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**Definition**. [Symmetric Matrices ]

An  $n \times n$  matrix A is called **symmetric** if  $A^T = A$ . If we write  $A = [a_{ij}]$ , then A is symmetric if and only if

$$a_{ij} = a_{ji}$$
 for all  $i, j \in \{1, 2, ..., n\}$ 

**Example 1** (Diagonalizing a Symmetric Matrix).  $A = \begin{bmatrix} 10 & 6 \\ 6 & 1 \end{bmatrix}$ .

$$l \quad det (A - \lambda I) = 0 \implies \lambda_{1} = -2 \quad \lambda_{2} = l3$$

$$2. \quad For \quad \lambda_{1} = -2, \quad a \quad basis \quad for \quad escenspace \quad E_{\lambda_{1}} = ker(A - \lambda_{1} I) \quad is \quad \left\{ \begin{bmatrix} -\frac{1}{2} \\ 1 \end{bmatrix} \right\}$$

$$For \quad \lambda_{2} = B, \quad a \quad basis \quad for \quad elgen \quad space \quad E_{\lambda_{2}} = bor(A - \lambda_{1} I) \quad is \quad \left\{ \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right\}$$

$$3. \quad A = HDH^{T} \quad D = \begin{bmatrix} 2 & 0 \\ 0 & 13 \end{bmatrix} \quad H = \begin{bmatrix} -l & 2 \\ 2 & l \end{bmatrix} \quad H^{T} = -\frac{l}{2} \begin{bmatrix} 1 & -2 \\ -5 \begin{bmatrix} 1 & -2 \\ 2 & -l \end{bmatrix}$$

**Example 2** (Diagonalizing a Symmetric Matrix).  $A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ .

**Example 3** (Diagonalizing a Symmetric Matrix).  $A = \begin{bmatrix} 1 & 1 & 7 \\ 1 & 7 & 1 \\ 7 & 1 & 1 \end{bmatrix}$ .

$$\int det (A - \lambda I) = \begin{vmatrix} i + \lambda & i + 7 \\ i + 7 + \lambda & j \\ 7 + 1 + i + \lambda \end{vmatrix} = (i + \lambda) \begin{vmatrix} 7 + \lambda & j \\ 1 + i + \lambda \end{vmatrix} - \begin{vmatrix} i + 1 & j \\ 7 + i + \lambda \end{vmatrix} + 7 \begin{pmatrix} i + 7 + \lambda \\ 7 + i \end{pmatrix}$$
$$= (i + \lambda) (x - 8\lambda + 6) - (-x - 6) + 7 (7 + \lambda - 48)$$
$$= -\lambda^3 + 9\lambda^2 + 36\lambda - 344$$
$$\lambda = -\lambda^3 + 9\lambda^2 + 36\lambda - 344$$
$$\lambda = 9, 6, -6$$
  
2. An eigenvector for  $\lambda = 9$  is  $\begin{bmatrix} i \\ j \\ 1 \end{bmatrix}$   
An eigenvector for  $\lambda = 6$  is  $\begin{bmatrix} i \\ 2 \\ 1 \end{bmatrix}$   
An eigenvector for  $\lambda = 6$  is  $\begin{bmatrix} i \\ 2 \\ 1 \end{bmatrix}$   
An eigenvector for  $\lambda = 6$  is  $\begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$   
An eigenvector for  $\lambda = -6$  is  $\begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$   
$$\lambda = HDH^{-1} \qquad H = \begin{bmatrix} i + 1 & -1 \\ 1 - 2 & 0 \\ 1 & 1 \end{bmatrix} \qquad D = \begin{bmatrix} 9 & 0 & 0 \\ 0 & 6 & 0 \\ 0 & 0 & 6 \end{bmatrix}$$

## Theorem.

Let A be a symmetric matrix and let  $\lambda, \mu$  be two distinct eigenvalues of A with associated eigenvectors  $\vec{v}, \vec{w}$ . Then

 $\vec{v}\cdot\vec{w}=0.$ 

## **Definition**. [Orthogonal Diagonalization]

An  $n \times n$  matrix is **orthogonally diagonalizable** if there exist  $n \times n$  matrices D and U, with D diagonal and U orthogonal (ie.  $U^T U = I_n$ ), and with

$$A = UDU^{-1} = UDU^T.$$

**Theorem**. [On Orthogonal Diagonalizability]

An  $n \times n$  matrix A is orthogonally diagnonalizable if and only if A is a symmetric matrix.

**Theorem**. [Spectral Theorem for Symmetric Matrices]

Evey  $n \times n$  symmetric matrix A has the following properties.

- 1. All eigenvalues of A are real, and there are exactly n of them if counted with their multiplicities.
- 2. The dimension of the eigenspace  $E_{\lambda}$  associated to the eigenvalue  $\lambda$ , equals precisely the algebraic multiplicity of  $\lambda$ .
- 3.  $E_{\lambda}$  is orthogonal to  $E_{\mu}$  for distinct eigenvalues  $\lambda, \mu$  (in that  $\vec{v} \cdot \vec{w} = 0$  for all  $\vec{v} \in E_{\lambda}$  and  $\vec{w} \in E_{\mu}$ ).
- 4. A is orthogonally diagonalizable.

**Example 4** (Orthogonal Diagonalization).  $A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$ .

$$A = PDp^{-1} \quad \text{where} \quad D = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad P = \begin{bmatrix} 1 & -1 & -1 \\ 1 & 1 & -1 \\ 1 & 0 & 2 \end{bmatrix}$$
$$A = UDu^{-1} \qquad U = \begin{bmatrix} \frac{1}{5} & \frac{1}{5} & \frac{1}{5} \\ \frac{1}{5} & \frac{1}{5} & \frac{1}{5} \\ \frac{1}{5} & 0 & \frac{1}{5} \end{bmatrix}$$

Example 5. (True or False)

1. If A and B are diagonalizable, then A + B is diagonalizable.

False. For example,  $A = \begin{bmatrix} 1 & 1 \\ 0 & 2 \end{bmatrix}$  and  $B = \begin{bmatrix} 0 & 0 \\ 0 & -1 \end{bmatrix}$  are diagonalizable. But  $A + B = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$  is not diagonalizable.

2. If A and B are orthogonally diagonalizable, then A + B is orthogonally diagonalizable.

True. Reason?

**Example 6** (Orthogonal Diagonalization).  $A = \begin{bmatrix} 1 & 1 & 7 \\ 1 & 7 & 1 \\ 7 & 1 & 1 \end{bmatrix}$ .

## 3. The Spectral Decomposition

Let A be an  $n \times n$  matrix and let D and U be a diagonal and orthogonal matrix with  $A = UDU^{-1}$ . Let  $\lambda_1, \ldots, \lambda_n$  be the diagonal entries of D, and let  $\vec{u}_1, \ldots, \vec{u}_n$  be the column vectors of U. Note that  $\vec{u}_i \cdot \vec{u}_j = 0$  for  $i \neq j$ .

A new decomposition of A in terms of  $\lambda_1, \ldots, \lambda_n$  and  $\vec{u}_1, \ldots, \vec{u}_n$  can be found by starting with the relation  $A = UDU^{-1}$ .

$$A = UDU^{-1} = UDU^{T}$$

$$= \begin{bmatrix} \vec{u}_{1} \dots \vec{u}_{2} \end{bmatrix} \begin{bmatrix} \lambda_{1} & 0 \dots & 0 \\ 0 & \lambda_{2} \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \dots & \lambda_{n} \end{bmatrix} \begin{bmatrix} (\vec{u}_{1})^{T} \\ \vdots \\ (\vec{u}_{n})^{T} \end{bmatrix}$$

$$= \begin{bmatrix} \lambda_{1}\vec{u}_{1} \dots & \lambda_{n}\vec{u}_{n} \end{bmatrix} \begin{bmatrix} (\vec{u}_{1})^{T} \\ \vdots \\ (\vec{u}_{n})^{T} \end{bmatrix}$$

$$= \lambda_{1}\vec{u}_{1} \cdot (\vec{u}_{1})^{T} + \dots + \lambda_{n}\vec{u}_{n} \cdot (\vec{u}_{n})^{T}$$

**Theorem**. [Spectral Decomposition for Symmetric Matrices]

Using above notations

$$A = \lambda_1 \left( \vec{u}_1 \cdot (\vec{u}_1)^T \right) + \dots + \lambda_n \left( \vec{u}_n \cdot (\vec{u}_n)^T \right)$$

For each i = 1, ..., n, the matrix  $\vec{u}_i \cdot (\vec{u}_i)^T$  is the projection matrix onto the line  $\text{Span}(\vec{u}_i)$  in the sense that

$$\operatorname{proj}_{\vec{u}_i}(\vec{x}) = \left(\vec{u}_i \cdot (\vec{u}_i)^T\right) \cdot \vec{x}, \quad \text{for each } \vec{x} \in \mathbb{R}^n.$$

Example 7 (Spectral Decomposition for Symmetric Matrices).

