

# Mathematical basics

---

Dr. Tushar Sandhan

# Contents

---

- Matrix multiplication
  - Vector Products
  - Properties of matrix multiplication
- Identity matrix
- Inverse matrix
- Diagonal Matrix:
- Transpose Matrix
- Trace matrix
- Determinant of matrix
- Eigendecomposition
  - Eigendecomposition with *Python Code*
  - Eigendecomposition with *Matlab Code*

# Matrix multiplication

- “When  $A$  is a  $m \times n$  matrix &  $B$  is a  $k \times l$  matrix,  $AB$  is only possible if  $n=k$ . The result will be an  $m \times l$  matrix”

$$\begin{array}{c} \mathbf{m} \downarrow \\ \begin{array}{ccc} \xrightarrow{\mathbf{n}} & & \\ A_1 & A_2 & A_3 \\ A_4 & A_5 & A_6 \\ A_7 & A_8 & A_9 \\ A_{10} & A_{11} & A_{12} \end{array} \end{array} \times \begin{array}{cc} \xrightarrow{\mathbf{l}} & \\ \begin{array}{cc} B_{13} & B_{14} \\ B_{15} & B_{16} \\ B_{17} & B_{18} \end{array} \downarrow \mathbf{k} \end{array} = \mathbf{m} \times \mathbf{l} \text{ matrix}$$

Number of columns in  $A$  = Number of rows in  $B$

# Vector Products

---

- Two vectors:

$$x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

- Inner product = scalar

$$\mathbf{x}^T \mathbf{y} = \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = x_1 y_1 + x_2 y_2 + x_3 y_3 = \sum_{i=1}^3 x_i y_i$$

- Outer product = matrix

$$\mathbf{x} \mathbf{y}^T = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \begin{bmatrix} y_1 & y_2 & y_3 \end{bmatrix} = \begin{bmatrix} x_1 y_1 & x_1 y_2 & x_1 y_3 \\ x_2 y_1 & x_2 y_2 & x_2 y_3 \\ x_3 y_1 & x_3 y_2 & x_3 y_3 \end{bmatrix}$$

# Properties of matrix multiplication

- In this table  $A$ ,  $B$ , and  $C$  are  $n \times n$  matrices,  $I$  is the  $n \times n$  identity matrix, and  $O$  is the  $n \times n$  zero matrix.

Property	Example
The commutative property of multiplication <b>does not hold!</b>	$AB \neq BA$
Associative property of multiplication	$(AB)C = A(BC)$
Distributive properties	$A(B + C) = AB + AC$ $(B + C)A = BA + CA$
Multiplicative identity property	$IA = A$ and $AI = A$
Multiplicative property of zero	$OA = O$ and $AO = O$
Dimension property	The product of an $m \times n$ matrix and an $n \times k$ matrix is an $m \times k$ matrix.

# Identity matrix

---

- An identity matrix is a **square matrix in which all the elements of principal diagonals are one, and all other elements are zeros**. It is denoted by the notation “ $I_n$ ” or simply “ $I$ ”.

$$I_n = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix}.$$

- For any  $n \times n$  matrix  $\mathbf{A}$ , we have  $\mathbf{A} I_n = I_n \mathbf{A} = \mathbf{A}$
- For any  $n \times m$  matrix  $\mathbf{A}$ , we have  $I_n \mathbf{A} = \mathbf{A}$ , and  $\mathbf{A} I_m = \mathbf{A}$  (so 2 possible matrices)

# Inverse matrix

---

- **Notation.** A common notation for the inverse of a matrix  $\mathbf{A}$  is  $\mathbf{A}^{-1}$ .

$$\boxed{\mathbf{A} \mathbf{A}^{-1} = \mathbf{A}^{-1} \mathbf{A} = \mathbf{I}_n .}$$

- The inverse matrix is unique when it exists. So if  $\mathbf{A}$  is invertible, then  $\mathbf{A}^{-1}$  is also invertible and then  $(\mathbf{A}^T)^{-1} = (\mathbf{A}^{-1})^T$

# Inverse matrix

- For a  $X \times X$  square matrix: 
$$A = \begin{pmatrix} x_{1,1} & \dots & x_{1,j} \\ \vdots & \ddots & \vdots \\ x_{i,1} & \dots & x_{i,j} \end{pmatrix}$$

- The inverse matrix is: 
$$A^{-1} = \frac{1}{\det(A)} \begin{pmatrix} \text{cof}(A, x_{1,1}) & \dots & \text{cof}(A, x_{1,j}) \\ \vdots & \ddots & \vdots \\ \text{cof}(A, x_{i,1}) & \dots & \text{cof}(A, x_{i,j}) \end{pmatrix}^T$$

- E.g.: 2x2 matrix 
$$\mathbf{A}^{-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}.$$

- **Properties:**

- $(A^{-1})^{-1} = A$
- $(A \times B)^{-1} = B^{-1} \times A^{-1}$
- $(A^T)^{-1} = (A^{-1})^T$



# Diagonal Matrix:

- A square matrix in which every element except the principal diagonal elements is zero is called a Diagonal Matrix.

$$A = \begin{bmatrix} a_{11} & 0 & 0 & \dots & 0 \\ 0 & a_{22} & 0 & \dots & 0 \\ 0 & 0 & a_{33} & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & a_{nn} \end{bmatrix} n \times n$$

Examples

$$\begin{bmatrix} 3 & 0 \\ 0 & 4 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -4 \end{bmatrix}$$

# Transpose Matrix

---

- **Properties:** Transpose matrix is obtained by interchanging the rows and columns.
  - The transpose of matrix  $A$  is denoted as  $A^T$ .

- $(A^T)^T = A$

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

- $(A \times B)^T = B^T \times A^T$

- $(kA)^T = kA^T$

# Trace matrix

---

- The trace of an  $n \times n$  square matrix  $A$  is defined as

$$\text{tr}(\mathbf{A}) = \sum_{i=1}^n a_{ii} = a_{11} + a_{22} + \cdots + a_{nn}$$

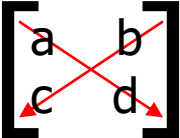
where  $a_{ii}$  denotes the entry on the  $i$ th row and  $i$ th column of  $A$ . The entries of  $A$  can be real numbers or (more generally) complex numbers.

- The trace is not defined for non-square matrices.

# Determinant of matrix

---

- Determinants can only be found for square matrices.
- For a 2x2 matrix A,  **$\det(A) = ad - bc$** . Lets have at closer look at that:

$$\det(A) = \begin{bmatrix} a & b \\ c & d \end{bmatrix} = ad - bc$$


- A matrix A has an inverse matrix  $A^{-1}$  if and only if  **$\det(A) \neq 0$** .

# Eigendecomposition

---

- Eigenvectors and eigenvalues are vectors and numbers associated to square matrices. Together they provide the eigen-decomposition of a matrix which analyzes the structure of this matrix.
- There are several ways to define eigenvectors and eigenvalues, the most common approach defines an eigenvector of the matrix  $A$  as a vector  $u$  that satisfies the following equation:

$$Au = \lambda u .$$

- when rewritten, the equation becomes:

$$(A - \lambda I)u = 0 ,$$

- where  $\lambda$  is a scalar called the eigenvalue associated to the eigenvector.
- In a similar manner, we can also say that a vector  $u$  is an eigenvector of a matrix  $A$  if the length of the vector (but not its direction) is changed when it is multiplied by  $A$ .

# Eigendecomposition

---

- Example:

$$\mathbf{A} = \begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$$

has the eigenvectors:

$$\mathbf{u}_1 = \begin{bmatrix} 3 \\ 2 \end{bmatrix} \quad \text{with eigenvalue } \lambda_1 = 4$$

and

$$\mathbf{u}_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad \text{with eigenvalue } \lambda_2 = -1$$

The length of  $\mathbf{u}_1$  and  $\mathbf{u}_2$  is changed when one of these two vectors is multiplied by the matrix  $\mathbf{A}$ .

# Eigendecomposition

---

$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 3 \\ 2 \end{bmatrix} = 4 \begin{bmatrix} 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 12 \\ 8 \end{bmatrix}$$

and

$$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} -1 \\ 1 \end{bmatrix} = -1 \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

For most applications we normalize the eigenvectors (i.e., transform them such that their length is equal to one):

$$\mathbf{u}^T \mathbf{u} = 1$$

# Eigendecomposition

- Traditionally, we put together the set of eigenvectors of  $A$  in a matrix denoted  $U$ . Each column of  $U$  is an eigenvector of  $A$ . The eigenvalues are stored in a diagonal matrix (denoted  $\Lambda$ ), where the diagonal elements gives the eigenvalues (and all the other values are zeros). We can rewrite the first equation as:

$$\mathbf{AU} = \mathbf{U}\Lambda$$

or also as:

$$\mathbf{A} = \mathbf{U}\Lambda\mathbf{U}^{-1}.$$

For the previous example we obtain:

$$\mathbf{A} = \mathbf{U}\Lambda\mathbf{U}^{-1}$$

$$= \begin{bmatrix} 3 & -1 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} .2 & .2 \\ -.4 & .6 \end{bmatrix}$$

$$= \begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}.$$

- It is important to note that not all matrices have eigenvalues.
- For example, the matrix  $\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$  does not have eigenvalues.



# Eigendecomposition with *Python* Code

```
import numpy as np
from numpy.linalg import eig
```

```
A = np.array([ [2, 3], [2, 1] ])
print (A)
```

```
[[2 3]
 [2 1]]
```

```
#getting the eigenvalues and eigenvector of M
Lambda, U = np.linalg.eig(A)
```

```
print(U)
```

```
[[ 0.83205029 -0.70710678]
 [ 0.5547002   0.70710678]]
```

```
print(Lambda)
```

```
[ 4. -1.]
```

```
# getting U inverse
inv_U = np.linalg.inv(U)
inv_U
```

```
array([[ 0.72111026,  0.72111026],
       [-0.56568542,  0.84852814]])
```

```
 $\Lambda$  = np.diag(Lambda)
 $\Lambda$ 
```

```
array([[ 4.,  0.],
       [ 0., -1.]])
```

```
def round(values, decs=0): # we don't want to include
    return np.round(values*10**decs)/(10**decs)
vec = np.dot(U,np.dot( $\Lambda$ , inv_U)) # taking the product
round(vec)
```

```
array([[2., 3.],
       [2., 1.]])
```

# Eigendecomposition with *Matlab* Code

---

```
clc
clear all
A = [2 3; 2 1];
Lambda = eig(A)
```

```
Lambda =
     4
    -1
```

```
[U,D] = eig(A)
```

```
U =
    0.8321   -0.7071
    0.5547    0.7071
```

```
D =
     4     0
     0    -1
```

```
U=[0.8321 -0.7071; 0.5547 0.7071];
U_inv = inv(U)
```

```
U_inv =
    0.7211    0.7211
   -0.5657    0.8486
```

```
A1=U*D*inv(U)
```

```
A1 =
    2.0001    3.0001
    1.9999    0.9999
```

- Quiz1 = total weightage of the course is 10%

	Wt.	Ht	width			
Sample#1:	10	1.2	0.5	0.5	0.9	0.8
Sample#2:	15	0.9	0.8			
		⋮				

- To make zero mean: subtract the mean from **all**
- To make it unit var: divide **all** by std. dev.
- Do it independently on each feature = each column

# Thank you

