# *Applied Linear Algebra*

MATH363

Dr. McKenzie

*Gonzaga University*

Edited by

Cameron Williamson

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# Linear Algebraic Systems

## Chapter 2

# Vector Spaces and Bases

## §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 $c$v$\in V$

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=($c$v) + ($d$v), and $c$(v+w)=($c$v)+($c$w).
- Assosiativity of Scalar Multiplication: $c(d$v) = ($cd$)v.

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

- $\mathbb{R}^n = \left\{ \begin{pmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{pmatrix} \middle| r_1, r_2, r_n \in \mathbb{R} \right\}$
- $M_{m \times n}$ = 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 $V = \mathbb{R}^3 = \left\{ \begin{pmatrix} a \\ b \\ c \end{pmatrix} \middle| a, b, c \in \mathbb{R} \right\}$. $V$ is a vector space. If we let $W = \left\{ \begin{pmatrix} a \\ b \\ 0 \end{pmatrix} \middle| a, b \in \mathbb{R} \right\}$, then $W$ is a subspace of $V$.

**Theorem 2.1.2**

et $V$ 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 $\left(\begin{smallmatrix} a \\ b \\ c \end{smallmatrix}\right)$. We can determine the following:

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

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

- $\mathbb{C}^\infty(I)$ = functions from $I \to \mathbb{R}$ 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 $f(a) + \frac{f'(a)(x-a)}{1!} + \frac{f''(a)(x-a)^2}{2!} + \ldots$ 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* $\vec{v_1} = \begin{pmatrix} x_1 \\ y_1 \\ 2x_1+y_1 \end{pmatrix}, \vec{v_2} = \begin{pmatrix} x_2 \\ y_2 \\ 2x_2+y_1 \end{pmatrix} \in V$

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

*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 $\vec{v_1}, \ldots, \vec{v_n} \in V$, then we can determine that the

$$span(\{\vec{v_1}, \ldots, \vec{v_n}\}) = \{c_1\vec{v_1} + \cdots + c_n\vec{v_n} | c_1, \ldots, c_n \in \mathbb{R}\} \quad (2.2)$$

**Proposition 2.3.1**

The span of $\{\vec{v_1}, \vec{v_2}\}$ is a subspace of $V$.

**Proof.**

$$c_1\vec{v_1} + \cdots + c_n\vec{v_n} \tag{2.3}$$
$$k_1\vec{v_1} + \cdots + k_n\vec{v_n} \in span \tag{2.4}$$
$$\tag{2.5}$$

If we add together both of the equations above we get

$$(c_1 + k_1)\vec{v_1} + \cdots + (c_n + k_n)\vec{v_n} \in span. \tag{2.6}$$
$$r(c_1\vec{v_1} + \cdots + c_n\vec{v_n}) \tag{2.7}$$
$$= rc_1\vec{v_1} + \cdots + rc_n\vec{v_n} \in span \tag{2.8}$$

■

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

$$\vec{v_1} = \begin{pmatrix}1\\2\\0\end{pmatrix}, span(\vec{v_1}) = \left\{ c\begin{pmatrix}1\\2\\0\end{pmatrix} \middle| c \in \mathbb{R} \right\} \tag{2.9}$$

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

$$c\begin{pmatrix}1\\2\\0\end{pmatrix} \tag{2.10}$$

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

$$\begin{pmatrix} c \\ 2c \\ 0 \end{pmatrix} \tag{2.11}$$

$$x = c \tag{2.12}$$

$$y = 2c \tag{2.13}$$

$$\frac{1}{2}y = c \tag{2.14}$$

$$\rightarrow x = \frac{1}{2}y \tag{2.15}$$

$$\rightarrow y = 2x \tag{2.16}$$

$$\tag{2.17}$$

*Now we are going to let* $\vec{v_2} = \left(\begin{smallmatrix} 1 \\ 1 \\ 0 \end{smallmatrix}\right)$. *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 span$\vec{v}$ is a line.

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

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

**Definition 2.3.1**

Let $v$ be a vector space. $\vec{v_1}, \ldots, \vec{v_n}$ are linearly dependant if there exists $c_1, \ldots, c_n$ are not all zero, such that $c_1\vec{v_1} + \cdots + c_n\vec{v_n} = \vec{0}$, otherwise, $\vec{v_1}, \ldots, \vec{v_n}$ are linearly independent.

If we let $\vec{v_1} = \left(\begin{smallmatrix} 1 \\ 2 \end{smallmatrix}\right), \vec{v_2} = \left(\begin{smallmatrix} 2 \\ 4 \end{smallmatrix}\right)$, 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 $2\vec{v_1} + -1\vec{v_2} = 0$. 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*

$$\vec{v_1} = \begin{pmatrix} 1 \\ 2 \\ 1 \end{pmatrix}, \vec{v_2} = \begin{pmatrix} 2 \\ 1 \\ 1 \end{pmatrix}, \vec{v_3} = \begin{pmatrix} 8 \\ 1 \\ 11 \end{pmatrix} \tag{2.18}$$

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

$$c_1\vec{v_1} + c_2\vec{v_2} + c_3\vec{v_3} = \vec{0} \tag{2.19}$$

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

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

$$= \begin{pmatrix} 1 & 2 & 8 & \vdots & 0 \\ 2 & -1 & 1 & \vdots & 0 \\ 1 & 3 & 0 & \vdots & 0 \end{pmatrix} \tag{2.21}$$

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

$$\begin{pmatrix} 1 & 2 & 8 & \vdots & 0 \\ 9 & 1 & 3 & \vdots & 0 \\ 0 & 0 & 0 & \vdots & 0 \end{pmatrix} \tag{2.22}$$

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

$$1c_1 + 2c_2 + 8c_3 = 0 \tag{2.23}$$
$$c_1 + 3c_3 = 0 \tag{2.24}$$
$$\tag{2.25}$$
$$c_3 = -3c_3 \tag{2.26}$$
$$c_1 = -2c_3 \tag{2.27}$$
$$c_3 = c_3 \tag{2.28}$$

*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 $\vec{v_1}, \ldots, \vec{v_n}$ that 1. span $v$ and 2. are linearly dependent.

**Problem 5.** *If we are looking at* $\mathbb{R}^2$*, with* $e_1 = \left(\begin{smallmatrix}1\\0\end{smallmatrix}\right)$*, and* $e_2 = \left(\begin{smallmatrix}0\\1\end{smallmatrix}\right)$ *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:*

$$a \times e_1 + b \times e_2 = \begin{pmatrix} a \\ b \end{pmatrix} \tag{2.29}$$

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

$$c_1\vec{e_1} + c_2\vec{e_2} + c_3\vec{e_3} = 0 \tag{2.30}$$

$$c_1 = c_2 = c_3 = 0 \tag{2.31}$$

*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 $v = n$

**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 $v = n$

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 dependent.

**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**

$\vec{v_1}, \ldots \vec{v_2}$ form a basis of $v$ if and only if for all $\vec{v} \in v$, there exist unique $c_1, \ldots, c_n$ such that $\vec{v} = c_1\vec{v_1} + \ldots c_n\vec{v_n}$

**Problem 8.** *Let $v = \mathbb{R}^2$. Let $\vec{v} = \left(\begin{smallmatrix}4\\3\end{smallmatrix}\right)$. We know from previous problems that $\left(\begin{smallmatrix}1\\0\end{smallmatrix}\right)\left(\begin{smallmatrix}0\\1\end{smallmatrix}\right)$ 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*

$$4\begin{pmatrix}1\\0\end{pmatrix} + \begin{pmatrix}0\\1\end{pmatrix} = \begin{pmatrix}4\\3\end{pmatrix}. \tag{2.36}$$

*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,*

$$\left\{\begin{pmatrix}1\\-3\end{pmatrix}, \begin{pmatrix}2\\-1\end{pmatrix}\right\} \tag{2.37}$$

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

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

$$\tag{2.39}$$

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

$$\left\{\begin{pmatrix}1\\-3\end{pmatrix}, \begin{pmatrix}2\\-1\end{pmatrix}\right\} \tag{2.40}$$

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

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

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

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

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

$$\begin{bmatrix} 1 & 2 & \vdots & 4 \\ 0 & 5 & \vdots & 5 \end{bmatrix} \tag{2.43}$$

$$5b = 15 \qquad a + 2b = 4 \tag{2.44}$$

$$b = 3 \qquad 1 + 2 * 3 = 4 \tag{2.45}$$

$$a = -2 \tag{2.46}$$

## §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.*

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

*When we multiply our the matrix, we see that the span of the columns give us all the possible $\left[\begin{smallmatrix} x \\ y \end{smallmatrix}\right]$ values. The span of the matrix*

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

*would be the values $\left[\begin{smallmatrix} 1 \\ 4 \end{smallmatrix}\right]$, $\left[\begin{smallmatrix} 2 \\ 5 \end{smallmatrix}\right]$, and $\left[\begin{smallmatrix} 3 \\ 6 \end{smallmatrix}\right]$*

**Definition 2.5.2**

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

$$A = Ker(A) \tag{2.49}$$
$$= \{\vec{x} | A\vec{x} = \vec{0}\} \tag{2.50}$$

Using definition (2.5.2), if $A = \left[\begin{smallmatrix} 1 & 0 \\ 5 & 0 \end{smallmatrix}\right]$, then

$$\vec{x_1} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \vec{x_2} = \begin{bmatrix} 0 \\ 5 \end{bmatrix}. \tag{2.51}$$

Something to keep in mind: If $\vec{x_1}, \vec{x_2} \in Ker(A)$, then $r_1\vec{x_1} + r_2\vec{x_2} \in Ker(A)$. 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 $z \in Ker(A)$

**Proposition 2.5.1**

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

1. $Ker(A) = \{\vec{0}\}$
2. $rank(A) = n$
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 $m \times n$.

$$coimg(A) = img(A^T) \tag{2.52}$$
$$coker(A) = ker(A^T) \tag{2.53}$$
$$\tag{2.54}$$

The image of $A$ is the span of its collumns. Thus the coimage is the span of its radius. Also the $\vec{r^T}$ in the cokernel of $A$ are those $\vec{r}$ such that $r \times A = \vec{0^T}$ since

$$(r \cdot A)^T = (\vec{0^T})^T \tag{2.55}$$
$$A^T \cdot r^T = \vec{0} \tag{2.56}$$

**Theorem 2.5.2**

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

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

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

$$dim(ker(A)) = n - r \tag{2.59}$$

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

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

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

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

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

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, $rank(A) = 0$. 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 $A$:

$$\begin{aligned} dim(ker(A)) + rank &= n & (2.63) \\ dim(key(A)) + 2 &= 4 & (2.64) \\ & & (2.65) \end{aligned}$$

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

$$\begin{aligned} w + 2x + 3y - z &= 0 & (2.66) \\ -3x - 3y + 3z &= 0 & (2.67) \\ x + y - z &= 0 & (2.68) \\ x &= -y + z & (2.69) \end{aligned}$$

$$\begin{aligned} w &= -2x - 3y + z & (2.70) \\ &= -2(-y + z) - 3y + z & (2.71) \\ &= -y - z & (2.72) \end{aligned}$$

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

$$\begin{pmatrix} -y - z \\ -y + z \\ y \\ z \end{pmatrix} = \begin{pmatrix} -y \\ -y \\ -y \\ 0 \end{pmatrix} + \begin{pmatrix} -z \\ z \\ 0 \\ z \end{pmatrix} = y \begin{pmatrix} -1 \\ -1 \\ 1 \\ 0 \end{pmatrix} + z \begin{pmatrix} -1 \\ 1 \\ 0 \\ 1 \end{pmatrix} \tag{2.73}$$

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 $< v_1, v_2, \ldots, v_n > \cdot < w_1, w_2, \ldots, w_3 >$ to show that the dot product is an inner product.

$$= v_1 w_1 + v_2 w_2 + \ldots + v_n w_n \tag{3.1}$$

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

$$\vec{v} \cdot \vec{v} = v_1^2 + v_2^2 + \ldots + v_n^2 \tag{3.2}$$

In general, we can assume that $||\vec{v}|| = \sqrt{\vec{v}\vec{v}}$. 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 $<, >: v \times v \to \mathbb{R}$ such that

-
$$< c\vec{u} + d\vec{v}, w > = c < \vec{u}, \vec{v} > + d < \vec{v}, \vec{u} > \tag{3.3}$$
$$< \vec{u}, c\vec{v} + d\vec{w} = c < \vec{u}, \vec{v} > + d < \vec{u}, \vec{w} > \tag{3.4}$$
- $< \vec{v}, \vec{w} > = < \vec{w}, \vec{v} >$
- $< \vec{v}, \vec{v} > \geq_0$ while $< 0, 0 > = \vec{0}$.

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

$$||\vec{v}|| = \sqrt{< \vec{v}, \vec{v} >} \tag{3.5}$$

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 $< \vec{v}, \vec{w} >$ as $r_1 v_1 w_1 + r_2 v_2 w_2 + r_3 v_3 w_3$

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

$$< f(x), g(x) >= \int_a^b f(x)g(x)dx \tag{3.6}$$

*This is an inner product, so we also know that*

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

*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

$$||\vec{v} \cdot \vec{w}|| \leq ||\vec{v}|| ||\vec{w}|| \tag{3.8}$$

This is the Cauchy-Shuartz inequality.

**Theorem 3.2.1**

For any inner product space

$$|| < \vec{v}, \vec{w} > || \leq ||\vec{v}|| ||\vec{w}|| \tag{3.9}$$

**Definition 3.2.1**

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

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

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

*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,

$$|| < \vec{v}, \vec{w} > || = ||\vec{v}|| + ||\vec{w}|| \tag{3.10}$$

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

$$\{\vec{v} \in V \Big| ||\vec{v}|| = 1\} \tag{3.11}$$

## §3.3 Norms

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

**Definition 3.3.1**

A norm on $V$ is a function $|| \cdot || : V \to \mathbb{R}$ 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 $|| < \vec{v}, \vec{w} > || \leq ||\vec{v}||||\vec{w}||$, 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*

$$\sqrt[p]{|\vec{v_1}|^p + |\vec{v_2}|^p + |\vec{v_3}|^p}. \tag{3.12}$$

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

$$|| < x, y > ||_2 = \sqrt{x^2 + y^2}. \tag{3.13}$$

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

$$|| < x, y > ||_3 = \sqrt[3]{x^3 + y^3} \tag{3.14}$$

*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 $\sqrt[4]{x^4 \cdot Y_4} = 1$

$$\boxed{x^4 + y^4 = 1} \tag{3.15}$$

Another norm on $R^n$ is the super-norm. This is where

$$|| < x_1, x_2, \ldots, x_n > ||_\infty = max\{|x_1|, |x_2|, \ldots, |x_n|\} \tag{3.16}$$

Here's a quick example: The super-norm for $< 3, 4 >$ is

$$|| < 3, 4 > ||_\infty = 4 \tag{3.17}$$

because the maximum value in the set is 4.
Something to keep in mind is $|| < x, y > || = |x| + |y|$.

**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

$$c \cdot ||\vec{v}||_A < ||\vec{v}||_B < k \cdot ||\vec{v}||_A \tag{3.18}$$

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

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

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

$$||A|| = max\{||A \cdot \vec{u}|| \Big| ||\vec{u}|| = 1 \tag{3.20}$$

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 $A = \left(\begin{smallmatrix} -3 & 2 \\ 5 & 4 \end{smallmatrix}\right)$. We can determine that the maximum absolute row sum of $A$ is 8. This is because we can do

$$|-3| + |2| = 5 \tag{3.21}$$
$$|5| + |3| = \boxed{8} \tag{3.22}$$

## §3.4 Positive Definite Matrices

Consider the following two equations:

$$\vec{x} = x_1\vec{e_1} + x_2\vec{e_2} + \ldots + x_n\vec{e_n} \tag{3.23}$$
$$\vec{y} = y_1\vec{e_1} + y_2\vec{e_2} + \ldots + v_n\vec{e_n} \tag{3.24}$$

We can analyze this as

$$< \vec{x}, \vec{y} >= [x_1, x_2, \ldots, x_n] \cdot \begin{bmatrix} k_{11} & \ldots & k_{1n} \\ \vdots & \ddots & \vdots \\ k_{n_1} & \ldots & k_{nn} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots y_n \end{bmatrix} \tag{3.25}$$

$$k_{ij} =< e_i, e_j > \tag{3.26}$$
$$= \vec{x}^T k \vec{y} \tag{3.27}$$
$$k = k^T \tag{3.28}$$

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

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

**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 $< x, y >= \vec{x}^T k \vec{y}$ where $k$ is a symmetrical positive definite matrix. So $< \vec{x}, \vec{y} >$ is a dot product or a weighted product.

$$< \vec{x}, \vec{y} > = \vec{x}^T k \vec{y} \tag{3.30}$$
$$k^T = k \tag{3.31}$$
$$\vec{v}^T k \cdot \vec{v} > 0 \tag{3.32}$$
$$\vec{v} \neq_0 \tag{3.33}$$

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

**Problem 13.** *Let $k = \left[\begin{smallmatrix} 2 & 0 \\ 0 & 3 \end{smallmatrix}\right]$. 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 $\left[\begin{smallmatrix} x \\ y \end{smallmatrix}\right]$ is the weighted inner product of the matrix $k$.*

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2x \\ 3x \end{bmatrix} \tag{3.34}$$
$$= 2x^2 + 2y^2 > 0 \tag{3.35}$$
$$\begin{bmatrix} x \\ y \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \end{bmatrix} \tag{3.36}$$

*Therefore we know that*

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

$$\begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 4 & -2 \\ -2 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{3.37}$$

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

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

$$= 4x^2 - 4xy + 3y^2 \tag{3.39}$$

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

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

If we are given a symmetric matrix, $k$, the polynomial $x^T kx$ 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:*

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

$$= x^3 - 3xy - 3xy + 2y^2 \tag{3.42}$$

$$= x^3 - 6xy + 2y^2 \tag{3.43}$$

$$\tag{3.44}$$

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

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

**Theorem 3.4.2**

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

$$< x, y >= x^T ky \text{ for } xy \in \mathbb{R}^n \tag{3.45}$$

Let $v$ be an inner product space and $\vec{v_1}, \ldots, \vec{v_2}$. The gram matrix of $v$

is

$$K = \begin{bmatrix} < v_1, v_2 > & < v_1, v_2 > & \dots & < v_1, v_n > \\ < v_2, v_1 > & < v_2, v_2 > & \dots & < v_2, v_n > \\ \vdots & \vdots & \ddots & \vdots \\ < v_n, v_1 > & < v_n, v_2 > & \dots & < v_n, v_n > \end{bmatrix} \tag{3.46}$$

**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 $R^m$ and the inner produt is the dot product. Let $\vec{v_1}, \dots \vec{v_n} \in \mathbb{R}^m$
Let $A = [v_1, v_2, v_3, \dots, v_n]$. Then $K = A^T$. Let A be a gram matrix generated by $v_1, \dots, v_n$ with the dot product.

$$K = A^T A = \begin{bmatrix} \vec{v_1} \\ \vec{v_2} \\ \vdots \\ \vec{v_n} \end{bmatrix} \begin{bmatrix} \vec{v_1} & \vec{v_2} & \dots & \vec{v_n} \end{bmatrix} \tag{3.47}$$

$$= \begin{bmatrix} < v_1, v_1 > & < v_1, v_2 > & \dots & < v_1, v_n > \\ < v_2, v_1 > & < v_2, v_2 > & \dots & < v_2, v_n > \\ \vdots & \vdots & \ddots & \vdots \\ < v_n, v_1 > & < v_n, v_2 > & \dots & < v_n, v_n > \end{bmatrix} \tag{3.48}$$

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

**Theorem 3.4.4**

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

$$< \vec{x}, \vec{y} >= \vec{x}^T \cdot c\vec{y} \tag{3.49}$$

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

Let $\vec{v_1}, \ldots, \vec{v_n} \in \mathbb{R}^n$. Let $A = [\vec{v_1} \vdots \vec{v_2} \vdots \ldots \vdots \vec{v_n}]$. 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 collumns. 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:

$$\begin{bmatrix} \frac{1}{1} & \frac{1}{2} & \frac{1}{3} \\ \frac{1}{2} & \frac{1}{3} & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{4} & \frac{1}{5} \end{bmatrix} \tag{3.50}$$

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

$$< f, g >= \int_0^1 f(x)g(x)dx. \tag{3.51}$$

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

$$< v_i, v_k > = \int_0^1 x^{i-1} x^{j-1} dx \tag{3.52}$$

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

$$= \frac{1}{i+j-1} x^{i+j-1} \tag{3.54}$$

$$= \frac{1}{i+j-1} \tag{3.55}$$

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

# Chapter 4

# Orthogonality

## §4.1

Recall that

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

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**

et $U$ be any inner product space. A basis $\vec{u}, \ldots, \vec{u_h} \in V$ is orthogonal if $\vec{u_j} \cdot \vec{u_i} = 0$ whenever $i \neq j$.
In addition, if $||u_i|| = 1$ for all $i$'s, the basis is orthonormal.

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

1. $\binom{1}{0}\binom{0}{1}$ is an orthonormal basis.
2. $\binom{2}{0}\binom{0}{1}$ 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 $\vec{v_1}, \ldots, \vec{v_n}$ is an orthogonal basis, then

$$\frac{\vec{v_1}}{||\vec{v_1}||}, \frac{\vec{v_2}}{||\vec{v_2}||}, \ldots, \frac{\vec{v_n}}{||v_n||} \tag{4.2}$$

is an orthonormal basis.

**Problem 17.** *Consider* $\vec{u_1} = \binom{1}{2}$ *and* $\vec{u_2} = \binom{2}{-1}$. *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.*

$$||\vec{u_1}|| = \sqrt{1^2 + 2^2} = \sqrt{5} \tag{4.3}$$

*so we know*

$$v_1 = \begin{pmatrix} \frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \end{pmatrix}, v_2 = \begin{pmatrix} \frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} \end{pmatrix} \tag{4.4}$$

**Proposition 4.1.1**

ssume $\vec{v_1}, \ldots, \vec{v_n} \in V$ with $\vec{v_i} \neq \vec{0}$ for all $i$. Assume that $< v_i, v_j \geq 0$ whenever $i \neq j$, then $\{v_1, \ldots, v_n\}$ is linearly independent.

**Proof.** Assume that $c_1\vec{v_1} + \ldots + c_n\vec{n} = 0$. Let $i \in \{1, \ldots, n\}$

$$\begin{aligned} < c_1\vec{v_1} + \ldots + c_n\vec{v_n}, v_i >=< 0, \vec{v_i} > \\ c_1 < v_1, v_i > +c_2 < v_2, v_i > + \ldots + c_i < v_i, v_i > + \ldots + c_n < v_i, v_n > \\ c_i < v_i, v_i >= 0 \\ c_i = 0. \end{aligned}$$

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

**Corollary 4.1.1**

f $dim(v) = n$ and $\vec{v_1}, \ldots, \vec{v_n}$ are $n$ vectors such that $< v_i, v_j >= 0$ wherever $i \neq j$, then $\{\vec{v_1}, \ldots, \vec{v_n}\}$ is a basis.

**Theorem 4.1.1**

et $\vec{u_1}, \ldots, \vec{u_n}$ be an orthonormal basis for $v$. Let $\vec{v} \in V$. Then we know

$\vec{v} = c_1\vec{u_1} + \ldots + c_n\vec{u_n}$. In fact, $c_i =< \vec{v}, \vec{u_i} >$ and

$$||\vec{v}|| = \sqrt{< \vec{v}, \vec{u_1}, >^2 + < \vec{v}, \vec{u_2}^2 + < \vec{v}, \vec{u_n} >^2} \tag{4.5}$$

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

$$< p, q >= \int_0^1 p(x)q(x)dx \tag{4.6}$$

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

$$< p_1, p_2 > = \int_0^1 x - \frac{1}{2}dx = 0 \tag{4.7}$$

$$< p_1, p_3 > = \int_0^1 x^2 - x + \frac{1}{6}dx = 0. \tag{4.8}$$

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

INSERT NOTES FROM 03.08 HERE
So if we have the basis $\{\binom{1}{2}, \binom{2}{1}\}, v_1 = \binom{1}{2}$. $v_2$ is equal to

$$
\begin{aligned}
\begin{pmatrix}2\\1\end{pmatrix} - \frac{\left\langle \begin{pmatrix}2\\1\end{pmatrix}, \begin{pmatrix}1\\2\end{pmatrix} \right\rangle}{|| \begin{pmatrix}1\\2\end{pmatrix}} \cdot \begin{pmatrix}1\\2\end{pmatrix} \\
\begin{pmatrix}2\\1\end{pmatrix} - \frac{4}{\left(\sqrt{1^2+2^2}\right)^2} \\
\begin{pmatrix}2\\1\end{pmatrix} - \frac{4}{5}\begin{pmatrix}1\\2\end{pmatrix} \\
\begin{pmatrix}2\\1\end{pmatrix} - \begin{pmatrix}\frac{4}{5}\\\frac{8}{5}\end{pmatrix} = \begin{pmatrix}\frac{10}{5}\\\frac{5}{5}\end{pmatrix} - \begin{pmatrix}\frac{4}{5}\\\frac{8}{5}\end{pmatrix} \\
= \begin{pmatrix}\frac{6}{3}\\-\frac{3}{5}\end{pmatrix} \begin{pmatrix}2\\1\end{pmatrix} - \frac{< \begin{pmatrix}2\\1\end{pmatrix}, \begin{pmatrix}1\\2\end{pmatrix} >}{||\begin{pmatrix}1\\2\end{pmatrix}||^2} \cdot \begin{pmatrix}1\\2\end{pmatrix} \begin{pmatrix}2\\1\end{pmatrix} - \frac{4}{(\sqrt{1^2+2^2})^2} \\
\begin{pmatrix}2\\1\end{pmatrix} - \frac{4}{5}\begin{pmatrix}1\\2\end{pmatrix} \\
\begin{pmatrix}2\\1\end{pmatrix} - \begin{pmatrix}\frac{4}{5}\\\frac{8}{5}\end{pmatrix} = \begin{pmatrix}\frac{10}{5}\\\frac{5}{5}\end{pmatrix} - \begin{pmatrix}\frac{4}{5}\\\frac{8}{5}\end{pmatrix} \\
\begin{pmatrix}\frac{6}{3}\\-\frac{3}{5}\end{pmatrix} \\
.
\end{aligned}
$$

We can conclude that our basis is $\{\begin{pmatrix}1\\2\end{pmatrix}, \begin{pmatrix}\frac{6}{5}\\-\frac{3}{5}\end{pmatrix}\}$. Let's now use our basis and rewrite it as

$$\begin{pmatrix}2\\3\end{pmatrix} = c_1 \begin{pmatrix}1\\2\end{pmatrix} + c_2 \begin{pmatrix}\frac{6}{5}\\-\frac{3}{5}\end{pmatrix}.$$

We can simplify this and solve for $c_1, c_2$

$$
\begin{aligned}
c_1 &=< \begin{pmatrix}2\\3\end{pmatrix}, \begin{pmatrix}1\\2\end{pmatrix} >= 2+6 = 8 \\
c_2 &=< \begin{pmatrix}2\\3\end{pmatrix}, \begin{pmatrix}\frac{6}{5}\\-\frac{3}{5}\end{pmatrix} >= \frac{12}{5} - \frac{9}{5} = \frac{3}{5} \\
&.
\end{aligned}
$$

Using Theorem 4.9 from the book, we do the following with an orthogonal basis to get its norm:

$$a_1 = \frac{8}{||v_1||^2} = \frac{8}{(\sqrt{1^2+2^2})^2} = \frac{8}{5}$$

$$a_2 = \frac{\frac{3}{5}}{||v_2||^2} = \frac{\frac{3}{5}}{\left(\frac{6}{5}\right)^2 + \left(-\frac{3}{5}\right)^2}$$

$$= \frac{\frac{3}{5}}{\frac{36}{25}+\frac{9}{25}} = \frac{15}{25}\cdots$$

$$\begin{pmatrix}2\\3\end{pmatrix} = a_1\begin{pmatrix}1\\2\end{pmatrix} + a_2\begin{pmatrix}\frac{6}{5}\\-\frac{3}{5}\end{pmatrix}$$

$$\frac{8}{5}\begin{pmatrix}1\\2\end{pmatrix} + \frac{1}{3}\begin{pmatrix}\frac{6}{5}\\-\frac{3}{5}\end{pmatrix}$$

$$= \begin{pmatrix}\frac{8}{5}\\\frac{16}{5}\end{pmatrix} + \begin{pmatrix}\frac{2}{5}\\-\frac{1}{5}\end{pmatrix} = \begin{pmatrix}2\\3\end{pmatrix}.$$

**Problem 19.** *Example of an orthogonal basis. Let $\mathbb{T}^n$ be the vector space of trigonometric polynomials.*

$$\mathbb{T}^n = \sum_{0\le j+k\le n} a_{jk}\sin^j(x)\cos^k(x).$$

*Using the $L^2$ norm:*

$$< f, g >= \int_{-\pi}^{\pi} f\cdot g.$$

*An orthogonal basis is $\{1, \cos(x), \sin(x), \cos(2x), \sin(2x), \cos(3x), \sin(3x), \ldots\}$. If we were going to do the $L^2$ norm for any of these equations we would need to do the following*

$$\int_{-\pi}^{\pi} \sin(2x)\cos(4x)dx.$$

*This equation is the Fourier series.*

Chapter 5

# Mimimization and Least Squares

Chapter 6

# Equilibrium

Chapter 7

# Linearity

Chapter 8

# Eigenvalues and Singular Values

Chapter 9

# Iteration

Chapter 10

# Dynamics