenvalue

of  $C$ , this means I have

$$C \underline{u} = \lambda \underline{u} \text{ where } \underline{u} \in \mathbb{R}^{m-\delta}$$

eigenvector of  $C$ . Construct

$$\hat{\underline{u}} \in \mathbb{R}^m \text{ where } \hat{\underline{u}} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ \underline{u} \end{bmatrix} \begin{array}{l} \rightarrow 1^{\text{st}} \text{ entry} \\ \cdots \\ \rightarrow \sigma^{\text{th}} \text{ entry} \end{array}$$

then we have

$$CV\hat{\underline{u}} = M\hat{\underline{u}} = \left[ \begin{array}{c|c} \lambda & 0 \\ \lambda & \ddots & 0 \\ \hline 0 & \ddots & C \end{array} \right] \begin{bmatrix} 0 \\ \vdots \\ \underline{u} \end{bmatrix}$$

$$= \begin{bmatrix} 0 \\ \vdots \\ \lambda \underline{u} \end{bmatrix} = \lambda \begin{bmatrix} 0 \\ \vdots \\ \underline{u} \end{bmatrix}$$

$$= \lambda \hat{\underline{u}}$$

This means  $\hat{\underline{u}}$  is a eigenvector

of  $\underline{V}^T \underline{S} \underline{V}$  corresponding to eigenvalue  $\lambda$ .

$$\text{i.e. } \underline{V}^T \underline{S} \underline{V} \hat{\underline{u}} = \lambda \hat{\underline{u}}$$

$$\Rightarrow \underline{S} \underline{V} \hat{\underline{u}} = \lambda \underline{V} \hat{\underline{u}}$$

$\Rightarrow \underline{V} \hat{\underline{u}}$  is an eigenvector of  $\underline{S}$

corresponding to eigenvalue  $\lambda$ .

clearly by construction  $\underline{V} \hat{\underline{u}}$  is

a vector which lies in the space

spanned by the  $\{\underline{v}_{r+1}, \underline{v}_{r+2}, \dots, \underline{v}_m\}$

i.e.  $V^\perp$  which is orthogonal to  $V^E$ .

This means we are able to find another linearly independent eigenvector

$\underline{V} \hat{\underline{u}}$  in addition to  $\{\underline{v}_1, \underline{v}_2, \dots, \underline{v}_r\}$ .

This means that geometric multiplicity of  $\xi$  is  $\infty$ . But this is a contradiction to the assumption that geometric multiplicity of  $\xi$  is  $\alpha$  corresponding to the eigenvalue  $\lambda$ .

Hence  $\lambda$  is not an eigenvalue of  $C$ . This means algebraic multiplicity of  $\xi$  is  $\alpha$  which is same as the geometric multiplicity of  $\xi$ .

This means I can find ' $\alpha$ ' orthogonal vectors which span this ' $\alpha$ ' dimensional invariant subspace which are the eigenvectors for my  $\xi$ .

Thm :- A symmetric matrix  
 $S \in \mathbb{R}^{n \times n}$  is always non-defective  
 and is orthogonally diagonalizable  
 with real eigenvalues i.e  

$$S = Q \Lambda Q^T$$
  
 where  $Q$  is orthogonal matrix  
 $\Lambda$  is a diagonal matrix

Thm :- A skew symmetric matrix  
 $W \in \mathbb{R}^{n \times n}$  which satisfies  $W = -W^T$ .  
 This skew symmetric is non-defective  
 and has purely imaginary eigenvalues.  
 and is unitarily diagonalizable  
 i.e  $W = Q \Lambda Q^+$

It turns out that there is a class of unitarily diagonalizable matrices and these set of matrices satisfy the property  $\underline{A}^T \underline{A} = \underline{\Lambda} \underline{\Lambda}^T$

\* A matrix is normal if

$$\underline{A}^T \underline{A} = \underline{A} \underline{A}^T$$

Thm:- A matrix is unitarily diagonalizable if and only if  $\underline{A}^T \underline{A} = \underline{\Lambda} \underline{\Lambda}^T$  for  $A \in \mathbb{R}^{m \times m}$

Pf:- Direction 1

If a matrix is unitary

diagonalizable then we need to show  $\underline{A}^T \underline{A} = \underline{A} \underline{A}^T$

Since the given matrix is unitarily diagonalizable we know

$$A = Q \Delta Q^+$$

$$\begin{aligned}
 A^T A - A A^T &= A^+ A - A A^+ \\
 &= (Q \Lambda Q^+)^+ (Q \Lambda Q^+) - (Q \Lambda Q^+) (Q \Lambda Q^+)^+ \\
 &= (Q^+)^+ \cancel{\Lambda}^+ Q^+ Q \Lambda Q^+ - Q \Lambda Q^+ \cancel{(Q^+)^+}^+ \Lambda Q^+ \\
 &= Q \Lambda^+ I \Lambda Q^+ - Q \Lambda \cancel{Q^+}^+ Q \Lambda^+ Q^+ \\
 &= Q \Lambda^+ \Lambda Q^+ - Q \Lambda \Lambda^+ Q^+
 \end{aligned}$$

Since  $\Lambda^+ \Lambda = \Lambda \Lambda^+$  as  $\Lambda$  is a diagonal matrix

$$= 0$$

$$\Rightarrow \boxed{A^T A - A A^T = 0}$$

To show that  $A^T A = A A^T$  implies unitary diagonalizability.

Every  $A \in \mathbb{R}^{m \times m}$  can be decomposed

$$\text{as } \underline{A} = \underline{A}_S + \underline{A}_{SS}$$

$$\underline{A}_S = \frac{1}{2}(A + A^T)$$

$$\underline{A}_{SS} = \frac{1}{2}(A - A^T)$$

What does

$$\underline{A}^T \underline{A} - \underline{A} \underline{A}^T = 0 \quad \text{result in?}$$

$$\begin{aligned} \underline{A}^T \underline{A} - \underline{A} \underline{A}^T &= (\underline{A}_S + \underline{A}_{SS})^T (\underline{A}_S + \underline{A}_{SS}) \\ &\quad - (\underline{A}_S + \underline{A}_{SS})(\underline{A}_S + \underline{A}_{SS})^T \end{aligned}$$

$$\begin{aligned} &= (\underline{A}_S - \underline{A}_{SS})(\underline{A}_S + \underline{A}_{SS}) \\ &\quad - (\underline{A}_S + \underline{A}_{SS})(\underline{A}_S - \underline{A}_{SS}) \end{aligned}$$

$$= \underbrace{2(\underline{A}_S \underline{A}_{SS} - \underline{A}_{SS} \underline{A}_S)}$$

We have  $\underline{A}^T \underline{A} - \underline{A} \underline{A}^T = \underline{\underline{0}}$

$$(A_S A_{SS} - A_{SS} A_S) = \underline{\underline{0}}$$
$$\Rightarrow \boxed{A_S A_{SS} = A_{SS} A_S}$$

(This means  $A_S$  and  $A_{SS}$  commute with each other)

Note :-

\* Two matrices commute if and only if they have same eigenvectors!

Here  $Q$  is a unitary matrix

$$A_S = Q \underline{A}_S \underline{Q}^+, \quad A_{SS} = Q \underline{A}_{SS} \underline{Q}^+$$

$$\Rightarrow \underline{A}_S = \underbrace{Q^+ A_S Q}_{\downarrow}, \quad \underline{A}_{SS} = \underbrace{Q^+ A_{SS} Q}_{\downarrow}$$

Consider

$$Q^+ \underline{A} \underline{Q} = Q^+ (A_S + A_{SS}) Q$$

$$= \underline{A}_S + \underline{A}_{SS} = \underline{A}$$

Hence  $\underline{Q}^+ \underline{A} \underline{Q} = \underline{\Lambda}$

$$\Rightarrow \boxed{\underline{A} = \underline{Q} \underline{\Lambda} \underline{Q}^+}$$

Schur factorization

A factorization of  $\underline{A} \in \mathbb{C}^{m \times m}$

of the form  $\underline{A} = \underline{Q} \underline{T} \underline{Q}^+$

where  $\underline{Q}$  is unitary ( $\underline{Q}^+ \underline{Q} = I$ )

and  $\underline{T}$  is upper triangular

is called Schur factorization

Note:- Since  $\underline{A}$  and  $\underline{T}$  are similar, the eigenvalues of  $\underline{A}$  and  $\underline{T}$  are same.

Thm: Every square matrix  $\underline{A} \in \mathbb{C}^{n \times n}$  has a Schur factorization of the form

$$\underline{A} = \underline{Q} \underline{T} \underline{Q}^+ \text{ as discussed before.}$$

If  $\underline{A} \in \mathbb{R}^{n \times n}$ , a factorization exists where real matrices exist  $\underline{U} \underline{T} \underline{U}^T$  where  $\underline{U}^T \underline{U} = \underline{U} \underline{U}^T = I$  where  $\underline{T}$  is quasi upper triangular.

Quasi upper triangular matrices are those with diagonal with  $1 \times 1$  block or  $2 \times 2$  block

Summary:-

- (i) A diagonalization  $\underline{A} = \underline{X} \underline{\Lambda} \underline{X}^{-1}$  exists if and only if  $\underline{A}$  is non-defective
- (ii) A unitary diagonalization  $\underline{A} = \underline{Q} \underline{\Lambda} \underline{Q}^+$

exists if  $A$  is normal

(iii) A unitary triangulization  
(Schur Factorization)

$$A = Q T Q^+ \text{ always exists}$$