

# Basic Introduction to Vectors and Matrices

Mark A. Austin

University of Maryland

*austin@umd.edu*

*ENCE 201, Fall Semester 2024*

October 14, 2024

# Overview

- 1 Definition of Vectors
- 2 Vector Properties
- 3 Definition of Matrices
- 4 Matrix Properties
- 5 Matrix Arithmetic
- 6 Matrix Operations with Python

# Definition of Vectors

# Definition of Row and Column Vectors

**Definition.** A row vector is simply a  $(1 \times n)$  matrix, i.e.,

$$V = \begin{bmatrix} v_1 & v_2 & v_3 & v_4 & \cdots & v_n \end{bmatrix} \quad (1)$$

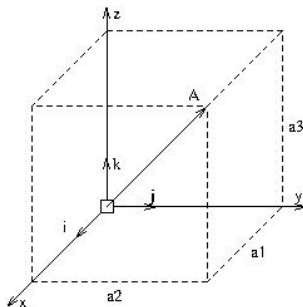
**Definition.** A column vector is a  $(m \times 1)$  matrix, e.g.,

$$V = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ \cdots \\ v_m \end{bmatrix} \quad (2)$$

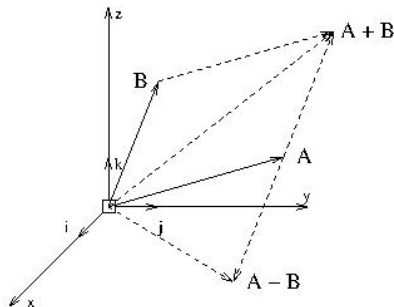
In both cases, the  $i$ -th element of the column vector is denoted  $v_i$ .

# Vector Properties

# Properties of Vector Arithmetic



Components of Three-Dimensional Vector



Vector Addition and Subtraction

- $a + b = b + a$
- $a + 0 = a$
- $c(a + b) = ca + cb$

- $(a + b) + c = a + (b + c)$
- $a + (-a) = 0$
- $1a = a.$

# Dot Product

**Definition.** The dot product of two vectors  $a = [a_1, a_2, a_3, \dots, a_n]$  and  $b = [b_1, b_2, b_3, \dots, b_n]$  is:

$$a \cdot b = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + a_3 b_3 + \dots + a_n b_n. \quad (3)$$

**Note:**  $a \cdot b = b \cdot a$ . If  $a$  and  $b$  are perpendicular then  $a \cdot b = 0$ .

## Engineering Applications

- Mechanical work is the dot product of force and displacement vectors (Jou).
- Power is the dot product of force and velocity vectors (W).
- Fluid Mechanics.

# Dot Product

**Example 1.** Let  $a = [1, 2, 3]$  and  $b = [0, -1, 2]$ . The dot product:

$$a \cdot b = \sum_{i=1}^n a_i b_i = 1 \times 0 + 2 \times -1 + 3 \times 2 = 4. \quad (4)$$

A dot product can also be written as a row vector multiplied by a column vector, e.g.,

$$\begin{bmatrix} 1, 2, 3 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ -1 \\ 2 \end{bmatrix} = 4. \quad (5)$$

The vector dimensions are:  $(1 \times 3) (3 \times 1) \rightarrow (1 \times 1)$ .



# Dot Product

**Properties.** Let  $a = [a_1, a_2, a_3, a_4]$ ,  $b = [b_1, b_2, b_3, b_4]$  and  $c = [c_1, c_2, c_3, c_4]$ . And let  $d$  be a non-zero constant.

The dot product:

$$a.b = a_1b_1 + a_2b_2 + a_3b_3 + a_4b_4 \quad (6)$$

obeys the properties:

- $a.a = \|a\|^2$ .
- $a.(b + c) = a.b + a.c$
- $a.b = b.a$
- $a.b = 0 \iff a = 0$  or  $b = 0$  or  $a \perp b$ .
- $0.a = 0$
- $(da).b = d(a.b)$
- $a.b = |a|.|b| \cos(\theta)$ .

# Dot Product

Fragment of Python Code:

Output:

```
import numpy as np
```

```
# Define vectors a and b
```

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

```
[1 2 3]
```

```
b = np.array([4, 5, 6])
```

```
[4 5 6]
```

```
# Compute dot product c = a.b ...
```

```
c = np.dot(a,b)
```

```
32.000000
```

# Cross Product

**Definition.** Consider two vectors  $A$  and  $B$  in three dimensions:

$$A = a_1 \hat{i} + a_2 \hat{j} + a_3 \hat{k}$$

$$B = b_1 \hat{i} + b_2 \hat{j} + b_3 \hat{k}$$

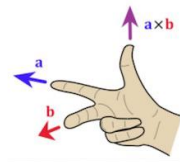
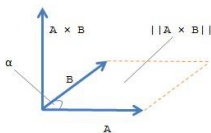
The cross product of  $A$  and  $B$  is:

$$\begin{aligned} C = A \times B &= \det \begin{pmatrix} \hat{i} & \hat{j} & \hat{k} \\ a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{pmatrix} \\ &= (a_2 b_3 - a_3 b_2) \hat{i} + (a_3 b_1 - a_1 b_3) \hat{j} + (a_1 b_2 - a_2 b_1) \hat{k}. \end{aligned}$$

# Cross Product

## Geometric Interpretation

$A \times B$  is a vector that is perpendicular to both  $A$  and  $B$ .



- The magnitude of  $\|A \times B\|$  is equal to the area of the parallelogram formed using  $A$  and  $B$  as the sides.
- The angle between  $A$  and  $B$  is:  $\|A \times B\| = \|A\| \|B\| \sin(\alpha)$ .
- The cross product is zero when the  $A$  and  $B$  are parallel.

# Cross Product

Fragment of Python Code:

Output:

-----

```
# Define vectors a and b
```

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

```
[1 2 3]
```

```
b = np.array([4, 5, 6])
```

```
[4 5 6]
```

```
# Compute cross product c = a x b ...
```

```
c = np.cross(a,b)
```

```
[-3  6 -3]
```

```
# Check that cross product is perpendicular to a and b ...
```

```
d1 = np.dot(c,a)
```

```
0.000000
```

```
d2 = np.dot(c,b)
```

```
0.000000
```

# Linear Independence of Vectors

## Linear Independence

A set of vectors  $(v_1, v_2, v_3, \dots, v_n)$  is said to be **linearly independent** if the equation

$$a_1 v_1 + a_2 v_2 + a_3 v_3 + \dots + a_n v_n = 0. \quad (7)$$

can only be satisfied by  $a_i = 0$  for  $i = 1, \dots, n$ .

Put another way: no vector in the sequence can be written as a linear combination of the other vectors.

# Linear Independence of Vectors

**Example 1.** Consider three vectors  $v_1 = (1, 1)$ ,  $v_2 = (-3, 2)$ , and  $v_3 = (2, 4)$  in two-dimensional space.

The vectors will be **linearly independent** if the only solutions to

$$a_1 \begin{bmatrix} 1 \\ 1 \end{bmatrix} + a_2 \begin{bmatrix} -3 \\ 2 \end{bmatrix} + a_3 \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (8)$$

are  $a_1 = a_2 = a_3 = 0$ . Writing these equations in matrix form:

$$\begin{bmatrix} 1 & -3 & 2 \\ 1 & 2 & 4 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (9)$$

# Linear Independence of Vectors

Apply row operations (details to follow):

$$\begin{bmatrix} 1 & 0 & 16/5 \\ 0 & 1 & 2/5 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (10)$$

which can be rearranged:

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} + a_3 \begin{bmatrix} 16/5 \\ 2/5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}. \quad (11)$$

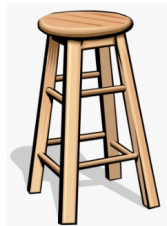
We conclude that since  $a_1$  and  $a_2$  can be written in terms of  $a_3$ , the equations are **linearly dependent**.



# Linear Independence of Vectors

## A Few Observations

- Vectors  $v_1$  through  $v_3$  are two dimensional.
- Can show that **three** (or more) **vectors** in **two-dimensional space** will always be **linearly dependent**.
- Can show that **four** (or more) **vectors** in **three-dimensional space** will always be **linearly dependent**.
- This is why a stool with three legs (**vectors**) will always be steady (**linearly independent**), but one with four legs (**vectors**) will sometimes rock (**linearly dependent**).



# Definition of Matrices

# Definition of a Matrix

**Definition.** A matrix (or array) of order  $m$  by  $n$  is simply a set of numbers arranged in a rectangular block of  $m$  horizontal rows and  $n$  vertical columns. We say

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad (12)$$

is a matrix of size (or dimension)  $(m \times n)$ .

In the double subscript notation  $a_{ij}$  for matrix element  $a(i, j)$ , the first subscript  $i$  denotes the row number, and the second subscript  $j$  denotes the column number.

# Matrix Properties

# Matrix Properties

## Properties of Matrix A:

- A matrix having the same number of rows and columns is called **square**.
- A square matrix of order  $n$  is also called a  $(n \times n)$  matrix.
- The elements  $a_{11}, a_{22}, \dots, a_{nn}$  are called the **principal diagonal**.
- A diagonal matrix with elements  $a_{ii} = 1$ , and all other matrix elements zero, is called the identity matrix  $I$ .

# Matrix Transpose

**Matrix Transpose.** The **transpose** of a  $(m \times n)$  matrix  $A$  is the  $(n \times m)$  matrix obtained by interchanging the rows and columns of  $A$ . The tranpose is denoted  $A^T$ .

**Example 1.** The matrix transpose of

$$A = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 \end{bmatrix} \quad \text{is} \quad A^T = \begin{bmatrix} 1 & 5 \\ 2 & 6 \\ 3 & 7 \\ 4 & 8 \end{bmatrix} \quad (13)$$

## Properties

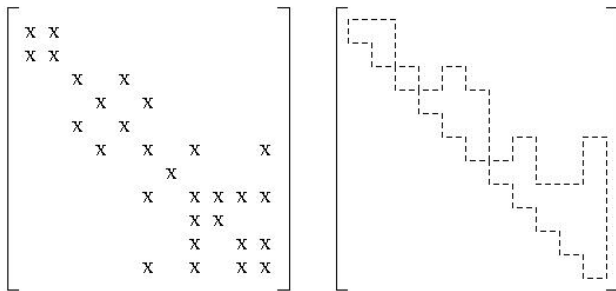
- $(A + B)^T = A^T + B^T$ .
- $(ABC)^T = C^T B^T A^T$ .

# Symmetric and Skew-Symmetric Matrices

## Matrix Symmetry:

- A square matrix  $A$  is **symmetric** if  $A = A^T$ .
- A square matrix  $A$  is **skew-symmetric** if  $A = -A^T$ .

Large symmetric matrices play a central role in structural analysis.



Schematic of Non-Zero Matrix Elements

Skyline Storage Pattern

# Matrix Inverse

**Definition:** When it exists, the **inverse of matrix A** is written  $A^{-1}$  and it has the property:

$$[A] [A^{-1}] = [A^{-1}] [A] = I. \quad (14)$$

## Nomenclature

- If matrix A has an inverse, then A is called **non-singular**.
- If matrix A has an inverse, then the inverse will be unique.
- If matrix A does not have an inverse, then A is called **singular**.

**Theorem.** For a  $(n \times n)$  matrix A, the inverse  $A^{-1}$  exists  $\iff$   $\text{rank}(A) = n$ .

- Conversely, matrix A is **singular** if  $\text{rank}(A) < n$  (i.e., rank deficient).



# Matrix Inverse

**Computational Procedure.** We want to carry out row operations such that:

$$[A|I] \xrightarrow{\text{row operations}} [I|A^{-1}]. \quad (15)$$

**Example.** Can apply row operations to get:

$$\left[ \begin{array}{ccc|ccc} -1 & 1 & 2 & 1 & 0 & 0 \\ 3 & -1 & 1 & 0 & 1 & 0 \\ -1 & 3 & 4 & 0 & 0 & 1 \end{array} \right] \xrightarrow{\text{row ops}} \left[ \begin{array}{ccc|ccc} 1 & 0 & 0 & -0.7 & 0.2 & 0.3 \\ 0 & 1 & 0 & -1.3 & -0.2 & 0.7 \\ 0 & 0 & 1 & 0.8 & 0.2 & -0.2 \end{array} \right]. \quad (16)$$

If  $A$  has  $\text{rank}(A) < n$ , then the last row in echelon form will be the  $O$  (zero) vector, and the **computation will fail**.

# Matrix Inverse

## Properties:

$$[A^{-1}]^{-1} = A. \quad (17)$$

$$(AB)^{-1} = B^{-1}A^{-1}. \quad (18)$$

$$(ABC)^{-1} = C^{-1}B^{-1}A^{-1}. \quad (19)$$

$$[A^T]^{-1} = [A^{-1}]^T. \quad (20)$$

# Lower and Upper Triangular Matrices

A lower triangular matrix  $L$  is one where  $a_{ij} = 0$  for all entries above the diagonal.

An upper triangular matrix  $U$  is one where  $a_{ij} = 0$  for all entries below the diagonal. That is,

$$L = \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ a_{21} & a_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad U = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ 0 & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{mn} \end{bmatrix} \quad (21)$$

# Matrix Arithmetic

# Matrix Addition and Subtraction

**Definition.** If  $A$  is a  $(m \times n)$  matrix and  $B$  is a  $(r \times p)$  matrix, then the matrix sum  $C = A + B$  is defined only when  $m = r$  and  $n = p$ , and is a  $(m \times n)$  matrix  $C$  whose elements are

$$c_{ij} = a_{ij} + b_{ij}, \text{ for } i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n. \quad (22)$$

## Properties

- $(kA) B = k (A.B)$
- $A(BC) = (AB)C.$
- $(A + B)C) = AB + AC.$
- $C(A + B) = CA + CB.$

# Matrix Addition and Subtraction

**Example 1.** Let

$$A = \begin{bmatrix} 2 & 1 \\ 4 & 6 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} 4 & 2 \\ 0 & 1 \end{bmatrix}. \quad (23)$$

The matrix sum is:

$$C = A + B = \begin{bmatrix} 2 & 1 \\ 4 & 6 \end{bmatrix} + \begin{bmatrix} 4 & 2 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 6 & 3 \\ 4 & 7 \end{bmatrix}. \quad (24)$$

# Matrix Multiplication

**Definition.** Let  $A$  and  $B$  be  $(m \times n)$  and  $(r \times p)$  matrices, respectively.

The matrix product  $A \cdot B$  is defined only when interior matrix dimensions are the same (i.e.,  $n = r$ ).

The matrix product  $C = A \cdot B$  is a  $(m \times p)$  matrix whose elements are

$$c_{ij} = \sum_{k=1}^n a_{ik} b_{kj} \quad (25)$$

for  $i = 1, 2, \dots, m$  and  $j = 1, 2, \dots, n$ .

# Matrix Multiplication

**Example 1.** Assuming that matrices A and B are as defined in the previous section:

$$\begin{aligned}
 C = A \cdot B &= \begin{bmatrix} 2 & 1 \\ 4 & 6 \end{bmatrix} \cdot \begin{bmatrix} 4 & 2 \\ 0 & 1 \end{bmatrix} \\
 &= \begin{bmatrix} 2 \cdot 4 + 1 \cdot 0 & 2 \cdot 2 + 1 \cdot 1 \\ 4 \cdot 4 + 6 \cdot 0 & 4 \cdot 2 + 6 \cdot 1 \end{bmatrix} \\
 &= \begin{bmatrix} 8 & 5 \\ 16 & 14 \end{bmatrix}.
 \end{aligned} \tag{26}$$

**Geometric Interpretation.** Matrix element  $c_{ij}$  is the **dot product** of the **i-th row** of A with the **j-th column** of B.



# Matrix Multiplication

## Properties.

- $A.B.C = (A.B).C = A.(B.C).$
- $A.(B + C) = A.B + A.C.$
- $(A + B).C = A.C + B.C.$
- $A.I = A.$
- In general,  $A.B \neq B.A.$
- $A.B = \phi$  does not necessarily imply  $A = \phi$  or  $B = \phi$ . Counter example:

$$A = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix} \text{ and } B = \begin{bmatrix} -1 & 1 \\ 1 & -1 \end{bmatrix}. \quad (27)$$

# Matrix Operations with Python

Fragment of Python Code:

-----

```
A = np.array([ [2, 1], [4, 6] ]);
```

```
B = np.array([ [4, 2], [0, 1] ]);
```

```
# Compute matrix transpose ...
```

```
C = A.T
```

-----

Output:

-----

Matrix: A

```
2.00    1.00
```

```
4.00    6.00
```

Matrix: B

```
4.00    2.00
```

```
0.00    1.00
```

Matrix: A<sup>T</sup>

```
2.00    4.00
```

```
1.00    6.00
```

-----

# Matrix Operations with Python

Fragment of Python Code:

Output:

```
-----
```

```
# Use numpy add() for matrix addition ...
```

```
C = np.add(A,B)
```

```
Matrix: np.add(A,B)
```

```
6.00      3.00
```

```
4.00      7.00
```

```
# Add matrices with + operator ...
```

```
C = A + B
```

```
Matrix: A + B
```

```
6.00      3.00
```

```
4.00      7.00
```

```
-----
```

# Matrix Operations with Python

Fragment of Python Code:

Output:

```
-----
```

```
# Use numpy matmul() for matrix multiplication ...
```

```
C = np.matmul( A, B )
```

Matrix: np.matmul(A,B)

8.00 5.00

16.00 14.00

```
# Use * operator for matrix element-level multiplies ...
```

```
C = A * B
```

Matrix: Element-level multiply A\*B

8.00 2.00

0.00 6.00