

Lecture – 15

Review of Matrix Theory – III

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Matrix

An $m \times n$ matrix is a rectangular or square array of elements with m rows and n columns.

$$\text{Eg: } A_{m \times n} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}$$

For each subscript, a_{ij} , i = the row, and j = the column.

If $m = n$, then the matrix is said to be a "square matrix".

Vector

If a matrix has just one row, it is called a "row vector"

$$\text{Eg. } [b_{11} \ b_{12} \ \cdots \ b_{1n}]$$

If a matrix has just one column, it is called a "column vector"

$$\text{Eg. } \begin{bmatrix} c_{11} \\ c_{21} \\ \vdots \\ c_{m1} \end{bmatrix}$$

Null Matrix / Diagonal Matrix

Null matrix : A matrix with all zero elements

$$\text{Eg. } A = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}$$

Diagonal Matrix : A square matrix with all off diagonal elements being zero

$$\text{Eg. } A = \begin{bmatrix} a_{11} & 0 & 0 & \cdots & 0 \\ 0 & a_{22} & 0 & \cdots & 0 \\ 0 & 0 & a_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}$$

Linear Dependence/Independence

A set of n column vectors s_1, s_2, \dots, s_n , is said to be "linearly dependent" if there exist constants

$\alpha_1, \alpha_2, \dots, \alpha_n$, not all zero, such that

$$\alpha_1 s_1 + \alpha_2 s_2 + \dots + \alpha_n s_n = 0$$

If the above equation holds only when

$\alpha_1 = \alpha_2 = \dots = \alpha_n$, then the vectors are

"linearly independent".

Example: Linear Dependence/Independence

Question : Are the vectors $a_1 = [1 \ 1 \ 0]^T$, $a_2 = [1 \ 0 \ 1]^T$, $a_3 = [0 \ 1 \ 1]^T$ linearly independent?

Answer : We must test whether

$xa_1 + ya_2 + za_3 = 0$ admits any non-trivial solution.

The determinant of the coefficient is

$$D = \begin{vmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{vmatrix} = -2 \neq 0$$

Hence the vectors are linearly independent.

Rank of a Matrix

The *rank* of a matrix $A_{m \times n}$ is equal to the number of linearly independent rows or columns. The rank can be found by finding the highest-order square submatrix that is non-singular.

$$\text{Eg. } A = \begin{bmatrix} 1 & -5 & 2 \\ 4 & 7 & -5 \\ -3 & 15 & -6 \end{bmatrix}$$

Here $|A| = 0$. So, the A matrix is singular and hence $\text{rank}(A) \neq 3$

Choosing the sub-matrix $B = \begin{bmatrix} 1 & -5 \\ 4 & 7 \end{bmatrix}$, $|B| = 27 \neq 0$

Hence $\text{rank}(A) = 2$

Matrix Operations

Addition

The sum of two matrices, written $A + B = C$, is defined

by $a_{ij} + b_{ij} = c_{ij}$ Eg.
$$\begin{bmatrix} 2 & -1 \\ 3 & 5 \end{bmatrix} + \begin{bmatrix} 7 & -5 \\ -4 & 3 \end{bmatrix} = \begin{bmatrix} 9 & -6 \\ -1 & 8 \end{bmatrix}$$

Subtraction

The difference between two matrices, written $A - B = C$, is defined

by $a_{ij} - b_{ij} = c_{ij}$ Eg.
$$\begin{bmatrix} 2 & -1 \\ 3 & 5 \end{bmatrix} - \begin{bmatrix} 7 & -5 \\ -4 & 3 \end{bmatrix} = \begin{bmatrix} -5 & 4 \\ 7 & 2 \end{bmatrix}$$

Matrix Operations

Multiplication

The product of two matrices, written $AB = C$, is defined by $c_{ij} = \sum_{k=1}^n a_{ik} b_{jk}$

$$\text{Eg. } A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}; B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}$$

$$AB = \begin{bmatrix} a_{11}b_{11} + a_{12}b_{21} + a_{13}b_{31} & a_{11}b_{12} + a_{12}b_{22} + a_{13}b_{32} & a_{11}b_{13} + a_{12}b_{23} + a_{13}b_{33} \\ a_{21}b_{11} + a_{22}b_{21} + a_{23}b_{31} & a_{21}b_{12} + a_{22}b_{22} + a_{23}b_{32} & a_{21}b_{13} + a_{22}b_{23} + a_{23}b_{33} \end{bmatrix}$$

Schur / Hadamard / Direct product

$$A \bullet B = [a_{ij} \bullet b_{ij}], \text{ if } A \text{ \& } B \text{ have same dimension}$$

Matrix Identities

Commutative Law

$$A + B = B + A$$

$$AB \neq BA$$

Associative Law

$$A + (B + C) = (A + B) + C$$

$$A(BC) = (AB)C$$

Transpose of sum

$$(A + B)^T = A^T + B^T$$

Transpose of product

$$(AB)^T = B^T A^T$$

Determinant identities

$$\det A^T = \det A$$

$$\det AB = \det A \det B$$

$$\det AB = \det BA$$

Trace

Trace of $A_{n \times n}$

$$T_r(A) = \sum_{i=1}^n a_{ij} \quad : \text{Sum of the diagonal elements}$$

$$\underline{\text{Eg}} \quad A = \begin{bmatrix} 1 & 3 \\ 2 & 4 \end{bmatrix}, \quad T_r(A) = 1 + 4 = 5$$

Example: Eigenvalues/Eigenvectors

Question : Find eigenvalues/eigenvecotrs of $A = \begin{bmatrix} 1 & 3 \\ 2 & 2 \end{bmatrix}$

Solution :

Eigenvalues: The characteristic equation is given by

$$\det(A - \lambda I_2) = \begin{vmatrix} 1 - \lambda & 3 \\ 2 & 2 - \lambda \end{vmatrix} = 0$$

$$(1 - \lambda)(2 - \lambda) - 6 = \lambda^2 - 3\lambda - 4 = (\lambda - 4)(\lambda + 1) = 0$$

Hence the eigenvalues are $\lambda_1 = -1, \lambda_2 = 4$

Example: Eigenvalues/Eigenvectors

Eigenvectors:

Let $X_1 = \begin{bmatrix} a_1 \\ b_1 \end{bmatrix}$. Then the equation $(A - \lambda_1 I_2) X_1 = 0$ leads to:

$$\begin{bmatrix} 1-4 & 3 \\ 2 & 2-4 \end{bmatrix} \begin{bmatrix} a_1 \\ b_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{cases} -3a_1 + 3b_1 = 0 \\ 2a_1 - 2b_1 = 0 \end{cases} \Rightarrow (a_1 = b_1)$$

The solutions can be expressed as $a_1 = b_1 = \alpha$

for any α . If we put $\alpha = 1$, then an eigenvector is

$$X_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Example: Eigenvalues/Eigenvectors

Similarly $(A - \lambda_2 I_2) X_2 = 0$ implies

$$\begin{bmatrix} 1+1 & 3 \\ 2 & 2+1 \end{bmatrix} \begin{bmatrix} a_2 \\ b_2 \end{bmatrix} = 0, \text{ or } \begin{cases} 2a_2 + 3b_2 = 0 \\ 2a_2 + 3b_2 = 0 \end{cases}$$

The eigenvectors for this case are

$$X_2 = \begin{bmatrix} \beta \\ -\frac{2}{3}\beta \end{bmatrix}$$

for any nonzero β . Assuming $\beta = 3$ gives the eigenvector

$$X_2 = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$$

Example: Eigenvalues/Eigenvectors

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Additional Properties of Eigenvalues/Eigenvectors

$$|A| = \lambda_1 \cdots \lambda_n$$

$$\text{Tr}(A) = \lambda_1 + \cdots + \lambda_n$$

$$\text{If } \det(\lambda I - A) = \lambda^n + a_{n-1}\lambda^{n-1} + \cdots + a_1\lambda + a_0$$

$$\text{then } a_{n-1} = -\text{Tr}(A), \quad a_0 = (-1)^n |A|$$

If $A_{n \times n}$ is Real and Skew-Symmetric ($A = -A^T$)

[or Complex and Skew-Hermitian ($A = -A^*$)],

Then its eigenvalues are all pure imaginary

Additional Properties of Eigenvalues/Eigenvectors

If $A_{n \times n}$ is Real and Symmetric [or Complex and Hermitian], then its eigenvalues are all real.

If A is a symmetrical matrix, then the eigenvectors associated with two distinct eigenvalues are orthogonal

If $A_{n \times n}$ is a symmetric matrix, then

$$\lambda_{\min} < R(X) < \lambda_{\max} \quad , \text{ where, } R(X) \triangleq \left(\frac{X^T A X}{X^T X} \right), X \neq 0$$

Proof

Proof

Proof

Proof

Generalized Eigenvectors

Suppose $A_{3 \times 3}$ has eigenvalues $\lambda_1, \lambda_2, \lambda_2$

Let $A_\varepsilon \triangleq A + \varepsilon B$, $|\varepsilon| \ll 1$

such that A_ε has distinct eigenvalues $\lambda_1, \lambda_2, \lambda_3$

where $\lambda_3 = \lambda_2 + \delta$, $|\delta| \ll 1$

and the corresponding eigenvectors $v_1, v_2, v_3 = v_2 + \delta w$

Then as $\varepsilon \rightarrow 0$, the following equations are satisfied:

$$(1) (A - \lambda_i I)v_i = 0 \quad i = 1, 2$$

$$(2) (A - \lambda_2 I)w = v_2$$

Note that $\{v_1, v_2, w\}$ are linearly independent

and w is called a "generalized eigenvector" of A .

Quadratic Forms

Suppose $X = [x_1, x_2, \dots, x_n]^T$. Then any polynomial function the elements in which every term is of degree two is known as a quadratic form. Thus, if $n = 3$, then

$$x_1^2 + 8x_1x_2 + x_2^2 + 6x_2x_3 + x_3^2$$

is an example of a quadratic form.

Quadratic forms can always be expressed as a matrix product of the form $X^T AX$

Utility: Optimization theory, Optimal control theory etc.

Example: Quadratic Form

The example above can be written as

$$\begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \begin{bmatrix} 1 & 4 & 0 \\ 4 & 1 & 3 \\ 0 & 3 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

In this representation, A is required to be symmetric matrix,
Nonsymmetric representations are possible with

$$\text{Eg: } A = \begin{bmatrix} 1 & 0 & 0 \\ 8 & 1 & 2 \\ 0 & 4 & 1 \end{bmatrix}$$

but the symmetric form is "standard"

Example: Singular Value Decomposition

$$A = \begin{bmatrix} 1 & 0 & -1 \\ -1 & 0 & 1 \end{bmatrix}, \quad A^T A = \begin{bmatrix} 2 & 0 & -2 \\ 0 & 0 & 0 \\ -2 & 0 & 2 \end{bmatrix}$$

$$\lambda_{1,2,3}(A^T A) = 4, 0, 0$$

$$X_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}, \quad X_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \quad X_3 = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 0 \\ -1 \end{bmatrix}$$

$$(for \ \lambda = 4) \quad (for \ \lambda = 0) \quad (for \ \lambda = 0)$$

Example: Singular Value Decomposition

$$\begin{bmatrix} \sigma_1 \\ \sigma_2 \\ \sigma_3 \end{bmatrix} = \begin{bmatrix} \sqrt{\lambda_1} \\ \sqrt{\lambda_2} \\ \sqrt{\lambda_3} \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix} \quad (\text{Note: The values are ordered})$$

$$Y_1 = \frac{1}{\sigma_1} (AX_1) = \frac{1}{2} \begin{bmatrix} 1 & 0 & -1 \\ -1 & 0 & 1 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

Next, find $Y_2 = [a \quad b]^T$ such that Y_1 and Y_2 will be orthonormal
i.e. $\langle Y_1, Y_2 \rangle = Y_1^T Y_2 = a - b = 0$ and $\langle Y_2, Y_2 \rangle = Y_2^T Y_2 = a^2 + b^2 = 1$

Example: Singular Value Decomposition

Solution: $a = b = 1/\sqrt{2}$. Hence, $Y_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

$$P = \begin{bmatrix} Y_1 & Y_2 \\ \downarrow & \downarrow \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} X_1 & X_2 & X_3 \\ \downarrow & \downarrow & \downarrow \end{bmatrix}^T = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 & -1 \\ 0 & \sqrt{2} & 0 \\ -1 & 0 & -1 \end{bmatrix}$$

$$D = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\text{Verify: } PDQ = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 & -1 \\ 0 & \sqrt{2} & 0 \\ -1 & 0 & -1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & -1 \\ -1 & 0 & 1 \end{bmatrix} = A$$

Derivative of $A^{-1}(t)$

Let $A^{-1}(t) = B(t)$; Then $A(t)B(t) = I$

Hence $\frac{d}{dt}(A(t)B(t)) = 0$

$$A(t)\frac{dB(t)}{dt} + \frac{dA(t)}{dt}B(t) = 0$$

$$\frac{dB(t)}{dt} = -A^{-1}(t)\frac{dA(t)}{dt}B(t)$$

$$\frac{dA^{-1}(t)}{dt} = -A^{-1}(t)\frac{dA(t)}{dt}A^{-1}(t)$$

Practice Problems

1. Let $A = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$. Find eigenvalues/eigenvectors of A . In addition, find the eigenvalues/eigenvectors of A^{-1} , A^m ($m = 3, 4$) and $I + 2A + 4A^2$ without computing these matrices.
2. Prove $(AB)^{-1} = B^{-1}A^{-1}$, if the indicated matrix inverses exist.
3. An $n \times n$ Hadamard matrix A has all elements that are ± 1 and satisfies $A^T A = nI$. Show that $|\det(A)| = n^{n/2}$
4. Show that the determinant of a negative definite $n \times n$ matrix is positive if n is even and negative if n is odd.
5. Let A and P be $n \times n$ matrices with P nonsingular. Show that $Tr(A) = Tr(P^{-1}AP)$

Practice Problems

6. Following the standard definitions,

Show that for a fixed $X \in R^n$ $\|X\|_p \rightarrow \|X\|_\infty$ as $p \rightarrow \infty$

7. Compute $\|A\|_1, \|A\|_2, \|A\|_\infty$ and $\rho(A)$ of the matrix in Problem-1

8. Find the singular value decomposition of

$A = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$. Give all the steps. Verify the results using MATLAB.

9. Show that $\frac{\partial}{\partial X} \left(\frac{1}{2} X^T A X \right) = AX$

10. Show that if $F(f(X)) \in R^n, X \in R^n,$

$$\text{then } \left[\frac{\partial F}{\partial X} \right]_{p \times n} = \left[\frac{\partial F}{\partial f} \right]^T \left[\frac{\partial f}{\partial X} \right]_{m \times n}$$

Thanks for the Attention...!



