

$$A = \text{diag}(\lambda_1, \dots, \lambda_n) \quad \text{diag}(1, 2, 4) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 4 \end{bmatrix}$$

$$A^2 = \text{diag}(\lambda_1, \dots, \lambda_n)^2 \quad \text{diag}(1, 2, 4)^2 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 16 \end{bmatrix} \quad A^m = \text{diag}(\lambda_1^m, \dots, \lambda_n^m)$$

$$A = PBP^{-1} \quad (\text{Where } B \text{ is the } \text{diag}(\lambda_1, \dots, \lambda_n))$$

$$A^m = \text{diag}(\lambda_1^m, \dots, \lambda_n^m) = PBP^{-1} \quad PBP^{-1}, \dots, PBP^{-1}, PBP^{-1} = PB^m P^{-1}$$

$$A = \begin{bmatrix} 2 & 1 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 3 \end{bmatrix} \quad \text{Find } A^{100} \quad A^{100} = P^{-1} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2^{100} & 0 \\ 0 & 0 & 3^{100} \end{bmatrix} * P$$

$$\text{We already found } P \text{ for } A = \begin{bmatrix} 2 & 1 & 0 \\ 0 & 1 & 0 \\ -1 & -1 & 3 \end{bmatrix} \text{ in section 28.... } P = \begin{bmatrix} 1 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

$$A^{100} = \begin{bmatrix} 0 & -1 & 0 \\ 2 & 2 & 0 \\ -3 & -3 & 3 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2^{100} & 0 \\ 0 & 0 & 3^{100} \end{bmatrix} * \begin{bmatrix} 1 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

$$C \text{ polynomial} \quad C(A) \quad C(x) = x^2 - 2x + 5 \quad C(A) = A^2 - 2A + 5I$$

$$C(\text{diag}(\lambda_1, \dots, \lambda_n)) = \text{diag}(C(\lambda_1), C(\lambda_2), \dots, C(\lambda_n))$$

$$C \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} = \begin{bmatrix} 4 & 0 \\ 0 & 8 \end{bmatrix} \quad \text{because } C(x) = x^2 - 2x + 5 \quad \text{so } 1^2 - 2(1) + 5 = 4 \quad \text{and } 3^2 - 2(3) + 5 = 8$$

$$\alpha \text{diag}(\lambda_1, \dots, \lambda_n) = \text{diag}(\alpha \lambda_1, \dots, \alpha \lambda_n)$$

$$\text{diag}(\lambda_1, \dots, \lambda_n) + \text{diag}(G_1, \dots, G_n) = \text{diag}(\lambda_1 + G_1, \dots, \lambda_n + G_n)$$

$$\text{diag}(\lambda_1, \dots, \lambda_n)^m = \text{diag}(\lambda_1^m, \dots, \lambda_n^m)$$

$$A = PBP^{-1}, \quad B \text{diag}, \quad C(x) = \sum_{k=0}^m d_k X^k, \quad C(A) = \sum_{k=0}^m \alpha_k A^k = C(A) = \sum_{k=0}^m \alpha_k A^k$$

$$= \sum_{k=0}^m P^{-1} \alpha_k B^k P = P^{-1} \left(\sum_{k=0}^m \alpha_k B^k \right) P = P^{-1} C(B) P$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \quad C(A) = A^2 - 2A + 5I \quad \text{yields} \quad \begin{bmatrix} 4 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 8 \end{bmatrix}$$

$$\text{Therefore } C(A) = P^{-1} * \begin{bmatrix} 4 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 8 \end{bmatrix} * P$$

Cayley-Hamilton Theorem (Page 199 Section 31)

Let A be a square matrix and let $C(A)$ be the characteristic polynomial of A then

$$C(A) = [0]$$

PROOF: For diagonalizable matrices:

$$C(A) = C(P^{-1}BP) = P^{-1} C(B)P = P^{-1} \text{diag}(C(\lambda_1), C(\lambda_2), \dots, C(\lambda_n))P = P^{-1} [0] P = [0]$$

Normed Space

V vector space

$v \in V$

$\|v\| \in \mathfrak{R}$

“Norm of V ”

1. $\|v\| = 0 \Leftrightarrow v = \vec{0}$
2. $\|\lambda v\| = |\lambda| \|v\|$
3. $\|v + w\| \leq \|v\| + \|w\|$