



# Linear Algebra

## Lecture 7c (Chap. 6)

### Introduction to Positive Definite Matrices, Similar Matrices, Jordan Form, & Singular Value Decomposition (SVD)

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# Definition:

## Positive Definite Matrices

- The eigenvalues of positive definite matrices are all positive real numbers.
- The Inertial tensor of rotation and the thermal pressure tensor are positive definite matrices.

# Definition: Similar Matrices

- Matrices have the same eigenvalues are similar matrices.

Let  $\Lambda$  and  $S$  be the eigenvalue matrix and the eigenvector matrix of  $A$ .

$$\Rightarrow A = S\Lambda S^{-1}$$

Let  $M$  be any invertible matrix and let  $B = M^{-1}AM$ .

$\Rightarrow B$  and  $A$  are similar matrices. They have the same eigenvalues.

Proof :

$$B = M^{-1}AM = M^{-1}(S\Lambda S^{-1})M = (M^{-1}S)\Lambda(M^{-1}S)^{-1}$$

$\Rightarrow$  The  $\Lambda$  and  $(M^{-1}S)$  are the eigenvalue matrix and the eigenvector matrix of  $B$ .

# The eigenvalues and eigenvectors of the similar matrices

- 經過 orthogonal matrix 的座標轉換，所產生的 inertial tensor 其 eigenvalues 不變，因此 這些形式不同的 inertial tensor，彼此為 similar matrices.
- 因為經過座標轉換，所以每個形式不同的 inertial tensor，其 eigenvectors 也都不相同！（也須經過適當的座標轉換！）
- The eigenvectors change with  $Q$ , where  $B=Q^T A Q=Q^{-1} A Q$

更多 similar matrices 的相關特性，  
請參考課本 page 344 最下方的 Table

# Jordan Form

- 如果一個  $n \times n$  matrix  $A$  有 repeated eigenvalues, 則  $A$  的 eigenvectors 的個數, “可能”少於  $n$ . 這時  $A$  無法被對角線化, 最多只能化簡為 對角線的 blocks 形態, 如右。  
這樣的 matrix 就叫做 Jordan form.
- 如果  $B = M^{-1}AM$  則  $A, B$  會有相同的 Jordan form, 且都無法對角線化!

$$\begin{bmatrix} 3 & 1 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 5 & 1 & 0 \\ 0 & 0 & 0 & 5 & 1 \\ 0 & 0 & 0 & 0 & 5 \end{bmatrix}$$

# Singular Value Decomposition (緣起)

- 物理問題中，所遇到的矩陣，多為  $n \times n$  的 symmetric matrix or Hermitian matrix.
- 隨著科技進步，觀測資料越來越多。分析觀測資料時，常常遇到“長方矩陣”的相關問題（請參考 Least Squares Fit 那份講義的範例說明）。
- Singular value decomposition 就是數學家針對“長方矩陣”，或是非對稱 square matrix 所研發出來的一種新的 decomposition method.

# Singular Value Decomposition (SVD)

- 如果矩陣A 是一個“長方矩陣”，或是非對稱的 square matrix, 則不再考慮  $AS=SL$ , 而是考慮  $AV=US$ , where matrices U and V are orthogonal matrices, and matrix S is a “semidiagonal” matrix.

Example of semidiagonal matrix

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \\ 0 & 0 & 0 \end{bmatrix}$$

- Matrix A can be decomposed into  $A=USV^{-1}$ .
- Objectives of this study is to find a way to determine the matrices U and V and the “singular matrix” S.

# Singular Value Decomposition (SVD)

- 在介紹 projection matrix 以及 least square fit 時，我們都遇到“長方矩陣”的問題。那時就介紹過一種將“長方矩陣”的問題，化為正方矩陣的問題的方法：
- If  $A$  is an  $m \times n$  matrix then  $A^T A$  is an  $n \times n$  matrix and  $A A^T$  is an  $m \times m$  matrix.
- If a matrix  $A$  can be decomposed into  $A = U S V^{-1}$ , then it can be shown that the matrices  $S^T S$  and  $S S^T$  are the eigenvalue matrices of matrices  $A^T A$  and  $A A^T$ , respectively. Whereas, the matrices  $V_{n \times n}$  and  $U_{m \times m}$  are the corresponding eigenvector matrices of the matrices  $A^T A_{n \times n}$  and  $A A^T_{m \times m}$ , respectively.



# Eigenvalue matrix and eigenvector matrix of $A^T A$

Let the singular value decomposition of matrix  $A = U\Sigma V^{-1}$   
where matrices  $U$  and  $V$  are invertible orthogonal matrices

$$\Rightarrow U^{-1} = U^T \text{ and } V^{-1} = V^T$$

$$A^T A = (U\Sigma V^{-1})^T U\Sigma V^{-1} = (V^{-1})^T \Sigma^T U^T U\Sigma V^{-1} = V(\Sigma^T \Sigma)V^{-1}$$

$\Rightarrow$

$V$  is the eigenvector matrix of the symmetric matrix  $A^T A$

$\Sigma^T \Sigma$  is the eigenvalue matrix of the symmetric matrix  $A^T A$

# Eigenvalue matrix and eigenvector matrix of $AA^T$

Let the singular value decomposition of matrix  $A = U\Sigma V^{-1}$   
where matrices  $U$  and  $V$  are invertible orthogonal matrices

$$\Rightarrow U^{-1} = U^T \text{ and } V^{-1} = V^T$$

$$AA^T = U\Sigma V^{-1}(U\Sigma V^{-1})^T = U\Sigma V^{-1}(V^{-1})^T \Sigma^T U^T = U(\Sigma\Sigma^T)U^{-1}$$

$\Rightarrow$

$U$  is the eigenvector matrix of the symmetric matrix  $AA^T$

$\Sigma\Sigma^T$  is the eigenvalue matrix of the symmetric matrix  $AA^T$

# SVD example 1

$$A = \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} \Rightarrow A^T A = \begin{bmatrix} 2 & 1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 5 & 5 \\ 5 & 5 \end{bmatrix} \text{ and } AA^T = \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 8 & 4 \\ 4 & 2 \end{bmatrix}$$

$$\det(A^T A - \lambda I) = (5 - \lambda)^2 - 25 = 0 \Rightarrow \lambda = 0 \text{ or } \lambda = 10$$

$$\text{For } \lambda_1 = 0, \mathbf{x}_1 = \begin{bmatrix} 1 \\ -1 \end{bmatrix}. \text{ For } \lambda_2 = 10, \mathbf{x}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}. \Rightarrow V = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$$

$$\det(AA^T - \lambda I) = (8 - \lambda)(2 - \lambda) - 16 = 0 \Rightarrow \lambda = 0 \text{ or } \lambda = 10$$

$$\text{For } \lambda_1 = 0, \mathbf{x}_1 = \begin{bmatrix} 1 \\ -2 \end{bmatrix}. \text{ For } \lambda_2 = 10, \mathbf{x}_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}. \Rightarrow U = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix}$$

$$\begin{aligned} \text{Let } \Sigma &= \begin{bmatrix} 0 & 0 \\ 0 & \sqrt{10} \end{bmatrix} \Rightarrow U \Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & \sqrt{10} \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \right)^{-1} \\ &= \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} = A \end{aligned}$$

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

## SVD example 2a

$$\Rightarrow A^T A = \begin{bmatrix} 1 & \sqrt{5} & -2 \\ -1 & \sqrt{5} & 2 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \text{ and } AA^T = \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} \begin{bmatrix} 1 & \sqrt{5} & -2 \\ -1 & \sqrt{5} & 2 \end{bmatrix} = \begin{bmatrix} 2 & 0 & -4 \\ 0 & 10 & 0 \\ -4 & 0 & 8 \end{bmatrix}$$

$$\det(A^T A - \lambda I) = (10 - \lambda)^2 = 0 \Rightarrow \lambda = 10 \Rightarrow V = ? \text{ Possible choices: } \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \text{ or } \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \text{ etc.}$$

$$\det(AA^T - \lambda I) = (2 - \lambda)(10 - \lambda)(8 - \lambda) - 16(10 - \lambda) = 0 \Rightarrow -\lambda(\lambda^2 - 20\lambda + 100) = 0 \Rightarrow \lambda = 10, 10, 0$$

$$\text{For } \lambda_1 = \lambda_2 = 10, \mathbf{x}_1 = \begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}. \text{ For } \lambda_3 = 0, \mathbf{x}_3 = \begin{bmatrix} 2 \\ 0 \\ 1 \end{bmatrix} \Rightarrow U = \frac{1}{\sqrt{5}} \begin{bmatrix} -1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ 2 & 0 & 1 \end{bmatrix}$$

$$\text{Let } \Sigma = \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \Rightarrow U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} -1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \\ = \begin{bmatrix} -1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & \sqrt{5} \\ 2 & 0 \end{bmatrix} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} = A$$

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

## SVD example 2b

$$\Rightarrow A^T A = \begin{bmatrix} 1 & \sqrt{5} & -2 \\ -1 & \sqrt{5} & 2 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \text{ and } AA^T = \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} \begin{bmatrix} 1 & \sqrt{5} & -2 \\ -1 & \sqrt{5} & 2 \end{bmatrix} = \begin{bmatrix} 2 & 0 & -4 \\ 0 & 10 & 0 \\ -4 & 0 & 8 \end{bmatrix}$$

$$\det(A^T A - \lambda I) = (10 - \lambda)^2 = 0 \Rightarrow \lambda = 10 \Rightarrow V = ? \text{ Possible choices: } \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \text{ or } \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \text{ etc.}$$

$$\det(AA^T - \lambda I) = (2 - \lambda)(10 - \lambda)(8 - \lambda) - 16(10 - \lambda) = 0 \Rightarrow -\lambda(\lambda^2 - 20\lambda + 100) = 0 \Rightarrow \lambda = 10, 10, 0$$

$$\text{For } \lambda_1 = \lambda_2 = 10, \mathbf{x}_1 = \begin{bmatrix} 1 \\ 0 \\ -2 \end{bmatrix}, \mathbf{x}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}. \text{ For } \lambda_3 = 0, \mathbf{x}_3 = \begin{bmatrix} 2 \\ 0 \\ 1 \end{bmatrix}. \Rightarrow U = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ -2 & 0 & 1 \end{bmatrix}$$

$$\text{Let } \Sigma = \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \Rightarrow U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ -2 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \right)^{-1}$$

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

# SVD : Summary of examples

$$A = \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} = U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} -1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ 2 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \right)^{-1} \text{ or}$$

$$A = \begin{bmatrix} 1 & -1 \\ \sqrt{5} & \sqrt{5} \\ -2 & 2 \end{bmatrix} = U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 0 & 2 \\ 0 & \sqrt{5} & 0 \\ -2 & 0 & 1 \end{bmatrix} \begin{bmatrix} \sqrt{10} & 0 \\ 0 & \sqrt{10} \\ 0 & 0 \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \right)^{-1} \text{ or ...}$$

likewise

$$A = \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} = U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & \sqrt{10} \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \right)^{-1} \text{ or}$$

$$A = \begin{bmatrix} 2 & 2 \\ 1 & 1 \end{bmatrix} = U\Sigma V^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} -1 & 2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 \\ 0 & \sqrt{10} \end{bmatrix} \left( \frac{1}{\sqrt{2}} \begin{bmatrix} -1 & 1 \\ 1 & 1 \end{bmatrix} \right)^{-1} \text{ or ....}$$

⇒ Matrix  $A$  has nonunique singular value decomposition form, but

has unique "singular values," which are the elements in the semi-diagonal matrix  $\Sigma$ .

# Summary of SVD

$$(A=USV^{-1}) \text{ p. 355}$$

- Meaning of  $Ax$ 
  1. Rotate the vector  $x$  based on the row vectors of  $V$  (or change to the new basis which consists of the column vectors of  $V$ )
  2. Stretch corresponding components by  $S$
  3. Rotate the resulting vector based on the column vectors of  $U$  (or change to the new basis, which consists of the row vectors of  $U$ )

# Summary of SVD

## ( $AV=US$ ) p. 356

- Matrix  $A$  maps the vectors in one orthogonal matrix  $V$  to the vectors in another orthogonal matrix  $U$  (with non-zero stretches).
- The function of  $A$  is very similar to the function of conformal mapping!
- Check for advanced example : ([http://ieeexplore.ieee.org/xpl/freeabs\\_all.jsp?arnumber=1196456&fromcon](http://ieeexplore.ieee.org/xpl/freeabs_all.jsp?arnumber=1196456&fromcon))



# Matrices for the Derivatives and Integral pp. 372-373

- Matrix form of derivatives

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \end{bmatrix}$$

- Matrix form of integration

$$A^{-1} = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1/2 & 0 \\ 0 & 0 & 1/3 \end{bmatrix}$$

- One-sided inverse:  $AA^{-1}=?$  ;  $A^{-1}A=?$