

# ***Primer on Linear Algebra***

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## *Linear Algebra*

- *Basic Concepts on Vectors and Matrices*

## *Reading:*

- *Many primers (check internet)*

# Matrices & Vectors

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- Vector  $\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = (x_1 \dots x_n)^T = [x_i]$
- Dot product  $\mathbf{x}^T \mathbf{y} = \sum_{i=1}^n x_i y_i$ , outer  $\mathbf{x}\mathbf{y}^T = \begin{pmatrix} x_1 y_1 & \cdots & x_1 y_n \\ \vdots & \ddots & \vdots \\ x_n y_1 & \cdots & x_n y_n \end{pmatrix}$
- Matrix  $A = \begin{bmatrix} a_{11} & \cdots & a_{1l} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nl} \end{bmatrix} = (\mathbf{a}_1 \dots \mathbf{a}_l) = \begin{bmatrix} \mathbf{\tilde{a}}_1^T \\ \vdots \\ \mathbf{\tilde{a}}_n^T \end{bmatrix} = [a_{ij}]$

# Matrix Multiplication

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- Matrix multiplication     $\mathbf{A} = [a_{ij}] \in R^{n \times l}$      $\mathbf{B} = [b_{ij}] \in R^{l \times m}$

$$\mathbf{AB} = \left[ \sum_{i=1}^M a_{ik} b_{kj} \right] = \begin{bmatrix} \tilde{\mathbf{a}}_1^T \\ \vdots \\ \tilde{\mathbf{a}}_n^T \end{bmatrix} [\mathbf{b}_1 \quad \cdots \quad \mathbf{b}_m] = [\tilde{\mathbf{a}}_i^T \mathbf{b}_j]$$

$$= [\mathbf{Ab}_1 \quad \cdots \quad \mathbf{Ab}_m] = \begin{bmatrix} \tilde{\mathbf{a}}_1^T \mathbf{B} \\ \vdots \\ \tilde{\mathbf{a}}_n^T \mathbf{B} \end{bmatrix}$$

# Matrix Multiplication

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- Matrix/vector multiplication  $\mathbf{A}\mathbf{b} = \begin{bmatrix} \tilde{\mathbf{a}}_1^T \\ \vdots \\ \tilde{\mathbf{a}}_n^T \end{bmatrix} \mathbf{b} = \begin{bmatrix} \tilde{\mathbf{a}}_1^T \mathbf{b} \\ \vdots \\ \tilde{\mathbf{a}}_n^T \mathbf{b} \end{bmatrix} = [\tilde{\mathbf{a}}_j^T \mathbf{b}]$
- Identity matrix  $\mathbf{AI} = \mathbf{IA} = \mathbf{A}$

$$\mathbf{I} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{3x3 Identity matrix}$$

# Matrix Transpose

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- Matrix transpose

$$\mathbf{A}^T = \begin{bmatrix} a_{11} & \cdots & a_{n1} \\ \vdots & \ddots & \vdots \\ a_{1l} & \cdots & a_{nl} \end{bmatrix} = (\tilde{\mathbf{a}}_1 \dots \tilde{\mathbf{a}}_n) = \begin{bmatrix} \mathbf{a}_1^T \\ \vdots \\ \mathbf{a}_l^T \end{bmatrix}$$

- Property  $(\mathbf{AB})^T = \mathbf{B}^T \mathbf{A}^T$

- Symmetric Matrix

$$\mathbf{A} = \mathbf{A}^T$$

Example

$$\begin{bmatrix} 4 & 5 & -3 \\ 5 & 7 & 2 \\ -3 & 2 & 10 \end{bmatrix}$$

# Trace

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$$tr(\mathbf{A}) = \sum_i^n a_{ii}$$

- properties

$$tr(\mathbf{A}^T) = tr(\mathbf{A})$$

$$tr(\mathbf{A} + \mathbf{B}) = tr(\mathbf{A}) + tr(\mathbf{B})$$

$$tr(\mathbf{AB}) = tr(\mathbf{BA})$$

- in general

$$tr(\mathbf{AB}) \neq tr(\mathbf{B})tr(\mathbf{A})$$

# Determinants

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$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$|A| = \begin{vmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{vmatrix} = a_{11}a_{22} - a_{21}a_{12}$$

$$\begin{vmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{vmatrix} = a_{11} \begin{vmatrix} a_{22} & a_{23} \\ a_{32} & a_{33} \end{vmatrix} - a_{21} \begin{vmatrix} a_{12} & a_{13} \\ a_{32} & a_{33} \end{vmatrix} + a_{31} \begin{vmatrix} a_{12} & a_{13} \\ a_{22} & a_{23} \end{vmatrix}$$

$$|A| = \sum_{j=1}^n (-1)^{j+k} a_{jk} |A_{jk}|$$

# Determinants

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- Properties

$$|AB| = |A||B| \quad |A + B| \neq |A| + |B|$$

$$A = \begin{bmatrix} a_{11} & 0 & \cdot & 0 \\ 0 & a_{22} & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & a_{nn} \end{bmatrix}, \text{ then } |A| = \prod_{i=1}^n a_{ii}$$

# Matrix Inverse

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- Matrix inverse     $A^{-1}$      $A^{-1}A = A A^{-1} = I$
- $A^{-1}$  exists iff     $|A| \neq 0$
- Solving systems     $Ax = b \Rightarrow x = A^{-1}b$
- Properties     $(AB)^{-1} = B^{-1}A^{-1}$      $A^{-1^T} = A^{T^{-1}}$   
 $|A^{-1}| = \frac{1}{|A|}$

# Matrix Inverse

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- Inverse is only for square matrices. What happens for non-square (pseudo-inverse)?
- Solving the system  $A \in R^{n \times l}$

$$Ax = b \xrightarrow{A^T} A^T A x = A^T b$$

$$\xrightarrow{(A^T A)^{-1}} x = (A^T A)^{-1} A^T b$$

- Pseudo-inverse  $A^+ = (A^T A)^{-1} A^T \quad A^+ A = I$

# ***Rank of matrix (Definition 1)***

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Equal to the dimension of the largest square sub-matrix of a matrix that has a non-zero determinant.

$$\begin{bmatrix} 4 & 5 & 2 & 14 \\ 3 & 9 & 6 & 21 \\ 8 & 10 & 7 & 28 \\ 1 & 2 & 9 & 5 \end{bmatrix} \text{ has rank 3}$$

$$|A| = 0 \quad \text{but} \quad \left| \begin{bmatrix} 4 & 5 & 2 \\ 3 & 9 & 6 \\ 8 & 10 & 7 \end{bmatrix} \right| = 63$$

# **Rank of matrix (Definition 2)**

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- A set of vectors  $\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \dots, \mathbf{a}_l$  are linearly independent then  $c_1\mathbf{a}_1 + c_2\mathbf{a}_2 + c_3\mathbf{a}_3 + \dots + c_l\mathbf{a}_l = 0$  iff  $c_1, c_2, c_3, \dots, c_n = 0$

**Alternative definition of rank:** the maximum number of linearly independent columns (or rows) of  $A$

Example:  $1 \begin{bmatrix} 4 \\ 3 \\ 8 \\ 1 \end{bmatrix} + 2 \begin{bmatrix} 5 \\ 9 \\ 10 \\ 2 \end{bmatrix} + 0 \begin{bmatrix} 2 \\ 6 \\ 7 \\ 9 \end{bmatrix} - 1 \begin{bmatrix} 14 \\ 21 \\ 28 \\ 5 \end{bmatrix} = 0$  Therefore,  
rank is not 4 !

# Properties

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- If  $A$  in  $n \times n$ ,  $\text{rank}(A) = n$  iff  $A$  is nonsingular (i.e., invertible)
- If  $A$  in  $n \times n$ ,  $\text{rank}(A) = n$  iff  $|A| \neq 0$  (full rank).
- If  $A$  in  $n \times n$ ,  $\text{rank}(A) < n$  iff  $A$  is singular.

# ***Orthogonal/Orthonormal matrices***

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$$A = \begin{bmatrix} \tilde{\mathbf{a}}_1^T \\ \vdots \\ \tilde{\mathbf{a}}_n^T \end{bmatrix} \quad \tilde{\mathbf{a}}_j^T \tilde{\mathbf{a}}_k = 0 \text{ for every } j \neq k \quad AA^T = \mathbf{L}$$

$$A = [\mathbf{a}_1 \dots \mathbf{a}_n] \quad \mathbf{a}_j^T \mathbf{a}_k = 0 \text{ for every } j \neq k \quad AA^T = \mathbf{L}$$

$$AA^T = \mathbf{I} \quad A^T A = \mathbf{I}$$

# *Eigenvalues & Eigenvectors*

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- Vector  $x$  is an eigenvector of matrix  $A$  and  $\lambda$  is an eigenvalue of  $A$  if:

$$Ax = \lambda x \quad x \neq 0$$

- **Interpretation:** the linear transformation implied by  $A$  cannot change the direction of the eigenvectors  $x$ , only their magnitude.

# Eigenvalues & Eigenvectors

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- To find the eigenvalues  $\lambda$  of a matrix  $A$ , find the roots of the *characteristic polynomial*:

$$|A - \lambda I| = 0$$

Example:  $A = \begin{bmatrix} 5 & -2 \\ 6 & -2 \end{bmatrix}$

$$|\begin{bmatrix} 5 - \lambda & -2 \\ 6 & -2 - \lambda \end{bmatrix}| = 0 \Rightarrow \lambda^2 - 3\lambda + 2 = 0 \Rightarrow \lambda_1 = 1, \lambda_2 = 2 \Rightarrow$$

# *Eigenvalues & Eigenvectors*

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Find the eigenvectors by solving the two homogenous systems:

$$(A - \lambda_1 I)v_1 = 0 \Rightarrow v_1 = k \begin{bmatrix} 1/2 \\ 1 \end{bmatrix}$$

$$(A - \lambda_2 I)v_2 = 0 \Rightarrow v_2 = k \begin{bmatrix} 1/3 \\ 1 \end{bmatrix}$$

# Eigenvalues & Eigenvectors

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- Eigenvalues and eigenvectors are only defined for square matrices (i.e.,  $n = l$ )
- Eigenvectors are not unique: If  $\mathbf{v}$  is an eigenvector, so is  $k\mathbf{v}$  (solution of a homogenous system)
- Suppose  $\lambda_1, \lambda_2, \dots, \lambda_n$  are the eigenvalues of  $\mathbf{A}$ , then:

$$\sum_{i=1}^n \lambda_i = \text{tr}(\mathbf{A}) \quad \prod_{i=1}^n \lambda_i = |\mathbf{A}| \quad \begin{aligned} \lambda_i = 0 \\ \Rightarrow \mathbf{A} \text{ is singular} \end{aligned}$$

# Diagonalisation

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- Given matrix  $A$ , find  $P$  such that  $P^{-1}AP$  is diagonal (i.e.,  $P$  diagonalises  $A$ )
- Take  $P = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n]$ , where  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$  are the eigenvectors of  $A$

$$AP = P \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots \\ 0 & 0 & \lambda_n \end{bmatrix} \quad \text{or} \quad P^{-1}AP = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ \vdots & \ddots & \vdots \\ \vdots & \ddots & \ddots \\ 0 & 0 & \lambda_n \end{bmatrix}$$

# **Diagonalisation**

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Are all  $n \times n$  matrices diagonalizable with  $\lambda_1, \lambda_2, \dots, \lambda_n > 0$ ?

- Only if  $P^{-1}$  exists (i.e.,  $A$  must have  $n$  linearly independent eigenvectors, that is,  $\text{rank}(A) = n$ )
- If  $A$  has  $n$  distinct eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ , then the corresponding eigen-vectors  $v_1, v_2, \dots, v_n$  form a basis:
  - (1) linearly independent
  - (2) span  $R^n$

# **Diagonalisation**

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## Symmetric Matrices

- The eigenvalues of symmetric matrices are all real.
- The eigenvectors corresponding to distinct eigenvalues are orthogonal.  $\mathbf{P}^{-1} = \mathbf{P}^T$

$$\mathbf{A} = \mathbf{P}\Lambda\mathbf{P}^T = \sum_{i=1}^n \lambda_i \mathbf{v}_i (\mathbf{v}_i)^T$$

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# Properties in the white board