

Matrices

Addition	$X + Y = [z_{ij}] = [x_{ij} + y_{ij}]$
Subtraction	$X - Y = [z_{ij}] = [x_{ij} - y_{ij}]$
Multiplication	$X * Y = [z_{ij}] = [x_i * y_j]$
Constant	$c * X = [z_{ij}] = [c * x_{ij}]$

Transpose & Identity

Transpose	$X^T = [z_{ij}] = [x_{ji}]$
Tr of Tr	$(X^T)^T = X$
Tr of Mul	$(XY)^T = Y^T X^T \neq X^T Y^T$
Sym Matrix	$X^T = X$
Identity Matrix I	$X I = I X = X$ [z _{ii} =1, z _{ij} =0]

Inverse

Inverse $X X^{-1} = I = X^{-1} X$

if X^{-1} exists then X is non singular or invertible

Inv of Inv $(X^{-1})^{-1} = X$

Inv of Mul $(XY)^{-1} = Y^{-1} X^{-1} \neq X^{-1} Y^{-1}$

Inv of Tr $(X^T)^{-1} = (X^{-1})^T$

Determinant $|A| = \sum_{i=1}^n a_{ij} \times \text{Det } |a_{ij}|$

Determinant is computed over first row of matrix where each element of first row is multiplied by its minor

minor M_{ij} is a determinant obtained by deleting the i^{th} row and j^{th} column in which a_{ij} lies. Minor of a_{ij} is denoted by m_{ij} .

Cofactor $A_{ij} = (-1)^{i+j} m_{ij}$

Adjoint $\text{adj}(A) = (\text{Cofactor})^T = (A_{ij})^T$

Inverse $A^{-1} = \text{adj}(A) / |A|$

Orthogonal

Two $n \times 1$ vectors are orthogonal if $X^T Y = 0$

A vector is orthonormal if $X^T X = ||X^2||$

Sq root of $||X||$ is length or norm of vector

$\{X_1, X_2, X_3, \dots, X_n\}$ are said to be orthonormal if, each pair is orthogonal and have unit length

A sq matrix is orthogonal if $X^T X = I$ or $X^T = X^{-1}$

Eigen Values & Eigen Vectors

A is $n \times n$ matrix, X is $n \times 1$ matrix, λ is a scalar, then

$AX = \lambda X$ or $(A - \lambda I)X = 0$ or $X = (A - \lambda I)^{-1}$

λ is the eigen value and X is the eigen vector (non zero)

Since X is non zero, $|A - \lambda I|$ should be 0

Determinant for $[a \ b] = ad - bc$
[c d]

If A => symmetric, then eigenvalues => real & eigenvectors => orthogonal

Diagonalization: P => orthogonal matrix, then $Z = P^T A P$, Z is diagonal matrix with eigen values of A

Linear Independence

Given $a_1 x_1 + a_2 x_2 + \dots + a_n x_n = 0$, if a vector $[a_1, a_2, \dots, a_n]$ exists such that

a. all a_i are 0, then x_i are linearly independent.

b. if some $a_i \neq 0$ then x_i are linearly dependent.

If a set of vectors are linearly dependent, then one of them can be written as some combination of others

A set of two vectors is linearly dependent if and only if one of the vectors is a constant multiple of the other.

Idempotence

a $n \times n$ matrix A is idempotent iff $A^2 = A$

The identity matrix I is idempotent.

Let X be an $n \times k$ matrix of full rank, $n \geq k$ then H exists as $H = X(X^T X)^{-1} X^T$ and is idempotent.

Rank

For a $n \times k$ matrix say X, the column vectors are $[x_1, x_2, \dots, x_k]$ and **rank** is given by max num of linearly independent vectors.

If X is a $n \times k$ matrix and $r(X) = k$, then X is of full rank for $n \geq k$.

$r(X) = r(X^T) = r(X^T X)$

If X is $k \times k$, then X is non singular iff $r(X) = k$.

If X is $n \times k$, P is $n \times n$ and non-singular, and Q is $k \times k$ and nonsingular, then $r(X) = r(PX) = r(XQ)$.

The rank of a diagonal matrix is equal to the number of non zero diagonal entries in the matrix.

$r(XY) \leq r(X) \ r(Y)$

Trace

The trace of a square $k \times k$ matrix X is sum of its diagonal entries -

$\text{tr}(X) = \sum x_{ii}$

If c is a scalar, $\text{tr}(cX) = c * \text{tr}(X)$

$\text{tr}(X \pm Y) = \text{tr}(X) \pm \text{tr}(Y)$.

If XY and YX both exist, $\text{tr}(XY) = \text{tr}(YX)$.

Quadratic Forms

A be a $k \times k$, y be $k \times 1$ vector containing variables $q = y^T A y$ is called a quadratic form in y, A is called the matrix of the quadratic form

$q = \sum \sum a_{ij} y_i y_j$

If $y^T A y > 0$ for all $y \neq 0$, $y^T A y$ & A are +ve definite

If $y^T A y \geq 0$ for all $y \neq 0$, $y^T A y$ & A are +ve semidefinite

Matrix Differentiation

$y = (y_1, y_2, \dots, y_k)^T$, $z = f(y)$ then $\partial z / \partial y = [\partial z / \partial y_1 \ \partial z / \partial y_2 \ \partial z / \partial y_3]^T$

$z = a^T y$, $\partial z / \partial y = a$

$z = y^T y$, $\partial z / \partial y = 2y$

$z = y^T A y$, $\partial z / \partial y = Ay + A^T y$, if A is symmetric then $\partial z / \partial y = 2Ay$

Theorems

Theorem 1

Let A be a symmetric $k \times k$ matrix. Then an orthogonal matrix P exists such that $P^T A P = \lambda \times I$, where $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_n]$ are the eigen values of A as $n \times 1$ vector

Theorem 2

The eigenvalues of idempotent matrices are always either 0 or 1.

Theorem 3

If A is a symmetric and idempotent matrix, $r(A) = \text{tr}(A)$

Theorem 4

Let A_1, A_2, \dots, A_m be a collection of symmetric $k \times k$ matrices.

Then the following are equivalent:

- There exists an orthogonal matrix P such that $P^T A_i P$ is diagonal for all $i = 1, 2, \dots, m$;
- $A_i A_j = A_j A_i$ for every pair $i, j = 1, 2, \dots, m$.

Theorem 5

Let A_1, A_2, \dots, A_m be a collection of symmetric $k \times k$ matrices.

Then any two of the following conditions implies the third:

- All $A_i, i = 1, 2, \dots, m$ are idempotent;
- $\sum A_i$ is idempotent;
- $A_i A_j = 0$ for $i \neq j$

Theorem 6

Let A_1, A_2, \dots, A_m be a collection of symmetric $k \times k$ matrices. If the conditions in Theorem 5 are true, then

$$r(\sum A_i) = \sum r(A_i)$$

Theorem 7

A symmetric matrix A is positive definite if and only if its eigen values are all (strictly) positive

Theorem 8

A symmetric matrix A is positive semi-definite if and only if its eigenvalues are all non-negative.



By Trina Dey

cheatography.com/trina-dey/

Published 3rd September, 2021.

Last updated 3rd September, 2021.

Page 2 of 2.

Sponsored by **Readable.com**

Measure your website readability!

<https://readable.com>