

- Eigenvalues and eigenvectors
- Diagonalization
- Symmetric Positive Definite matrices
- Systems of Differential Equations

## Eigenvalues and Eigenvectors

### Definition 0.0.1: Eigenvalues and Eigenvectors

Let  $A$  be an  $n \times n$  matrix. A scalar  $\lambda$  is called an eigenvalue of  $A$  if there exists a nonzero vector  $\vec{v}$  such that  $A\vec{v} = \lambda\vec{v}$ . The vector  $\vec{x}$  is called an eigenvector of  $A$  corresponding to  $\lambda$ .

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

### Definition 0.0.2: Eigenvector properties

Let  $A$  be an  $n \times n$  matrix with eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$  and corresponding eigenvectors  $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ . Then the following properties hold:

- The eigenvectors are linearly independent.
- The matrix  $A$  can be diagonalized as  $A = X\Lambda X^{-1}$ , where  $X$  is the matrix whose columns are the eigenvectors of  $A$  and  $\Lambda$  is the diagonal matrix with the eigenvalues of  $A$  on the diagonal.
- The eigenvectors of similar matrices are the same. EX: the eigenvectors of  $A$  are the same as the eigenvectors of  $A^9 + cI$ .

### Definition 0.0.3: Eigenvalue properties

Let  $A$  be an  $n \times n$  matrix with eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$  and corresponding eigenvectors  $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n$ . Then the following properties hold:

- The sum of the eigenvalues is equal to the trace of the matrix:  $\sum \lambda_i = \text{Trace}$ .
- The product of the eigenvalues is equal to the determinant of the matrix:  $\prod_{i=1}^n \lambda_i = \det(A)$ .
- For a markov matrix, the largest eigenvalue is 1. A markov matrix is a matrix whose columns add to 1.
- For a singular matrix, the determinant is 0 and at least one eigenvalue is 0. A singular matrix is a matrix whose columns are linearly dependent.
- For a symmetric matrix, the eigenvalues are real and the eigenvectors are orthogonal.

### Note:-

Imaginary Eigenvalues: If a matrix has imaginary eigenvalues, then the matrix is not diagonalizable.

Complex Eigenvectors: If a matrix has complex eigenvectors, then the matrix is not diagonalizable.

Eigenvalues of  $AB$  and  $A+B$ : Eigenvalues are not the same for  $AB$  and  $A+B$ .  $A$  and  $B$  share  $n$  independent Eigenvectors if  $AB=BA$ .

## Diagonalization

### Definition 0.0.4: Diagonalization

A matrix  $A$  is diagonalizable if it can be written as  $A = X\Lambda X^{-1}$ , where  $X$  is the matrix whose columns are the eigenvectors of  $A$  and  $\Lambda$  is the diagonal matrix with the eigenvalues of  $A$  on the diagonal.

## Symmetric Positive Definite Matrices

### Definition 0.0.5: Symmetric Positive Definite Matrices

A symmetric matrix has  $n$  real eigenvalues  $\lambda_i$  and  $n$  orthogonal eigenvectors  $q_i$ .

$S$  is diagonalized by an orthogonal matrix  $Q$ :  $S = Q\Lambda Q^T = Q\Lambda Q^{-1}$ .

$S$  is positive definite if all eigenvalues are positive.

Positive Semi-Definite: All eigenvalues are non-negative (allows  $\lambda = 0$ ).

### Definition 0.0.6: Positive Definite Matrices Tests

**Energy Test:** A matrix  $A$  is positive definite if for all nonzero vectors  $\vec{x}$ ,  $\vec{x}^T A \vec{x} > 0$ .

**Eigenvalue Test:** A matrix  $A$  is positive definite if all of its eigenvalues are positive.

**Cholesky Decomposition:** A matrix  $A$  is positive definite if it can be written as  $A = LL^T$ , where  $L$  is a lower triangular matrix with positive diagonal entries. Works when  $L$  has independent columns.

**Pivot Test:** A matrix  $A$  is positive definite if all of its pivots are positive.

**Upper Left Determinants:** A matrix  $A$  is positive definite if all of its upper left determinants are positive.

**Note:-**

$S = CAC^T$  is pos definite if  $C$  is invertible

If  $S_1$  and  $S_2$  are pos def, then  $S_1 + S_2$  is pos def

## Systems of Differential Equations

### Definition 0.0.7: Systems of Differential Equations

If  $Ax = \lambda x$ , then  $u(t) = e^{\lambda t}x$  will solve  $\frac{du}{dt} = Au$ . Each  $\lambda$  and  $x$  is a solution  $e^{\lambda t}x$ .

If  $A = X\Lambda X^{-1}$ , then  $u(t) = e^{At}u(0) = Xe^{\Lambda t}X^{-1}u(0)$  will solve  $\frac{du}{dt} = Au$ .

Matrix Exponential:  $e^{At} = I + At + \frac{A^2t^2}{2!} + \frac{A^3t^3}{3!} + \dots$

Taylor Series:

- $e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$
- $\cos x = 1 - \frac{x^2}{2!} + \frac{x^4}{4!} - \frac{x^6}{6!} + \dots$
- $\sin x = x - \frac{x^3}{3!} + \frac{x^5}{5!} - \frac{x^7}{7!} + \dots$

$A$  is stable and  $u(t)$  approaches 0 as  $t$  approaches infinity if all eigenvalues of  $A$  have negative real parts  $\neq 0$ .

Second order eqn:  $\frac{d^2u}{dt^2} + 2\zeta\omega_n \frac{du}{dt} + \omega_n^2 u = 0 \dots$  First order System:  $\frac{du}{dt} = Au$ , where  $A = \begin{bmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{bmatrix}$ .

$$u'' + Bu' + Cu = 0 \rightarrow \begin{bmatrix} u \\ u' \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ -C & -B \end{bmatrix} \begin{bmatrix} u \\ u' \end{bmatrix}$$