

# Linear Algebra<sup>1</sup>

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<sup>1</sup>Partially based on courses taught by Dr. Eric Brussel and Dr. Morgan Sherman at California Polytechnic State University San Luis Obispo

# Contents

# Preface

This document compiles all my notes on linear algebra including any self-study (e.g. advanced applications in modern physics). This also serves as a foundation for the other analysis topics covered in my notes series.

For most engineers, linear algebra is simply the study of matrices and vectors in  $\mathbb{R}^n$ . For a mathematician, linear algebra is the study of vector spaces and linear transformations. This definition means linear algebra is more abstract than vectors describing physical quantities or systems of linear equations. They can be functions for example, and thinking of functions in a vector space is surprisingly useful for advanced differential equations. In modern or quantum physics, all the behaviors of particles can be modeled using complex vector spaces (see sections on Hilbert spaces and complex vector spaces). This way of thinking is more useful and I found thinking of all vector spaces to be fascinating.

- Christopher

# Chapter 1

## Matrices

### 1.1 Defining Matrices

Let  $n, m$  be two integers  $\geq 1$ . A **matrix** is an array of numbers with  $m$  rows and  $n$  columns (called a  $m \times n$  matrix).

We call  $a_{ij}$  the **ij-entry** which is the entry in the  $i$ th row and the  $j$ th column. We write a matrix often as  $A = (a_{ij})$  and define  $a_{ij}$ .

Each column of an  $m \times n$  matrix is a **column vector**. Each row of an  $m \times n$  matrix is a **row vector**.

*Example* (Identity Matrix):

The Kronecker delta is defined as follows:

$$\delta_{ij} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$

Then we define the **identity matrix** as:

$$I_n = (\delta_{ij}) = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

*Example:*

If we have a matrix,  $A = \begin{bmatrix} 3 & 4 \\ 1 & -1 \\ 2 & 2 \end{bmatrix}$ , the second column vector of  $A$  is  $\begin{bmatrix} 4 \\ 1 \\ 2 \end{bmatrix}$  and the second row vector of  $A$  is  $[1 \quad -1]$ .

We can describe matrices using their column or row vectors. For example:

$$A = \begin{bmatrix} \vec{r} \\ \vec{s} \\ \vec{t} \end{bmatrix}$$

where

$$\vec{r} = \begin{bmatrix} 3 & 4 \end{bmatrix}, \vec{s} = \begin{bmatrix} 1 & -1 \end{bmatrix}, \vec{t} = \begin{bmatrix} 2 & 2 \end{bmatrix}$$

Or:

$$A = \begin{bmatrix} \vec{a} & \vec{b} \end{bmatrix}$$

where

$$\vec{a} = \begin{bmatrix} 3 \\ 1 \\ 2 \end{bmatrix}, \vec{b} = \begin{bmatrix} 4 \\ -1 \\ 2 \end{bmatrix}$$

### 1.1.1 Matrix Operations

We treat matrices the same way as numbers. Let  $A$  be an  $m \times n$  matrix and  $B$  be an  $p \times q$  matrix.

- We can add  $A$  and  $B$ . If  $m = p$  and  $n = q$ , then  $A + B = (a_{ij} + b_{ij})$
- We can multiply by a scalar  $c$ :  $c \cdot A = (c \cdot a_{ij})$
- We can multiply  $A$  and  $B$ . If  $n = p$ , then  $A \cdot B = (c_{ij})$  where  $c_{ij} = \vec{r}_i(A) \cdot \vec{c}_j(B)$ .  
Caution: In general,  $A \cdot B \neq B \cdot A$ .
- We also define the transpose of a matrix. The transpose of  $A$  is  $A^t = (d_{ij})$  where  $d_{ij} = a_{ji}$ . When we take a transpose, we switch the columns into rows and vice versa.

Certain special matrices can be described with other terminology. Suppose we have a matrix,  $A = (a_{ij}), i = 1, \dots, m$  and  $j = 1, \dots, n$ .

- If  $m = n$ , then  $A$  is a **square matrix**.
- If  $A^t = A$ , then  $A$  is a **symmetric matrix**. Note: this means  $A$  must also be square.
- If  $A^t = -A$ , then  $A$  is said to be **skew-symmetric**.
- If for all  $i, j$  such that  $i \neq j$ ,  $a_{ij} = 0$ , then  $A$  is called **diagonal**.

### Determinants

The determinant is a property of a square matrix,  $A$ .

#### Geometric Def'n.

Let  $A = [\vec{c}_1, \vec{c}_2, \dots, \vec{c}_n]$  (vectors in  $\mathbb{R}^n$ ). Let  $\Pi$  = parallelotope defined by basing them all at the same point. Then  $V^\sigma(\Pi) = \det [\vec{c}_1, \vec{c}_2, \dots, \vec{c}_n]$  (signed  $n$  volume).

*Example:*

$$A = [\vec{c}_1 \quad \vec{c}_2] = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

$$\det A = -1$$

### Algebraic Def'n.

Let  $A = (a_{ij})$ ,  $n \times n$ . Let  $A_{ij}$  = submatrix obtained from  $A$  by eliminating row  $i$  and column  $j$ ,  $(n-1) \times (n-1)$  matrix.

The minor of  $A$  is  $M_{ij} = \det A_{ij}$ . The cofactor of  $A$  is  $C_{ij} = (-1)^{i+j} \det A_{ij}$ .

Then  $\det A = \sum_{j=1}^n a_{ij} C_{ij}$  (for any  $i$ ,  $1 \leq i \leq n$ ). We call this the cofactor expansion along the  $i$ th row.

*Example:*

$$A = \begin{bmatrix} 7 & 3 & 12 \\ 2 & 5 & 8 \\ 1 & 5 & 2 \end{bmatrix}$$

Find the determinant.

Use row 3.

$$\det A = \sum_{j=1}^3 a_{3j} C_{3j} = a_{31} C_{31} + a_{32} C_{32} + a_{33} C_{33}$$

$$\left. \begin{aligned} C_{31} &= (-1)^{3+1} \begin{vmatrix} 3 & 12 \\ 5 & 8 \end{vmatrix} = -36 \\ C_{32} &= (-1)^{3+2} \begin{vmatrix} 7 & 12 \\ 2 & 8 \end{vmatrix} = -32 \\ C_{33} &= (-1)^{3+3} \begin{vmatrix} 7 & 3 \\ 2 & 5 \end{vmatrix} = 29 \end{aligned} \right\} \det A = 1(-36) + 5(-32) + 2(29) = \boxed{-138}$$

### Properties of Determinants

1.  $\det A = \det A^t$

(Therefore, we can also use the cofactor expansion along any column as well.)

2.  $\det A \neq 0 \iff A$  is invertible

3.  $\det AB = \det A \det B$

4.  $\det \begin{bmatrix} \vec{r}_1 \\ \vec{r}_i + \vec{r}_i' \\ \vec{r}_n \end{bmatrix} = \det \begin{bmatrix} \vec{r}_1 \\ \vec{r}_i \\ \vec{r}_n \end{bmatrix} + \det \begin{bmatrix} \vec{r}_1 \\ \vec{r}_i' \\ \vec{r}_n \end{bmatrix}$

Moreover, suppose  $A \xrightarrow{\vec{1}} B$  is an ERO. Then,

5. If  $1.P_{ij}$ , then  $\det B = -\det A$ .

6. If  $1.M_i(k)$ , then  $\det B = k \cdot \det A$ .

7. If  $1.A_{ij}(k)$ , then  $\det B = \det A$ .

*Note.* By (3),  $\det(A^{-1}) = (\det A)^{-1}$

### 1.1.2 Inverse Matrices

An  $n \times n$  matrix  $A$  may or may not have an **inverse**: A matrix  $B$  such that

$$AB = BA = \mathbf{I}_n = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix}$$

We write  $B = A^{-1}$ .

For a linear system,  $A\vec{x} = \vec{b}$  with  $A$ ,  $n \times n$ , if  $A$  is invertible:

$$\underbrace{A^{-1}A}_{\mathbf{I}_n} \vec{x} = A^{-1}\vec{b}$$

$$\therefore \text{Sol'n. is } \vec{x} = A^{-1}\vec{b}$$

We can vary  $\vec{b}$  and the solutions are immediate.

For the  $2 \times 2$  case,  $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$

$A$  has an inverse  $\iff |A| = ad - bc \neq 0$ .

Then

$$A^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

*Example:*

$$A = \begin{bmatrix} 2 & 5 \\ 7 & 9 \end{bmatrix}$$

Invertible?

$$18 - 35 = -17 \neq 0 \checkmark$$

$$A^{-1} = \frac{-1}{17} \begin{bmatrix} 9 & -5 \\ -7 & 2 \end{bmatrix}$$

Check

$$\frac{-1}{17} \begin{bmatrix} 9 & -5 \\ -7 & 2 \end{bmatrix} \begin{bmatrix} 2 & 5 \\ 7 & 9 \end{bmatrix} = \frac{-1}{17} \begin{bmatrix} -17 & 0 \\ 0 & -17 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

**Theorem 1.**  $A$   $n \times n$  matrix  $A$  has an inverse  $\iff \text{rk} A = n$ . If  $A$  has an inverse, then  $A^{-1}$  is given by  $\text{rref}[A \ I_n] = [I_n \ A^{-1}]$

Example:

$$A = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 5 & -1 \\ 1 & 2 & 0 \end{bmatrix}$$

Is it invertible?

$$\begin{aligned} & \begin{bmatrix} 1 & 2 & -1 & 1 & 0 & 0 \\ 2 & 5 & -1 & 0 & 1 & 0 \\ 1 & 2 & 0 & 0 & 0 & 1 \end{bmatrix} \\ & \xrightarrow{\substack{1. A_{12}(-2) \\ 2. A_{13}(-1)}} \begin{bmatrix} 1 & 2 & -1 & 1 & 0 & 0 \\ 0 & 1 & 1 & -2 & 1 & 0 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{bmatrix} \\ & \xrightarrow{\substack{3. A_{32}(-1) \\ 4. A_{31}(1)}} \begin{bmatrix} 1 & 2 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & -1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{bmatrix} \\ & \xrightarrow{5. A_{21}(-2)} \begin{bmatrix} 1 & 0 & 0 & 2 & -2 & 3 \\ 0 & 1 & 0 & -1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 & 1 \end{bmatrix} \\ & A^{-1} = \begin{bmatrix} 2 & -2 & 3 \\ -1 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix} \end{aligned}$$

$$AA^{-1} = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 5 & -1 \\ 1 & 2 & 0 \end{bmatrix} \begin{bmatrix} 2 & -2 & 3 \\ -1 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

### Properties of $A^{-1}$

1. If  $A$  is invertible, so is  $A^{-1}$ ,  $(A^{-1})^{-1} = A$ .
2. If  $A, B$  are invertible,  $n \times n$ , then so is  $A \cdot B$  and  $(BA)^{-1} = B^{-1}A^{-1}$ .

Witness  $A(B \cdot B^{-1})A^{-1} = AI_nA^{-1} = I_n$ .

3. If  $A$  is invertible, so is  $A^t$ ,  $(A^t)^{-1} = (A^{-1})^t$ .

**Theorem 2.** Suppose  $A$  is  $n \times n$ . Then the following are equivalent

1.  $A$  is invertible
2.  $A\vec{x} = \vec{b}$  has a unique solution for all  $\vec{b}$
3.  $\text{rk}(A) = n$



4.  $\text{rref}(A) = I_n$

5.  $\det(A) \neq 0$

### Computing Inverses

Recall if  $A = a_{ij}$  is a  $2 \times 2$  matrix, then if A is invertible,

$$A^{-1} = \frac{1}{a_{11}a_{22} - a_{12}a_{21}} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix} = \frac{1}{\det A} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

**Theorem 3.** *If A is invertible then*

$$A^{-1} = \frac{1}{\det A} (b_{ij})$$

where  $b_{ij}$  = the  $ji$ -th cofactor of  $A = (-1)^{i+j} \det A_{ij}$ .

*Example:*

Is A invertible? If so, find  $A^{-1}$ .

$$A = \begin{bmatrix} 1 & 2 & -1 \\ 2 & 5 & -1 \\ 1 & 2 & 0 \end{bmatrix}$$

$$\det A = \begin{vmatrix} 5 & -1 \\ 2 & 0 \end{vmatrix} - 2 \begin{vmatrix} 2 & -1 \\ 1 & 0 \end{vmatrix} - \begin{vmatrix} 2 & 5 \\ 1 & 2 \end{vmatrix} = 2 - 1 + 1$$

Therefore, A is invertible.

$$\text{Then } \frac{1}{\det A} \begin{bmatrix} C_{11} & C_{21} & C_{31} \\ C_{12} & C_{22} & C_{32} \\ C_{13} & C_{23} & C_{33} \end{bmatrix} \Bigg\} (C_{ij})^t$$

$$C_{11} = (-1)^2 \cdot 2 = 2 \quad C_{21} = -1 \quad C_{31} = 0$$

$$C_{12} = (-1)^3 \cdot 2 = -2 \quad C_{22} = 1 \quad C_{32} = -1$$

$$C_{13} = 3 \quad C_{23} = 1 \quad C_{33} = 1$$

$$\text{Then } A^{-1} = \begin{bmatrix} 2 & -2 & 3 \\ -1 & 1 & -1 \\ -1 & 0 & 1 \end{bmatrix}$$

## 1.2 Matricies as Linear Transformations

Matricies can be used to model transformations of vectors from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ . This is accomplished by having an  $m \times n$  matrix, A, written as:

$$A : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

*Example* ( $\mathbb{R}^n$  to  $\mathbb{R}^m$ ):

Let  $A = \begin{bmatrix} 3 & 4 \\ 1 & -1 \\ 2 & 2 \end{bmatrix}$ , and  $\vec{v} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$ . Thus,  $A : \mathbb{R}^2$  to  $\mathbb{R}^3$  and:

$$A\vec{v} = \begin{bmatrix} 3 & 4 \\ 1 & -1 \\ 2 & 2 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 10 \\ 1 \\ 6 \end{bmatrix}$$

*Note.* We are getting a linear combination of the column vectors of A. In other words,  $A\vec{v} = x\vec{a} + y\vec{b}$ .

# Chapter 2

## Interlude: Systems of Linear Equations

### 2.1 Systems of Linear Equations

Another application of matrices of great interest is representing systems of linear equations.

*Definition* (Linear):

An equation is **linear** in  $n$  variables  $x_1, x_2, \dots, x_n$  if each term contains at most one  $x_i$  and that  $x_i$  appears to the first power.

A “system of  $m$  linear equations in  $n$  unknowns.”

*Example* (Cutting  $n$  by  $n - 1$  dimensional objects):

Suppose we have two planes which will separate regions in a three dimensional space.

$$3x + 2y - z = 1$$

$$2x + 2y + z = 0$$

*Sol’n.*  $\{(x, y, z) : \text{satisfy all equations}\}$

The solution would be the intersection of these planes. Since they extend out infinitely, we would expect them to meet long a line contained in both planes.

*Note.* Multiplying by a constant, adding a multiple of one to another, and permuting the rows all do not change the solution.

Possible Outcomes: A system of  $m$  linear equations in  $n$  unknowns has either 0, 1, or inf solutions.

The technique to solving systems of linear equations is to develop a faster, simple method using matrices. We represent the system as a matrix, perform a series of operations to obtain a simpler matrix, and get our solution from the simpler solution.

*Example:*

$$\begin{aligned} 3x + 2y - z &= 1 \\ 2x + 2y + z &= 0 \end{aligned}$$

We take the coefficients and constants and put them into a matrix:

$$\begin{aligned} &\begin{bmatrix} 3 & 2 & -1 & 1 \\ 2 & 2 & 1 & 0 \end{bmatrix} \\ &\quad \left| \begin{array}{l} \vec{r}_1 \rightarrow \vec{r}_1 - \vec{r}_2 \\ \downarrow \end{array} \right. \\ &\begin{bmatrix} 1 & 0 & -2 & 1 \\ 2 & 2 & 1 & 0 \end{bmatrix} \\ &\quad \left| \begin{array}{l} \vec{r}_2 \rightarrow \vec{r}_2 - 2\vec{r}_1 \\ \downarrow \end{array} \right. \\ &\begin{bmatrix} 1 & 0 & -2 & 1 \\ 0 & 2 & 5 & 2 \end{bmatrix} \\ &\quad \left| \begin{array}{l} \vec{r}_2 \rightarrow \frac{1}{2}\vec{r}_2 \\ \downarrow \end{array} \right. \\ &\begin{bmatrix} 1 & 0 & -2 & 1 \\ 0 & 1 & \frac{5}{2} & 1 \end{bmatrix} \end{aligned}$$

Thus, we find:

$$\begin{aligned} x - 2z &= 1 \\ y + \frac{5}{2}z &= -1 \end{aligned}$$

*Sol'n.*  $z = t$  as a free variable

$$\begin{aligned} x &= 1 + 2t \\ y &= -1 - \frac{5}{2}t \end{aligned}$$

It's a line as expected!

$$L(t) = \left( 1 + 2t, -1 - \frac{5}{2}t, t \right)$$

## 2.2 Vector Form

Given:

$$\begin{aligned} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n &= b_1 \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n &= b_2 \\ &\vdots \\ a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n &= b_m \end{aligned}$$

The **vector form** of the system is:  $A\vec{x} = \vec{b}$  The **coefficient matrix** is  $A = (a_{ij})$ ,  $\vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$

and  $\vec{b} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix}$ .

The **augmented matrix** is  $A^\# = \begin{bmatrix} A & \vec{b} \end{bmatrix}$ .

*Definition* (Elementary Row Operations):

**Elementary row operations** (EROs) are defined as follows:

- $P_{ij} : \vec{r}_i \leftrightarrow \vec{r}_j$
- $M_i(c) : \vec{r}_i \leftarrow c\vec{r}_i$
- $A_{ij}(c) : \vec{r}_j \leftarrow \vec{r}_j + c\vec{r}_i$

These elementary row operations let us solve systems of linear equations in the same way we learned in early math classes. Adding equations together is the same as the row sum operation etc. Using EROs, the process to solve these systems is to write the augmented matrix of the system, perform EROs to get a reduced matrix and obtain the simpler linear system.

*Example:*

Solve if possible.

$$\begin{aligned} x + y + z &= 3 \\ 2x + 3y + z &= 5 \\ x - y - 2z &= -5 \end{aligned}$$

We write the augmented matrix of the system and perform EROs:

$$\begin{aligned}
 A^\# &= \begin{bmatrix} 1 & 1 & 1 & 3 \\ 2 & 3 & 1 & 5 \\ 1 & -1 & -2 & -5 \end{bmatrix} \xrightarrow{\substack{1. A_{12}(-2) \\ 2. A_{13}(-1)}} \begin{bmatrix} 1 & 1 & 1 & 3 \\ 0 & 1 & -1 & -1 \\ 0 & -2 & -3 & -8 \end{bmatrix} \\
 &\xrightarrow{3. A_{23}(2)} \begin{bmatrix} 1 & 1 & 1 & 3 \\ 0 & 1 & -1 & -1 \\ 0 & 0 & 1 & 2 \end{bmatrix} = \text{ref } A^\# \\
 &\xrightarrow{\substack{5. A_{32}(1) \\ 6. A_{31}(-1)}} \begin{bmatrix} 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix} \\
 &\xrightarrow{7. A_{21}(-1)} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix} = \text{rref } A^\#
 \end{aligned}$$

We obtain two matrices, the row echelon form and the reduced row echelon form. From  $\text{ref } A^\#$ , we find:

$$\begin{aligned}
 x + y + z &= 3 \\
 y - z &= -1 \\
 z &= 2
 \end{aligned}$$

From  $\text{rref } A^\#$ , we find:

$$\begin{aligned}
 x &= 0 \\
 y &= 1 \\
 z &= 2 \\
 \boxed{(0, 1, 2)}
 \end{aligned}$$

Thus,  $(0, 1, 2)$  solves the system of equations.

$$\begin{bmatrix} 1 & 1 & 1 \\ 2 & 3 & 1 \\ 1 & -1 & -2 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ 5 \\ -5 \end{bmatrix}$$

*Note.* If the number of leading 1's equals the number of unknowns, we obtain one solution.

*Definition* (Echelon Forms):

The **row echelon form** (ref) of any matrix is one such that:

- (a) The first nonzero entry of each nonzero row is 1. ("Leading one")
- (b) If a row has a leading one, each row above it has a leading 1 further to the left.

The **reduced row echelon form** (rref) of any matrix also has the condition:

- (c) Each entry above a leading 1 is 0.

To put a matrix into its ref or rref form:

1. Use  $P_{ij}$  so row  $i$  has the left most nonzero entry among rows  $\geq i$ .
2. Use  $M_i(k)$  to create a leading 1 in  $\vec{r}_i$ .
3. Use  $A_{ij}(k)$  to zero out column below leading 1 in  $\vec{r}_i$ . For rref, zero out columns above as well.
4. If there is no nonzero row below  $i$ , stop.

Else:

5. Replace  $i = i + 1$ , repeat on submatrix with rows  $\geq i + 1$ .

## 2.3 Theorem of Rank

*Definition (Rank):*

The number of leading 1's in  $\text{ref}(A)$  is the rank of  $A$ , usually written as " $\text{rk}(A)$ ."

**Theorem 4.** *Let  $A$ ,  $A^\#$  be the coefficient and augmented matrix for a system of linear equations with  $m$  equations and  $n$  unknowns.*

*Then, there are three cases:*

1. *No solutions if  $\text{rk } A < \text{rk } A^\#$ .*
2. *Unique solutions if  $\text{rk } A = \text{rk } A^\# = n$ .*
3. *Infinitely many solutions if  $\text{rk } A = \text{rk } A^\# < n$ .*

*Note.* There are unique solutions if exactly all variables are bound and infinitely many if there are  $n - \text{rk } A$  free variables.

*Example:*

Here is an illustration of this. Suppose we have:

$$\text{rref } A^\# = \begin{array}{cccccc} x_1 & x_2 & x_3 & x_4 & x_5 & b \\ \left[ \begin{array}{cccccc} 1 & * & 0 & * & 0 & a \\ 0 & 0 & 1 & * & 0 & b \\ 0 & 0 & 0 & 0 & 1 & c \\ 0 & 0 & 0 & 0 & 0 & d \end{array} \right] \end{array}$$

If  $d \neq 0$ , there are no solutions. If  $d = 0$ , there are infinitely many solutions. There are no unique solutions possible since there are two free variables:  $x_2 = s$  and  $x_4 = t$ . The bound variables are  $x_1$ ,  $x_2$ , and  $x_5$ .

From this illustration, we can see two important cases:

1. If we have a homogenous system,  $A\vec{x} = 0$ , then we always have the trivial solution  $\vec{x} = 0$ . There exists nontrivial solutions if and only if  $\text{rk}(A) < n$ .

2. If  $A$  is  $m \times n$  and  $m < n$ , then since  $\text{rk}(A) \leq m$ ,  $\text{rk}(A) < n$ .

Therefore, there are either 0 or infinitely many solutions.

*Example:*

Fix  $\vec{v} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$ . Find  $\vec{w}$  (all) such that  $\vec{v} \times \vec{w} = \vec{b} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$ .

$$\vec{v} \times \vec{w} = \begin{bmatrix} w_3 - w_2 \\ w_1 - w_3 \\ w_2 - w_1 \end{bmatrix}$$

Now we have a system of linear equations with  $\vec{w}$  as the unknown.

$$A = \begin{bmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{bmatrix}$$

$$\begin{aligned} A^\# = \begin{bmatrix} 0 & -1 & 1 & b_1 \\ 1 & 0 & -1 & b_2 \\ -1 & 1 & 0 & b_3 \end{bmatrix} &\xrightarrow{1. P_{12}} \begin{bmatrix} 1 & 0 & -1 & b_2 \\ 0 & -1 & 1 & b_1 \\ -1 & 1 & 0 & b_3 \end{bmatrix} \xrightarrow[3. M_2(-1)]{2. A_{13}(1)} \begin{bmatrix} 1 & 0 & -1 & b_2 \\ 0 & 1 & -1 & -b_1 \\ 0 & 1 & -1 & b_2 + b_3 \end{bmatrix} \\ &\xrightarrow{4. A_{23}(-1)} \begin{bmatrix} 1 & 0 & -1 & b_2 \\ 0 & 1 & -1 & -b_1 \\ 0 & 0 & 0 & b_1 + b_2 + b_3 \end{bmatrix} \end{aligned}$$

We have solutions  $\iff b_1 + b_2 + b_3 = 0 = \vec{v} \cdot \vec{b}$ . Then we have one free variable

$$\left. \begin{aligned} w_3 &= t \\ w_2 &= -b_1 + t \\ w_1 &= b_2 + t \end{aligned} \right\} = \boxed{(b_2 + t, -b_1 + t, t)}$$



# Chapter 3

## Vectors and Vector Spaces

### 3.1 Defining Vector Spaces and Subspaces

We've seen the sets  $\mathbb{R}^2$  and  $\mathbb{R}^3$  where the elements are vectors as translations in plane and 3-space. These sets have an algebraic structure.

*Definition (Vector Space):*

Any set following axioms A1-A10 is called a **vector space**.

Given a vector space  $A$ , vectors  $u, v, w \in A$  and scalars  $r, s$ :

- A1. We can define addition (and the space is closed under addition).
- A2. We can define scalar multiplication (and the space is closed under scalar multiplication).
- A3.  $u + v = v + u$
- A4.  $(u + v) + w = u + (v + w)$
- A5. There exists an additive identity in  $A$ .
- A6. There exists an additive inverse for any  $u \in A$ .
- A7. There exists a multiplicative identity in  $A$ .
- A8.  $(rs)v = r(sv)$
- A9.  $r(u + v) = ru + rv$
- A10.  $(r + s)v = rv + sv$

By studying vector spaces, we can develop algebraic machinery to apply to all kinds of other objects. For example, this idea will be explored for Fourier series.

*Example:*

$Q = \{a_0 + a_1x + a_2x^2 \mid a_i \in \mathbb{R}\}$  (Polynomials of degree 2 or less)

This is a vector space!

A1. Adding doesn't increase the degree. ✓

A2. Scalar multiplication similarly doesn't increase the degree. ✓

A3. Addition in  $\mathbb{R}$  is commutative. ✓

A4. By the associative property of  $\mathbb{R}$ ,

$$\begin{aligned} & \left( (a_0 + a_1x + a_2x^2) + (b_0 + b_1x + b_2x^2) \right) + (c_0 + c_1x + c_2x^2) \\ &= \left( (a_0 + b_0) + c_0 \right) + \left( (a_1 + b_1) + c_1 \right)x + \left( (a_2 + b_2) + c_2 \right)x^2 \\ &= \left( a_0 + (b_0 + c_0) \right) + \left( a_1 + (b_1 + c_1) \right)x + \left( a_2 + (b_2 + c_2) \right)x^2 \\ &= a_0 + a_1x + a_2x^2 + (b_0 + c_0) + (b_1 + c_1)x + (b_2 + c_2)x^2 \quad \checkmark \end{aligned}$$

A5. 0 polynomial ✓

A6.  $-(a_0 + a_1x + a_2x^2) = -a_0 - a_1x - a_2x^2$  ✓

A7.  $1 \cdot (a_0 + a_1x + a_2x^2) = a_0 + a_1x + a_2x^2$  ✓

A8. ✓

A9. ✓

A10. ✓

*Example:*

$$V = \mathbb{R}^2$$

$$S = \{(x, y) \mid x^2 - y^2 = 0\}$$

Is  $S$  a vector space?

No, since addition is not closed.

*Example:*

$$V = M_{3 \times 2}(\mathbb{R}) = \left\{ \begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix} \mid a, b, c, d, e, f \in \mathbb{R} \right\}$$

$$S = \{A \in V \mid \text{columns each sum to } 0\}$$

Is  $S$  a vector space?

$$\text{For example, } \begin{bmatrix} 1 & 0 \\ 0 & 2 \\ -1 & -2 \end{bmatrix} \in S. \text{ Now, } \vec{0} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}.$$

Closed under scalar mult? ✓

Consider  $\begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix}$  s.t.  $a + b + c = 0$  and  $d + e + f = 0$ .

Then  $m \begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix} = \begin{bmatrix} ma & md \\ mb & me \\ mc & mf \end{bmatrix}.$

So  $ma + mb + mc = m(a + b + c) = m(0)$  and  $md + me + mf = m(d + e + f) = m(0)$ . ✓

Closed under addition? ✓

Consider  $\begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix}, \begin{bmatrix} a' & d' \\ b' & e' \\ c' & f' \end{bmatrix} \in S.$

Now  $\begin{bmatrix} a & d \\ b & e \\ c & f \end{bmatrix} + \begin{bmatrix} a' & d' \\ b' & e' \\ c' & f' \end{bmatrix} = \begin{bmatrix} a + a' & d + d' \\ b + b' & e + e' \\ c + c' & f + f' \end{bmatrix}$

Check  $(a + a') + (b + b') + (c + c') = (a + b + c) + (a' + b' + c') = 0$ .

*Note.* Since the above examples of  $S$  are subsets of known vector spaces, we just have to check:

1. Closed under  $+, -$
2. Closed under scalar multiplication

These are called **subspaces**.

Vectors spaces do not just include  $\mathbb{R}^n$  and  $\mathbb{C}^n$ . We have:

- $C^k(I)$ : function on an interval  $I$  with  $k$  continuous derivatives
- $P_n(\mathbb{R})$ : polynomials with degree up to  $n$
- $M_{m \times n}(\mathbb{R})$

*Example:*

Consider  $y'' + a_1(x)y' + a_2(x)y = 0$  on an interval  $I$ . Let  $S$  be the set of solutions to this LODE. Is  $S$  a vector space?

- Addition: If  $y_1, y_2 \in S$ , is  $y_1 + y_2 \in S$ ?

$$(y_1 + y_2)'' + a_1(x)(y_1 + y_2)' + a_2(x)(y_1 + y_2) = y_1'' + y_2'' + a_1(x)(y_1' + y_2') + a_2(x)(y_1 + y_2) = 0 + 0$$

Therefore,  $S$  is closed under addition.

- Scalar Multiplication: If  $y \in S$ , is  $cy \in S$ ? Yes since  $(cy)'' = cy''$  and  $(cy)' = cy'$ .

Therefore  $S$  is a vector space, a subspace of  $C^2(I)$ .

*Example:*

Let  $V = \mathbb{R}^3$  and  $S$  be the solutions to the linear system:

$$\begin{aligned} 2x + 3y + z &= 0 \\ x + 2y + 3z &= 0 \end{aligned}$$

Then  $S \subset V$  is a subspace. All vectors in the subspace lie on a line through the origin contained on both planes.

Using this concept of subspaces, we can find solutions to certain differential equations or systems of linear equations.

*Definition* (Null Space):

The solutions of a homogeneous linear system  $A\vec{x} = 0$  is called the **null space** of  $A$ , any  $A_{m \times n}$ . It is a subspace of  $\mathbb{R}^n$  and is also known as the **kernel** of  $A$ .

For  $\mathbb{R}^3$ , subspaces consist of either a point  $\vec{0}$ , a line through  $\vec{0}$ , or a plane through  $\vec{0}$ .

## 3.2 Spanning Sets

*Definition* (Span):

A linear combination of vectors  $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \in V$  is a vector  $\vec{v} = c_1\vec{v}_1 + c_2\vec{v}_2 + \dots + c_n\vec{v}_n$  in  $V$ .

The **span** of  $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$  is the set of all linear combinations. The span is a subspace of the vector space  $V$ .

*Example:*

Compute the span of  $\{(-4, 1, 3), (5, 1, 6), (6, 0, 2)\}$  in  $\mathbb{R}^3$ .

We want the set  $\{(a, b, c)\}$  that are linear combinations of the three vectors. In other words, the solutions of the linear system:

$$\begin{bmatrix} -4 & 5 & 6 & a \\ 1 & 1 & 0 & b \\ 3 & 6 & 2 & c \end{bmatrix}$$

$$\xrightarrow{1. \ 2. \ 3.} \begin{bmatrix} 1 & 1 & 0 & b \\ 0 & 9 & 6 & a + 4b \\ 0 & 3 & 2 & c - 3b \end{bmatrix} \xrightarrow{4. \ 5.} \begin{bmatrix} 1 & 1 & 0 & b \\ 0 & 3 & 2 & c - 3b \\ 0 & 0 & 0 & a + 13b - 3c \end{bmatrix}$$

1.  $P_{12}$
2.  $A_{12}(4)$
3.  $A_{13}(-3)$
4.  $P_{23}$
5.  $A_{23}(-3)$

There is a solution if and only if  $\text{rk} A = \text{rk} A^\#$ . So  $a + 13b - 3c = 0$ . We conclude the span is on a plane  $\boxed{x + 13y - 3z = 0}$ .

*Note.* One of the three vectors is redundant.

*Example:*

Write  $(-4, 1, 3)$  as a linear combination of  $(5, 1, 6)$  and  $(6, 0, 2)$ .

We want constants  $c_1, c_2$  such that:

$$c_1 \begin{bmatrix} 5 \\ 1 \\ 6 \end{bmatrix} + c_2 \begin{bmatrix} 6 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} -4 \\ 1 \\ 3 \end{bmatrix}$$

We need to solve  $\begin{bmatrix} 5 & 6 & -4 \\ 1 & 0 & 1 \\ 6 & 2 & 3 \end{bmatrix}$

$$\xrightarrow[2. \ 3.]{1.} \begin{bmatrix} 1 & 0 & 1 \\ 0 & 6 & -9 \\ 0 & 2 & -3 \end{bmatrix} \xrightarrow{4. \ 5.} \begin{bmatrix} 1 & 0 & 1 \\ 0 & 2 & -3 \\ 0 & 0 & 0 \end{bmatrix} \xrightarrow{6.} \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & \frac{-3}{2} \\ 0 & 0 & 0 \end{bmatrix}$$

Thus  $\begin{bmatrix} 5 \\ 1 \\ 6 \end{bmatrix} - \frac{3}{2} \begin{bmatrix} 6 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} -4 \\ 1 \\ 3 \end{bmatrix}.$

The moral of this example is that sometimes a spanning set has redundant vectors. We would like a spanning set to have no redundant vectors or a "minimally spanning set."

*Definition* (Linear Dependence):

A set  $\{\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n\}$  in a vector space  $V$  is **linearly dependent** if there exists some  $c_1, c_2, \dots, c_n$  not all zero such that:  $c_1\vec{v}_1 + c_2\vec{v}_2 + \dots + c_n\vec{v}_n = \vec{0}$ . (This is called the dependence relation, and we would say one of the vectors is redundant.)

Otherwise, the set is **linearly independent** and the relation  $c_1\vec{v}_1 + c_2\vec{v}_2 + \dots + c_n\vec{v}_n = \vec{0}$  implies  $c_1 = c_2 = \dots = c_n = 0$ .

*Example:*

The vectors  $\vec{v}_1 = \begin{bmatrix} 2 \\ -1 \\ 1 \end{bmatrix}$ ,  $\vec{v}_2 = \begin{bmatrix} -1 \\ 2 \\ -1 \end{bmatrix}$ ,  $\vec{v}_3 = \begin{bmatrix} -1 \\ -1 \\ 2 \end{bmatrix}$  are linearly dependent.

Find the dependence relation.

We need to solve  $A\vec{x} = \vec{0}$  and  $\text{rk}A \leq 2$  for there to be nontrivial solutions.

$$\begin{bmatrix} 2 & -1 & -1 & 0 \\ -1 & 2 & -1 & 0 \\ -1 & -1 & 2 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & -2 & 0 \\ 0 & 3 & -3 & 0 \\ 0 & -3 & 3 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 1 & -2 & 0 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

Parameterizing, we find that  $c_3 = t$ ,  $c_2 = t$ ,  $c_1 = 2t - t = t$ .

Therefore  $\boxed{\vec{v}_1 + \vec{v}_2 + \vec{v}_3 = \vec{0}}.$

### 3.2.1 Method for Testing Spans

Given  $\{\vec{v}_1, \dots, \vec{v}_n\}$ , to determine if they are linearly dependent, form a matrix  $A = [\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n]$ . Then the set is linearly dependent if and only if  $A\vec{c} = \vec{0}$  has nontrivial solutions. In other

