

# Linear algebra for AI & ML

(October-6)

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Let  $A \in \mathbb{R}^{n \times n}$  ; let  $\lambda_1$  and  $\lambda_2$  be two distinct eigenvalues of  $A$  with corresponding eigenvectors  $v_1$  and  $v_2$ . Then  $v_1$  and  $v_2$  are linearly independent.

$$Av_1 = \lambda_1 v_1 \quad \text{and} \quad Av_2 = \lambda_2 v_2$$

To prove:  $v_1$  &  $v_2$  are linearly independent.

$$\text{Consider } \alpha_1 v_1 + \alpha_2 v_2 = 0 \quad \checkmark$$

then we want to prove  $\alpha_1 = \alpha_2 = 0$ .

$$\alpha_1 v_1 + \alpha_2 v_2 = 0 \quad \text{--- (1)}$$

$$\Rightarrow A(\alpha_1 v_1 + \alpha_2 v_2) = A(0) = 0$$

$$\Rightarrow \alpha_1 Av_1 + \alpha_2 Av_2 = \alpha_1 \lambda_1 v_1 + \alpha_2 \lambda_2 v_2 = 0 \quad \text{--- (2)}$$

multiply first eq<sup>n</sup> by  $\lambda_1$  and subtract it from (2)

we get  $\alpha_2(\lambda_2 - \lambda_1)v_2 = 0$

Note  $v_2 \neq 0$  (Because it's an eigen vector)

further  $\lambda_1 \neq \lambda_2 \Rightarrow \lambda_2 - \lambda_1 \neq 0$

$$\underbrace{(\lambda_2 - \lambda_1)}_{\neq 0} v_2 \neq 0 \Rightarrow \alpha_2 = 0$$

Similarly, we can show that  $\alpha_1 = 0$ .

$\Rightarrow v_1$  and  $v_2$  are linearly independent.

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$A \in \mathbb{R}^{n \times n}$ ; let  $\lambda_1, \dots, \lambda_n$  be eigenvalues of  $A$ ,  
all distinct. Then corresponding eigenvectors  
 $v_1, v_2, \dots, v_n$  are linearly independent.

$$Av_i = \lambda_i v_i \quad \text{for } i=1, 2, \dots, n$$

Then  $\{v_1, \dots, v_n\}$  will be a basis of  $\mathbb{R}^n$ .

$$T = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix} \in \mathbb{R}^{n \times n}$$

$$AT = T \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{bmatrix}$$

← from eigenvalue  
eigenvector  
relationship.

Note that  $\text{rank}(T) = n \Rightarrow T$  is invertible.

$$A = T \begin{bmatrix} \lambda_1 & & & 0 \\ & \lambda_2 & & \\ & & \ddots & \\ 0 & & & \lambda_n \end{bmatrix} T^{-1}$$

$$\boxed{A = T \Lambda T^{-1}}$$

... diagonalization of  
the matrix  $A$ .

$A \in \mathbb{R}^{n \times n}$ , let  $\lambda_1, \dots, \lambda_n$  be the distinct eigenvalues of  $A$ .  
 $\updownarrow$   
 let  $v_1, \dots, v_n$  be the corresponding eigenvectors.

for any vector  $x \in \mathbb{R}^n$

$$\underline{x} = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_n v_n$$

$$Ax = A(\alpha_1 v_1 + \dots + \alpha_n v_n)$$

$$= \alpha_1 \lambda_1 v_1 + \alpha_2 \lambda_2 v_2 + \dots + \alpha_n \lambda_n v_n$$

$$A(Ax) = A^2 x = A(\alpha_1 \lambda_1 v_1 + \alpha_2 \lambda_2 v_2 + \dots + \alpha_n \lambda_n v_n)$$

$$= \alpha_1 \lambda_1^2 v_1 + \alpha_2 \lambda_2^2 v_2 + \dots + \alpha_n \lambda_n^2 v_n$$

continuing this process,

$$A^n x = \alpha_1 \lambda_1^n v_1 + \alpha_2 \lambda_2^n v_2 + \dots + \alpha_n \lambda_n^n v_n$$

Let  $\lambda_1, \lambda_2, \dots, \lambda_n$  be such that

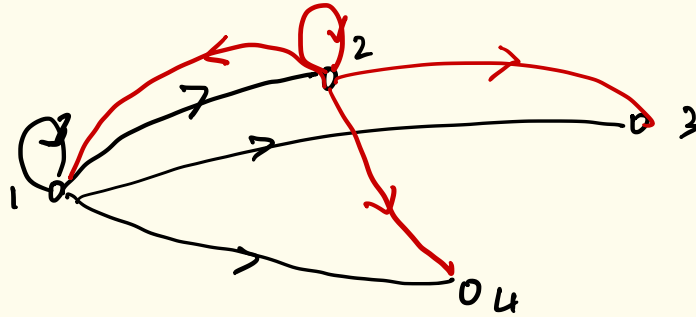
$$|\lambda_1| > |\lambda_2| \geq |\lambda_3| \geq |\lambda_4| \geq \dots \geq |\lambda_n| \geq 0$$

$$\frac{A^n x}{\lambda_1^n} = \alpha_1 \underbrace{\left(\frac{\lambda_2}{\lambda_1}\right)^n}_{\rightarrow 0} v_2 + \dots + \alpha_n \left(\frac{\lambda_n}{\lambda_1}\right)^n v_n$$

Let  $n \rightarrow \infty$

Idea leads to power iteration / power method to compute dominant eigenvector and then corresponding eigenvalue.

# Markov chains (with finite state space)



4x4 : matrix of transition probabilities

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{\lambda} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

eigenvector

eigenvalue

What we are interested in is the eigenvectors of  $P^T$ .

(check: Eigenvalues of  $A$  and  $A^T$  are same!!)

$$\det(A^T - \lambda I) = \det(A^T - \lambda I^T) = \det(A - \lambda I)^T = \det(A - \lambda I)$$

We, in particular, are interested in the eigenvector corresponding to eigenvalue 1 of  $P^T$ . (stationary distribution of the Markov chain)

$$P^T \left( P^T \left( P^T \begin{pmatrix} \cdot \\ \cdot \end{pmatrix} \right) \right) = \begin{pmatrix} \cdot \\ \cdot \end{pmatrix}$$

↑

$$\begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \end{pmatrix}$$

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