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# *Applied Linear Algebra*

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MATH363

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## Chapter 1

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# Linear Algebraic Systems

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## Chapter 2

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# Vector Spaces and Bases

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### §2.1 Real Vector Spaces

A vector space is the abstract reformulation of the quintessential properties of  $n$ -dimensional Euclidean Space  $\mathbb{R}^n$ , which is defined as the set of all real (column) vectors with  $n$  entries. The basic laws of vector addition and scalar multiplication in  $\mathbb{R}$

#### Definition 2.1.1

A vector space is a set of  $V$  equipped with two operations:

- Addition: adding any pair of vectors  $v, w \in V$  produces another vector  $v + w \in V$ ;
- Scalar Multiplication: multiplying a vector  $v \in V$  by a scalar  $c \in \mathbb{R}$  produces a vector  $cv \in V$

These are subject to the following axioms, valid for all  $u, v, w \in V$  and all scalars  $c, d \in \mathbb{R}$ :

- Commutativity of Addition:  $v + w = w + v$ .
- Associativity of Addition:  $u + (v + w) = (u + v) + w$ .
- Additive Identity: There is a zero element  $0 \in V$  satisfying  $v + 0 = v = 0 + v$ .
- Additive Inverse: For each  $v \in V$  there is an element  $-v \in V$  such that  $v + (-v) = 0 = (-v) + v$ .
- Distributivity:  $(c + d)v = (cv) + (dv)$ , and  $c(v + w) = (cv) + (cw)$ .
- Associativity of Scalar Multiplication:  $c(dv) = (cd)v$ .

- Unit for Scalar Multiplication: the scalar  $1 \in \mathbb{R}$  satisfies  $1\mathbf{v} = \mathbf{v}$ .

**Theorem 2.1.1**

Let  $V$  be a vector space.

- $0 \times \vec{V} = \vec{0}$
- $-1\vec{V} = -\vec{V}$
- $c \times \vec{0} = \vec{0}$
- If  $c \times \vec{V} = \vec{0}$ , then  $c = 0$  or  $\vec{V} = \vec{0}$

Here are some examples of vector spaces:

- $\mathbb{R}^n = \left\{ \begin{pmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{pmatrix} \mid r_1, r_2, r_n \in \mathbb{R} \right\}$
- $M_{m \times n} =$  The  $m$  by  $n$  matrices over  $\mathbb{R}$ .
- $\mathbb{P}^n =$  the polynomials of degree  $\leq n$ .

**Definition 2.1.2**

Let  $V$  be a vector space over  $F$ .  $W \leq V$  is a subspace of  $V$  if  $W$  is a vector space over  $F$  under the same operation as  $V$ .

An example of definition (2.1.2). Let  $V = \mathbb{R}^3 = \left\{ \begin{pmatrix} a \\ b \\ c \end{pmatrix} \mid a, b, c \in \mathbb{R} \right\}$ .  $V$  is a vector space. If we let  $W = \left\{ \begin{pmatrix} a \\ b \\ 0 \end{pmatrix} \mid a, b \in \mathbb{R} \right\}$ , then  $W$  is a subspace of  $V$ .

**Theorem 2.1.2**

Let  $V$  be a vector space. Let  $W \leq V$ .  $W$  is a subspace of  $V$  if

- $w \neq 0$
- $\forall w_1, w_2 \in W; w_1 + w_2 \in W$
- $\forall c \in F; \vec{W} \in W; c \cdot \vec{W} \in W$

If we were to let  $V = \mathbb{R}^3$  for  $\begin{pmatrix} a \\ b \\ c \end{pmatrix}$ . We can determine the following:

- $\{\vec{0}\}$  is a subspace of  $V$ .
- $\left\{ \begin{pmatrix} a \\ 0 \\ c \end{pmatrix} \mid a, c \in \mathbb{R} \right\}$  is a subspace of  $V$ .
- Consider the equation  $\left\{ \begin{pmatrix} x \\ x \\ 0 \end{pmatrix} \mid x \in \mathbb{R} \right\} = W$  Show that  $W$  is a subspace of  $V$ .
  - $\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \in W$  so  $W \neq 0$ .
  - $\begin{pmatrix} x \\ x \\ 0 \end{pmatrix}, \begin{pmatrix} y \\ y \\ 0 \end{pmatrix} \in W$ . Then  $\begin{pmatrix} x \\ x \\ 0 \end{pmatrix} + \begin{pmatrix} y \\ y \\ 0 \end{pmatrix} = \begin{pmatrix} x+y \\ x+y \\ 0 \end{pmatrix}$
  - $\begin{pmatrix} x \\ x \\ 0 \end{pmatrix} \in W$ , then  $c \times \begin{pmatrix} x \\ x \\ 0 \end{pmatrix} = \begin{pmatrix} cx \\ cx \\ 0 \end{pmatrix} \in W$ .
  - Therefore we know that  $W$  is a subspace of  $V$  with respect to scalar multiplication and addition.
- $W = \left\{ \begin{pmatrix} x \\ y \\ 2x+3y \end{pmatrix} \mid x, y \in \mathbb{R} \right\}$ .  $W$  is a subspace of  $V$ .

$\mathbb{R}^3$  only has 4 kinds of subspaces.  $\mathbb{R}^3$ ,  $\{\vec{0}\}$ , planes passing through the origin and lines that are passing through the origin.

## §2.2 Subspaces

### Definition 2.2.1

Let  $I$  be an interval in  $\mathbb{R}$ . Let  $\mathbb{F}(I)$  be the vector space of functions  $\mathbb{F} = I \rightarrow \mathbb{R}$ .

- $\mathbb{C}^0(I)$  = the continuous functions from  $I \rightarrow \mathbb{R}$  is a subspace.
- $\mathbb{P}^n(I)$  = polynomials of degree  $\leq n$  restricted to  $\mathbb{F}(I)$ . This is a subspace of  $\mathbb{C}^0(I)$ .
- $\mathbb{P}^\infty(I)$  = all polynomials on  $I$ . This is a subspace of  $\mathbb{F}(I)$ .
- $\mathbb{C}^n(I)$  = the set of functions  $f : I \rightarrow \mathbb{R}$  such that  $f', f'' \dots f^{(n)}$  all exist and are continuous.

- $\mathbb{C}^\infty(I)$  = functions from  $I \rightarrow \mathbb{R}$  such that  $f', f'', f'''$  all exist and are smooth functions.
- $A(I)$  = the functions in  $\mathbb{C}^\infty(I)$  such that all  $A \in I$ , the power series  $f(a) + \frac{f'(a)(x-a)}{1!} + \frac{f''(a)(x-a)^2}{2!} + \dots$  converges for all  $x \in I$  sufficiently close to  $a$ .

**Problem 1.** Show that  $v = \begin{pmatrix} x \\ y \\ 2x+y \end{pmatrix}$  is a subspace of  $\mathbb{R}^3$ .

- Because  $\begin{pmatrix} 0 \\ 0 \\ 2(0)+0 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$  is in  $v$ ,  $v$  is not empty.
- Let  $\vec{v}_1 = \begin{pmatrix} x_1 \\ y_1 \\ 2x_1+y_1 \end{pmatrix}, \vec{v}_2 = \begin{pmatrix} x_2 \\ y_2 \\ 2x_2+y_2 \end{pmatrix} \in V$

$$v_1 + v_2 = \begin{pmatrix} x_1 + x_2 \\ y_1 + y_2 \\ 2x_1 + y_1 + 2x_2 + y_2 \end{pmatrix} = \begin{pmatrix} x_1 + x_2 \\ y_1 + y_2 \\ 2(x_1 + x_2) + (y_1 + y_2) \end{pmatrix} \in V \quad (2.1)$$

so  $v$  is closed with respect to addition.

- Let  $r \in \mathbb{R}$  and  $\begin{pmatrix} x \\ y \\ 2x+y \end{pmatrix} = \vec{v} \in v$

## §2.3 Span and Linear Independence

If we let  $V$  be a vector space over  $\mathbb{R}$  and let  $\vec{v}_1, \dots, \vec{v}_n \in V$ , then we can determine that the

$$\text{span}(\{\vec{v}_1, \dots, \vec{v}_n\}) = \{c_1\vec{v}_1 + \dots + c_n\vec{v}_n \mid c_1, \dots, c_n \in \mathbb{R}\} \quad (2.2)$$

### Proposition 2.3.1

The span of  $\{\vec{v}_1, \vec{v}_2\}$  is a subspace of  $V$ .

**Proof.**

$$c_1\vec{v}_1 + \cdots + c_n\vec{v}_n \quad (2.3)$$

$$k_1\vec{v}_1 + \cdots + k_n\vec{v}_n \in \text{span} \quad (2.4)$$

$$(2.5)$$

If we add together both of the equations above we get

$$(c_1 + k_1)\vec{v}_1 + \cdots + (c_n + k_n)\vec{v}_n \in \text{span}. \quad (2.6)$$

$$r(c_1\vec{v}_1 + \cdots + c_n\vec{v}_n) \quad (2.7)$$

$$= rc_1\vec{v}_1 + \cdots + rc_n\vec{v}_n \in \text{span} \quad (2.8)$$

■

**Problem 2.** Let  $V \in \mathbb{R}^3$ . Also we are going to let

$$\vec{v}_1 = \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}, \text{span}(\vec{v}_1) = \left\{ c \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix} \middle| c \in \mathbb{R} \right\} \quad (2.9)$$

$\begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}$  is a vector in 3-space.  $c \times \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}$  expands, contracts, changes direction. This is a line which goes through  $\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$ .

$$c \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix} \quad (2.10)$$

is in the  $xy$ -plane, let's solve for  $y$  to find the equation of the line that is drawn by the vector:



$$\begin{pmatrix} c \\ 2c \\ 0 \end{pmatrix} \quad (2.11)$$

$$x = c \quad (2.12)$$

$$y = 2c \quad (2.13)$$

$$\frac{1}{2}y = c \quad (2.14)$$

$$\rightarrow x = \frac{1}{2}y \quad (2.15)$$

$$\rightarrow y = 2x \quad (2.16)$$

$$(2.17)$$

Now we are going to let  $\vec{v}_2 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ . Consider the span of  $(\{\vec{v}_1, \vec{v}_2\})$ . The span of  $(\{\vec{v}_1, \vec{v}_2\})$  is a plane.

In  $\mathbb{R}^3$ , if  $\vec{0} \neq \vec{v} \in \mathbb{R}$ , then the  $\text{span}\vec{v}$  is a line.

**Problem 3.** Let  $v = \mathbb{P}^2$ .  $v$  is the set of polynomials of degree  $\leq 2 \in \mathbb{R}$ .

- $\text{span}(1, x, x^2) = \mathbb{P}^2$
- $\text{span}(4, 2x) = \mathbb{P}^1$ , which means all polynomials of degree  $\leq 1$

### Definition 2.3.1

Let  $v$  be a vector space.  $\vec{v}_1, \dots, \vec{v}_n$  are linearly dependant if there exists  $c_1, \dots, c_n$  are not all zero, such that  $c_1\vec{v}_1 + \dots + c_n\vec{v}_n = \vec{0}$ , otherwise,  $\vec{v}_1, \dots, \vec{v}_n$  are linearly independent.

If we let  $\vec{v}_1 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$ ,  $\vec{v}_2 = \begin{pmatrix} 2 \\ 4 \end{pmatrix}$ , we can do a simple test to see if they are linearly independent. We know that  $2\vec{v}_1 = \vec{v}_2$ , which means that  $2\vec{v}_1 + -1\vec{v}_2 = \vec{0}$ . Because we can make  $\vec{v}_1 + \vec{v}_2$  by using a simple scalar value, these functions are linearly dependent.

**Problem 4.** Consider the following three matrices

$$\vec{v}_1 = \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}, \vec{v}_2 = \begin{pmatrix} 2 \\ 1 \\ 1 \end{pmatrix}, \vec{v}_3 = \begin{pmatrix} 8 \\ 1 \\ 11 \end{pmatrix} \quad (2.18)$$

Are these matrices linearly dependent or independent from each other? The following equation will let us set up a matrix to determine the results:

$$c_1\vec{v}_1 + c_2\vec{v}_2 + c_3\vec{v}_3 = \vec{0} \quad (2.19)$$

We must try to see if there are any  $c_n$  values that are not zero to make this true.

$$\begin{pmatrix} 1 & 2 & 8 \\ 2 & -1 & 1 \\ 1 & 3 & 11 \end{pmatrix} \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \quad (2.20)$$

$$= \begin{pmatrix} 1 & 2 & 8 & : & 0 \\ 2 & -1 & 1 & : & 0 \\ 1 & 3 & 0 & : & 0 \end{pmatrix} \quad (2.21)$$

By doing some elementary row operations, we can find that in row echelon form, the matrix from equation (2.21) can be written as

$$\begin{pmatrix} 1 & 2 & 8 & : & 0 \\ 9 & 1 & 3 & : & 0 \\ 0 & 0 & 0 & : & 0 \end{pmatrix} \quad (2.22)$$

And from here we can solve for the different  $c_n$  values.

$$1c_1 + 2c_2 + 8c_3 = 0 \quad (2.23)$$

$$c_1 + 3c_3 = 0 \quad (2.24)$$

$$(2.25)$$

$$c_3 = -3c_3 \quad (2.26)$$

$$c_1 = -2c_3 \quad (2.27)$$

$$c_3 = c_3 \quad (2.28)$$

Because we have this relationship where  $c_1, c_2, c_3$  all depend on each other, we can tell that this is linearly independent.

### §2.3.1 Linear Independence and Dependence

## §2.4 Basis and Dimension

#### Definition 2.4.1

A basis of a vector space  $v$  is a collection of vectors  $\vec{v}_1, \dots, \vec{v}_n$  that 1. span  $v$  and 2. are linearly dependent.

**Problem 5.** *If we are looking at  $\mathbb{R}^2$ , with  $e_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$ , and  $e_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$  We can tell that this is a basis of  $\mathbb{R}^2$ . We can tell this because the span of  $v$  is linearly independent. We can also see this because:*

$$a \times e_1 + b \times e_2 = \begin{pmatrix} a \\ b \end{pmatrix} \quad (2.29)$$

**Problem 6.** *Now we are going to look at an example in  $\mathbb{R}^3$ , with  $e_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$ ,  $e_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$ , and  $e_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$ . We can figure out that this is a basis by doing the same technique as we did before:*

$$c_1 \vec{e}_1 + c_2 \vec{e}_2 + c_3 \vec{e}_3 = 0 \quad (2.30)$$

$$c_1 = c_2 = c_3 = 0 \quad (2.31)$$

*Because  $c_1$ ,  $c_2$ , and  $c_3$  are all equal to zero,  $\vec{e}_1$ ,  $\vec{e}_2$ , and  $\vec{e}_3$  form a basis.*

**Theorem 2.4.1**

If a vector space  $v$  has a basis with  $n$  elements, then every basis of  $v$  has  $n$  elements. We say  $v$  has dimension  $n$ . We write down  $\dim v = n$

**Theorem 2.4.2**

If the dimension of  $v$  is  $n$ , then any collection of  $n + 1$  or more vectors must be linearly dependent.

**Theorem 2.4.3**

Suppose  $\dim v = n$

1. Every collection of more than  $n$  vectors is linearly dependent.
2. No set of fewer than  $n$  vectors spans  $v$ .
3. A set of  $n$  vectors is a basis if and only if it spans  $v$ .
4. A set of  $n$  vectors is a basis if and only if it is linearly independent.

**Problem 7.** Assume  $1, x, x^2$  is a basis for  $\mathbb{P}^2$ . We are going to multiply  $1 \times 5$ ,  $x \times 6$ , and  $x^2 \times 2$ .

$$5 + 6x + 2x^2 \tag{2.32}$$

$$c_1 \times 1 + c_2 \times x + c_3 \times x^2 = 0 \tag{2.33}$$

$$\dim(\mathbb{P}^2) = 3 \tag{2.34}$$

$$\tag{2.35}$$

**Theorem 2.4.4**

$\vec{v}_1, \dots, \vec{v}_n$  form a basis of  $v$  if and only if for all  $\vec{v} \in v$ , there exist unique  $c_1, \dots, c_n$  such that  $\vec{v} = c_1\vec{v}_1 + \dots c_n\vec{v}_n$

**Problem 8.** Let  $v = \mathbb{R}^2$ . Let  $\vec{v} = \begin{pmatrix} 4 \\ 3 \end{pmatrix}$ . We know from previous problems that  $\begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{pmatrix} 0 \\ 1 \end{pmatrix}$  is a basis of  $\mathbb{R}^2$ . We can also figure out what our basis is by trying to figure out what our  $c_1$  and  $c_2$  values should be. Because the matrices we know are a basis consist of 1's and 0's, we can see that

$$4 \begin{pmatrix} 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 4 \\ 3 \end{pmatrix}. \quad (2.36)$$

The coordinates of  $\vec{v}$  with respect to this basis, are  $(4, 3)$ . Let's consider a different basis. We are now going to look at the basis,

$$\left\{ \begin{pmatrix} 1 \\ -3 \end{pmatrix}, \begin{pmatrix} 2 \\ -1 \end{pmatrix} \right\} \quad (2.37)$$

Now we need to figure out the  $a$  and  $b$  values for this basis respectively.

$$a \begin{pmatrix} 1 \\ -3 \end{pmatrix} + b \begin{pmatrix} 2 \\ -1 \end{pmatrix} = \begin{pmatrix} 4 \\ 3 \end{pmatrix} \quad (2.38)$$

$$(2.39)$$

The coordinates of  $\vec{v}$  with respect to this basis are  $(4, 3)$ . Let's consider the same problem but with the following basis:

$$\left\{ \begin{pmatrix} 1 \\ -3 \end{pmatrix}, \begin{pmatrix} 2 \\ -1 \end{pmatrix} \right\} \quad (2.40)$$

Now, we are going to do the same thing as before, where we solve for  $a$  and  $b$  in the following equation

$$a \begin{pmatrix} 1 \\ -3 \end{pmatrix} + b \begin{pmatrix} 2 \\ -1 \end{pmatrix} = \begin{pmatrix} 4 \\ 3 \end{pmatrix} \quad (2.41)$$

We can setup this to be a system of equations that we can turn into a matrix

$$\begin{cases} 1a + 2b = 4 \\ -3a + (-1)b = 3 \end{cases} \rightarrow \begin{bmatrix} 1 & 2 & \vdots & 4 \\ -3 & -1 & \vdots & 3 \end{bmatrix} \quad (2.42)$$

And now we can use the basic row operation  $R_2 = R_2 + 3R_1$  in order to solve for  $a$  and  $b$ :

$$\begin{bmatrix} 1 & 2 & \vdots & 4 \\ 0 & 5 & \vdots & 5 \end{bmatrix} \quad (2.43)$$

$$5b = 15 \quad a + 2b = 4 \quad (2.44)$$

$$b = 3 \quad 1 + 2 * 3 = 4 \quad (2.45)$$

$$a = -2 \quad (2.46)$$

## §2.5 The fundamental Matrix Subspaces (Kernel and Image)

### Definition 2.5.1

The image of an  $m \times n$  matrix  $A$  is the subspace spanned by the columns of  $A$ .

**Problem 9.** Let's consider the following equation.

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} r_1 \\ r_2 \\ r_3 \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \quad (2.47)$$

When we multiply our the matrix, we see that the span of the columns give us all the possible  $\begin{bmatrix} x \\ y \end{bmatrix}$  values. The span of the matrix

$$\begin{bmatrix} 1 \times r_1 & 2 \times r_2 & 3 \times r_3 \\ 4 \times r_1 & 5 \times r_2 & 6 \times r_3 \end{bmatrix} \quad (2.48)$$

would be the values  $\begin{bmatrix} 1 \\ 4 \end{bmatrix}$ ,  $\begin{bmatrix} 2 \\ 5 \end{bmatrix}$ , and  $\begin{bmatrix} 3 \\ 6 \end{bmatrix}$

**Definition 2.5.2**

A space,  $A$ , is an  $m \times m$  matrix, The kernel of  $A$  is

$$A = \text{Ker}(A) \quad (2.49)$$

$$= \{\vec{x} | A\vec{x} = \vec{0}\} \quad (2.50)$$

Using definition (2.5.2), if  $A = \begin{bmatrix} 1 & 0 \\ 5 & 0 \end{bmatrix}$ , then

$$\vec{x}_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \vec{x}_2 = \begin{bmatrix} 0 \\ 5 \end{bmatrix}. \quad (2.51)$$

Something to keep in mind: If  $\vec{x}_1, \vec{x}_2 \in \text{Ker}(A)$ , then  $r_1\vec{x}_1 + r_2\vec{x}_2 \in \text{Ker}(A)$ . So the kernel of  $A$  is a subspace of the domain of the function.

**Theorem 2.5.1**

Assume  $\vec{x}_1$  solves  $A\vec{x} = \vec{b}$ . Then,  $\vec{x}_2$  is another solution to  $A\vec{x} = \vec{b}$  if and only if  $\vec{x}_2 = \vec{x}_1 + \vec{z}$ , where  $z \in \text{Ker}(A)$

**Proposition 2.5.1**

Let  $A$  be an  $m \times n$  matrix. The following are true:

1.  $\text{Ker}(A) = \{\vec{0}\}$
2.  $\text{rank}(A) = n$
3.  $A\vec{x} = \vec{b}$  has a unique solution for any  $\vec{b}$  in the integer of  $A$ .
4.  $A\vec{x} = \vec{b}$  has no free variables.
5.  $A$  is non-singular.

**Definition 2.5.3**

Let  $A$  be  $m \times n$ .

$$\text{coimg}(A) = \text{img}(A^T) \quad (2.52)$$

$$\text{coker}(A) = \ker(A^T) \quad (2.53)$$

$$(2.54)$$

The image of  $A$  is the span of its columns. Thus the coimage is the span of its rows. Also the  $r^T$  in the cokernel of  $A$  are those  $r^T$  such that  $r \times A = 0^T$  since

$$(r \cdot A)^T = (0^T)^T \quad (2.55)$$

$$A^T \cdot r^T = 0 \quad (2.56)$$

### Theorem 2.5.2

The Fundamental Theorem of Linear Algebra: Let  $A$  be an  $m \times n$  matrix and let  $r$  be its rank. Then

$$\dim(\text{coimg}(A)) = \dim(\text{img}(A)) = \text{rank}(A) = \text{rank}(A^T) = r \quad (2.57)$$

$$\text{span}(A_{\text{rows}}) = \text{span}(A_{\text{columns}}) \quad (2.58)$$

$$\dim(\ker(A)) = n - r \quad (2.59)$$

$$\dim(\text{coker}(A)) = m - r \quad (2.60)$$

Let's take a look at an example using the fundamental theorem of linear algebra. Let

$$A = \begin{bmatrix} 1 & 2 & 3 & -1 \\ 1 & -1 & 0 & 2 \\ -1 & 1 & 0 & -2 \\ 2 & 1 & 3 & 1 \end{bmatrix} \quad (2.61)$$



Let's do some row operations to get this matrix into row echelon form:

$$A = \begin{bmatrix} 1 & 2 & 3 & -1 \\ 0 & -3 & -3 & 3 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (2.62)$$

From this form, we can tell that  $v_3$  and  $v_4$  both depend on  $v_1$  and  $v_2$ . Because there are only two pivot points within  $A$  that are filled with values other than 0,  $\text{rank}(A) = 2$ . We also know that the dimension of the column space is equal to the dimension of the row space. Let's find the dimension of the kernel of  $A$ :

$$\dim(\ker(A)) + \text{rank} = n \quad (2.63)$$

$$\dim(\ker(A)) + 2 = 4 \quad (2.64)$$

$$(2.65)$$

From here, we know that both  $y$  and  $z$  are free variables.

$$w + 2x + 3y - z = 0 \quad (2.66)$$

$$-3x - 3y + 3z = 0 \quad (2.67)$$

$$x + y - z = 0 \quad (2.68)$$

$$x = -y + z \quad (2.69)$$

$$w = -2x - 3y + z \quad (2.70)$$

$$= -2(-y + z) - 3y + z \quad (2.71)$$

$$= -y - z \quad (2.72)$$

Now we need to determine the basis for  $\ker(A)$ .

$$\begin{pmatrix} -y - z \\ -y + z \\ y \\ z \end{pmatrix} = \begin{pmatrix} -y \\ -y \\ y \\ 0 \end{pmatrix} + \begin{pmatrix} -z \\ z \\ 0 \\ z \end{pmatrix} = y \begin{pmatrix} -1 \\ -1 \\ 1 \\ 0 \end{pmatrix} + z \begin{pmatrix} -1 \\ 1 \\ 0 \\ 1 \end{pmatrix} \quad (2.73)$$

Our basis for  $\ker(A)$  is  $\begin{pmatrix} -1 \\ -1 \\ 1 \\ 0 \end{pmatrix}$  and  $\begin{pmatrix} -1 \\ 1 \\ 0 \\ 1 \end{pmatrix}$ .

## Chapter 3

# Inner Products and Norms

### §3.1 Inner Products

Dot products are a form of inner product.

Let's apply the dot product to the vectors  $\langle v_1, v_2, \dots, v_n \rangle \cdot \langle w_1, w_2, \dots, w_n \rangle$  to show that the dot product is an inner product.

$$= v_1 w_1 + v_2 w_2 + \dots + v_n w_n \quad (3.1)$$

Therefore,  $v \cdot v$  goes to  $\mathbb{R}$ . So we know that

$$\vec{v} \cdot \vec{v} = v_1^2 + v_2^2 + \dots + v_n^2 \quad (3.2)$$

In general, we can assume that  $\|\vec{v}\| = \sqrt{\vec{v} \cdot \vec{v}}$ . We should also keep in mind that  $\vec{v} \cdot \vec{w} = \|\vec{v}\| \|\vec{w}\| \cos \theta$

#### Definition 3.1.1

An inner product of  $V$  is a function  $\langle, \rangle: V \times V \rightarrow \mathbb{R}$  such that

•

$$\langle c\vec{u} + d\vec{v}, \vec{w} \rangle = c \langle \vec{u}, \vec{v} \rangle + d \langle \vec{v}, \vec{u} \rangle \quad (3.3)$$

$$\langle \vec{u}, c\vec{v} + d\vec{w} \rangle = c \langle \vec{u}, \vec{v} \rangle + d \langle \vec{u}, \vec{w} \rangle \quad (3.4)$$

•  $\langle \vec{v}, \vec{w} \rangle = \langle \vec{w}, \vec{v} \rangle$

•  $\langle \vec{v}, \vec{v} \rangle \geq 0$  while  $\langle 0, 0 \rangle = 0$ .

A vector space with an inner product is an inner product space.

#### Definition 3.1.2

If  $V$  is an inner product space, then it's magnitude is

$$||\vec{v}|| = \sqrt{\langle \vec{v}, \vec{v} \rangle} \quad (3.5)$$

Let's take a look at a weighted inner product on  $\mathbb{R}^3$ . We are going to let  $r_1, r_2, r_3 > 0$ . We can define  $\langle \vec{v}, \vec{w} \rangle$  as  $r_1 v_1 w_1 + r_2 v_2 w_2 + r_3 v_3 w_3$

**Problem 10.** Let's define  $[a, b] \subseteq \mathbb{R}$ . Consider  $\mathbb{C}^0[a, b]$ . This is a vector space. Define

$$\langle f(x), g(x) \rangle = \int_a^b f(x)g(x)dx \quad (3.6)$$

This is an inner product, so we also know that

$$||f|| = \sqrt{\int_a^b (f(x))^2 dx} \quad (3.7)$$

This equation is the  $L^2$  norm.

## §3.2 Inequalities

Recall that  $\vec{v} \cdot \vec{w} = ||\vec{v}|| ||\vec{w}|| \cos \theta$ , where  $\theta$  is the angle between  $\vec{v}$  and  $\vec{w}$ . Now  $-1 \leq \cos \theta \leq 1$ , so we know that

$$||\vec{v} \cdot \vec{w}|| \leq ||\vec{v}|| ||\vec{w}|| \quad (3.8)$$

This is the Cauchy-Shuartz inequality.

### Theorem 3.2.1

For any inner product space

$$||\langle \vec{v}, \vec{w} \rangle|| \leq ||\vec{v}|| ||\vec{w}|| \quad (3.9)$$

### Definition 3.2.1

If  $\vec{v}, \vec{w} \in V$ , we say  $\vec{v}$  and  $\vec{w}$  are orthogonal if  $\langle \vec{v}, \vec{w} \rangle = 0$

**Problem 11.** *Let's look at an example of checking orthogonality of two equations  $x, x^2 - \frac{1}{2} \in \mathbb{C}^0[0, 1]$ . In order to do this we need to find the  $L^2$  norm of the equations.*

$$\begin{aligned} \left\langle x, x^2 - \frac{1}{2} \right\rangle &= \int_0^1 x \left( x^2 - \frac{1}{2} \right) dx \\ &= \int_0^1 \left( x^3 - \frac{1}{2}x \right) dx \\ &= \left. \frac{1}{4}x^4 - \frac{1}{4}x^2 \right|_0^1 = 0. \end{aligned}$$

*Because the result of the inner product was zero, we know that  $x, x^2 - \frac{1}{2}$  are orthogonal in the  $L^2$  norm.*

### Theorem 3.2.2

The triangle inequality states that if  $V$  is an inner product space,

$$\| \langle \vec{v}, \vec{w} \rangle \| = \|\vec{v}\| + \|\vec{w}\| \quad (3.10)$$

Because we know that if we take the dot product of the same vector itself,  $\langle a, b, c \rangle \cdot \langle a, b, c \rangle$ , we get all of the items squared  $\langle a^2, b^2, c^2 \rangle$ , and because we know that  $\|\vec{v}\| = \sqrt{\langle \vec{v}, \vec{v} \rangle}$ , we get an idea of size. So we can define the unit ball to be

$$\{\vec{v} \in V \mid \|\vec{v}\| = 1\} \quad (3.11)$$

## §3.3 Norms

Equation (3.5) gives us the "size" of  $\vec{V}$ .

### Definition 3.3.1

A norm on  $V$  is a function  $\|\cdot\| : V \rightarrow \mathbb{R}$  such that

- $\|\vec{v}\| = 0$  if and only if  $\vec{v} = 0$

- $||c\vec{v}|| = |c| \cdot ||\vec{v}||$
- $||\vec{v} + \vec{w}|| \leq ||\vec{v}|| + ||\vec{w}||$

If  $||\langle \vec{v}, \vec{w} \rangle|| \leq ||\vec{v}|| ||\vec{w}||$ , then that is a norm. There are other norms to learn about.

**Problem 12.** Consider  $V = \mathbb{R}^n$ . We know that the magnitude of  $\vec{V}_p$  is

$$\sqrt[p]{|\vec{v}_1|^p + |\vec{v}_2|^p + |\vec{v}_3|^p}. \quad (3.12)$$

So if  $v = \mathbb{R}^2$ ,  $p = 2$  we have

$$||\langle x, y \rangle||_2 = \sqrt{x^2 + y^2}. \quad (3.13)$$

But if we were to have  $p = 3$ , we would have

$$||\langle x, y \rangle||_3 = \sqrt[3]{x^3 + y^3} \quad (3.14)$$

In  $||\cdot||_3$ , the size is  $\sqrt[3]{3^3 + 4^3} \approx 4.5$

In the 4 term,  $||\cdot||_4$ , the unit circle is the  $(x, y)$ 's such that  $\sqrt[4]{x^4 + y^4} = 1$

$$\boxed{x^4 + y^4 = 1} \quad (3.15)$$

Another norm on  $\mathbb{R}^n$  is the super-norm. This is where

$$||\langle x_1, x_2, \dots, x_n \rangle||_\infty = \max\{|x_1|, |x_2|, \dots, |x_n|\} \quad (3.16)$$

Here's a quick example: The super-norm for  $\langle 3, 4 \rangle$  is

$$||\langle 3, 4 \rangle||_\infty = 4 \quad (3.17)$$

because the maximum value in the set is 4.

Something to keep in mind is  $||\langle x, y \rangle|| = |x| + |y|$ .

### Theorem 3.3.1

Let  $||\cdot||_A$  and  $||\cdot||_B$  be two norms on  $\mathbb{R}^n$ . Then there exists positive

numbers  $0 < c < k$  such that

$$c \cdot \|\vec{v}\|_A < \|\vec{v}\|_B < k \cdot \|\vec{v}\|_A \quad (3.18)$$

Let's consider  $V \in \mathbb{R}^2$ . Let's take a look at  $\|\cdot\|_2$  and  $\|\cdot\|_\infty$ . Where  $\vec{V} = \langle v_1, v_2 \rangle$ .

$$\frac{1}{\sqrt{2}} \cdot \|\vec{v}\|_2 \leq \|\vec{v}\|_\infty < 1 \cdot \|\vec{v}\|_2 \quad (3.19)$$

We can also define norms on matrices.

### Theorem 3.3.2

If  $\|\cdot\|$  is a norm on  $\mathbb{R}^2$  and  $A$  is an  $m \times n$  matrix, then

$$\|A\| = \max\{\|A \cdot \vec{u}\| \mid \|\vec{u}\| = 1\} \quad (3.20)$$

These matrix norms satisfy the following:

1.  $\|A \cdot \vec{v}\| \leq \|A\| \cdot \|\vec{v}\|$
2.  $\|A \cdot B\| \leq \|A\| \cdot \|B\|$
3.  $\|A^k\| \leq \|A\|^k$

Let's take a quick look at  $\|A\|_\infty$

### Definition 3.3.2

The  $i^{th}$  absolute row sum of  $A$  is the sum of the absolute values of the entries in the  $i^{th}$  row.

### Theorem 3.3.3

$\|A\|_\infty$  the maximum absolute row sum.

Here's an example of using the  $\|A\|_\infty$  value. Let  $A = \begin{pmatrix} -3 & 2 \\ 5 & 4 \end{pmatrix}$ . We can determine that the maximum absolute row sum of  $A$  is 8. This is because we can do

$$|-3| + |2| = 5 \quad (3.21)$$

$$|5| + |4| = \boxed{8} \quad (3.22)$$

### §3.4 Positive Definite Matrices

Consider the following two equations:

$$\vec{x} = x_1\vec{e}_1 + x_2\vec{e}_2 + \dots + x_n\vec{e}_n \quad (3.23)$$

$$\vec{y} = y_1\vec{e}_1 + y_2\vec{e}_2 + \dots + y_n\vec{e}_n \quad (3.24)$$

We can analyze this as

$$\langle \vec{x}, \vec{y} \rangle = [x_1, x_2, \dots, x_n] \cdot \begin{bmatrix} k_{11} & \dots & k_{1n} \\ \vdots & \ddots & \vdots \\ k_{n1} & \dots & k_{nn} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots y_n \end{bmatrix} \quad (3.25)$$

$$k_{ij} = \langle e_i, e_j \rangle \quad (3.26)$$

$$= \vec{x}^T k \vec{y} \quad (3.27)$$

$$k = k^T \quad (3.28)$$

This means that  $k$  is symmetrical across the diagonal.

$$\begin{bmatrix} k_{11} & k_{12} & k_{13} \\ k_{12} & k_{22} & k_{23} \\ k_{13} & k_{23} & k_{33} \end{bmatrix} \quad (3.29)$$

#### Definition 3.4.1

A  $n \times n$  matrix  $A$  is a symmetrical positive definite matrix if  $A = A^T$  and  $x^T k x > 0$ .

**Theorem 3.4.1**

Every inner product on  $\mathbb{R}^n$  is given by  $\langle x, y \rangle = \vec{x}^T k \vec{y}$  where  $k$  is a symmetrical positive definite matrix. So  $\langle \vec{x}, \vec{y} \rangle$  is a dot product or a weighted product.

$$\langle \vec{x}, \vec{y} \rangle = \vec{x}^T k \vec{y} \quad (3.30)$$

$$k^T = k \quad (3.31)$$

$$\vec{v}^T k \cdot \vec{v} > 0 \quad (3.32)$$

$$\vec{v} \neq \vec{0} \quad (3.33)$$

Let's take a look at an example for this:

**Problem 13.** Let  $k = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$ . First we need to check to see if  $k^T = k$ . By just looking at  $k$ , we can see that  $k^T = k$ . Next we need to do the following calculation to see if  $\begin{bmatrix} x \\ y \end{bmatrix}$  is the weighted inner product of the matrix  $k$ .

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2x \\ 3x \end{bmatrix} \quad (3.34)$$

$$= 2x^2 + 2y^2 > 0 \quad (3.35)$$

$$\begin{bmatrix} x \\ y \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (3.36)$$

Therefore we know that

**Problem 14.** Let's consider the following problem

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 4 & -2 \\ -2 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (3.37)$$

If we let  $A$  be the numerical matrix, we can see that  $A^T = A$ . Let's simplify the equation from before



$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 4x - 2y \\ -2x + 3y \end{bmatrix} = 4x^2 - 2xy - 2xy + 3x^2 \quad (3.38)$$

$$= 4x^2 - 4xy + 3y^2 \quad (3.39)$$

$$(2x - y)^2 + 2y^2 > 0 \begin{bmatrix} x \\ y \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad (3.40)$$

Now we can see that this is a positive definite matrix.

If we are given a symmetric matrix,  $k$ , the polynomial  $x^T k x$  is a quadratic form of  $k$ .

**Problem 15.** Let's consider  $k = \begin{bmatrix} 1 & -3 \\ -3 & 2 \end{bmatrix}$ . Let's find the quadratic form of  $k$ . First we need to write  $k$  like so:

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & -3 \\ -3 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} x - 3y \\ -3x + 2y \end{bmatrix} \quad (3.41)$$

$$= x^3 - 3xy - 3xy + 2y^2 \quad (3.42)$$

$$= x^3 - 6xy + 2y^2 \quad (3.43)$$

$$(3.44)$$

Therefore we know that the quadratic form of  $k$  is  $x^3 - 6xy - 2y^2$ .

For a positive definite matrix,  $k = k^T$  and  $x^T k x > 0$  for all  $\vec{x} \neq 0$

### Theorem 3.4.2

Every inner product in  $\mathbb{R}^n$  is given by

$$\langle x, y \rangle = x^T k y \text{ for } x, y \in \mathbb{R}^n \quad (3.45)$$

Let  $v$  be an inner product space and  $\vec{v}_1, \dots, \vec{v}_2$ . The gram matrix of  $v$

is

$$K = \begin{bmatrix} \langle v_1, v_1 \rangle & \langle v_1, v_2 \rangle & \dots & \langle v_1, v_n \rangle \\ \langle v_2, v_1 \rangle & \langle v_2, v_2 \rangle & \dots & \langle v_2, v_n \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle v_n, v_1 \rangle & \langle v_n, v_2 \rangle & \dots & \langle v_n, v_n \rangle \end{bmatrix} \quad (3.46)$$

### Definition 3.4.2

A is a matrix that is  $n \times n$ . A is a positive semidefinite matrix if  $A^T = A$  and  $\vec{x}^T A \vec{x} \geq 0$

### Theorem 3.4.3

All gram matrices are positive semi-definite. They are positive definite if and only if  $\vec{v}_1, \dots, \vec{v}_n$  are linearly independent.

Suppose we are in  $\mathbb{R}^m$  and the inner product is the dot product. Let  $\vec{v}_1, \dots, \vec{v}_n \in \mathbb{R}^m$ . Let  $A = [\vec{v}_1, \vec{v}_2, \vec{v}_3, \dots, \vec{v}_n]$ . Then  $K = A^T A$ . Let A be a gram matrix generated by  $v_1, \dots, v_n$  with the dot product.

$$K = A^T A = \begin{bmatrix} \vec{v}_1 \\ \vec{v}_2 \\ \vdots \\ \vec{v}_n \end{bmatrix} \begin{bmatrix} \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_n \end{bmatrix} \quad (3.47)$$

$$= \begin{bmatrix} \langle v_1, v_1 \rangle & \langle v_1, v_2 \rangle & \dots & \langle v_1, v_n \rangle \\ \langle v_2, v_1 \rangle & \langle v_2, v_2 \rangle & \dots & \langle v_2, v_n \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle v_n, v_1 \rangle & \langle v_n, v_2 \rangle & \dots & \langle v_n, v_n \rangle \end{bmatrix} \quad (3.48)$$

### Proposition 3.4.1

Given an  $m \times n$  matrix A. The following are true

1. The  $m \times n$  matrix  $k = A^T A$  is positive definite.
2. A has linearly independent columns.

3.  $\text{rank}(A) = n$
4.  $\text{Ker}(A) = \{0\}$

**Theorem 3.4.4**

Every inner product on  $\mathbb{R}^n$  is given by

$$\langle \vec{x}, \vec{y} \rangle = \vec{x}^T \cdot C \vec{y} \quad (3.49)$$

where  $C$  is a symmetric, positive definite  $n \times n$  matrix.

Let  $\vec{v}_1, \dots, \vec{v}_n \in \mathbb{R}^n$ . Let  $A = [\vec{v}_1 : \vec{v}_2 : \dots : \vec{v}_n]$ . Then  $K = A^T C A$  is the gram matrix with respect to the inner product  $\vec{v}^T C \vec{w}$ .

**Theorem 3.4.5**

Suppose  $A$  is an  $m \times n$  matrix with linearly independent columns. Suppose  $C$  is any positive definite  $m \times m$  matrix. Then  $\vec{v}^T C \vec{w}$

**Definition 3.4.3**

The hilbert matrix  $H = (h_{ij})$  where  $h_{ij} = \frac{1}{i+j-1}$

The  $3 \times 3$  hilbert matrix:

$$\begin{bmatrix} \frac{1}{1} & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \end{bmatrix} \quad (3.50)$$

**Problem 16.** Make a gram matrix, not in  $\mathbb{R}^m$ . Let  $V = \mathbb{C}^0[0, 1]$ . Use the  $L^2$  inner product.

$$\langle f, g \rangle = \int_0^1 f(x)g(x)dx. \quad (3.51)$$

$1, x, x^2$  are linearly independent.

$$\langle v_i, v_k \rangle = \int_0^1 x^{i-1} x^{j-1} dx \quad (3.52)$$

$$= \int_0^1 x^{i+j-2} dx \quad (3.53)$$

$$= \frac{1}{i+j-1} x^{i+j-1} \quad (3.54)$$

$$= \frac{1}{i+j-1} \quad (3.55)$$

$$\rightarrow \begin{bmatrix} \frac{1}{1} & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \end{bmatrix}. \quad (3.56)$$

## Chapter 4

# Orthogonality

### §4.1

Recall that

$$\vec{v} \cdot \vec{w} = v_1 \cdot w_1 + \dots + v_n \cdot w_n = \|\vec{v}\| \|\vec{w}\| \cos(\theta), \quad (4.1)$$

where  $\theta$  is the angle between  $\vec{v}$  and  $\vec{w}$ . Because  $\cos\left(\frac{\pi}{2}\right) = 0$ , we know that  $\vec{v} \cdot \vec{w} = 0$  if and only if  $\vec{v}$  is orthogonal to  $\vec{w}$ . In general, given  $\vec{v}, \vec{w} \in \mathbb{R}^n$ ,  $\vec{v}$  is orthogonal to  $\vec{w}$  if and only if the angle between them is  $\frac{\pi}{2}$ .

#### Definition 4.1.1

Let  $U$  be any inner product space. A basis  $\vec{u}_1, \dots, \vec{u}_n \in U$  is orthogonal if  $\vec{u}_j \cdot \vec{u}_i = 0$  whenever  $i \neq j$ .

In addition, if  $\|\vec{u}_i\| = 1$  for all  $i$ 's, the basis is orthonormal.

Here are a few examples of orthonormal and orthogonal basis's:

1.  $\begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}$  is an orthonormal basis.
2.  $\begin{pmatrix} 2 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}$  is an orthogonal basis.
3.  $\begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$  is an orthonormal basis.

If  $\vec{v}_1, \dots, \vec{v}_n$  is an orthogonal basis, then

$$\frac{\vec{v}_1}{\|\vec{v}_1\|}, \frac{\vec{v}_2}{\|\vec{v}_2\|}, \dots, \frac{\vec{v}_n}{\|\vec{v}_n\|} \quad (4.2)$$

is an orthonormal basis.

**Problem 17.** Consider  $\vec{u}_1 = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$  and  $\vec{u}_2 = \begin{pmatrix} 2 \\ -1 \end{pmatrix}$ . We know that these two matrices are not linearly dependent because  $\vec{u}_1$  is not a multiple of  $\vec{u}_2$ . We can see that this is an orthogonal basis.

$$\|\vec{u}_1\| = \sqrt{1^2 + 2^2} = \sqrt{5} \quad (4.3)$$

so we know

$$v_1 = \begin{pmatrix} \frac{1}{\sqrt{5}} \\ \frac{2}{\sqrt{5}} \end{pmatrix}, v_2 = \begin{pmatrix} \frac{2}{\sqrt{5}} \\ -\frac{1}{\sqrt{5}} \end{pmatrix} \quad (4.4)$$

#### Proposition 4.1.1

Assume  $\vec{v}_1, \dots, \vec{v}_n \in V$  with  $\vec{v}_i \neq \vec{0}$  for all  $i$ . Assume that  $\langle v_i, v_j \rangle = 0$  whenever  $i \neq j$ , then  $\{v_1, \dots, v_n\}$  is linearly independent.

**Proof.** Assume that  $c_1\vec{v}_1 + \dots + c_n\vec{v}_n = \vec{0}$ . Let  $i \in \{1, \dots, n\}$

$$\begin{aligned} \langle c_1\vec{v}_1 + \dots + c_n\vec{v}_n, v_i \rangle &= \langle \vec{0}, v_i \rangle \\ c_1 \langle v_1, v_i \rangle + c_2 \langle v_2, v_i \rangle + \dots + c_i \langle v_i, v_i \rangle + \dots + c_n \langle v_n, v_i \rangle &= 0 \\ c_i \langle v_i, v_i \rangle &= 0 \\ c_i &= 0. \end{aligned}$$

Now we know that  $v_1, \dots, v_n$  are linearly independent. ■

#### Corollary 4.1.1

If  $\dim(V) = n$  and  $\vec{v}_1, \dots, \vec{v}_n$  are  $n$  vectors such that  $\langle v_i, v_j \rangle = 0$  whenever  $i \neq j$ , then  $\{\vec{v}_1, \dots, \vec{v}_n\}$  is a basis.

#### Theorem 4.1.1

Let  $\vec{u}_1, \dots, \vec{u}_n$  be an orthonormal basis for  $V$ . Let  $\vec{v} \in V$ . Then we know

$\vec{v} = c_1\vec{u}_1 + \dots + c_n\vec{u}_n$ . In fact,  $c_i = \langle \vec{v}, \vec{u}_i \rangle$  and

$$\|\vec{v}\| = \sqrt{\langle \vec{v}, \vec{u}_1 \rangle^2 + \langle \vec{v}, \vec{u}_2 \rangle^2 + \dots + \langle \vec{v}, \vec{u}_n \rangle^2} \quad (4.5)$$

**Problem 18.**  $\mathbb{P}^2$  polynomials of degree  $\leq 2$  on  $[0,1]$ . Use the  $L^2$  norm.

$$\langle p, q \rangle = \int_0^1 p(x)q(x)dx \quad (4.6)$$

Let  $p_1 = 1, p_2 = x - \frac{1}{2}, p_3 = x^2 - x + \frac{1}{6}$ .

$$\langle p_1, p_2 \rangle = \int_0^1 x - \frac{1}{2} dx = 0 \quad (4.7)$$

$$\langle p_1, p_3 \rangle = \int_0^1 x^2 - x + \frac{1}{6} dx = 0. \quad (4.8)$$

We have an orthogonal basis because of this. In order to check to see if it is orthonormal we must also do  $\langle p_1, p_1 \rangle, \langle p_2, p_2 \rangle, \langle p_3, p_3 \rangle$

## Chapter 5

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# Mimization and Least Squares

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## Chapter 6

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# Equilibrium

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## Chapter 7

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# Linearity

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## Chapter 8

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# Eigenvalues and Singular Values

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## Chapter 9

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# Iteration

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## Chapter 10

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# Dynamics

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