MATH405: Linear Algebra

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1 Vector Space

Goals of this course is to discuss

- Vector spaces
- Linear transformations between vector spaces
- Other operations on vector spaces

1.1 Definitions

Definition - Field: A set of numbers containing 0,1 that can be added, subtracted, multiplied, and divided (except cannot divide by 0) that satisfy the following **Field Axioms**

- 1. $a, b \in K \implies a + b, ab \in K$
- 2. +, \times are commutative so a + b = b + a and ab = ba
- 3. +, \times are associative so (a+b)+c=a+(b+c) and a(bc)=(ab)c
- 4. Distributive Law: a(b+c) = ab + ac
- 5. Additive Identity: a + 0 = 0 + a = a
- 6. Multiplicative Identity: $a \cdot 1 = 1 \cdot a = a$
- 7. Additive Inverse: $\forall a \in K, \exists b \text{ such that } a+b=0, \text{ namely } b=-a \text{ which is unique}$
- 8. Multiplicative Inverse: $\forall a \in K, \exists b \text{ such that } ab = 1, \text{ name } b = 1/a \text{ which is unique}$

Example: R, Q are fields. Z is not a field since there is no multiplicative inverse of 2

Example: $C = \{a + bi \mid a, b \in R\}$, where $i = \sqrt{-1}$ is a field under

- +: (a+bi) + (c+di) = (a+c) + (b+d)i
- \times : (a+bi)(c+di) = (ac-bd) + (ad+bc)i

Example: $F_2 = \{0, 1\}$ is a field under

- +: where
 - 0 + 0 = 0
 - 0+1=1+0=1
 - 1 + 1 = 0
- \times : where
 - $0 \cdot 0 = 0$
 - $0 \cdot 1 = 1 \cdot 0 = 0$
 - $1 \cdot 1 = 1$

Example: For a prime p, let $F_p = \{0, \dots, p-1\}$. Then F_p is a field under

- $+: a+b \pmod{p}$
- $\times : ab \pmod{p}$

Definition - Vector Space: For an arbitrary field K, a K-vector space is a set V, with a distinguished element O, such that any 2 elements in V can be added and scalar multiplied by $c \in K$

- $u, v \in V \implies u + v \in V$
- $c \in K, u \in V \implies cu \in V$

Satisfying the following properties

- 1. Commutative Addition: u + v = v + u
- 2. Associative Addition: (u+v)+w=u+(v+w)

- 3. Additive Identity: u + O = u
- 4. Additive Inverse: $\forall u \in V, \exists v \in V \text{ such that } u + v = O, \text{ namely } v = -u \text{ which is unique}$
- 5. Distributive Laws: $\forall a, b \in K, a(u+v) = au + av$ and (a+b)u = au + bu
- 6. Commutative Scalar Multiplication: (ab)u = a(bu)
- 7. Multiplicative Identity: $1 \cdot u = u$

Example: \mathbb{R}^3 is an \mathbb{R} -vector space defined by the operations

$$R^3 = \{(x, y, z) \mid x, y, z \in R\}$$

- +: add componentwise so (a,b,c)+(d,e,f)=(a+d,b+e,c+f)
- Scalar \times : for $r \in R$, r(a, b, c) = (ra, rb, rc)
- Additive Identity is O = (0, 0, 0)

Example: For any field K, K^2 is a K-vector space defined by the operations

$$K^2 = \{(x,y) \mid x,y \in K\}$$

- +: add componentwise so (a,b) + (c,d) = (a+c,b+d)
- Scalar \times : for $k \in K$, k(a,b) = (ka,kb)
- Additive Identity is O = (0,0)

Example: R is an R-vector space since clearly the necessary properties hold

Example R is a Q-vector space since clearly the necessary properties hold

• Notably, for $q \in Q$ and $r \in R$, we have $qr \in R$. Thus scalar multiplication is closed

Example: For any field K, the set $\{O\}$ is a K-vector space

Example: Let X be any non-empty set and let $\mathcal{F}(X)$ be the set of all functions $f: X \to R$. Then \mathcal{F} is an R-vector space under the operations

- +: for $f, g \in \mathcal{F}(X)$, define f + g := (f + g)(x)
- Scalar \times : let $r \in R$, then define rf := r(f(x))
- Additive Identity is O = f(x) = 0, the function that takes any x to 0

Example: Take X = N and let $F(X) = \{$ all functions $f: N \to R \}$ is a vector space

• Note: $f: N \to R$ is a sequence (a_0, \ldots, a_n) where $a_n = f(n)$

Lemma 1 - Cancellation: For $u, v, w \in V$ and if u + v = w + v, then u = w

Proof: $v \in V$ has an additive inverse, namely -v. Thus we have

$$u + v - v = w + v - v \implies u = w$$

Lemma 2 - Unique Additive Inverse: For all $v \in V$, there is a unique additive inverse, namely -v

Proof: Suppose u, w are both additive inverses of v. Then we have

$$v + u = v + w \implies u = w$$

Lemma 3 - 0 Times a Vector: For all $v \in V$, 0v = O

Proof:
$$v = 1v = (0+1)v = 0v + 1v = 0v + v \implies 0v = 0$$

Lemma 4 - (-1)v is the Additive Inverse: For all $v \in v, (-1)v$ is the unique additive inverse of v

Proof: (-1)v + v = (-1+1)v = 0v = 0. Thus (-1)v is the additive inverse of v, which is unique by Lemma 2

Definition - Subspace: For a K-vector space V and a non-empty subset $W \subseteq V$, W is a subspace if it satisfies

- $w_1, w_2, \in W \implies w_1 + w_2 \in W$
- $\forall a \in K, w \in W \implies aw \in W$
- O ∈ W

Theorem 1: Every subspace of a K-vector space is a K-vector space

Proof: We need to show that $W \subseteq V$ satisfies all the necessary properties of a vector space

1. Verify $O \in W$

Since W is non-empty and closed under scalar multiplication, take $0w = O \in W$ by Lemma 3

- 2. $u, v \in W \implies u + v \in W$ and $a \in K, v \in W \implies aw \in W$ by definition of subspace
- 3. Every $w \in W$ has an additive inverse, namely -w

Since W is closed under scalar multiplication, $(-1)w = -w \in W$ by Lemma 4

4. Other conditions (associative addition, commutative addition, etc.) hold because $u, v, w \in W \implies u, v, w \in V$ For example, choose $u, v \in W$, then u + v = v + u, since $u, v \in V$. Thus commutative addition is satisfied

Example: Take $(5,3,2) \in \mathbb{R}^3$. Then let $W = \{r(5,3,2) \mid r \in \mathbb{R}\}$

Then W is an R-vector space. We prove this by showing that W is a subspace of \mathbb{R}^3

• +: Choose 2 arbitrary elements of W, r(5,3,2) and s(5,3,2) for $r,s \in R$

Then
$$r(5,3,2) + s(5,3,2) = (r+s)(5,3,2) \in W$$

• \times : Choose $r(5,3,2) \in W$ and take $s \in R$

Then
$$s(r(5,3,2)) = (sr)(5,3,2) \in W$$

Example: Let $U = \{(x, y, z) \in \mathbb{R}^3 \mid 2x + 3y = 0\}$. We show that U is a vector space by showing it's a subspace of \mathbb{R}^3

• +: Take (x_1, y_1, z_1) and $(x_2, y_2, z_2) \in U \implies 2x_1 + 3y_1 = 0$ and $2x_2 + 3y_2 = 0$

Then
$$2(x_1 + x_2) + 3(y_1 + y_2) = 0$$

Thus
$$(x_1 + x_2, y_1 + y_2, z_1 + z_2) \in U$$

• \times : Let $(x, y, z) \in U$ and $r \in R$

Then
$$2x + 3y = 0 \implies r(2x + 3y) = 2rx + 3ry = 0$$

Thus $r(x, y, z) \in U$

Example: Consider $\sin(x)$, $\cos(x) \in \mathcal{F}(R)$ and let $W = \{a\sin(x) + b\cos(x) \mid a, b \in R\}$. Then W is a subspace of $\mathcal{F}(R)$

- +: Take $a_1 \sin(x) + b_1 \cos(x)$ and $a_2 \sin(x) + b_2 \cos(x) \in W$. Then $(a_1 + a_2) \sin(x) + (b_1 + b_2) \cos(x) \in W$
- \times : Take $r \in R$. Then $r(a\sin(x) + b\cos(x)) = (ra)\sin(x) + (rb)\cos(x) \in W$

1.2 Basis

Definition - Linear Combination: For vectors $\{v_1, \dots, v_n\} \subseteq V$, a **linear combination** of $\{v_1, \dots, v_n\}$ is a vector of the form $a_1v_1 + \dots + a_nv_n \qquad a_i \in K$

Definition - Span: span($\{v_1, \ldots, v_n\}$) = { all linear combinations of $\{v_1, \ldots, v_n\}$ }

Proposition 1: $W = \text{span}(\{v_1, \dots, v_n\})$ is a subspace of V and thus is itself a K-Vector Space

Proof: We show that W satisfies the necessary criteria to be a subspace of V

• +: Let $a = a_1v_1 + \cdots + a_nv_n \in W$ and $b = b_1v_1 + \cdots + b_nv_n \in W$

Then $a + b = (a_1 + b_1)v_1 + \dots + (a_n + b_n)v_n \in W$

Thus W is closed under addition

• Scalar \times : Let $a = a_1v_1 + \cdots + a_nv_n \in W$ and let $c \in K$

Then $ca = (ca_1)v_1 + \cdots + (ca_n)v_n \in W$

Thus W is closed under scalar multiplication

Example: Take (5,3,1) and $(4,0,-2) \in \mathbb{R}^3$ span $(\{(5,3,1),(4,0,-2)\})$ is a plane in \mathbb{R}^3 passing through (0,0,0)

Example: Take (5, 3, 1) and $(10, 6, 2) \in \mathbb{R}^3$

 $\text{span}(\{(5,3,1),(10,6,2)\})$ is a line in \mathbb{R}^3 passing through (0,0,0)

• Note: (10,6,2) = 2(5,3,1). Thus span $(\{(5,3,1),(10,6,2)\}) = a_1(5,3,1) + a_2(10,6,2) = (a_1 + 2a_2)(5,3,1)$

Definition - Linearly Independent: $\{v_1, \dots, v_n\}$ is **linearly independent** if whenever $a_1v_1 + \dots + a_nv_n = 0$, then $a_1 = \dots = a_n = 0$

• Otherwise $\{v_1, \ldots, v_n\}$ is linearly dependent

Proposition 2: $\{v_1, \ldots, v_n\}$ is linearly independent if and only if no v_i is a linearly combination of the other n-1 vectors

Proof: \implies Assume $\{v_1, \ldots, v_n\}$ is linearly independent

BWOC, assume some $v_i = a_1v_1 + \cdots + a_nv_n$ for some $v_i \notin \{v_1, \dots, v_n\}$

Then we have

$$O = a_1 v_1 + \dots + a_n v_n + (-1)v_i$$

Since v_i is a linear combination of $\{v_1, \ldots, v_n\}$, the above equation shows that $\{v_1, \ldots, v_n\}$ is linearly dependent. Contradiction

Thus v_i cannot be written as a linear combination of the other vectors

 \iff Assume by way of contraposition that $\{v_1,\ldots,v_n\}$ is not linearly independent

Thus choose $a_1, \ldots, a_n \in K$, not all 0 such that

$$a_1v_1 + \dots + a_nv_n = O$$

WLOG, assume $a_1 \neq 0$. Then $v_2 a_2 + \cdots + a_n v_n = a_1 v_n$

Since $a_1 \neq 0$ and K is a field, we have

$$v_1 = \frac{a_2}{-a_1}v_2 + \dots + \frac{a_n}{-a_1}v_n$$

Thus we have shown that v_1 is a linear combination of the other n-1 vectors

Corollary 3: $\{v_1, \ldots, v_n\}$ is linearly independent if and only if for each $i, v_i \notin \text{span}(\{v_1, \ldots, v_n\} \setminus \{v_i\})$

Proof: This follows from the previous proposition

Definition - Spans: Let W be a K-Vector Space and $\{v_1, \ldots, v_n\} \subseteq W$. If $\operatorname{span}(\{v_1, \ldots, v_n\}) = W$, then $\{v_1, \ldots, v_n\}$ spans W, so every $w \in W$ is a linear combination of $\{v_1, \ldots, v_n\}$

Definition - Basis: $\{v_1, \ldots, v_n\}$ is a **basis** of W if it spans W and is linearly independent

Example: $\{(5,3,1),(4,0,-2)\}$ is a basis for span $(\{(5,3,1),(4,0,-2)\})$

Example: $\{(5,3,1),(10,6,2)\}$ is not a basis for span $(\{(5,3,1),(10,6,2)\})$ since it is not linearly independent

Proposition 4: Let $\{v_1, \ldots, v_n\}$ be a basis for W and let $w \in W$ be arbitrary. Then w can be written uniquely as

$$w = a_1 v_1 + \dots + a_n v_n$$
 $a_i \in K$

Proof: Since $\{v_1, \ldots, v_n\}$ spans W, every $w \in W$ is a linear combination of $\{v_1, \ldots, v_n\}$

For uniqueness, suppose

$$w = a_1 v_1 + \dots + a_n v_n = b_1 v_1 + \dots + b_n v_n$$

Then we have

$$O = (b_1 - a_1)v_1 + \cdots (b_n - a_n)$$

Since $\{v_1, \ldots, v_n\}$ is linearly independent, we must have $b_i - a_i = 0$, and thus $b_i = a_i$ for each i

Thus each $w \in W$ can be written uniquely as a linear combination of $\{v_1, \ldots, v_n\}$

Example: Let $W = \text{span}(\{\sin(x), \cos(x)\} = \{a\sin(x) + b\cos(x) \mid a, b \in R\}$

We know that W is an R-Vector Space

 $\{\sin(x),\cos(x)\}\$ is linearly independent. Otherwise $\sin(x)=r\cos(x)$ for all $x\in X$ and some $r\in R$. However, this cannot hold for when $x=\pi/2$ since $\sin(\pi/2)=1\neq r\cos(\pi/2)=r0$

1.3 Dimension

Let $\{v_1, \ldots, v_n\} \subseteq V$ and let $W = \operatorname{span}(\{v_1, \ldots, v_n\})$

Now let $X = \{w_1, \dots, w_m\} \subseteq W$. Then there are 2 desirable properties of X

- X is Big: X spans W if span(X) = W, i.e. all $w \in W$ is a linear combination of elements from X
- X is Small: X is linearly independent, i.e. no element in X is a linear combination of the remaining elements

Note: the empty set \emptyset is linearly independent since no element in \emptyset is a linear combination of the others. More notably, \emptyset is a basis for $\{O\}$

Shrinking Lemma: Let $X = \{w_1, \dots, w_m\} \subseteq W$ and spans W but X is not linearly independent. Then $X \setminus \{w_i\}$ still spans W for some $w_i \in X$

Proof: Since X is not linearly independent, we know that some w_i is a linear combination of elements in $X \setminus \{w_i\}$. Suppose

$$w_i = a_1 w_1 + \dots + a_m w_m$$
 without w_i occurring

Then take arbitrary $u \in W$ where

$$u = b_1 w_1 + \dots + b_m w_m$$

Replacing w_i above with the previous equation, we see that u is a linear combination of $X \setminus \{w_i\}$

Thus $X \setminus \{w_i\} = \operatorname{span}(W)$

Shrinking Theorem: Let $X = \{w_1, \dots, w_m\}$ span W. Then for some subset $Y \subseteq X$ is a basis of W

Proof:

Case 0: If X is linearly independent, then X is a basis by definition

Otherwise, apply the shrinking lemma to get $X_1 = X \setminus \{w_i\}$, which spans W

Case 1: If X_1 is linearly independent, then X_1 is a basis

. . .

Since X is finite (it has m elements), we will stop eventually. Either

- Some X_i is linearly independent. Thus X_i is a basis for W
- Otherwise if we hit case m: $X_m = \emptyset$, which is linearly independent, and thus X_m spans $W = \{O\}$

Corollary: If $W = \text{span}(\{v_1, \dots, v_n\})$, then some subset of $\{v_1, \dots, v_n\}$ is a basis

• Note: In particular, W has to have a basis

Enlarging Lemma: Suppose $X = \{w_1, \dots, w_m\} \subseteq W$ and is linearly independent but doesn't span W. Then for any $w \in W \setminus \text{span}(X), X \cup \{w\}$ is still linearly independent

Proof: Suppose $a_1w_1 + \cdots + a_mw_m + bw = O$. We show that $a_1 = \cdots = a_m = b = 0$

Suppose BWOC, $b \neq 0$, then we can solve for w

$$w = \frac{-a_1}{b}w_1 + \dots + \frac{-a_m}{b}w_m$$

Which means that $w \in \text{span}(X)$. Contradiction

Thus b = 0. This gives

$$a_1w_1 + \dots + a_mw_m + 0w = O$$

Since $X = \{w_1, \dots, w_m\}$ is linearly independent, we also have $a_1 = \dots = a_m = 0$

Thus $X \cup \{w\}$ is linearly independent

Main Question: does the enlarging process above terminate? After some steps, do we get a set $\{w_1, \ldots, w_m\}$ that spans W?

Exchanging Lemma: Let $X = \{v_1, \ldots, v_n\}$ be any basis for W. Choose any $w \in W$ but $w \notin \text{span}(\{v_k, \ldots, v_n\})$. Then $\exists v_i, i < k$, such that $Y = (X \setminus \{v_i\}) \cup \{w\}$ is still a basis

• Note: If k > n, then $\{v_k, \ldots, v_n\} = \emptyset$

Proof: First we show that span(Y) = W. Since X spans W, we can write

$$w = a_1 v_1 + \dots + a_n v_n \implies v_1 = \frac{1}{a_1} w + \frac{-a_2}{a_1} v_2 + \dots + \frac{-a_m}{a_1} v_m$$

Since $w \notin \text{span}(\{v_k, \dots, v_n\})$, we must have $a_i \neq 0$ for some i < k

WLOG, let $a_1 \neq 0$. We show that Y spans W

Since X spans W, for arbitrary $u \in W$, we have

$$u = d_1 v_1 + \dots + d_n v_n$$

Replacing v_1 above with the previous equation, we see that u is a linear combination of elements of Y and thus $u \in \text{span}(Y)$

Thus $\operatorname{span}(Y) = W$

Next we show that Y is linearly independent

Suppose we have

$$cw + b_2v_2 + b_nv_n = O$$

We show that $c = b_2 = \cdots = b_n = 0$

- If $c=0 \implies b_2=\cdots=b_n=0$ since $\{b_2,\ldots,b_n\}$ is linearly independent
- Otherwise suppose $c \neq 0$, then we can solve for w

$$w = \frac{-b_2}{c}v_2 + \dots + \frac{-b_n}{c}v_n \implies v_1 = \frac{1}{a_1}(\frac{-b_2}{c}v_2 + \dots + \frac{-b_n}{c}v_n) + \frac{-a_1}{a_1}v_2 + \dots + \frac{-a_m}{a_1v_m}$$

Thus v_1 is a linear combination of $\{v_2, \ldots, v_n\}$. Contradiction since we said X was linearly independent. Thus c=0

Theorem: Let $X = \{v_1, \dots, v_n\}$ be a basis for W, and let $\{w_1, \dots, w_m\} \subseteq W$ be linearly independent. Then $m \leq n$

Proof: If m < n, we are done

Now assume $m \geq n$, we show that m = n

Since $\{w_1, \ldots, w_m\}$ is linearly independent, we have that $w_1 \neq O = \operatorname{span}(\emptyset)$

Now apply the Exchanging Lemma to the basis X, with k > n and w_1 Then $\exists v_i$ such that $X_1 = (X \setminus \{v_i\}) \cup \{w_1\}$ is a basis

After reindexing, we see that X_1 has n-1 vectors from X and 1 vector from w_1

Now take k = n. Since $\{w_1, \dots, w_m\}$ is linearly independent, $w_2 \notin \text{span}(\{w_1\})$

Thus applying the Exchanging Lemma again, there exists j < k = n such that $X_2 = (X_1 \setminus \{v_i\}) \cup \{w_2\}$ is a basis

Reindexing again, we get that $X_2 = \{v_1, \dots, v_{n-2}, w_1, w_2\}$ is a basis

After n steps, X_n has no elements from X and $X_n = \{w_1, \dots, w_n\}$ is a basis

Furthermore, we see that $w_m \in \text{span}(\{w_1, \dots, w_n\})$, contradicting that $\{w_1, \dots, w_m\}$ is linearly independent

Thus m = n

Corollary: If W is any K-vector space and some basis of W has n elements, then every basis of W has n elements

Definition - Finite Dimensional: Let W be a K-vector space. Then W is **finite dimensional** if some basis for W is finite

Definition - Dimension: Number of elements in any basis for a vector space W

Corollary: Suppose $\dim(W) = n$ and $X = \{w_1, \dots, w_n\}$ are any *n*-vectors

- 1. If X spans W, then X is a basis for W
- 2. If X is linearly independent, then X is a basis for W

Proof:

1. By Shrinking Theorem, there exists a basis $Y \subseteq X$

However, |Y| < n contradicts that $\dim(W) = n$

Thus Y = X, i.e. X is a basis

2. By Enlarging Lemma, we can expand X to a basis Y

However, |Y| > n contradicts that $\dim(W) = n$

Thus Y = X, i.e. X is a basis

1.3.1 Toolbox Corollaries and Results

The following are useful corollaries that can be used to prove additional interesting results

Let V be a K-Vector Space with $\dim(V) = n$, i.e. V has some basis with n elements

- 1. Every basis for V has n elements
- 2. If $X \supseteq V$ and span(X) = V, then X has at least n elements and some subset $Y \subseteq X$ is a basis for V
- 3. If $Z \subseteq V$ is linearly independent, then Z has at most n elements and Z can be extended to a basis $Y \supseteq Z$ for V

Example: Let $V = R^3$. Since $\dim(V) = 3$, V has a basis with 3 elements

• Consider the **Standard Basis**: $B = \{(1,0,0), (0,1,0), (0,0,1)\}$

Suppose $X = \{v_1, v_2, v_3\} \subseteq V$ for arbitrary vectors

- If $\operatorname{span}(X) = V$ then X is a basis
- If X is linearly independent, since |X| = 3, X is a basis for V

Example: Describe all subspaces $W \subseteq \mathbb{R}^3$

Note: Since $\dim(V) = 3$, we must have $\dim(W) \leq \dim(V) = 3$

- Case 0: $\dim(W) = 0$
 - Clearly $W = \{O\}$
- Case 1: $\dim(W) = 1$

W is a line going through (0,0,0)

Thus a basis for W will be $\{w\}$ for any nonzero $w \in W$

• Case 2: $\dim(W) = 2$

W is a plane containing (0,0,0)

Thus a basis for W will be any 2 element set $\{w_1, w_2\} \subseteq W$ such that

- Neither element is O
- $-w_2$ is not a scalar multiple of w_1
- Case 3: $\dim(W) = 3$

Only possibility is $W = V = R^3$

Examples: Consider subspaces of $\mathcal{F}(R)$ and look at small subspaces

• $W = \text{span}(\{e^x\}) = \{re^x \mid r \in R\}$

This can be thought of as a 1-dimensional subpsace of $\mathcal{F}(R)$

• $V = \text{span}(\{\sin(x), \cos(x)\}) = \{a\sin(x) + b\cos(x) \mid a, b \in R\}$

Clearly $\dim(V) = 2$

Consider $f(x) = \sin(x)$ $g(x) = \cos(x)$ $h(x) = 3\sin(x) - 2\cos(x)$

Since h = 3f + (-2)g, $\{f, g, h\}$ is not linearly independent

Thus $\operatorname{span}(\{f, g, h\}) = \operatorname{span}(\{f, g\})$

1.4 Direct Sums

Let V be a K-Vector Space with $\dim(V) = n$. Let $W \subseteq V$ be a subspace of V. Then $\dim(W) \leq n$

Now choose another subspace $U \subseteq V$

Note: $W \cap U \neq \emptyset$ since both must contain O

Thus the smallest we can make $W \cap U$ is $\{O\}$

Furthermore, it can be shown that both $U \cap W$ and U + W are both subspaces of V

Definition - Direct Sum: $U \oplus W$ is called a **direct sum** if

• $U \oplus W = U + W$

•
$$U \cap W = \{O\}$$

We often look at cases where $V = U \oplus W$

Example: Consider R^3 and let W be any plane containing (0,0,0)

If U is any line through (0,0,0) such that $U \notin W$, then $R^3 = W \oplus U$

Theorem: Let V be a K-Vector Space with $\dim(V) = n$. Let $W \subseteq V$ be any subspace of V. Then there exists a subspace $U \subseteq V$ such that

$$V = U \oplus W$$

Proof: Choose any basis $Z = \{w_1, \ldots, w_m\}$ of W (we know that $m \leq n$)

Now extend Z to $Y = Z \cup \{u_1, \dots, u_r\}$, which is a basis for V

Let $U = \text{span}(\{u_1, \dots, u_r\})$. Then U is a subspace of V and $\{u_1, \dots, u_r\}$ is a basis for U

• Show that $U \cap W = \{O\}$

Choose $v \in U \cap W$

Then we have $v = a_1u_1 + \cdots + a_ru_r = b_1w_1 + \cdots + b_mw_m$

Since Y is a basis for V, then $\{u_1, \ldots, u_r, b_1, \ldots, b_m\}$ is linearly independent

Thus
$$v - v = a_1 u_1 + \dots + a_r u_r - b_1 w_1 - \dots - b_m w_m = 0 \implies a_1 = \dots = a_r = b_1 = \dots = b_m = 0$$

Thus v = O

• Show that V = U + W

Choose any $v \in V$

Since Y is a basis for V

$$v = \underbrace{a_1 u_1 + \dots + a_r u_r}_{u \in U} + \underbrace{b_1 w_1 + \dots + b_m w_m}_{w \in W}$$

Thus $v = u + w \implies V = U + W$

2 Matrices

Definition - m \times **n Matrix**: Entries $\in K$ of the form

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

Example: $A = \begin{bmatrix} 4 & 0 & 2 \\ -1 & 3 & 6 \end{bmatrix}$ is a 2×3 matrix with entries $\in Q$

Note: Any 2×3 matrices can be added together componentwise or multiplied by a scalar, resulting in a 2×3 matrix

• Here the additive identity is $\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$

• Here the additive inverse of A (from previous example) is $-A = \begin{bmatrix} -4 & 0 & -2 \\ 1 & -3 & -6 \end{bmatrix}$

Thus $\mathrm{Mat}_{2\times 3}(K)$, the set of all 2×3 matrices with entries in K is a K-Vector Space

Here the basis is $B = \{ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \}$

- Clearly spans since any 2×3 matrix $\begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \end{bmatrix}$ can be written as a linear combination of elements in B
- Clearly B is linearly independent since the only way to write O is to take each scalar $a_i = 0$

Thus $\dim(\operatorname{Mat}_{2\times 3}(K)) = 6$

Upshot: We can generalize the discussion above to show that $\operatorname{Mat}_{m \times n}(K)$ is a K-Vector Space of $\dim = m \times n$

Example: $\left\{\begin{bmatrix} a & b \\ b & d \end{bmatrix}\right\}$, **symmetric 2** × **2 matrices**, is a subspace of $\operatorname{Mat}_{2\times 2}(K)$, which has dimension 4

Non-Example: Mat(K) is NOT a Vector Space since addition between 2×2 and 3×3 matrices is not defined

Notation: $A_i = (a_{i1}, \dots, a_{in})$, the *i*th row vector, is a $1 \times n$ matrix

Notation: $A^j = (a_{1j}, \dots, a_{mj})$, the jth column vector, is a $m \times 1$ matrix

Definition - Transpose: Given an $m \times n$ matrix A, the **transpose** tA is an $n \times m$ matrix that swaps the rows and columns, and vice versa

• Note: If A is a square $n \times n$ matrix, then tA is also a square $n \times n$ matrix

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

Definition - Matrix Multiplication: An $m \times n$ matrix A can multiply with an $n \times k$ matrix B where

$$C_{il} = \sum_{d=1}^{n} a_{ij} b_{d,l}$$

- Note: If A, B are both $n \times n$ matrices, then AB is an $n \times n$ matrix
- Upshot: Square matrices are closed under transposition and matrix multiplication

Example: $\begin{bmatrix} 2 & 3 & 4 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 6 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 22 \\ 4 \end{bmatrix}$

2.1 Linear Equations

Consider

$$5x_1 + 3x_2 - 6x_3 = 8$$
$$x_1 - 2x_2 + x_3 = 4$$

We can represent this using

$$A = \begin{bmatrix} 5 & 3 & -6 \\ 1 & -2 & 1 \end{bmatrix} \qquad X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad B = \begin{bmatrix} 8 \\ 4 \end{bmatrix} \implies AX = B$$

3 Mappings

Definition - Function: Mapping between 2 sets D, R such that for each $x \in D$, there exists a unique $y \in R$ such that f(x) = y

$$F:D\to R$$

• Note: D here is the domain of F and R is the range of F

Definition - Image: $F(D) = \{F(x) \mid x \in D\} \subseteq R$

Example: $F: R \to R$ $F(x) = x^2$

- Domain(F) = Range(F) = R
- Image of $F = \{y \in R \mid y \ge 0\} = [0, \infty)$

Example: $G[0,\infty) \to R$ $G(x) = \sqrt{x}$

• Image of $G = [0, \infty)$

Example: $\mathcal{F} = \text{all functions } F : \to R$

Let S be all "infinitely" differentiable functions

Let $\frac{d}{dx}: S \to S$ where $\frac{d}{dx}(f) = f'$

Thus $\frac{d}{dx}$ is a function

Example: $t: \operatorname{Mat}_{2\times 3}(K) \to \operatorname{Mat}_{3\times 2}(K)$

Then $t(A) = {}^{t} A$ is a function

Definition - Onto: A function $F: D \to R$ is **onto** if Image of F = R

Definition - 1-1: A function $F: D \to R$ is **1-1** if different elements from D get mapped to different elements of R

$$F(d) = F(e) \implies d = e$$

Definition - Bijection: A function that is both onto and 1-1

Definition - Inverse Function: If $F: D \to R$ is a bijection, there exists an inverse function $F^{-1}: R \to D$ such that

$$\forall r, \in R, F(F^{-1}(r)) = r$$

$$\forall d, \in D, F^{-1}(F(d)) = d$$

Definition - Linear Transformation: For fixed K-Vector Spaces V, W, a linear transformation $T: V \to W$ is a function satisfying

- 1. $\forall v_1, v_2 \in W, T(v_1 + v_2) = T(v_1) + T(v_2)$
- 2. $\forall c \in K, v \in W, T(cv) = cT(v)$

Examples

- 1. $F: R \to R, F(x) = x^2$
 - Not onto since x^2 cannot be negative

- Not 1-1 since $1^2 = (-1)^2 = 1$
- Not a linear transformation since $(1+2)^2 = 9 \neq 1^2 + 2^2$
- 2. $F: [0, \infty) \to R, F(x) = \sqrt{x}$
 - Not onto since x^2 cannot be negative
 - 1-1 since $\sqrt{x} = \sqrt{y} \implies x = y$
 - Not a linear transformation since $[0, \infty)$ isn't a Vector Space
- 3. Let S be the set of all infinite differentiable functions. Consider $\frac{d}{dx}: S \to S$ where $\frac{d}{dx}(f) = f'$
 - Onto by the Fundamental Theorem of Calculus
 - Not 1-1 since f and f + 5 share the same derivative
 - Is a linear transformation by addition and scalar multiplication properties of derivatives
- 4. Let C be the set of continuous functions on [0,1]. Consider $I:C\to R, I(f)=\int_0^1 f(t)\,dt$
 - Onto since we can generate any value of R by taking the integral of the constant function
 - Not 1-1 since the definite integral of 2 functions could yield the same result
 - Is a linear transformation by additional and scalar multiplication properties of integrals
- 5. $I^*: G \to C, I^*(f) = \int_0^x f(t) dt$
 - Not onto since not all functions of f(0) = 0
 - 1-1 since indefinite integral yields a unique function
 - Is a linear transformation by additional and scalar multiplication properties of integrals
- 6. Fix (4,0,2) and consider $T_{(4,0,2)}: \mathbb{R}^3 \to \mathbb{R}^3, T_{(4,0,2)}((x,y,z)) = (x+4,y,z+2)$
 - · Clearly onto
 - Clearly 1-1
 - Not a linear transformation since $T_{(4,0,2)}((0,0,0)+(1,1,1))=(5,0,3)\neq T_{(4,0,2)}((0,0,0))+T_{(4,0,2)}((1,1,1))$
- 7. $E_{\pi}: \mathbb{R}^3 \to \mathbb{R}^3, E_{\pi}((x, y, z)) = (\pi x, \pi y, \pi z)$
 - · Clearly onto
 - Clearly 1-1
 - Is a linear transformation since $E_{\pi}((a,b,c)+(d,e,f)) = (\pi(a+d),\pi(b+e),\pi(c+f)) = E_{\pi}((a,b,c)) + E_{\pi}((d,e,f))$

3.1 Consequences of Properties of Linear Transformations

Proposition: For any linear transformation $T: V \to W$, we have that

$$T(O_V) = O_W$$

Proof: Let $w = T(O_V)$

Since $O_V = 0 * O_V$, we have that

$$T(O_V) = T(0 * O_V) = 0 * T(O_V) = 0 * w = O_W$$

Proposition: $T(a_1v_1 + \cdots + a_nv_n) = a_1T(v_1) + \cdots + a_nT(v_n)$

Proof: Follows from linearly properties of linear transformations

• Note: If $x = \{v_1, \dots, v_n\}$ is a basis for V and if w_1, \dots, w_n are arbitrary vectors in W, then there is a unique linear transformation $T: V \to W$ such that

$$T(v_1) = w_1, \ldots, T(v_n) = w_n$$

Lemma: Im(T) is a subspace of W

Proof: We show the necessary conditions for a subspace

• $+: w_1, w_2 \in \operatorname{Im}(T) \implies \exists v_1, v_2 \in V \text{ such that } T(v_1) = w_1 \text{ and } T(v_2) = w_2$

Then
$$w_1 + w_2 = T(v_1) + T(v_2) = T(\underbrace{v_1 + v_2}_{\in V}) \in \text{Im}(T)$$

• $\times: w \in \text{Im}(T) \implies \exists v \in V \text{ such that } T(v) = w$ Then for $c \in K$, we have $cw = c(Tv) = T(\underbrace{cv}_{\in V}) \in \text{Im}(T)$

Definition - Pull Back: Suppose $Y = \{w_1, \dots, w_m\} \subseteq \text{Im}(T)$. Then a **pull-back** is any set $\{v_1, \dots, v_m\} \subseteq V$ such that

$$T(v_1) = w_1, \dots, T(v_m) = w_m$$

Lemma: If $\{w_1, \ldots, w_m\}$ is linearly independent in Im(T) (or in W), then any pull back $\{v_1, \ldots, v_m\} \subseteq V$ is linearly independent in V

Proof: Let $a_1v_1 + \cdots + a_mv_m = O_V$

Thus $T(a_1, v_1 + \cdots + a_m v_m = O_V) = a_1 w_1 + \cdots + a_m w_m = O_W$

Since $\{w_1, \ldots, w_m\}$ is linearly independent, we have $a_1 = \cdots = a_m = 0$ as desired

Pull Back Property: Suppose $\{w_1, \ldots, w_m\}$ is a basis for Im(T), and let $\{v_1, \ldots, v_m\} \subseteq V$ be any pull back. Furthermore, let $S = \text{span}(\{v_1, \ldots, v_m\}) \subseteq V$ be a subspace. Then $\{v_1, \ldots, v_m\}$ is a basis for S

Proof: By the previous lemma, $\{v_1, \ldots, v_m\}$ is linearly independent

Furthermore, $\{v_1, \ldots, v_m\}$ spans S by definition

Corollary: If $T: V \to W$ is any linearly transformation and if $\dim(V) = n$, then $\dim(\operatorname{Im}(T)) \leq n$

Proof: BWOC, suppose $\dim(\operatorname{Im}(T)) > n$, thus we can create a set of n+1 linearly independent elements in $\operatorname{Im}(T)$.

By the Pull Back Property, this pulls back to n+1 linearly independent elements in V. Contradiction since $n+1>n=\dim(V)$

Note: $T: V \to W$ where $T(v) = \{O_W\}$ is a linearly transformation with $\dim(\operatorname{Im}(T)) = 0$, regardless of the value of $\dim(V)$

3.2 Kernel

Definition - Kernel: For $T: V \to W$, the **kernel** $Ker(T) = \{v \in V \mid T(v) = O_W\}$

Proposition: Ker(T) is a subspace of V

Proof: Clearly $O_V \in \text{Ker}(T)$

- +: For $v_1, v_2 \in \text{Ker}(T)$, we see that $T(v_1 + v_2) = T(v_1) + T(v_2) = O_W + O_W = O_W$. Thus $v_1 + v_2 \in \text{Ker}(T)$
- \times : For $c \in K$ and $v \in \text{Ker}(T)$, we see that $T(cv) = cT(v) = O_W$. Thus $cv \in \text{Ker}(V)$

Proposition: Let $T: V \to W$ be any linear transformation. For any basis $B = \{w_1, \dots, w_m\} \subseteq \text{Im}(T)$ and for any pullback $\{v_1, \dots, v_m\} \subseteq V$, we have

$$V = \operatorname{Ker}(T) \oplus S$$
 $S = \operatorname{span}(\{v_1, \dots, v_m\})$

Proof: We need to show V = Ker(T) + S and $\text{Ker}(T) \cap S = \{O_V\}$

• Take arbitrary $v \in V \implies T(v) \in \text{Im}(T) = a_1 w_1 + \cdots + a_m w_m$

Let $s = a_1 v_1 + \cdots + a_m v_m \in S$.

Then
$$T(s) = T(v) \implies T(v - s) = T(v) - T(s) = O_W \implies v - s \in \text{Ker}(T)$$

Let $u = v - s \in Ker(T)$

Thus clearly v = u + s for $u \in \text{Ker}(T)$ and $s \in S$

• Clearly $O_V \in \text{Ker}(T) \cap S$ since both are subspaces of V

Take any arbitrary $v \in \text{Ker}(T) \cap S$

$$v \in S \implies v = b_1 v_1 + \cdots + b_m v_m \implies T(v) = b_1 w_1 + \cdots + b_m w_m$$

Since $v \in \text{Ker}(T)$, we have that $T(v) = O_W \implies b_1 = \cdots = b_m = 0$ since $\{w_1, \ldots, w_m\}$ is linearly independent

Thus we have $v = 0v_1 + \cdots + 0v_m = O_V \implies \operatorname{Ker}(T) \cap S = \{O_V\}$

Thus we have shown the necessary properties for $V = \operatorname{Ker}(T) \oplus S$

Theorem: $\dim(V) = \dim(\operatorname{Ker}(T)) + \dim(\operatorname{Im}(T))$

Proof: Choose a basis $B = \{w_1, \dots, w_m\}$ for Im(T) and a pullback $\{v_1, \dots, v_m\}$

Let $S = \operatorname{span}(\{v_1, \dots, v_m\})$

Since $V = \text{Ker}(T) \oplus S$, we have $\dim(\text{Ker}(T)) + \dim(S) = \dim(\text{Ker}(T)) + \dim(\text{Im}(T)) = \dim(V)$

3.2.1 Consequences of Kernel

Corollary 1: For linear $T: \mathbb{R}^3 \to \mathbb{R}^4$, T is NOT onto

Proof: $\dim(\operatorname{Im}(T)) \leq \dim(R^3) = 3 < 4 \implies \operatorname{Im}(T) \neq R^4 \implies T$ is NOT onto

Corollary 2: For linear $T: \mathbb{R}^4 \to \mathbb{R}^3$, T is NOT 1-1

Proof:
$$\dim(\operatorname{Ker}(T)) + \underbrace{\dim(\operatorname{Im}(T))}_{\leq 3} = \dim(R^4) = 4 \implies \dim(\operatorname{Ker}(T)) \geq 1$$

Thus $\operatorname{Ker}(T)$ has something non-zero mapped to $O_W \implies T$ is NOT 1-1

Definition - Isomorphism: $T:V\to W$ such that T is linear transformation and a bijection

Corollary 3: $\dim(V) = \dim(W)$ and $T: V \to W$ is a linear transformation and 1-1 $\Longrightarrow T$ is an isomorphism (i.e. T is onto)

Proof: $\dim(\text{Ker}(T)) + \dim(\text{Im}(T)) = \dim(V)$

But we know that $\dim(\operatorname{Ker}(T)) = 0 \implies \dim(\operatorname{Im}(T)) = \dim(V) = \dim(W)$

Furthermore $\operatorname{Im}(T)$ is a subspace of W and $\operatorname{dim}(\operatorname{Im}(T)) = \operatorname{dim}(W) \implies T$ is onto

Corollary 4: $\dim(V) = \dim(W)$ and $T: V \to W$ is a linear transformation and onto $\implies T$ is an isomorphism (i.e. T is 1-1)

Proof: $\dim(\text{Ker}(T)) + \dim(\text{Im}(T)) = \dim(V)$

But we know that $\dim(\operatorname{Im}(T)) = \dim(V) \implies \dim(\operatorname{Ker}(T)) = 0$

3.3 Compositions and Inverse Linear Mappings

Consider Vector Spaces U, V, W and linear transformations $T: U \to V$ and $S: V \to W$

Proposition: $S \circ T : V \to W$ is a linear transformation

Proof:

• +: For $u_1, u_2 \in U$ we have that

$$S \circ T(u_1 + u_2) = S(T(u_1 + u_2))$$

$$= S(T(u_1) + T(u_2))$$

$$= S(T(u_1)) + S(T(u_2))$$

$$= S \circ T(u_1) + S \circ T(u_2)$$

• \times : For $u \in U$ and $c \in K$

$$S \circ T(cu) = S(T(cu))$$

$$= S(cT(u))$$

$$= cS(T(u))$$

$$= cS \circ T(u)$$

Thus $S \circ T : V \to W$ is a linear transformation

Definition - Inverse Mapping: $T^{-1}: W \to V$ where $T^{-1}(w) =$ the unique $v \in V$ such that T(v) = w

Proposition: $T^{-1}: W \to V$ is a linear transformation (and thus an isomorphism) *Proof*:

• +: Take $w_1, w_2 \in W$ such that $T(v_1) = w_1$ and $T(v_2) = w_2$ for $v_1, v_2 \in V$. Then we see that

$$T(v_1 + v_2) = T(v_1) + T(v_2) = w_1 + w_2$$

However, by definition of inverse mapping, $v_1 + v_2$ is the unique element such that $T(v_1 + v_2) = w_1 + w_2$ Thus by definition of T^{-1} , we have that $T^{-1}(w_1 + w_2) = v_1 + v_2 = T^{-1}(w_1) + T^{-1}(w_2)$

• \times : Similar

4 Linear Maps and Matrices

Definition - L_A: For a $m \times n$ matrix A, L_A determines a linear transformation from $R^n \to R^m$

Example: Consider $L_A: R^3 \to R^2$ where $A = \begin{bmatrix} 2 & 3 & 1 \\ 0 & 4 & 2 \end{bmatrix}$

Then we see that
$$A \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} 2x + 3y + z \\ 4y + 2z \end{bmatrix}$$

It can be clearly shown that L_A is a linear transformation (follows from logic of dot products)

4.1 Bases, Matrices, and Linear Maps

For a given transformation $T: V \to W$, the matrix of T with respect to the standard basis is given by

$$A = (T(E_1), \dots, T(E_n))$$

Example:
$$T: \mathbb{R}^2 \to \mathbb{R}^3$$
 $T(x,y) = (5x + y, x - y, x)$

$$T(E_1) = (5, 1, 1)$$
 $T(E_2) = (1, -1, 0)$

Thus we see that
$$A = \begin{bmatrix} 5 & 1 \\ 1 & -1 \\ 1 & 0 \end{bmatrix}$$

•
$$T(^{t}(3,2)) = \begin{bmatrix} 5 & 1 \\ 1 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 3 \\ 2 \end{bmatrix} = ^{t} (17,1,3)$$

Example: $T: \mathbb{R}^2 \to \mathbb{R}^2$ where we stretch the x-coordinate by 2

$$T(^{t}(1,0)) = ^{t}(2,0)$$
 $T(^{t}(0,1)) = ^{t}(0,1)$

Thus we see that $A = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$

Example: $S \circ T : \mathbb{R}^2 \to \mathbb{R}^2$ where we first stretch by x by 3 then stretch y by 3

$$T(^{t}(1,0)) = ^{t}(2,0)$$
 $T(^{t}(0,1)) = ^{t}(0,3)$

Thus we see that $A = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$

• Note: we see that applying functions just corresponds to matrix multiplication $\begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix}$

Example: Fix $\theta \in R$, then rotate by θ

$$R_{\theta}(t(1,0)) = t(\cos(\theta), \sin(\theta))$$
 $R_{\theta}(t(0,1)) = t(-\sin(\theta), \cos(\theta))$

Thus
$$A = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

Thus given any
$$t(x,y) \in R^2$$
, we see that $T_{\theta}(t(x,y)) = \begin{bmatrix} x\cos(\theta) - y\sin(\theta) \\ x\sin(\theta) + y\cos(\theta) \end{bmatrix}$

Example: Stretch x by 2, rotate by $\pi/4$, and stretch y by 3

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} \sqrt{2}/2 & -\sqrt{2}/2 \\ \sqrt{2}/2 & \sqrt{2}/2 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$$

Note: Given $T: K^n \to K^m$, the matrix A for T depends on our choosing of bases for K^n and K^m

Example: $T: \mathbb{R}^2 \to \mathbb{R}^3$ T(x,y) = (5x + y, x - y, x)

Let
$$B = \{\underbrace{(1,4)}_{v_1},\underbrace{(3,0)}_{v_2}\}$$
 be a basis for R^2 and $B' = \{\underbrace{(3,0,0)}_{w_1},\underbrace{(0,5,0)}_{w_2},\underbrace{(0,0,1)}_{w_3}\}$ be a basis for R^3

We can define a matrix of T with respect to B and B'

$$M_{B'}^B(T) = (\underbrace{T(v_1) \qquad T(v_2)}_{\text{in terms of } w_1, w_2, w_3})$$

$$T(v_1) = T(1,4) = (9,-3,1) = 3w_1 - \frac{3}{5}w_2 + w_3$$

$$T(v_2) = T(1,4) = (15,3,3) = 5w_1 + \frac{3}{5}w_2 + 3w_3$$

Thus we see that
$$M_{B'}^B(T) = \begin{bmatrix} 3 & 5 \\ -3/5 & 3/5 \\ 1 & 3 \end{bmatrix}$$

Upshot: Any vector, written in B coordinates, when multiplied by this matrix, yields an answer in B' coordinates. Thus for $v = av_1 + bv_2$, we have

$$T(v) = (3a+5b)w_1 + (-3/5a+3/5b)w_2 + (a+3b)w_3$$

- As a sanity check, for $v = (5,8) \in \mathbb{R}^2$
 - Normal Transformation: T(v) = (33, -3, 5)

- Linear Map: writing v in terms of v_1, v_2 , we get $(5, 8) = a(1, 4) + b(3, 0) \implies (5, 8) = 2(1, 4) + 2(3, 0)$ Thus we have

$$M_{B'}^B(T) \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 3 & 5 \\ -3/5 & 3/5 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 11 \\ -3/5 \\ 5 \end{bmatrix} \implies 11(3,0,0) - 3/5(0,5,0) + 5(0,0,1) = (33,-3,5)$$

Example: Consider $P_n = \{a_0 + a_1x + \dots + a_nx^n \mid a_i \in R\}$

It's easily verifiable that P_n is a subspace of $\mathcal{F}(R)$. Furthermore, the basis for P_n is $\{1, x, \dots, x^n\} \implies \dim(P_n) = n+1$

Let $D: P_2 \to P_2$ be the derivative

$$D(a_0 + a_1x + a_2x^2 = a_1 + 2a_2x)$$

Easily verifiable that D is a linear transformation. Consider what is the matrix of D with respect to $B = \{1, x, x^2\}$?

$$A = \begin{bmatrix} D(1) & D(x) & D(x^2) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Thus we see that for $p(x) = 5 + 3x + 4x^2$, D(p(x)) = 3 + 8x = 5(0,0,0) + 3(0,1,0) + 4(0,2,0)

Upshot: For a linear transformation $T: V \to W$, with $\dim(V) = n$ and $\dim(W) = m$, if $B = \{v_1, \dots, v_n\}$ and $B' = \{w_1, \dots, w_m\}$ are bases for V, W, then

$$M_{B'}^B(T) = \begin{bmatrix} T(v_1) & T(v_2) & \cdots & T(V_n) \end{bmatrix}$$

is a $m \times n$ matrix with column vectors containing coefficients of $T(v_1)$ WRT B'

Furthermore, for any $v \in V, v = x_1v_1 + \cdots + x_nv_n$, we have

$$M_{B'}^B(T) \begin{bmatrix} x_1 \\ \cdots \\ x_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \cdots \\ y_m \end{bmatrix}$$

Thus $T(v) = y_1 w_1 + \cdots + y_m w_m$ (Note coordinate is WRT to B')

Definition - Change of Basis: Let $B = \{v_1, \dots, v_n\}$ and $B' = \{w_1, \dots, w_n\}$ be basis for the same vector space V, and let $T: V \to V$ be the identity mapping. Then

$$M_{B'}^{B}(\mathrm{id}) = \underbrace{\left[\mathrm{id}(v_1) \quad \mathrm{id}(v_2) \quad \cdots \quad \mathrm{id}(v_n)\right]}_{\mathrm{WRT } B'}$$

is the Change of Basis matrix for V

Example: Let $V = P_1 = \{a_0 + a_1x \mid a_i \in R\}$ and let $B = \{1, x\}$ and $B' = \{3 + x, 5 + 2x\}$, which are both bases for V

$$1 = a(3+x) + b(5+2x) \implies a = 2, b = -1 \implies 1 = 2(3+x) - (5+2x)$$

$$x = c(3+x) + d(5+2x) \implies c = -5, d = 3 \implies x = -5(3+x) + 3(5+2x)$$

$$M_{B'}^{B}(\mathrm{id}) = \underbrace{\begin{bmatrix} 2 & -5 \\ -1 & 3 \end{bmatrix}}_{\mathrm{WRT} \ B'}$$

Furthermore, consider

$$M_B^{B'}(\mathrm{id}) = \underbrace{\left[\mathrm{id}(w_1) \quad \mathrm{id}(w_2)\right]}_{\mathrm{WRT } B} = \begin{bmatrix} 3 & 5\\ 1 & 2 \end{bmatrix}$$

Finally, we see that $M_B^{B'}(M_{B'}^B(\mathrm{id})) = \mathrm{id}$

Thus the inverse of $M_{B'}^B$ is $M_{B'}^{B'}$

5 Scalar Products and Orthogonality

5.1 Scalar Products

Definition - Scalar Product: For a Vector Space V, we define $<,>:V\times V\to K$

• Example: Think of dot products in $\mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$

Properties of Scalar Products

- 1. $\langle v, w \rangle = \langle w, v \rangle$
- $2. < v, w_1 + w_2 > = < v, w_1 > + < v, w_2 >$
- 3. < v, cw > = c < v, w > < cv, w > = c < v, w >

Consequences of Properties

• $\forall v_1, v_2, w \in V, \langle v_1 + v_2, w \rangle = \langle v_1, w \rangle + \langle v_2, w \rangle$

Proof: Follows from applying properties 1 and 2

• $\forall v \in V, < v, O_v >= 0 = < O_v, v >$

Proof: For any $w \in V$, we have $\langle v, O_V \rangle = \langle v, 0w \rangle = 0 \langle v, w \rangle$

Definition - Non-Degenerate: Scalar product that satisfies $\forall v \neq 0, \exists w \in V \text{ such that } < v, w > \neq 0$

Example: $\mathcal{F}([0,1])$, all functions $f:[0,1] \to R$

Let C([0,1]) be the set of all continuous functions $f:[0,1]\to R$, which is clearly an R subspace

Now define $\langle f, g \rangle = \int_0^1 f(x)g(x) dx$. We claim that this is a scalar product

Proof:

- $\int_0^1 f(x)g(x) dx = \int_0^1 g(x)f(x) dx$ so property 1 holds
- $\int_0^1 f(x)(g_1(x) + g_2(x)) dx = \int_0^1 f(x)g_1(x) dx + \int_0^1 f(x)g_2(x) dx$ so property 2 holds
- $\int_0^1 f(x)cg(x) dx = c \int_0^1 f(x)g(x)$ so property 3 holds

We also claim that $\langle f, g \rangle$ is non-degenerate since for $f \neq 0$, we have $\langle f, f \rangle = \int_0^1 f(x)^2$, which is always ≥ 0 and is continuous

Example: f(x) = 2x + 3 $g(x) = x^2$

$$\langle 2x+3, x^2 \rangle = \int_0^1 (2x+3)x^2 dx = 3/2$$

Defintion - Orthogonal: Elements $v, w \in V$ are **orthogonal**, denote $v \perp w$, if $\langle v, w \rangle = 0$

Definition - Orthogonal Complement: Suppose $W \subseteq V$ is a subspace, then the **orthogonal complement** of W is

$$W^{\perp} = \{ v \in V \mid v \perp w \} \qquad \text{for } w \in W$$

• Note: $W^{\perp} \subseteq V$ is a subspace

Definition - Positive Definite: Scalar product that satisfies $\forall v \neq 0, \langle v, v \rangle \geq 0$. Otherwise $\langle v, v \rangle = 0 \implies v = 0$

Definition - Length: $||v|| = \sqrt{\langle v, v \rangle}$

• Length between v and w: ||v-w||

- ||c|| = |c|||v||

Pythagoras Theorem: For $v \perp w$,

$$||v + w||^2 = ||v||^2 + ||w||^2$$

Proof:

$$||v + w||^2 = \langle v + w, v + w \rangle$$

$$= \langle v, v \rangle + 2 \langle v, w \rangle + \langle w, w \rangle$$

$$= ||v||^2 + ||w, w||^2$$

Parallelogram Law: For any $v, w \in V$, we have

$$||v + w||^2 + ||v - w||^2 = 2||v||^2 + 2||w||^2$$

Proof: Follows from the definition/properties of length

Definition - Unit Vector: $v \in V$ such that ||v|| = 1

• If $v \neq O$, then $(\frac{1}{\|v\|})v$ is a unit vector

Definition - Projection: $\operatorname{proj}_w v$ represents v as a scalar multiple of w where $\operatorname{proj}_w v = (\frac{\langle v, w \rangle}{\langle w, w \rangle})w$

- Definition comes from creating a right triangle where $v cw \perp cw \implies \langle v cw, cw \rangle = 0$ Thus we have $\langle v, cw \rangle - \langle cw, cw \rangle = c \langle v, w \rangle - c^2 \langle w, w \rangle \Longrightarrow c = \frac{\langle v, w \rangle}{\langle w, w \rangle}$
- Special case where $< w, w>=1 \implies \operatorname{proj}_w v = < v, w>w$

Schwartz Inequality: For any $v, w \in V$ we have

Proof: If w = O, then $|\langle v, w \rangle| \le 0$

Otherwise, using the definition of projection, we have $cw \perp v - cw$. Thus we see

$$||v||^{2} = ||v - cw||^{2} + ||cw||^{2}$$

$$\implies ||cw^{2}|| \le ||v^{2}||$$

$$c^{2}||w||^{2} \le ||v||^{2}$$

$$\frac{\langle v, w \rangle^{2}}{\langle w, w \rangle^{2}} ||w||^{2} \le ||v||^{2}$$

$$\implies \langle v, w \rangle^{2} \le ||v||^{2} ||w||^{2}$$

Triangle Inequality: For $v, w \in V$, we have

$$||v + w|| \le ||v|| + ||w||$$

Proof:

$$||v + w||^{2} = \langle v + w, v + w \rangle$$

$$= ||v||^{2} + 2 \langle v, w \rangle + ||w||^{2}$$

$$\leq ||v||^{2} + 2||v|| ||w|| + ||w||^{2}$$

$$\leq (||v|| + ||w||)^{2}$$

$$\implies ||v + w|| \leq ||v|| + ||w||$$

Proposition: Suppose $\{w_1, \ldots, w_r\} \subseteq V$ is pairwise orthogonal and assume that each $w_i \neq O$. Then $\{w_1, \ldots, w_r\}$ is linearly independent

Proof: Let $a_1w_1 + \cdots + a_rw_r = O_V$. Then we have

 $\langle w_i, a_1w_1 + \cdots + a_rw_r \rangle = \langle w_i, a_1w_1 \rangle + \cdots + \langle w_i, a_nw_n \rangle = 0$ since each w is pairwise orthogonal

Thus $\langle w_i, a_i w_i \rangle = 0 \implies a \langle w_i, w_i \rangle = 0 \implies a_i = 0$ since $\langle w_i, w_i \rangle > 0$ since positive definite

Let $W = \operatorname{span}(\{w_1, \dots, w_r\}) \subseteq V$. Then clearly $\dim(W) = r$

Now take $v \in V$ and define $\underset{W}{\text{proj}} v = \sum_{i=1}^{r} c_i w_i$ where $c_i w_i = \underset{w}{\text{proj}}_{w_i} v$

Clearly $\operatorname{proj}_W v \in W$

Proposition: $\left(v - \sum_{i=1}^{r} c_j w_j\right) \perp \text{ each } w_i$

Proof: Fix i, then

$$\sum_{j=1}^{r} c_j w_j = c_i w_i + \sum_{j \neq i} c_j w_j$$

Now take

$$v - \sum_{j=1}^{r} c_j w_j = (v - c_i w_i) - \sum_{j \neq i} c_j w_j$$

and take the inner product with w_i

$$\underbrace{\langle w_i, v - c_i w_i \rangle}_{\text{Ob/c of projection}} - \langle w_i, \sum_{j \neq i} c_j w_j \rangle$$

Thus we have $w_i \perp v - \sum_{j=1}^r c_j w_j$

Corollary: $(v - \sum_{j=1}^{r} c_j w_j) \perp \text{ every } w \in W$

Proof: Since each w_i in the basis is orthogonal to $v - \sum_{j=1}^{r} c_j w_j$, we must have

$$< w, v - \sum_{j=1}^{r} c_j w_j > = 0$$

Corollary:
$$(v - \sum_{j=1}^{r} c_j w_j) \in W^{\perp}$$

Geometric Interpretation: For any $v \in V$, $\operatorname{proj}_W v$ is the closest point to v in W

$$\|v - \operatorname*{proj}_{w} v\| \leq \|v - w\|$$

Proof: Choose any $w \in W = \text{span}(\{v_w, \dots, w_r\})$, then $w = \sum_{i=1}^r a_i w_i$. Then we have

$$||v - w||^2 = ||v - \sum_{i=1}^r a_i w_i||^2$$

$$= ||v - \sum_{i=1}^r c_i w_i| + \sum_{i=1}^r (c_i a_i) w_i||^2$$

$$= ||v - \sum_{i=1}^r c_i w_i||^2 + ||\sum_{i=1}^r (c_i - a_i) w_i||^2 \quad \text{by Pythagoras}$$

Thus
$$||v - w||^2 \ge ||v - \sum_{c_i}^{w_i}||^2 \implies ||v - w|| \ge ||v - \sum_{i=1}^r c_i w_i||^2$$

Corollary: Suppose $w \in W$, then $\operatorname{proj}_W w$ is the element of W closest to w

But we have
$$w = \sum_{i=1}^{r} c_i w_i \implies c_i = \frac{\langle w, w_1}{\|w_i\|^2}$$

5.2 Orthonormal Basis

Definition - Orthonormal Basis: $\{w_1, \ldots, w_r\} \subseteq W$ is an **orthonormal basis** if

- 1. $\{w_1, \ldots, w_r\}$ are pairwise orthogonal and non are zero
- 2. $||w_i|| = 1$

Corollary: If $\{w_1, \dots, w_r\}$ is orthonormal, then $\forall w \in W, w = \sum_{i=1}^r \langle w, w_i \rangle w_i$

Gram-Schmidt Process: Turn any basis $B = \{v_1, \dots, v_n\}$ into an orthnonormal basis $B' = \{u_1, \dots, u_n\}$

- 1. Given v_w , let $u_1 = \frac{1}{\|v_1\|} v_1$. Then we have $\text{span}(\{u_1\}) = \text{span}(\{v_1\})$
- 2. Let $p_2 = v_2 \text{proj}_{u_1} v_2 = v_2 \langle v_2, u_1 u_1 \rangle$ Now let $u_2 = \frac{1}{\|p_2\|} p_2$. Then $\text{span}(\{u_1, u_2\}) = \text{span}(\{v_1, v_2\})$
- 3. Let $p_3 = v_3 \text{proj}_{\text{span}(\{u_1, u_2\})} v_3 = v_3 \langle v_3, u_1 \rangle u_1 \langle v_3, u_2 \rangle u_2$ Now let $u_3 = \frac{1}{\|p_3\|} p_3$. Then $\text{span}(\{u_1, u_2, u_3\}) = \text{span}(\{v_1, v_2, v_3\})$

4. ...

Upshot: Any finite R Vector Space V with a positive definite inner product has an orthonormal basis

Theorem Let B ve a finite dimension R Vector Space with a positive definite scalar product. Then for any subspace $W \subseteq S$

$$V=W\oplus W^\perp$$

Proof:

• Show that $V = W + W^{\perp}$

Choose $v \in V$ and let $w^* = \operatorname{proj}_W v \in W$. Then $v - w^* \in W^{\perp}$

Thus
$$v = \underbrace{w^*}_{\in W} + \underbrace{(v - w^*)}_{\in W^{\perp}}$$

• Show that $W \cap W^{\perp} = \{O\}$

Choose $w \in W \cap W^{\perp}$

Since $w \in W^{\perp}$, w is orthogonal to all vectors in W

In particular, $w \perp w \implies < w, w >= 0 \implies w = O$ since the scalar product is positive definite

Corollary: If $W \subseteq V$ is a subspace, then

$$\dim(V) = \dim(W) + \dim(W^{\perp})$$

5.3 Application to Linear Equations: Rank

Let A be an $m \times n$ matrix with entries in R

- Let $C_A \subseteq \mathbb{R}^m$ be the span of column vectors of A
- Let $R_A \subseteq R^n$ be the span of row vectors of A
- Let $Null(A) = \{v \in R^m \mid Av = O\}$

Recall that any $m \times n$ matrix A describes a linear transformation $L_A : \mathbb{R}^n \to \mathbb{R}^m$ where $L_a(v) = Av \in \mathbb{R}^m$

Thus $Im(L_A) = C_A$

Furthermore, $Ker(L_A) = \{v \in \mathbb{R}^n \mid Av = O\} = Null(A)$

Thus we have

$$\dim(R^n) = \dim(\operatorname{Im}(L_A)) + \dim(\operatorname{Ker}(L_A))$$
$$= \dim(C_A) + \dim(\operatorname{Null}(A))$$

Now consider using scalar products

Take $v \in \text{Null}(A)$. Thus Av = O

Thus
$$A_i \cdot v = 0 \iff A_i \perp v \iff v \perp \text{all } u \in R_A \implies v \in (R_A)^{\perp}$$

Thus $Null(A) = Ker(A) = (R_A)^{\perp}$

Thus $R_A \subseteq R^n$ is a subspace of R^n .

Thus we have

$$\dim(R^n) = \dim(R_A) + \dim((R_A)^{\perp})$$
$$n = \dim(R_A) + \dim(\text{Null}(A))$$

Thus we have $\dim(R_A) = \dim(C_A)$

Definition - Rank: The rank of a matrix A is $\dim(R_A) = \dim(C_A)$

5.4 Scalar Products under Complex Numbers

We want a positive definite scalar product for C

Take the complex conjugate

$$(a+bi)(a-bi) = a^2 = b^2$$

Then we see that

$$||z|| = \sqrt{\langle z, \bar{z} \rangle} \in R$$

Definition - Hermitian Inner Product: For (y_1, \ldots, y_n) and $(z_1, \ldots, z_n) \in C^n$, define

$$\langle y, z \rangle = y_1 \overline{z_1} + \dots + y_n \overline{z_n}$$

• Note: This is NOT a scalar product

Now we list the properties of the Hermitian Inner Product

- $\langle w, v \rangle = \overline{\langle v, w \rangle}$
- $\langle v, w_1 + w_2 \rangle = \langle v, w_1 \rangle + \langle v, w_2 \rangle$
- $\langle cv, w \rangle = c \langle v, w \rangle$ AND $\langle v, cw \rangle = \overline{c} \langle v, w \rangle$

Proposition: The Hermitian Inner Product is positive definite

Proof: We look at

$$< v, v > = x_1 \overline{x_1} + \dots + x_n \overline{x_n} = ||x_1||^2 + \dots + ||x_n||^n \in R$$

We see that $\langle v, v \rangle \geq 0$. If it happens that $\langle v, v \rangle = 0 \implies x_1 = \cdots = x_n = 0$

5.5 General Orthogonal Bases

Now we relax the assumption of <, > being positive definite

Suppose V be a finite dimension Vector Space over R and let <,> be a scalar product, not necessarily positive definite. Then V has an orthogonal basis

• Note: Not orthonormal, since we could have the mapping to 0, and thus $v_i \perp v_j$

Consider the trivial case: Let $\langle v, w \rangle = 0$ for all $v, w \in V$

Then any basis for V is an orthogonal basis