

MATH223 - Linear Algebra (class notes)

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January 7th 2019

Should know how to solve a linear system and calculate a determinant... things like that.

- Written assignments (5) : 10%
- Webwork assignments (5) : 5%
- Midterm : 20%
- Final : 65%

Textbook: **Schaum's Outline - Linear Algebra.**

Motivation

We have linear systems, with two equations, like such:

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

$$x - y + z = 1$$

There is an algebraic way of seeing this, but we can also see this, from the geometric standpoint, as the intersection of the two planes in R^3 . Linear algebra has to do with things that are "flat", like a plane. As soon as we add in exponents to these equations, we get some curvature, and the techniques to solve these are different.

- Linear equations are the simplest kind, so you *must* understand them. Also, you *can* understand 'everything' about them.
- Theory used to describe solutions, etc.
- Linear equations are often used to approximate or model more complicated equations/situations.
- In applications, linear systems are often quite big (10000 equations/variables)

Complex numbers

Def: Let i be a symbol. We declare $i^2 = -1$.

Now, what we'd like to do is take this symbol i and combine it with the usual real numbers that we are familiar with. We set, for example,

$$\begin{aligned} 3i \\ i - 4 \\ 3i - \pi \\ \sqrt{i} + 21 \end{aligned}$$

Def: The field of complex numbers C consists of all expressions of the form $a + bi$, where $a, b \in R$.

Def: Addition (subtraction) and multiplication of complex numbers is defined by the following rules:

(i)

$$(a + bi) + (c + di) = (a + c) + (b + d)i$$

(ii)

$$\begin{aligned} (a + bi)(c + di) &= ac + adi + bci + bdi^2 \\ &= ac + adi + bci - bd \\ &= (ac - bd) + (ad + bc)i \end{aligned}$$

Notation:

- $0 + bi = bi$
- $a + 0i = a$ (a *real* number)
- $0 + 0i = 0$

Ex: If $z_1 = 2 - i$, $z_2 = 5i$, then

$$z_1 + z_2 = 2 + 4i$$

and

$$z_1 z_2 = (2 - i)(5i) = 10i - 5i^2 = 5 + 10i$$

Def: Let $z = a + bi \in C$

(i) $\bar{z} = a - bi$, called the *complex conjugate* of z

(ii) $|z| = \sqrt{a^2 + b^2}$, called the *absolute value* or *modulus*

Def: If $z = a + bi \in C$ and $z \neq 0$ (ie $z \neq 0 + 0i$), then the number

$$\begin{aligned} z^{-1} &= \frac{\bar{z}}{|z|^2} \\ &= \frac{a}{a^2 + b^2} - \frac{b}{a^2 + b^2}i \end{aligned}$$

is called the (multiplicative) inverse of z . It has the property $zz^{-1} = 1 = z^{-1}z$.

Proof. We have

$$\begin{aligned}
 zz^{-1} &= (a + bi)\left(\frac{a}{a^2 + b^2} - \frac{b}{a^2 + b^2}i\right) \\
 &= \frac{a^2 - abi + abi - b^2i^2}{a^2 + b^2} \\
 &= \frac{a^2 + 0 + b^2}{a^2 + b^2} \\
 &= 1
 \end{aligned}$$

Note: Since $z \neq 0 + 0i$, $a^2 + b^2 \neq 0$

□

Def: If $z, w \in \mathbb{C}$ and $z \neq 0$ then

$$\frac{w}{z} = wz^{-1}$$

Ex: If $z = 1 + 2i$, $w = 3 - i$ then

$$\begin{aligned}
 \frac{w}{z} &= wz^{-1} \\
 &= (3 - i)\left(\frac{1}{5} - \frac{2}{5}i\right) \\
 &= \frac{3}{5} - \frac{6}{5}i - \frac{i}{5} + \frac{2}{5}i^2 \\
 &= \frac{3}{5} - \frac{2}{5} - \frac{7}{5}i \\
 &= \frac{1}{5} - \frac{7}{5}i
 \end{aligned}$$

Or,

$$\begin{aligned}
 \frac{3 - i}{1 + 2i} \cdot \frac{(1 - 2i)}{(1 - 2i)} &= \frac{3 - 6i - i + 2i^2}{1 - 2i + 2i - 4i^2} \\
 &= \frac{1 - 7i}{5}
 \end{aligned}$$

January 9th 2019

Complex numbers as points in \mathbb{R}^2

You can view $a + bi$ as a point $(a, b) \in \mathbb{R}^2$. The usefulness of this is that we can consider, say, $(3 + 2i)$ and $(3 - i)$ as vectors in \mathbb{R}^2 , and they will conserve the same properties (addition of complex numbers corresponds to vector addition in \mathbb{R}^2). For the interpretation of multiplication to make sense, it's necessary to use polar coordinates.

Equations with complex numbers

Fact: Every real number $a \neq 0$ has two square roots:

- if $a > 0$, roots $\pm\sqrt{a}$

- if $a < 0$, two roots are $\pm i\sqrt{|a|}$, since:

$$\begin{aligned} (\pm i\sqrt{|a|})^2 &= i^2(\sqrt{|a|})^2 \\ &= -1 \cdot |a| \\ &= a \end{aligned} \quad (\text{since } a < 0)$$

Fact: Quadratic equation $ax^2 + bx + c = 0$ has solution

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

which may be in \mathbb{C} .

Ex: Solve $x^2 - 2x + 3 = 0$, and factor $x^2 - 2x + 3$.

Sol:

$$\begin{aligned} x &= \frac{-2 \pm \sqrt{4 - 4(1)(3)}}{2} \\ &= \frac{2 \pm \sqrt{-8}}{2} \\ &= \frac{2 \pm i\sqrt{8}}{2} \\ &= \frac{2 \pm i2\sqrt{2}}{2} \\ &= 1 \pm i\sqrt{2} \end{aligned}$$

Note: If $ax^2 + bx + c$ has $a, b, c \in \mathbb{R}$ has a non-real root, say z , its other root is \bar{z} ($z = a + bi$, $\bar{z} = a - bi$). This is not necessarily true if $a, b, c \in \mathbb{C}$.

Back to problem. Factor $x^2 - 2x + 3 = (x - (1 + i\sqrt{2}))(x - (1 - i\sqrt{2}))$.

Caution: -1 has two roots, namely $\pm i$, so you may write $i = \sqrt{-1}$, but be careful:

$$\begin{aligned} -1 &= i^2 \\ &= i \cdot i \\ &= \sqrt{-1} \cdot \sqrt{-1} \\ &= \sqrt{(-1)(-1)} \quad (\text{this step doesn't quite work}) \\ &= \sqrt{1} \\ &= 1 \end{aligned}$$

Theorem 1 (Fundamental Theorem of Algebra). *If*

$$p(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_0 x^0$$

is a polynomial with $a_n \neq 0$, and $a_n, a_{n-1}, \dots, a_0 \in \mathbb{C}$, then $p(x)$ factors into linear factors,

$$p(x) = a_n \cdot (x - r_1) \cdot (x - r_2) \cdot \dots \cdot (x - r_n)$$

for some complex numbers r_1, r_2, \dots, r_n . Some r_i 's may be equal.

Corollary 1.1. Every such polynomial has at least one root, and at most n distinct roots.

Note: Finding the roots is, in general, quite difficult.

Ex: Factor $2x^3 + 2x$ (over \mathbb{C}).

Sol:

$$\begin{aligned} 2(x^3 + x) &= 2(x - 0)(x^2 + 1) \\ &= 2(x - 0)(x^2 - i^2) \\ &= 2(x - 0)(x - i)(x + i) \end{aligned}$$

Ex: Solve $x^2 - i = 0$

Sol: $x^2 = i$ so $x = \pm\sqrt{i}$. Want \sqrt{i} in format $a + bi$, $a, b \in \mathbb{R}$.

$$\begin{aligned} \sqrt{i} &= a + bi \\ i &= (a + bi)^2 \\ &= a^2 + 2abi + b^2i^2 \\ 0 + i &= (a^2 - b^2) + 2abi \end{aligned}$$

$$0 = a^2 - b^2$$

$$1 = 2ab$$

$$a = \pm b$$

$$ab = \frac{1}{2} \quad (\text{so } a=b \text{ both } + \text{ or both } -)$$

$$a^2 = \frac{1}{2}$$

$$a = \pm \frac{1}{\sqrt{2}} = b$$

Two solutions, $\frac{1}{\sqrt{2}} + \frac{1}{\sqrt{2}}i$ and $-\frac{1}{\sqrt{2}} - \frac{1}{\sqrt{2}}i$.

Vector spaces (Ch 4)

Def. The sets \mathbb{R} and \mathbb{C} (and also \mathbb{Q} , rational numbers, although we won't go into details of this) are called *fields* (or *fields of scalars*). In this class, "a field of K " means that K is either \mathbb{R} or \mathbb{C} .

January 11th 2019

Last time: Field K is \mathbb{R} or \mathbb{C} (for this class).

Geometric vectors ('arrows')

You can add two vectors (arrows) (see figure 1)

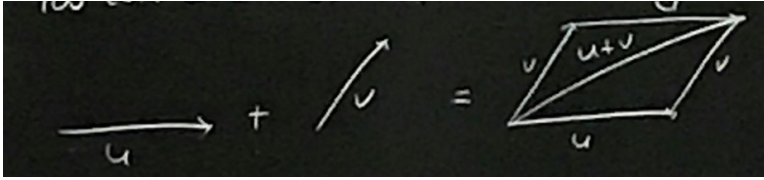


Figure 1: Vector addition

Observation: $\vec{u} + \vec{v} = \vec{v} + \vec{u}$.

You can rescale a vector (see figure 2) **Observation:** $a(b\vec{u}) = (ab)\vec{u}$.

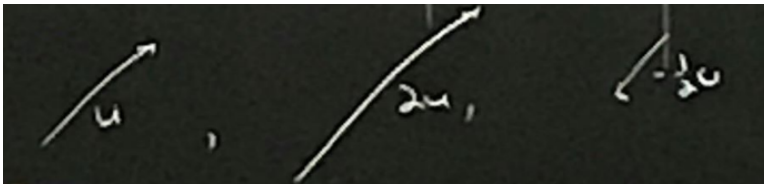


Figure 2: Vector rescaling

Also: $1\vec{u} = \vec{u}$

Question: What properties are interesting? What other objects obey the same properties?

Abstraction: Focus on properties more than on the objects.

Definition of a vector space

Let V be a set, called set of "vectors", and let K be a field (R or C) (elements of K called *scalars*). Assume that we have already defined two operations:

- (1) One called *addition*, which takes two vectors $\vec{u}, \vec{v} \in V$ and produces another vector denoted $\vec{u} + \vec{v} \in V$.
- (2) One called *scalar multiplication* which takes a vector $\vec{u} \in V$ and a scalar $a \in K$ and produces another vector denoted $a\vec{u} \in V$

Then if, for all vectors $\vec{u}, \vec{v}, \vec{w} \in V$ and all scalars $a, b \in K$, the following 8 properties are true, then V is called a *vector space* (over K).

- (A1) $u + v = v + u$ (commutative laws)
- (A2) There exists a vector in V , named *zero vector* and denoted 0 (or $\vec{0}$) such that for all $u \in V$, $u + 0 = u$
- (A3) For each $u \in V$, there is a vector in V , called the (additive) inverse of u and denoted $-u$, having the property $u + (-u) = 0$ (where 0 is the zero vector defined in A2)
- (A4) $(u + v) + w = u + (v + w)$

(SM1) $a(u + v) = au + av$ (distributive laws)

(SM2) $(a + b)u = au + bu$

(SM3) $a(bu) = (ab)u$

(SM4) $1u = u$ ($1 \in R$ or C)

These are called the vector space *axioms*.

Examples of vector spaces

Some examples:

(1) $K^n = \{(a_1, a_2, \dots, a_n) | a_1, a_2, \dots, a_n \in K\}$, with addition defined by

$$(a_1, a_2, \dots, a_n) + (b_1, b_2, \dots, b_n) = (a_1 + b_1, a_2 + b_2, \dots, a_n + b_n)$$

and scalar multiplication by

$$c(a_1, a_2, \dots, a_n) = (ca_1, ca_2, \dots, ca_n)$$

where $c \in K$ (and K = set of scalar).

Proof that K^n is a vector space

Need to prove all 8 properties. We will do 2, the rest are exercises.

(A4) To prove for all $u, v \in V$, $u + v = v + u$.

Proof concept: To prove "for all $x \in A$, something", say "let $x \in A$ " (means x is an arbitrary element of A , ie you only know $x \in A$). Then, prove something for that x .

Proof: Let $u, v \in K^n$. This means $u = (a_1, a_2, \dots, a_n)$, $v = (b_1, b_2, \dots, b_n)$ for some $a_1, a_2, \dots, a_n, b_1, b_2, \dots, b_n \in K$. Then

$$\begin{aligned} u + v &= (a_1, \dots, a_n) + (b_1, \dots, b_n) \\ &= (a_1 + b_1, \dots, a_n + b_n) \quad (\text{definition of addition in } K^n) \\ &= (b_1 + a_1, \dots, b_n + a_n) \quad (\text{since } a + b = b + a \text{ for } R \text{ and } C) \\ &= (b_1, \dots, b_n) + (a_1, \dots, a_n) \quad (\text{definition of addition in } K^n) \\ &= v + u \end{aligned}$$

(A2) *Proof concept:* To prove "there exists" something, one method is to describe the thing directly.

Define $0 = (0, 0, \dots, 0)$ (which is in K^n). To prove for all $u \in K^n$, $u + 0 = u$, let $u \in K^n$. This means $u = (a_1, a_2, \dots, a_n)$, so

$$\begin{aligned} u + 0 &= (a_1, a_2, \dots, a_n) + (0, 0, \dots, 0) \\ &= (a_1 + 0, a_2 + 0, \dots, a_n + 0) \\ &= (a_1, a_2, \dots, a_n) \\ &= u \end{aligned}$$

- (2) In the vector space C^2 , $(2 + 3i, 5 - 7i) \in C^2$ is an example of a vector and $2i \in C$ is a scalar, so an example of scalar mult is :

$$\begin{aligned} 2i(u) &= 2i(2 + 3i, 5 - 7i) \\ &= (4i + 6i^2, 10i - 14i^2) \\ &= (-6 + 4i, 14 + 10i) \end{aligned}$$

January 14th 2019

Problem: Let $J = \{(x, y) | x \in R, y \in R\}$ but define addition by

$$(x_1, y_1) + (x_2, y_2) = (-x_1 - x_2, y_1 + y_2)$$

and scalar multiplication by

$$c(x, y) = (cx, cy)$$

Show that J is not a vector space.

Solution: Show *one* of the 8 vector space axioms is false. Consider (A1):

$$(x_2, y_2) + (x_1, y_1) = (-x_2 - x_1, y_2 + y_1)$$

This is actually ok! Now consider (A4):

$$\begin{aligned} (x_1, y_1) + ((x_2, y_2) + (x_3, y_3)) &= (x_1, y_1) + (-x_2 - x_3, y_2 + y_3) \\ &= (-x_1 - (-x_2 - x_3), y_1 + y_2 + y_3) \\ &= (-x_1 + x_2 + x_3, y_1 + y_2 + y_3) \end{aligned}$$

While

$$\begin{aligned} ((x_1, y_1) + (x_2, y_2)) + (x_3, y_3) &= (-x_1 - x_2, y_1 + y_2) + (x_3, y_3) \\ &= (-(-x_1 - x_2) - x_3, y_1 + y_2 + y_3) \\ &= (x_1 + x_2 - x_3, y_1 + y_2 + y_3) \end{aligned}$$

This does not quite yet prove that the axiom is false. To do so, give *specific* case where the equation is false.

Actual proof: Let $u = (1, 1)$, $v = (2, 2)$ and $w = (3, 3)$. Then,

$$\begin{aligned} u + (v + w) &= (1, 1) + ((2, 2) + (3, 3)) \\ &= (1, 1) + (-2 - 3, 5) \\ &= (1, 1) + (-5, 5) \\ &= (-1 + 5, 6) \\ &= (4, 6) \end{aligned}$$

Whereas,

$$\begin{aligned}
 (u + v) + w &= ((1, 1) + (2, 2)) + (3, 3) \\
 &= (-1 - 2, 3) + (3, 3) \\
 &= (-3, 3) + (3, 3) \\
 &= -(-3) - 3, 6 \\
 &= (0, 6)
 \end{aligned}$$

Hence, the axiom does not hold.

More examples of vector spaces

- (1) K^n (ie R^n or C^n). See before
- (2) $P(K)$ = polynomials, where coefficients are in K . Addition, scalar multiplication are "as expected", ie for multiplication:

$$\begin{aligned}
 f(x) &= x^2 + 2ix - 4 \in P(C) \\
 g(x) &= -x^2 + ix \in P(C) \quad (\text{and also in } P(R))
 \end{aligned}$$

For addition,

$$f(x) + g(x) = 3ix - 4$$

And for scalar multiplication,

$$\begin{aligned}
 2if(x) &= 2ix^2 + 4i^2x - 8i \\
 &= 2ix^2 - 4x - 8i
 \end{aligned}$$

- (3) $P_n(K)$ = polynomials of degree n or less, coefficient from K . For example,

$$\begin{aligned}
 x^2 - 2x + 2 &\in P_2(R) \\
 x^2 - 2x + 2 &\in P_3(R) \\
 x^2 - 2x + 2 &\in P_2(C) \\
 x^2 - 2x + 2 &\notin P_1(R)
 \end{aligned}$$

Note: In $P(K)$, $P_n(K)$ the "vectors" are polynomials.

- (4) $M_{m \times n}(K)$ = $m \times n$ matrices with entries from K . Scalars are K ,

addition and scalar multiplication as expected.

$$\begin{aligned}
 A &= \begin{pmatrix} 2 & i \\ 0 & \pi \end{pmatrix} \in M_{2 \times 2}(\mathbb{C}) \\
 B &= \begin{pmatrix} -2 & 1 \\ 1+i & -\pi \end{pmatrix} \in M_{2 \times 2}(\mathbb{C}) \\
 A+B &= \begin{pmatrix} 0 & 1+i \\ 1+i & 0 \end{pmatrix} \\
 2iA &= \begin{pmatrix} 4i & 2i^2 \\ 0 & 2i\pi \end{pmatrix} \\
 &= \begin{pmatrix} 4i & -2 \\ 0 & 2\pi i \end{pmatrix}
 \end{aligned}$$

The “zero vector” in $M_{m \times n}(K)$ is the $m \times n$ matrix with all entries 0.

- (5) Let X be any set (think $x = \mathbb{R}$ or \mathbb{C} , but not required). Define

$F(X, K) = \{f : X \rightarrow K\}$ = all functions from X to K .

Ex: $f(x) = x^2 \in F(\mathbb{R}, \mathbb{R})$.

Ex: Let $x = \{1, 2\}$. Then g defined by

$$\begin{aligned}
 g(1) &= 3 \\
 g(2) &= \sqrt{2}
 \end{aligned}$$

Addition in this space is defined by:

If $f, g \in F(X, K)$ then $f + g$ is the function defined by

$$(f + g)(x) = f(x) + g(x)$$

Note that $f(x) \in K$ and $g(x) \in K$, in other words they are *numbers* (scalars). The $+$ in $(f + g)$ is the addition of vectors f and g , while the other $+$ is scalar addition.

Scalar multiplication in this space is defined by: if $f \in F(X, K), c \in K$ then cf is the function defined by

$$(cf)(x) = cf(x)$$

Note that cf is the name of the function, that “multiplication” is scalar multiplication $F(X, K)$ and $cf(x)$ is the multiplication of two scalars (numbers).

The fact that $F(X, K)$ is a vector space and the axioms are followed is not so obvious.

Prove (A2) true for $F(X, K)$. Define $z \in F(X, K)$ by

$$z(x) = 0 \quad (\text{for all } x \in X)$$

Note that 0 here is a scalar. Then if $f \in F(X, K)$ is an arbitrary element, then we need to prove $f + z = f$. This is true since for all $x \in X$,

$$\begin{aligned}(f + z)(x) &= f(x) + z(x) \\ &= f(x) + 0 \\ &= f(x)\end{aligned}$$

Hence, $f + z, f$ have the same output (namely $f(x)$) for every input. Hence, $f + z = f$.

Exercise: Try (A₃).

January 16th 2019

Theorem 2 (Cancellation Law). Suppose v is a vector space over K . For all vectors $u, v, w \in V$, if $u + w = v + w$ then $u = v$.

Note: To prove "for all" you say let $u \in V$ (means u is an arbitrary vector).

To prove "if p then q ", denoted $p \rightarrow q$, assume p is true and use it to prove q .

Proof. Let $u, v, w \in V$. Assume $u + w = v + w$. By vector space axiom A₃, there is a vector $(-w) \in V$. Add $(-w)$ to both sides:

$$\begin{aligned}(u + w) + (-w) &= (v + w) + (-w) \\ u + (w + (-w)) &= v + (w + (-w)) && \text{(by A1)} \\ u + \vec{0} &= v + \vec{0} && \text{(by A3)} \\ &= u = v && \text{(by A2)}\end{aligned}$$

□

Theorem 3. Two points:

1. The zero vector is unique
2. For each $u \in V$, $-u$ is unique

Note: To prove something is unique, suppose you have two of them and show they are the same.

Proof. 1) Assume 0 and z both satisfy the property (A₂: $\forall u \in V, u + 0 = u$ (*) and $u + z = u$ (**)). Goal is to prove $0 = z$.

$$\begin{aligned}z &= z + 0 && \text{(by *, with } u = z) \\ &= 0 + z && \text{(by A4)} \\ z &= 0 && \text{(by **, with } u = 0)\end{aligned}$$

So the zero vector is unique.

2) Exercise.

□

Theorem 4. $\forall u \in V, c \in K,$

$$1) \quad c\vec{0} = \vec{0}$$

$$2) \quad 0u = \vec{0}$$

$$3) \quad -(cu) = ((-c)u)$$

Proof. Of 2). Let $u \in V$. Then,

$$0u + 0u = (0 + 0)u \quad (\text{By SM2})$$

$$0u + 0u = 0u \quad (\text{by R addition})$$

$$0u + 0u = 0u + \vec{0} \quad (\text{by A2})$$

$$0u + 0u = \vec{0} + 0u \quad (\text{by A4})$$

$$0u = \vec{0} \quad (\text{by cancellation law})$$

□

Note: $0 + u = u$ is true for all $u \in V$ (same as $u + 0 = u$ then apply A4)

Linear combinations and spans

Def: Let $u, v_1, v_2, \dots, v_n \in V$. If there are scalars $a_1, a_2, \dots, a_n \in K$ such that $u = a_1v_1 + a_2v_2 + \dots + a_nv_n$ then u is said to be a linear combination of v_1, v_2, \dots, v_n .

Ex: In $P(R)$, $x^2 + 2x - 4$ is a linear comb of $x^2, x, 1$.

Important problem: Given vectors u, v_1, v_2, \dots, v_n , determine if u is a linear combination of v_1, v_2, \dots, v_n and if so find a_1, a_2, \dots, a_n .

Ex: Determine if $f(x) = 2x^2 + 6x + 8$ is a linear combination of

$$g_1(x) = x^2 + 2x + 1$$

$$g_2(x) = -2x^2 - 4x - 2$$

$$g_3(x) = 2x^2 - 3$$

Sol. Are there a_1, a_2, a_3 s.t.

$$\begin{aligned} 2x^2 + 6x + 8 &= a_1(x^2 + 2x + 1) + a_2(-2x^2 - 4x - 2) + a_3(2x^2 - 3) \\ &= (a_1 - 2a_2 + 2a_3)x^2 + (2a_1 - 4a_2)x + (a_1 - 2a_2 - 3a_3) \end{aligned}$$

Equating coefficients,

$$a_1 - 2a_2 + 2a_3 = 2$$

$$2a_1 - 4a_2 = 6$$

$$a_1 - 2a_2 - 3a_3 = 8$$

Solve the linear system:

$$\left[\begin{array}{ccc|c} 1 & -2 & 2 & 2 \\ 2 & -4 & 0 & 6 \\ 1 & -2 & -3 & 8 \end{array} \right]$$

↓

$$\left[\begin{array}{ccc|c} 1 & -2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{array} \right]$$

(row reduce)

∴ No solution, because of the last row. f is not a linear combination of g_1, g_2, g_3 .

Def: Let $S \subseteq V$ (S is a subset of V) and assume $s \neq 0$. The span of s , denoted $\text{span}(s)$ is the set of all linear combinations of vectors from S , ie

$$\begin{aligned} \text{span}(s) = \{u \in V \mid \exists v_1, v_2, \dots, v_n \in S \\ \text{and scalars } a_1, a_2, \dots, a_n \text{ s.t.} \\ u = a_1v_1 + a_2v_2 + \dots + a_nv_n\} \end{aligned}$$

January 18th 2019

Last class

$$S \subseteq V$$

$$\text{span}(s) = \{u \in V \mid \exists v_1, v_2, \dots, v_n \in S$$

and scalars a_1, a_2, \dots, a_n s.t.

$$u = a_1v_1 + a_2v_2 + \dots + a_nv_n\}$$

Ex: $S = \left\{ \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 1 \end{pmatrix} \right\} \subseteq \mathbb{R}^2$. Prove $\text{span}(S) = \mathbb{R}^2$.

Note: $\begin{pmatrix} a \\ b \end{pmatrix}$ means (a, b) .

Proof note: To prove two sets A, B are equal, ie $A = B$, you can prove $A \subseteq B$ and $B \subseteq A$.

Sol:

- (1) Prove $\text{span}(S) \subseteq \mathbb{R}^2$. Trivial, since any linear combination of vectors in \mathbb{R}^2 is still in \mathbb{R}^2 .

- (2) Prove $R^2 \subseteq \text{span}(S)$. Let $\begin{pmatrix} a \\ b \end{pmatrix} \in R^2$ (arbitrary). To prove that there exists scalars $x_1, x_2 \in K$ so that

$$\begin{pmatrix} a \\ b \end{pmatrix} = x_1 \begin{pmatrix} 1 \\ 2 \end{pmatrix} + x_2 \begin{pmatrix} 3 \\ 1 \end{pmatrix}$$

In other words,

$$a = x_1 + 3x_2$$

$$b = 2x_1 + x_2$$

Want to show this has a solution (for all a, b). System is:

$$\begin{pmatrix} 1 & 3 \\ 2 & 1 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} a \\ b \end{pmatrix}$$

But,

$$\begin{vmatrix} 1 & 3 \\ 2 & 1 \end{vmatrix} = 1 - 2(3) \neq 0$$

hence the system has (exactly one) solution. $\begin{pmatrix} a \\ b \end{pmatrix} \in \text{span}(S)$ so $R^2 \subseteq \text{span}(S)$. So by (1), (2), $\text{span}(S) = R^2$. \square

Note: $Ax = b$, $A_{n \times n}$ if A inv, $x = A^{-1}b$.

Theorem 5. Let $S \subseteq V$, $S \neq \emptyset$ ($\emptyset = \text{empty set}$). Then,

- (1) If $u, v \in \text{span}(S)$ then $u + v \in \text{span}(S)$
- (2) If $u \in \text{span}(S)$ and $c \in K$, then $cu \in \text{span}(S)$
- (3) $\vec{0} \in \text{span}(S)$

Proof. By direct proof.

- (1) (Note, "if $u, v \in \text{span}(S)$ " means for all $u, v \in \text{span}(S)$).

Let $u, v \in \text{span}(S)$. Then,

$$u = a_1u_1 + a_2u_2 + \dots + a_nu_n \text{ where } u_1, \dots, u_n \in S, a_1, \dots, a_n \in K$$

$$v = b_1v_1 + b_2v_2 + \dots + b_mv_m \text{ where } v_1, \dots, v_m \in S, b_1, \dots, b_m \in K$$

Then $u + v = a_1u_1 + \dots + a_nu_n + b_1v_1 + \dots + b_mv_m$ which is in $\text{span}(S)$ since $u_1, \dots, u_n, v_1, \dots, v_m \in S$.

- (2) Let $u \in \text{span}(S)$, $c \in K$. Then,

$$u = a_1u_1 + a_2u_2 + \dots + a_nu_n \text{ where } u_1, \dots, u_n \in S, a_1, \dots, a_n \in K$$

So,

$$\begin{aligned} cu &= c(a_1u_1) + c(a_2u_2) + \dots + c(a_nu_n) \\ &= (ca_1)u_1 + (ca_2)u_2 + \dots + (cna_n)u_n \end{aligned}$$

Note: If you want to be very formal, you need to write down all of the vector space axioms. Which is in $\text{span}(S)$ since it is a linear combination of a_1, \dots, a_n which are in S .

- (3) (Prove $\vec{0} \in \text{span}(S)$) Let $u \in S$. **Note:** This is possible only because $S \neq \emptyset$.

Then $u = 1u$, so $u \in \text{span}(S)$. Then using $c = 0$ and (2) and fact that $u \in \text{span}(S)$,

$$cu = 0u = \vec{0}$$

is also in $\text{span}(S)$. **Note:** Since $u = 1u$, $S \subseteq \text{span}(S)$.

□

Subspaces

Def. Let V be a vector space and $W \subseteq V$ (subset). If W , using addition and scalar multiplication as defined in V , satisfies the definition of vector space, then W is called a subspace of V , denoted $W \leq V$ (less than equal sign, read as "subspace").

Note: Main issue is that addition and scalar multiplication with vector from W produce vectors which are still in W .

Theorem 6. Let $W \subseteq V$. Then, if the following three properties hold, $W \leq V$ (subspace).

(SS1) For all $w_1, w_2 \in W$, we have $w_1 + w_2 \in W$ ("closure under addition")

(SS2) For all $w \in W$ and scalars $c \in K$, we have $cw \in W$ ("closure under scalar multiplication")

(SS3) $\vec{0} \in W$.

These are the same properties we just proved for spans; in other words, we proved earlier that $\text{span}(S)$ is a subspace.

Proof. For W to have operations addition, scalar multiplication, just means (SS1) and (SS2) are true. So now, check (A1) - (SM4). Most of them are true because they are true in a larger vector space.

- (A1) Let $u, v, w \in W$. Then since $u, v, w \in V$, and (A1) holds in V ,
 $u + (v + w) = (u + v) + w$.

(A2) This is (SS₃).

(A3) This is the one we have to do a bit more work for. Let $w \in W$.

Want to show $-w \in W$. Then, using (SS₂) with $c = -1$ gives

$$-1(w) = -w \quad (\text{thm from last class})$$

is in W , as needed.

(A4) Still true because it is true in V .

(SM1-SM4) All hold because they hold in V .

□

January 21st 2019

A note on logic

Let P, Q be statements that are true or false.

- (1) "If P then Q ", also written symbolically as " $P \Rightarrow Q$ " (P implies Q) means if P is true, then Q is also true. To *prove* " $P \Rightarrow Q$ ", assume P and prove Q is true. If you *know* that " $P \Rightarrow Q$ " is true, you can *use it*: if you can establish that P is true, you may conclude Q is true.
Ex: Let A be an $n \times n$ matrix:

$$P : \det(A) = 1 \quad Q : "A \text{ is invertible}"$$

Thm: $P \Rightarrow Q$

- (2) The *converse* of " $P \Rightarrow Q$ " is " $Q \Rightarrow P$ ". This is a (logically) different statement.
Ex: With P and Q as above, " $Q \Rightarrow P$ " is not true because $A_{inv} \not\Rightarrow \det(A) = 1$.
- (3) The *contrapositive* of " $P \Rightarrow Q$ " is " $\neg Q \Rightarrow \neg P$ " ie "if Q false, then P also false". Logically, this is the same as " $P \Rightarrow Q$ ".
- (4) The *equivalence* " P if and only if Q ", written " $P \iff Q$ " means " $P \Rightarrow Q$ and also $Q \Rightarrow P$ " is true. Also means that either both P and Q are true or both are false.
Ex: $\det(A) \neq 0 \iff A$ is invertible.
 To prove " $P \iff Q$ ", need to prove " $P \Rightarrow Q$ " and " $Q \Rightarrow P$ ".
Note: $\neg P \Rightarrow \neg Q$ is the same as $Q \Rightarrow P$.

*Subspaces (cont'd)***Thm (last class):** Let $W \subseteq V$ (subset). If

1. For all $u, v \in W$, $u + v \in W$
2. For all $u \in W$, $c \in K$, $cu \in W$
3. $\vec{0} \in W$

then $W \leq V$ (subspace). (ie: (1), (2), (3) are true $\Rightarrow W \leq V$)**Theorem 7.** Let $W \subseteq V$. Then

$$W \leq V \Rightarrow (1), (2), (3) \text{ are true}$$

(ie the converse of last theorem is true).

Proof. Exercise.**Theorem 8.** Let $W \subseteq V$. Then

$$W \leq V \iff (1), (2), (3) \text{ are true}$$

Examples of subspaces and non-subspaces

Is each subset a subspace?

- (a) $W = \left\{ \begin{pmatrix} 1 \\ 2 \end{pmatrix}, \begin{pmatrix} 3 \\ 1 \end{pmatrix} \right\} \subseteq \mathbb{R}^2$. Not a subspace, since the zero vector is not in W . The others are also false, but it's enough to prove that one of the statements does not hold. But $\text{span}(W) = \mathbb{R}^2$ (so $\text{span}(W) \leq \mathbb{R}^2$)

- (b) $W = \left\{ \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3 \mid x + y - z = 0 \right\}$. Need to check (1), (2), (3):

- (1) Let $\begin{pmatrix} x \\ y \\ z \end{pmatrix}, \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} \in W$. Then we know $x + y - z = 0$ and $x' + y' - z' = 0$. Check:

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} x + x' \\ y + y' \\ z + z' \end{pmatrix}$$

Verify

$$\begin{aligned} (x + x') + (y + y') - (z + z') &= (x + y - z) + (x' + y' - z') \\ &= 0 + 0 \\ &= 0 \end{aligned}$$

So yes, it is in W .

(2) Let $\begin{pmatrix} x \\ y \\ z \end{pmatrix} \in W$ (means $x + y - z = 0$), let $c \in K$. To prove

$$c \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} cx \\ cy \\ cz \end{pmatrix} \in W$$

Here, $cx + cy - cz = c(x + y - z) = c(0) = 0$. So $c \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in W$

(3) $\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \in W$, since $0 + 0 - 0 = 0$

Since (1), (2), (3) true, $W \leq \mathbb{R}^3$ (subspace)

(c) $W = \left\{ \begin{pmatrix} x \\ y \\ z \end{pmatrix} \in \mathbb{R}^3 \mid x + y - z = 1 \right\}$. This is *not* a subspace. (3) is false.

(d) $W = \{A \in M_{2 \times 2} \mid A_{ij} \geq 0 \forall i, j\}$, where A_{ij} is the entry of A in row i , column j . (1) and (3) are true:

(1) Add two matrices with non-negatives entries, result has non-negative entries.

(2) $\begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \in W$

Note, we wrote these out very informally. Now, (2) is false since,

for example $\begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \in W$ but

$$(-1) \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix} \notin W$$

Two special subspaces

Let V be a vector space.

(1) $V \leq V$ is true

(2) $\{\vec{0}\} \leq V$ is true ("zero subspace")

A refinement on the definition of span

Def. If $S = \emptyset$ (emptyset), define $\text{span}(S) = \{\vec{0}\}$ (if $S \neq \emptyset$, $\text{span}(S)$ defined as before).

Theorem 9. $\text{span}(S) \leq V$.

Proof Two cases :

1. If $S = \emptyset$, $\text{span}(S) = \{\vec{0}\} \leq V$
2. If $S \neq \emptyset$, you already proved $\text{span}(S)$ satisfies (1), (2), (3).
So $\text{span}(S) \leq V$.

Theorem 10. (improved version of subspace conditions) Let $W \subseteq V$. Then

$$W \leq V \iff W \neq \emptyset \text{ and } \forall w_1, w_2 \in W \text{ and } c \in K \text{ we have } cw_1 + w_2 \in W$$

Proof We will actually prove $(1), (2), (3) \iff \text{RHS (right-hand side)}$. Two parts to proof.

- (1) " $(1), (2), (3) \Rightarrow \text{RHS}$ " or " \Rightarrow "

January 23rd 2019

Recap:

- (1) If $u, v \in W$ then $u + v \in W$
- (2) if $u \in W, c \in K$ then $cu \in W$
- (3) $\vec{0} \in W$

Theorem 11. Let $W \subseteq V$. Then

$$W \leq V \iff W \neq \emptyset \text{ and } \forall u, v \in W, c \in K \text{ we have } cu + v \in W$$

Proof: Suffices to prove $(1), (2), (3) \iff \text{RHS}$.

1. \Rightarrow Assume $(1), (2), (3)$ (prove right-hand side). Two things to prove:

- (1) Since $\vec{0} \in W$ (by (3)), $W \neq \emptyset$
- (2) Let $u, v \in W$ and $c \in K$. Since (2) holds, $cu \in W$. Since (1) holds, $cu \in W$ and $v \in W$, so $cu + v \in W$.

2. \Leftarrow Assume RHS, prove $(1), (2), (3)$.

- (1) Let $u, v \in W$. Apply RHS with \Leftarrow to get

$$cu + v = 1u + v = u + v \in W$$

- (2) (Prove $\vec{0} \in W$) Since $W \neq \emptyset$, there is a vector $w \in W$. Apply right-hand side with $u = w, v = w, c = -1$. So $cu + v = (-1)w + w = -w + w = \vec{0} \in W$.
- (3) Let $u \in W, c \in K$. Apply RHS ($cu + v \in W$) with $u = u, c = c, v = \vec{0}$ (note: $\vec{0} \in W$ by (3) above). Then $cu + v = cu + \vec{0} = cu \in W$ \square

Ex: In $F(R, R) = V$ (functions $f : R \rightarrow R$), prove that

$$W = \{f \in V \mid f(3) = 0\}$$

is a subspace. Eg: $f(x) = (x - 3)e^x \in W$.

Solution: (1), (2) together (by last thm). Let $f, g \in W, c \in R$ (prove $cf + g \in W$). We know $f(3) = 0$ and $g(3) = 0$. Then, check $(cf + g)(3) = cf(3) + g(3) = 0 + 0 = 0$. So $cf + g \in W$.

Also, prove $w \neq \emptyset$. $f(x) = x - 3 \in W$, since $f(3) = 0$ (or, $z(3) = 0$ satisfies $z(3) = 0$ so $z \in W$. Note that z is the zero vector of $F(R, R)$).

Theorem 12. Let $A \in M_{m \times n}(K), b \in K^m$. Define

$$S = \{x \in K^n \mid Ax = b\}$$

ie S = solution set to linear system $Ax = b$. Then,

$$S \leq K^n \iff b = \vec{0} \text{ (ie system is homogeneous)}$$

Proof

- (i) \Rightarrow Assume $S \leq K^n$. Then $\vec{0}_n \in S$ (by (3)). So $A\vec{0} = b$ but $A\vec{0}_n = \vec{0}_m$ so $\vec{0} = b$.
- (ii) \Leftarrow Assume $b = \vec{0}_m$ (prove $S \leq K^n$). Then $A\vec{0}_n = \vec{0}_m$, so $\vec{0}_n \in S$. Next, let $u, v \in S, c \in K$. So $u, v \in K^n$ and $Au = b, Av = b$. Verify $cu + v$ is a solution.

$$\begin{aligned} A(cu + v) &= A(cu) + Av && \text{(prop of matrix multiplication)} \\ &= c(Au) + Av && \text{(prop of matrix multiplication)} \\ &= cb + b \\ &= c\vec{0} + \vec{0} \\ &= \vec{0} \\ &= b \quad \square \end{aligned}$$

Ex: Equation $ax + by + cz = d$ describes a plane in R^3 (eg $x + y + z = 1$) (and also, every plane can be described this way). That is,

$$\{(x, y, z) \in R^3 \mid ax + by + cz = d\}$$

is a plane.

By last thm,

P is a subspace $\iff ax + by + cz = d$ is a homogeneous system

$$\iff d = 0$$

$$\iff P \text{ passes through origin } (0,0,0)$$

Theorem 13. Let $S \subseteq V$. Then,

(1) $\text{span}(S) \leq V$ and $S \subseteq \text{span}(S)$

(2) If $S \subseteq W$, and $W \leq V$ (subspace) then $\text{span}(S) \subseteq W$ (actually, $\text{span}(S) \leq W$, subspace by (1))

Proof:

(1) \leq We know already. Let $u \in S$. Then $u = 1u$, so $u \in \text{span}(S)$

(2) Assume $S \subseteq W$, and $W \leq V$. Let $v \in \text{span}(S)$. Then $v = a_1u_1 + a_2u_2 + \dots + a_nu_n$ for some scalars and vectors $u_1, u_2, \dots, u_n \in S$. Since $S \subseteq W$, $u_1, u_2, \dots, u_n \in W$. But W subspace. So $a_1u_1, a_2u_2, \dots, a_nu_n \in W$ (by prop (2) subspace) then $a_1u_1 + a_2u_2 \in W$ (by prop (1) of subspaces). So then $(a_1u_1 + a_2u_2) + a_3u_3 \in W$ (etc). So $a_1u_1 + a_2u_2 + \dots + a_nu_n \in W$.

Note: "etc" here is actually a proof by mathematical induction.

Omit for now.

January 25th 2019

Interlude : Symbolic logic (briefly)

Let P, Q be statements that could be true (T) or false (F). Define:

- (1) $\neg P$, "not P", is F when P is T, T when P is F
- (2) $P \wedge Q$, "P and Q", is T exactly when P, Q both T
- (3) $P \vee Q$, "P or Q" is T when P, Q both F
- (4) $P \Rightarrow Q$, "P implies Q", is T unless P is T and Q is F. Hence, $P \Rightarrow Q$ is equivalent to $\neg P \vee Q$. We will write $P \Rightarrow Q \equiv \neg P \vee Q$.
- (5) $P \iff Q$, "P if and only if Q", is T if both T or both F.

De Morgan's Laws

- $\neg(P \wedge Q) \equiv \neg P \vee \neg Q$
- $\neg(P \vee Q) \equiv \neg P \wedge \neg Q$

Quantifiers

- \forall means "for all"
- \exists means "there exists"

Ex. (A4) (commutativity) $\forall u, v \in V \quad u + v = v + u$.

Ex. 2 (A2) (zero vector) $\exists z \in V \quad \forall u \in V \quad (u + z = u) \wedge (z + u = u)$
(textbook version)

Negating quantifiers

- $\neg \forall u \in V P(u) \equiv \exists u \in V \neg P(u)$
- $\neg \exists u \in V P(u) \equiv \forall u \in V \neg P(u)$

Ex.

$$\begin{aligned} \neg(A2) &\equiv \neg \exists z \in V \forall u \in V \quad u + z = u \wedge z + u = u \\ &\equiv \forall z \in V \neg \forall u \in V \quad u + z = u \wedge z + u = u \\ &\equiv \forall z \in V \exists u \in V \quad \neg(u + z = u \wedge z + u = u) \\ &\equiv \forall z \in V \exists u \in V \quad (u + z \neq u \vee z + u \neq u) \end{aligned}$$

Proof by contradiction

You want to prove some statement P . Proof by contradiction works this way:

- (1) Assume $\neg P$
- (2) Derive a contradiction (hard part)
- (3) Conclude P is true

Ex. Outline of how to prove (A2) *does not hold* in some vector space.
You want to prove $\neg(A2)$.

$$\begin{aligned} \neg(A2) &\equiv \neg \exists z \in V \forall u \in V \quad u + z = u \wedge z + u = u \\ &\equiv \forall z \in V \neg \forall u \in V \quad u + z = u \wedge z + u = u \end{aligned}$$

Let $z \in V$. Prove the right-hand part ($\neg \forall u \in V \quad u + z = u \wedge z + u = u$) by contradiction. Assume (for contradiction) that

$$\forall u \in V \quad u + z = u \wedge z + u = u \tag{1}$$

Use (1) by substituting u = some specific vector (derive a contradiction). Conclude that ($\neg \forall u \in V \quad u + z = u \wedge z + u = u$) is true.

Last time

Theorem 14. If $S \subseteq W$, $W \leq V$ then $\text{span}(S) \subseteq W$.

Note. This means if you "promote" a subset to a subspace, adding in only what's necessary, what you get is $\text{span}(S)$. Or, $\text{span}(S)$ is the "smallest" subspace containing S .

Fact. Subspaces are "closed under taking linear combinations". Ie if $W \leq V$, $w_1, \dots, w_n \in W$ and $a_1, \dots, a_n \in K$ then

$$a_1 w_1 + a_2 w_2 + \dots + a_n w_n \in W$$

Caution. Linear combinations are *finite* sums by definition. So you can't sum up infinitely many vectors.

Illustration of this theorem

Let $S = \left\{ \begin{pmatrix} 1 \\ 2 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 3 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 \\ 4 \\ 0 \end{pmatrix} \right\} \subseteq W = \left\{ \begin{pmatrix} x \\ y \\ 0 \end{pmatrix} \mid x, y \in R \right\}$. Then

$\text{span}(S) \subseteq W$ ie $\text{span}(S)$ is in xy plane. In fact, $\text{span}(S) = W$.

Def. If $W = \text{span}(S)$, we say that S spans W or is a spanning set for W .

Ex. $S = \left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \right\}$, $\text{span}(S) = xy\text{-plane in } R^3$. So S spans the $xy\text{-plane}$.

Ex. 2. $S = \left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \right\}$, $\text{span}(S) = \left\{ \begin{pmatrix} x \\ x \\ 0 \end{pmatrix} \mid x \in R \right\} = \text{line}$.

Intersection of two subspaces

Theorem 15. Let $W_1 \leq V$, $W_2 \leq V$. Then $W_1 \cap W_2 \leq V$ (ie intersection of two subspaces is a subspace).

Proof. $W_1 \cap W_2 = \{w \in V \mid w \in W_1 \wedge w \in W_2\}$.

- (1) $\vec{0} \in W_1, \vec{0} \in W_2$ (because subspace). So $\vec{0} \in W_1 \cap W_2$.
- (2) Let $u, v \in W_1 \cap W_2, c \in K$. So $u, v \in W_1$ and $W_1 \leq V$ so $cu + v \in W_1$ and $u, v \in W_2$ and $W_2 \leq V$ so $cu + v \in W_2$. Hence $cu + v \in W_1 \cap W_2$. \square

January 28th 2019

Last time: $W_1 \leq V$ and $W_2 \leq V \Rightarrow W_1 \cap W_2 \leq V$.

Corollary 15.1. *The intersection of any number of subspaces is a subspace.*

Problem. Prove that $W = \{f : \mathbb{R} \rightarrow \mathbb{R} \mid f(1) = 0 \wedge f(2) = 0\}$ is a subspace of $F(\mathbb{R}, \mathbb{R})$.

Sol #1: Directly from subspace properties (omit)

Sol #2: We saw an example proving that $\{f : \mathbb{R} \rightarrow \mathbb{R} \mid f(3) = 0\}$ is a subspace. The "3" is not important, so similarly:

$$W_1 = \{f : \mathbb{R} \rightarrow \mathbb{R} \mid f(1) = 0\}$$

$$W_2 = \{f : \mathbb{R} \rightarrow \mathbb{R} \mid f(2) = 0\}$$

both subspaces of $F(\mathbb{R}, \mathbb{R})$. Then $W_1 \cap W_2 = \{f : \mathbb{R} \rightarrow \mathbb{R} \mid f(1) = 0 \wedge f(2) = 0\}$ is a subspace.

Q: Is union of two subspaces also a subspace?

A: Not in general.

Eg: $W_1 = x\text{-axis} = \left\{ \begin{pmatrix} x \\ 0 \end{pmatrix} \mid x \in \mathbb{R} \right\} \leq \mathbb{R}^2$

$$W_2 = y\text{-axis} = \left\{ \begin{pmatrix} 0 \\ y \end{pmatrix} \mid y \in \mathbb{R} \right\} \leq \mathbb{R}^2$$

$W_1 \cup W_2 = xy\text{-axis} = \left\{ \begin{pmatrix} x \\ y \end{pmatrix} \mid x = 0 \vee y = 0 \right\}$, which, importantly, is not \mathbb{R}^2 . Not a subspace, since $\begin{pmatrix} 1 \\ 0 \end{pmatrix} \in W_1 \cup W_2$, $\begin{pmatrix} 0 \\ 1 \end{pmatrix} \in W_1 \cup W_2$, but $\begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \notin W_1 \cup W_2$.

Note: To promote $W_1 \cup W_2$ to a subspace, you form $\text{span}(W_1 \cup W_2)$.

Def: Let $W_1 \leq V$ and $W_2 \leq V$. The *sum* of W_1 and W_2 is

$$W_1 + W_2 = \{v \in V \mid \exists w_1 \in W_1, w_2 \in W_2, \text{ such that } v = w_1 + w_2\}$$

Ex:

$$W_1 = \{ax^2 \mid a \in \mathbb{R}\} \leq P(\mathbb{R})$$

$$W_2 = \{ax \mid a \in \mathbb{R}\} \leq P(\mathbb{R})$$

We have,

$$W_1 + W_2 = \{ax^2 + bx \mid a, b \in \mathbb{R}\}$$

Theorem 16. *Let $W_1 \leq V$, $W_2 \leq V$. Then*

(a) $W_1 + W_2 = \text{span}(W_1 \cup W_2)$ (hence $W_1 + W_2$ is a subspace)

(b) $W_1 \leq W_1 + W_2$, $W_2 \leq W_1 + W_2$

Proof:

(a)(1) Prove $W_1 + W_2 \subseteq \text{span}(W_1 \cup W_2)$. Let $v \in W_1 + W_2$, so $v = w_1 + w_2$ where $w_1 \in W_1$ and $w_2 \in W_2$. Then $w_1, w_2 \in W_1 \cup W_2$ so $v \in \text{span}(W_1 \cup W_2)$

- (2) " \supseteq ". Let $v \in \text{span}(W_1 \cup W_2)$. Means $v = a_1u_1 + a_2u_2 + \dots + a_nu_n$, $u_1, u_2, \dots, u_n \in W_1 \cup W_2$ and $a_1, a_2, \dots, a_n \in K$. Each u_i is in $W_1 \cup W_2$. Separate into two groups and relabel, so that:

- Those in W_1 , call these

$$u_1, u_2, \dots, u_l$$

So $0 \leq l \leq n$, $l = 0$ means *none* in W_1 .

- Those in $W_2 \setminus W_1 = \{w \in W_2 | w \notin W_1\}$ ("set difference"), call these

$$u_{l+1}, \dots, u_n$$

So $l = 0$ means all in $W_2 \setminus W_1$, $l = n$ means all in W_1 .

Then, let $w_1 = a_1u_1 + a_2u_2 + \dots + a_lu_l$ (or $w_1 = \vec{0}$ if $l = 0$),
 $w_2 = a_{l+1}u_{l+1} + \dots + a_nu_n$ (or $w_2 = \vec{0}$ if $l = n$).

Then $w_1 \in W_1$ since W_1 is a subspace, similarly $w_2 \in W_2$. So

$$\begin{aligned} v &= a_1u_1 + \dots + a_nu_n \\ &= w_1 + w_2 \in W_1 + W_2 \text{ as required} \end{aligned}$$

- (b) $W_1 \leq W_1 + W_2$, $W_2 \leq W_1 + W_2$. Follows from (a), since $S \subseteq \text{span}(S)$ \square .

Linear independence

Def: Vectors $u_1, u_2, \dots, u_n \in V$ (all distinct) are said to be *linearly dependent* if \exists scalars $a_1, a_2, \dots, a_n \in K$ *not all 0* such that

$$a_1u_1 + a_2u_2 + \dots + a_nu_n = \vec{0}$$

Above equation called a *dependence relation*.

Note: If $a_1u_1 + a_2u_2 + \dots + a_nu_n = \vec{0}$ and $a_1 \neq 0$, then you can solve for u_1 :

$$u_1 = \frac{-a_2}{a_1}u_2 - \frac{a_3}{a_1}u_3 - \dots - \frac{a_n}{a_1}u_n$$

ie u_1 is linear combination of others, "depends on" others.

Ex: $\{x^2 + x, 2x^2, \frac{x}{10}\}$ is a dependent set of vectors in $P(\mathbb{R})$ since

$$(x^2 + x) - \frac{1}{2}(2x^2) - 10(\frac{x}{10}) = 0$$

Def: A set of vectors $S \subseteq V$ (possibly infinite) is dependent if \exists a finite subset $\{v_1, v_2, \dots, v_n\} \subseteq S$ of it which is dependent.

Def: Vectors v_1, v_2, \dots, v_n are linearly independent if they are *not* dependent. That is,

$$\begin{aligned} \neg \exists a_1, \dots, a_n \in K \quad (a_1u_1 + \dots + a_nu_n = \vec{0} \wedge \neg(a_1 = 0 \wedge a_2 = 0 \wedge \dots \wedge a_n = 0)) \\ \forall a_1, \dots, a_n \in K \quad \neg(a_1u_1 + \dots + a_nu_n = \vec{0} \wedge \neg(a_1 = 0 \wedge a_2 = 0 \wedge \dots \wedge a_n = 0)) \\ \forall a_1, \dots, a_n \in K \quad (\neg(a_1u_1 + \dots + a_nu_n = \vec{0}) \vee (a_1 = 0 \wedge a_2 = 0 \wedge \dots \wedge a_n = 0)) \end{aligned}$$

Note that $P \implies Q \equiv \neg P \vee Q$. In other words, u_1, u_2, \dots, u_n are linearly independent if

$$\forall a_1, \dots, a_n \in K (a_1 u_1 + \dots + a_n u_n = \vec{0} \implies a_1 = 0 \wedge \dots \wedge a_n = 0)$$

Which is to say that the only solution to $a_1 u_1 + \dots + a_n u_n = \vec{0}$ is the trivial solution $a_1 = 0, a_2 = 0, \dots, a_n = 0$.

January 30th 2019

Last class

v_1, v_2, \dots, v_n independent if $x_1 v_1 + \dots + x_n v_n = \vec{0}$ has only trivial solution $x_1 = x_2 = \dots = x_n = 0$.

Ex: Prove that $\{1 + x^2, x + x^2, 1 + x + x^2\}$ is independent.

Solution: Consider equation

$$a(1 + x^2) + b(x + x^2) + c(1 + x + x^2) = 0 = 0(1) + 0x + 0x^2$$

Want to show $a = b = c = 0$ is the only solution.

Equation means for all $x \in K$ (\mathbb{R} or \mathbb{C}),

$$a(1 + x^2) + b(x + x^2) + c(1 + x + x^2) = 0$$

So, substitute any scalar for x :

$$x = 0 \quad a + c = 0$$

$$x = 1 \quad 2a + 2b + 2c = 0$$

$$x = -1 \quad 2a + 0b + c = 0$$

Can translate into linear system:

$$\begin{pmatrix} 1 & 0 & 1 & 0 \\ 2 & 2 & 3 & 0 \\ 2 & 0 & 1 & 0 \end{pmatrix}$$

Row-reduce:

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

Only solution is $a = 0, b = 0, c = 0$ so vectors are independent.

If we obtain infinitely many, then you can find dependent set so dependent.

Some important cases

- (i) $S = \emptyset$ is linearly independent since there are no vectors with which to form a dep. relation.
- (ii) If $\vec{0} \in S$, then dependent (since $1\vec{0} = \vec{0}$ is a dep. relation)
- (iii) $\{u\}$ is independent $\iff u \neq \vec{0}$.
Note: $u + (-1)u = \vec{0}$ is *not* a dep. relation, since u is repeated. But, $\{u, -u\}$ is dependent since

$$u + (-u) = \vec{0}$$

is a dep. relation.

Proposition 17. Let $A, B \subseteq V$ where $A \subseteq B$.

- (i) If A is dependent, B is also dependent
- (ii) If B is independent, A is also independent (contrapositive)

Proof:

- (i) If A dep, we have a dep relation

$$a_1v_1 + a_2v_2 + \dots + a_nv_n = \vec{0} \quad (\text{not all scalars } 0, v_1, \dots, v_n \in A)$$

which is also a dependence relation in B since $v_1, \dots, v_n \in B$.

- (ii) This is the contrapositive of (i). \square

Note: Converse is false, $B \text{ dep} \not\Rightarrow A \text{ dep}$.

Extending an independent set

Theorem 18. Let $S \subseteq V$ be linearly independent and suppose $u \notin S$. Then, $S \cup \{u\}$ independent $\iff u \notin \text{span}(S)$.

Proof:

- (i) " \rightarrow " We will prove this as the contrapositive, ie $u \in \text{span}(S) \rightarrow \text{dep}$. Assume $u \in \text{span}(S)$. So,

$$\begin{aligned} u &= a_1v_1 + \dots + a_nv_n \quad \text{where } v_1, v_2, \dots, v_n \in S \\ \vec{0} &= (-1)u + a_1v_1 + \dots + a_nv_n \end{aligned}$$

Which is a linear combination of vectors from $S \cup \{u\}$, not all coefficients 0 since first is -1 . Also, the vectors u, v_1, v_2, \dots, v_n are all distinct, since $u \notin S$. So this is a dependence relation on $S \cup \{u\}$, so the set is dependent.

- (ii) " \leftarrow " Also by contrapositive. Assume $S \cup \{u\}$ dep, want to show that $u \in \text{span}(S)$. So there is a dependence relation on $S \cup \{u\}$. Two cases:

- **Case 1:** Dependence relation does not involve u (or, involves u but with coefficient 0), ie we have

$$a_1 v_1 + \dots + a_n v_n = \vec{0} \quad (\text{not all scalars } 0, v_1, \dots, v_n \in S)$$

But this contradicts independence of S , so case 1 does not occur.

- **Case 2:** Dependence relation involves u (with coeff *not* 0), so

$$au + a_1 v_1 + \dots + a_n v_n = \vec{0} \quad v_1, \dots, v_n \in S$$

and $a \neq 0$. Rewrite:

$$u = \frac{-a_1}{a} v_1 - \frac{a_2}{a} v_2 - \dots - \frac{a_n}{a} v_n \quad (a \neq 0)$$

Hence $u \in \text{span}(S)$. \square

Note: Conclusion can be restated as

$$S \cup \{u\} \text{ dependent} \iff u \in \text{span}(S)$$

Basis and dimension

Fact: If W is subspace, then $\text{span}(W) = W$. (Exercise)

So every subspace is a span. But thinking of W as $\text{span}(W)$ is excessive. Would like to find the *smallest* S such that

$$\text{span}(S) = W$$

Def: Let $W \leq V$. A *basis* of W is a set $B \subseteq V$ such that

- $\text{span}(B) = W$ ("enough vectors to produce W ")
- B is linearly independent ("no extra vectors in B ")

Examples:

(i) Let $e_i = \begin{pmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{pmatrix} \leftarrow (\text{row } i)$. Then,

$$\{e_1, e_2, \dots, e_n\}$$

is a basis for K^n . For example,

$$\left\{ \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} \right\}$$

is a basis for K^3 .

More next class.

February 1st 2019

Recall: B is a basis of W if $\text{span}(B) = W$ and B is linearly independent.

Examples:

- (1) $P_n(K)$ has basis $\{1, x, x^2, \dots, x^n\}$
- (2) $P(K)$ has basis $\{1, x, x^2, x^3, \dots\}$ (infinitely many)
- (3) $M_{m \times n}(K)$ has basis $\{E^{ij} | 1 \leq i \leq m, 1 \leq j \leq n\}$ where $E^{ij} = m \times n$ matrix of 0s except 1 in row i , column j . eg: $M_{2 \times 2}(\mathbb{R})$ has basis

$$E^{11} = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}, E^{12} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}, E^{21} = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix}, E^{22} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

- (4) $W = \{\vec{0}\}$ has basis \emptyset since
 - (i) $\text{span } \emptyset = \{\vec{0}\}$ (by special def)
 - (ii) \emptyset is independent

Two important questions

- (1) Does W *always* have basis? (spoiler: yes)
- (2) How to *find* a basis?

Theorem 19 (Bases exist). *Let V be vector space and S a finite set with $\text{span}(S) = V$. Then there is a subset $B \subseteq S$ which is a basis of V .*

Proof. Algorithm to produce B .

- (1) If $V = \{\vec{0}\}$, use $B = \emptyset$.
- (2) Take one vector, $u_1 \in S (u_1 \neq \vec{0})$. Consider $\text{span}\{u_1\}$
- (3) If $\text{span}\{u_1\} = V$, done. $B = \{u_1\}$ is a basis (set of one non-zero vector is independent)
- (4) If $\text{span}\{u_1\} \neq V$, there must be a vector $u_2 \in S$ where $u_2 \notin \text{span}\{u_1\}$ (Why? If not, $S \subseteq \text{span}\{u_1\} \leq V$, then $\text{span}(S) \subseteq \text{span}\{u_1\}$, but $\text{span}(S) = V$ contradicts $V \neq \text{span}\{u_1\}$). By previous theorem, since $u_2 \notin \text{span}\{u_1\}$, $\{u_1, u_2\}$ is linearly independent.
- (5) Consider $\{u_1, u_2\}$. If $\text{span}\{u_1, u_2\} = V$, done: $B = \{u_1, u_2\}$. Else, continue as before, finding $u_3 \in S, u_3 \notin \text{span}\{u_1, u_2\}$ (etc)

Since S is *finite*, this must *stop* and at that point you have basis $B \subseteq S$. □

Illustration of this thm

Find basis of \mathbb{R}^3 that is a subset of

$$\left\{ \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 2 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 3 \\ 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 2 \\ 0 \end{pmatrix} \right\}$$

Following this algorithm,

$$u_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad u_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, \quad u_3 = \begin{pmatrix} 0 \\ 2 \\ 0 \end{pmatrix}$$

Theorem 20. Let V be a vector space, $L \subseteq V$ a linearly independent set, and $S \subseteq V$ a spanning set (ie $V = \text{span}(S)$). Then \exists a subset $E \subseteq S$ such that $L \cup E$ is a basis of V (ie you can always extend it to a basis)

Proof Omitted.

Theorem 21. Suppose V has a finite spanning set S . Then V has a basis and all bases have the same size, which is at most $|S|$.

Proof Omitted.

Def If V has a finite basis B , then the *dimension* of V is

$$\dim V = |B|$$

If V does not have a finite basis, it is called *infinite dimensional*.

Ex:

(1) $\dim K^n = n$.

$$\left(\left\{ \begin{pmatrix} 1 \\ 0 \\ \dots \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ \dots \\ 0 \end{pmatrix}, \dots, \begin{pmatrix} 0 \\ 0 \\ \dots \\ 1 \end{pmatrix} \right\} \right)$$

(2) $\dim P_n(K) = n + 1$ (basis $\{1, x, x^2, \dots, x^n\}$)

(3) $P(K)$ is infinite dimensional (A#1, proved a finite set of polynomials cannot span $P(K)$)

(4) $\dim M_{m \times n}(K) = mn$ (see basis E^{ij} , defined above)

Theorem 22. Every vector space (including the infinite dimensional ones) has a basis.

Proof Uses Axiom of Choice. Difficult.

Theorem 23. Suppose $\dim V = n$. Let $A \subseteq V$. Then,

- (1) If $\text{span}(A) = V$, then $|A| \geq n$ (or, if $|A| < n$ then A does not span V) and if also $|A| = n$ then A is linearly independent, hence basis.
- (2) If A is linearly independent, then $|A| \leq n$ (or, if $|A| > n$ then A dep) and if also $|A| = n$ then $\text{span}(A) = V$ hence A is a basis.

Proof Omitted.

Note: If you have *correct number* of vectors, you need only check spanning or independent, not both, to check if basis.

Ex: If you have 7 matrices in $M_{3 \times 2}(K)$, they *will be* dependent. If you have 5, it's *not* a basis.

February 4th 2019

Last class

Suppose $\dim V = n$, $S \subseteq V$, $|S| = n$. Then $S \text{ span } V \iff S \text{ linearly independent}$ (only in case $|S| = \dim V$).

Lagrange Interpolation

Problem Given "data points" $(a_1, b_1), (a_2, b_2), \dots, (a_n, b_n)$ where all a_i are different. Find a polynomial $p(x)$ of degree $n - 1$, $p(x) = c_{n-1}x^{n-1} + c_{n-2}x^{n-2} + \dots + c_1x + c_0$ whose graph $y = p(x)$ passes through all the points.

Sol #1 Substitute (a_1, b_1) into $y = p(x)$:

$$b_1 = c_{n-1}a_1^{n-1} + \dots + c_1a_1 + c_0 \quad (\text{for each } i = 1, \dots, n)$$

Which is a system of n linear equations (vars = c_{n-1}, \dots, c_0) in n variables.

We'll do something different.

Def For scalars a_1, a_2, \dots, a_n (all different), define the *Lagrange polynomials* for each $i = 1, 2, \dots, n$ set

$$\begin{aligned} l_i(x) &= \prod_{k=1, k \neq i}^n \frac{(x - a_k)}{(a_i - a_k)} \\ &= \frac{(x - a_1)}{(a_i - a_1)} \cdot \frac{(x - a_2)}{(a_i - a_2)} \cdot \dots \cdot \frac{(x - a_n)}{(a_i - a_n)} \quad (\text{omitting } \frac{(x - a_i)}{(a_i - a_i)}) \end{aligned}$$

Ex For $a_1 = 2, a_2 = 4, a_3 = 6$ we would have

$$\begin{aligned}l_1(x) &= \frac{(x-4)}{2-4} \cdot \frac{(x-6)}{(2-6)} \\l_2(x) &= \frac{(x-2)}{4-2} \cdot \frac{(x-6)}{(4-6)} \\l_3(x) &= \frac{(x-2)}{6-2} \cdot \frac{(x-4)}{(6-4)}\end{aligned}$$

Note: All degree 2, $l_1(4) = 0, l_1(6) = 0, l_1(2) = 1$.

Fact $l_i(a_j) = 0$ if $i \neq j$ and 1 if $i = j$.

Proof If $i \neq j$, there is a factor $\frac{x-a_j}{a_i-a_j}$, so at $x = a_j$, $\frac{a_j-a_j}{a_i-a_j} = 0$. If $i = j$,

$$l_i(a_i) = \prod_{k=1, k \neq i}^n \frac{(a_i - a_k)}{(a_i - a_i)} = 1$$

Proposition 24. Lagrange polynomials $l_1(x), \dots, l_n(x)$ form a basis of $P_{n-1}(\mathbb{R})$.

Proof We have n polynomials (they are distinct), $\dim P_{n-1}(\mathbb{R}) = n - 1 + 1 = n$. So correct number. Suffices to prove *span* or *lin* independence. We'll prove independence. Suppose

$$d_1 l_1(x) + d_2 l_2(x) + \dots + d_n l_n(x) = 0 \quad (\text{note: for all } x \in \mathbb{R})$$

Substitute $x = a_1, x = a_2$, etc into the above. At $x = a_1$, $l_1(a_1) = 1$ but $l_j(a_1) = 0$ for $j \neq 1$ so

$$d_1 1 + d_2 0 + \dots + d_n 0 = 0$$

so $d_1 = 0$. Similarly, $d_j = 0$ for all j . More formally, for any $j = 1, 2, \dots, n$ we have at $x = a_j$

$$\sum_{i=1}^n d_i l_i(a_j) = 0$$

but all terms are 0 *except* when $i = j$. Set

$$d_j = d_j(1) = d_j l_j(a_j) = 0$$

Hence Lagrange polynomials form a basis.

Problem Find poly degree $n - 1$ through points $(a_1, b_1), \dots, (a_n, b_n)$.

Sol: Set $p(x) = b_1 l_1(x) + b_2 l_2(x) + \dots + b_n l_n(x)$ (it has degree $n - 1$).

Then

$$\begin{aligned}p(a_1) &= b_1 l_1(a_1) + b_2 l_2(a_1) + \dots + b_n l_n(a_1) \\&= b_1(1) + 0 + 0 + \dots + 0 \\&= b_1\end{aligned}$$

For each $i = 1, 2, \dots, n$,

$$\begin{aligned} p(a_i) &= \sum_{j=1}^n b_j l_j(a_i) \\ &= 0 + 0 + \dots + b_i l_i(a_i) + \dots + 0 \\ &= b_i \end{aligned}$$

Dimension of subspaces

Theorem 20. Let $W \leq V$, V finite-dimensional. Then

(i) $\dim W \leq \dim V$

(ii) $\dim W = \dim V \iff W = V$

Proof

- (i) Similar to proof that V has basis. Use W as a spanning set for W . Pick out vectors one at a time (similar to before) to build a basis. You cannot put more than $\dim V$ vectors into your basis, as this would give an independent set in V of size *more than* $\dim V$ (impossible). So this process has to stop, and it produces a basis for W .
- (ii) " \rightarrow " Assume $\dim W = \dim V = n$. Take basis B of W . It is a size n linearly independent set inside V , hence B also basis for V , hence,

$$V = \text{span } B = W$$

" \leftarrow " If $W = V$, clearly $\dim W = \dim V$. \square

Subspaces of \mathbb{R}^3 If $W \leq \mathbb{R}^3$, $\dim W = 0, 1, 2$ or 3 .

This allows us to make the following classification: **Problem** Let

$\dim W$	Classification
0	$\{\vec{0}\}$
1	$\text{span}\{u\} = \text{line through origin}$
2	$\text{span}\{u, v\} = \text{plane through origin}$
3	\mathbb{R}^3

$W = \{A \in M_{n \times n}(\mathbb{R}) \mid \text{tr}(A) = 0\}$, where $\text{tr}(A) = \text{trace of } A = \text{sum of entries on diagonal} = A_{11} + A_{22} + \dots + A_{nn}$.

Exercise Prove W is a subspace.

Will do next class: Find $\dim W$ and find a basis of W .

February 6th 2019

Intuition

Solution set W to a homogeneous system $A\vec{x} = \vec{0}$ is a subspace of K^n ($n = \#$ of variables). If no equations, $W = K^n$, $\dim W = n$. For each equation, *expect* the dimension of W to drop by 1, unless the equation is *redundant*.

Eg: In \mathbb{R}^3 , one equation

$$a_1x + b_1y + c_1z = 0 \quad (= \text{plane})$$

add in $a_2x + b_2y + c_2z = 0$ (intersection of two planes, = line)

add in $a_3x + b_3y + c_3z = 0$ (intersection of three planes, (o,o))

Problem: $W = \{A \in M_{n \times n}(\mathbb{R}) \mid \text{tr } A = 0\}$. Find $\dim W$, basis of W .

Solution #1: Clever way: "guess" a basis. Note: $\text{tr } A = A_{11} + A_{22} + \dots + A_{nn}$ (one linear condition). Expecting

$$\dim W = n^2 - 1$$

Observe that $\dim W \neq n^2$. This happens only if $W = M_{n \times n}(\mathbb{R})$, and obviously there are matrices which don't have trace 0. Specifically:

$$\text{tr} \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \dots & \\ & & & 1 \\ & & & & 1 \end{pmatrix}$$

(In proofs, can choose any example, provided property holds).

Know $\dim W \leq n^2 - 1$. If you can find independent set of size $n^2 - 1$ in W , it *will be* a basis. Try first $n = 3$. Looking for $3^2 - 1 = 8$ independent 3×3 matrices, all trace 0.

Want trace = 0. Therefore, consider all matrices which have all 0's in the diagonal:

$$\begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}$$

These 6 are obviously independent. Now, take two more which are independent:

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \end{pmatrix}$$

Now we have 8 independent matrices (check carefully). So for $n = 3$, $\dim W = 8$, this is a basis.

General case

Two types of basis matrices:

- (I) All E^{ij} (1 in (i, j) -pos, 0 elsewhere)) where $i \neq j$. How many are there?

$$\begin{aligned}\# \text{ of non-diagonal entries} &= \text{entries} - \text{entries on diagonal} \\ &= n^2 - n\end{aligned}$$

Or, $\binom{n}{2}$ ways to choose 2 distinct values from $\{1, 2, \dots, n\}$, 2 ways to order each pair. Total:

$$\begin{aligned}\binom{n}{2} 2 &= \frac{n!}{2!(n-2)!} 2 \\ &= n(n-1) \\ &= n^2 - n\end{aligned}$$

- (II) Looking for $n-1$ more, since $n^2 - n + n - 1 = n^2 - 1$

$$\begin{pmatrix} 1 & & & \\ & -1 & & \\ & & \dots & \\ & & & 0 \\ & & & & 0 \end{pmatrix}, \begin{pmatrix} 0 & 1 & & \\ & -1 & & \\ & & \dots & \\ & & & 0 \\ & & & & 0 \end{pmatrix}, \begin{pmatrix} 0 & & & \\ & \dots & & \\ & & 1 & \\ & & & -1 \end{pmatrix}, \dots$$

(n-1 of those)

Formally, let, for $i = 1, 2, \dots, n-1$, D_i = matrix with 1 in pos (i, i) and -1 in pos $(i+1, i+1)$, 0 elsewhere.

Verifying all matrices E^{ii} , D_i are independent; clear that suffices to check D_1, D_2, \dots, D_{n-1} independent. Suppose

$$x_1 D_1 + x_2 D_2 + \dots + x_n D_n = n \times n \text{ zero matrix}$$

The $(1, 1)$ -entry on left is x_1 , so $x_1 = 0$. The $(2, 2)$ -entry on left is $-x_1 + x_2$,

$$x_1 \begin{pmatrix} 1 & & & \\ & -1 & & \\ & & \dots & \\ & & & 0 \\ & & & & 0 \end{pmatrix} + x_2 \begin{pmatrix} 0 & 1 & & \\ & -1 & & \\ & & \dots & \\ & & & 0 \\ & & & & 0 \end{pmatrix} + \dots = \begin{pmatrix} 0 & & & \\ & 0 & & \\ & & \dots & \\ & & & 0 \end{pmatrix}$$

but $x_1 = 0$ so $x_2 = 0$ also, etc. So similarly for all $x_i = 0$, so independent. Formally you'd do a proof by induction, but this is good enough.

Now have $n^2 - 1$ independent vectors in W_1 so $\dim W \geq n^2 - 1$. Already, know $\dim W \leq n^2 - 1$. So $\dim W = n^2 - 1$, have independent set of correct size, so basis.

Solution #2: Let x_{ij} be the (i, j) -entry of A . So have n^2 variables $(x_{ij}, i, j = 1, 2, \dots, n)$ one equation,

$$x_{11} + x_{22} + \dots + x_{nn} = 0 \quad (\text{tr } A = 0)$$

Solve system. All $x_{ij}, i \neq j$ free variables, so are x_{22}, \dots, x_{nn} .

Theorem 21. Let U, W be finite dimension subspaces of V . Then,

$$\dim(U + W) = \dim U + \dim W - \dim U \cap W$$

It's like sets, $|A \cup B| = |A| + |B| - |A \cap B|$.

Proof Omitted.

Ex: If W is a plane in \mathbb{R}^3 (through $(0,0)$) and L is a line in \mathbb{R}^3 (through $(0,0)$) and L is not in the plane, prove $W + L = \mathbb{R}^3$.

Sol: L not in plane gives $L \cap W = \{\vec{0}\}$. So

$$\begin{aligned} \dim(L + W) &= \dim L + \dim W - \dim L \cap W \\ &= 1 + 2 - 0 \\ &= 3 \end{aligned}$$

Hence $L + W = \mathbb{R}^3$.

Problem: Suppose $\dim V = n$, and U, W subspaces, each of dimension more than $\frac{n}{2}$. Prove that $U \cap W \neq \{\vec{0}\}$.

Proof By contradiction. Suppose $U \cap W = \{\vec{0}\}$. So $\dim U \cap W = 0$. Then

$$\begin{aligned} \dim(U + W) &= \dim U + \dim W - \dim U \cap W \\ &> \frac{n}{2} + \frac{n}{2} - 0 = n \end{aligned}$$

Says $U + W$ is a subspace of V of \dim more than $\dim V$. Impossible, so $U \cap W \neq \{\vec{0}\}$.

END OF MIDTERM MATERIAL.

February 8th 2019

Monday: No class, office hours during class time. Tuesday night : Midterm!

Linear transformations - Definition and basic properties

(Chap. 5 in the text) **Def.** Let U, V be vector spaces, both over field K . A function $T : U \rightarrow V$ is called a *linear transformation* if

- (i) $\forall u_1, u_2 \in U \quad T(u_1 + u_2) = T(u_1) + T(u_2)$. The first '+' is in U , while the second '+' is in V . The vector spaces need not be related in any way, except that they must be over the same field of scalars.
- (ii) $\forall u \in U, c \in K \quad T(cu) = cT(u)$. Again, the first scalar multiplication happens in U , while the second scalar multiplication happens in V .

Comment: Linear transformations are the functions that are somehow “compatible” with the vector space operations.

Ex: Prove that $T : P_2(\mathbb{R}) \rightarrow \mathbb{R}^2$ defined by

$$T(ax^2 + bx + c) = \begin{pmatrix} a + b \\ b + c \end{pmatrix}$$

Sol:

(i) Let $p_1(x) = a_1x^2 + b_1x + c_1$, $p_2(x) = a_2x^2 + b_2x + c_2$ be in $P_2(x)$.

Then,

$$\begin{aligned} T(p_1(x) + p_2(x)) &= T((a_1 + a_2)x^2 + (b_1 + b_2)x + c_1 + c_2) \\ &= \begin{pmatrix} a_1 + a_2 + b_1 + b_2 \\ b_1 + b_2 + c_1 + c_2 \end{pmatrix} \\ T(p_1(x)) + T(p_2(x)) &= \begin{pmatrix} a_1 + b_1 \\ b_1 + c_1 \end{pmatrix} + \begin{pmatrix} a_2 + b_2 \\ b_2 + c_2 \end{pmatrix} \\ &= \begin{pmatrix} a_1 + b_1 + a_2 + b_2 \\ b_1 + c_1 + b_2 + c_2 \end{pmatrix} \end{aligned}$$

(ii) Let $p(x) = ax^2 + bx + c \in P_2(\mathbb{R})$, $d \in K$.

$$\begin{aligned} T(dp(x)) &= T(dax^2 + dbx + dc) \\ &= \begin{pmatrix} da + db \\ db + dc \end{pmatrix} \\ &= d \begin{pmatrix} a + b \\ b + c \end{pmatrix} \\ &= dT(ax^2 + bx + c) \\ &= dT(p(x)) \end{aligned}$$

So T is a linear transformation.

Ex Define $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ by $T(x, y) = (x^2, x + y)$. Show that T is *not* a linear transformation.

Sol Try $u = (2, 3)$, $v = (3, 4)$.

$$\begin{aligned} T(u + v) &= T(5, 7) \\ &= (25, 12) \end{aligned}$$

On the other hand,

$$\begin{aligned} T(u) + T(v) &= T(2, 3) + T(3, 4) \\ &= (4, 5) + (9, 7) \\ &= (13, 12) \\ &\neq (25, 12) \end{aligned}$$

So T is *not* linear.

Ex: Define $\frac{d}{dx} : P(\mathbb{R}) \rightarrow P(\mathbb{R})$ by

$$\frac{d}{dx}p(x) = p'(x) \quad (\text{derivative})$$

Then $\frac{d}{dx}$ is a linear transformation, since we know from calculus that

$$\begin{aligned} \frac{d}{dx}(p(x) + q(x)) &= \frac{d}{dx}p(x) + \frac{d}{dx}q(x) \\ \frac{d}{dx}(cp(x)) &= c\frac{d}{dx}p(x) \quad (c \in \mathbb{R}) \end{aligned}$$

Proposition 22. Let $T : U \rightarrow V$ be a linear transformation. Then,

(i) $T(\vec{0}) = \vec{0}$ (where the first $\vec{0}$ is the zero vector of U and the second is the zero vector of V)

(ii) $\forall u_1, u_2, \dots, u_n \in U$ and $c_1, c_2, \dots, c_n \in K$,

$$\begin{aligned} T(c_1u_1 + c_2u_2 + \dots + c_nu_n) &= \\ c_1T(u_1) + c_2T(u_2) + \dots + c_nT(u_n) \end{aligned}$$

Proof. (i)

$$\begin{aligned} T(\vec{0}_U) &= T(\vec{0}_U + \vec{0}_U) \\ T(\vec{0}_U) &= T(\vec{0}_U) + T(\vec{0}_U) \quad (\text{T linear}) \\ \vec{0}_V + T(\vec{0}_U) &= T(\vec{0}_U) + T(\vec{0}_U) \quad (\text{A2}) \\ \vec{0}_V &= T(\vec{0}_U) \quad (\text{cancellation law}) \end{aligned}$$

(ii)

$$\begin{aligned} T(c_1u_1 + (c_2u_2 + \dots + c_nu_n)) &= T(c_1u_1) + T(c_2u_2 + \dots + c_nu_n) \quad (\text{T linear}) \\ &= c_1T(u_1) + T(c_2u_2 + \dots + c_nu_n) \quad (\text{T linear}) \\ &= \dots \quad (\text{proof by induction}) \\ &= c_1T(u_1) + \dots + c_nT(u_n) \end{aligned}$$

□

Proposition 23. Let $T : U \rightarrow V$ function (U, V vector spaces). Then,

$$\begin{aligned} T \text{ is linear transformation} &\iff \\ \forall u_1, u_2 \in U \ c \in K, T(cu_1 + u_2) &= cT(u_1) + T(u_2) \end{aligned}$$

Proof: Exercise. □

February 15th 2019

Def ("matrix defines a linear transformation") Let $A \in M_{m \times n}(K)$.

Define a function $L_A : K^n \rightarrow K^m$ by

$$L_A(v) = Av \quad (\text{A an } m \times n \text{ matrix, } v \text{ } n \times 1)$$

ie multiply matrix by vector.

Proposition 24. L_A is a linear transformation.

Proof. Let $u, v \in K^n, c \in K$. Then

$$\begin{aligned} L_A(cu + v) &= A(cu + v) \\ &= A(cu) + Av \quad (\text{prop of matrix multiplication}) \\ &= cAu + Av \\ &= cL_A(u) + L_A(v) \end{aligned}$$

□

Ex $A = \begin{pmatrix} 3 & 1 & 4 \\ 2 & -1 & 2 \end{pmatrix}, L_A : \mathbb{R}^3 \rightarrow \mathbb{R}^2$. Calculate:

$$\begin{aligned} L_A(1, 3, -2) &= \begin{pmatrix} 3 & 1 & 4 \\ 2 & -1 & 2 \end{pmatrix} \begin{pmatrix} 1 \\ 3 \\ -2 \end{pmatrix} \\ &= \begin{pmatrix} -2 \\ 2 - 3 - 4 \end{pmatrix} \\ &= \begin{pmatrix} -2 \\ -5 \end{pmatrix} \end{aligned}$$

Spoiler: All linear transformations between finite-dim vector spaces can be described in this way, "matrix transformation".

Two special linear transformations

- (1) **Zero transformations:** $0 : V \rightarrow W$ defined by $0(v) = \vec{0}$ ($\vec{0}$ of W) for all $v \in V$.
- (2) **Identity transformation,** $I : V \rightarrow V$ (same vector space) $I(v) = v$ for all $v \in V$

Both are linear transformations (exercise).

Kernel and Image (ch. 5.4)

Def Let $T : V \rightarrow W$ be a linear transformation. Define:

(i) **Kernel or nullspace** of T ,

$$\text{Ker}(T) = \{v \in V \mid T(v) = \vec{0}\}$$

Note: Always one vector which satisfies this.

(ii) **Image** of T is

$$\text{Im}(T) = \{w \in W \mid \exists v \in V \ w = T(v)\}$$

Note: $\text{Ker}(T) \subseteq V$, $\text{Im}(T) \subseteq W$.

Ex Define $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ by

$$T(x, y) = (x, 0) \quad (\text{"proj onto x-axis"})$$

Then

$$\begin{aligned} \text{Ker}(T) &= \{(x, y) \in \mathbb{R}^2 \mid T(x, y) = (0, 0)\} \\ &= \{(0, y) \mid y \in \mathbb{R}\} \\ &= \text{"y-axis"} \\ \text{Im}(T) &= \{(x, y) \in \mathbb{R}^2 \mid (x, y) = T(x', y') \text{ some } x', y' \in \mathbb{R}\} \\ &= \{(x, 0) \mid x \in \mathbb{R}\} \\ &= \text{"x-axis"} \end{aligned}$$

Ex Define $D : P_n(\mathbb{R}) \rightarrow P_n(\mathbb{R})$ to be derivative, $D(f(x)) = f'(x)$. Find kernel and image of D .

Sol We have

$$\begin{aligned} \text{Ker}(D) &= \{f \in P_n(\mathbb{R}) \mid f'(x) = 0\} \\ &= \text{const. polys} \\ &= \{a \mid a \in \mathbb{R}\} \\ &= P_0(\mathbb{R}) \end{aligned}$$

Claim $\text{Im}(D) = P_{n-1}(\mathbb{R})$.

Proof. Prove inclusion " \subseteq " and " \supseteq ".

- (i) " \subseteq " Let $f(x) \in \text{Im}(D)$. Then $\exists g(x) \in P_n$ s.t. $f(x) = D(g(x)) = g'(x)$. Since $\deg(g) \leq n$, $\deg(f) = \deg(g') \leq n - 1$ (property of differentiation). So $f(x) \in P_{n-1}$.
- (ii) " \supseteq " Let $f(x) \in P_{n-1}$. Need to find $g(x) \in P_n$ such that $D(g(x)) = g'(x) = f(x)$. Set $g(x) = \int f(x)dx$. Know from calculus that the degree of g is one higher, ie

$$\deg(g(x)) = 1 + \deg(f(x))$$

So $\deg(g) \leq n$. So $g(x) \in P_n$ and $g'(x) = f(x)$ (calculus).

□

Theorem 25. Let $T : V \rightarrow W$ be linear transformation. Then,

$$(i) \text{ Ker}(T) \leq V$$

$$(ii) \text{ Im}(T) \leq W$$

ie they are subspaces.

Proof. By direct proof.

- (i) $T(\vec{0}) = \vec{0}$ always (lin transform) so $\vec{0} \in \text{Ker}(T)$. Let $v_1, v_2 \in \text{Ker}(T), c \in K$. We know $T(v_1) = \vec{0}, T(v_2) = \vec{0}$. Then

$$\begin{aligned} T(cv_1 + v_2) &= cT(v_1) + T(v_2) && \text{(T linear)} \\ &= c\vec{0} + \vec{0} \\ &= \vec{0} \end{aligned}$$

Hence $cv_1 + v_2 \in \text{Ker}(T)$. So $\text{Ker}(T) \subseteq V$ (we already knew $\text{Ker}(T) \subseteq V$)

- (ii) $T(\vec{0}) = \vec{0}$, hence $\vec{0}_w = T(\text{something})$, ie $\vec{0}_w \in \text{Im}(T)$. Let $w_1, w_2 \in \text{Im}(T), c \in K$. We know $w_1 = T(v_1), w_2 = T(v_2)$ for some $v_1, v_2 \in V$. Then

$$\begin{aligned} cw_1 + w_2 &= cT(v_1) + T(v_2) \\ &= T(cv_1 + v_2) && \text{(T linear)} \end{aligned}$$

Hence $cw_1 + w_2 \in \text{Im}(T)$. So $\text{Im}(T) \leq W$.

□

Def $T : V \rightarrow W$ linear. The *nullity* of T is $\dim \text{Ker}(T)$ (dim nullspace). The *rank* of T is $\dim \text{Im}(T)$.

Note: $\text{Ker}(T) \leq V$ so $\text{nullity}(T) \leq \dim V$, $\text{Im}(T) \leq W$ so $\text{rank}(T) \leq \dim W$.

Ex In $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$, proj onto x-axis,

$$\begin{aligned} \text{Ker}(T) &= y - \text{axis} && \text{(so nullity}(T) = 1) \\ \text{Im}(T) &= x - \text{axis} && \text{(so rank}(T) = 1) \end{aligned}$$

Ex 2 For $D : P_n(\mathbb{R}) \rightarrow P_n(\mathbb{R})$, differentiation.

$$\begin{aligned} \text{Ker } D &= P_0(\mathbb{R}) && \text{(so nullity}(D) = 1) \\ \text{Im } D &= P_{n-1} && \text{(so rank}(D) = n) \end{aligned}$$

February 18th 2019

Notation For set $S = \{v_1, v_2, \dots, v_n\}$, $T : V \rightarrow W$ denotes $T(S) = \{T(v_1), T(v_2), \dots, T(v_n)\}$.

Proposition 26. $T : V \rightarrow W$ linear and $V = \text{span}(S)$. Then $\text{Im } T = \text{span}(T(S))$. In particular, if B basis of V , $T(B)$ **spans** $\text{Im } T$ (but need not be a basis).

Proof. By direct proof.

- (i) " \subseteq ". Let $w \in \text{Im}(T)$, ie $w = T(v)$, some $v \in V$. Since S spans V , $v = \sum_{i=1}^n a_i v_i$, some $v_i \in S$. So

$$\begin{aligned} w = T(v) &= T\left(\sum_{i=1}^n a_i v_i\right) \\ &= \sum_{i=1}^n a_i T(v_i) \quad (T(v_i) \in T(S), \text{ by } T \text{ linear}) \end{aligned}$$

All of which is $\in \text{span}(T(S))$.

- (ii) " \supseteq " Let $w \in \text{span } T(S)$. So

$$\begin{aligned} w &= \sum_{i=1}^n a_i T(v_i) && (\text{for some vectors } v_i \in S) \\ &= T\left(\sum_{i=1}^n a_i v_i\right) && (T \text{ linear}) \\ &= T(\text{something}) && (\text{so } w \in \text{Im}(T)) \end{aligned}$$

□

Ex Define $T : P_2(\mathbb{R}) \rightarrow \mathcal{M}_{2 \times 2}(\mathbb{R})$ by

$$T(f(x)) = \begin{pmatrix} f(1) - f(2) & 0 \\ 0 & f(0) \end{pmatrix}$$

Exercise: T is linear. Find basis for $\text{Im } T$.

Sol Take basis $\{1, x, x^2\}$ for P_2 . Calculate

$$\begin{aligned} T(1) &= \begin{pmatrix} 1 - 1 & 0 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix} \\ T(x) &= \begin{pmatrix} 1 - 2 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix} \\ T(x^2) &= \begin{pmatrix} 1 - 4 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} -3 & 0 \\ 0 & 0 \end{pmatrix} \end{aligned}$$

$$\text{So } \text{Im } T = \text{span}\left\{\begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix}, \begin{pmatrix} -3 & 0 \\ 0 & 0 \end{pmatrix}\right\}.$$

$$\text{Basis for } \text{Im } T \text{ is } \left\{\begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}, \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix}\right\}$$

$$(\text{so } \text{Im } T = \left\{\begin{pmatrix} a & 0 \\ 0 & b \end{pmatrix} \mid a, b \in \mathbb{R}\right\})$$

Note: The next theorem is very important!

Theorem 27. ("Dimension theorem") Let $T : V \rightarrow W$ linear with V finite-dimensional. Then,

$$\dim V = \dim \ker(T) + \dim \text{Im}(T)$$

$$\dim V = \text{nullity}(T) + \text{rank}(T)$$

Note $\dim W$ is not involved.

Proof. Let $B = \{v_1, v_2, \dots, v_k\}$ be basis $\text{Ker } T$ (so $k = \dim \text{Ker } T$). Let $n = \dim V$. Note $T(v_i) = 0$, ($i = 1, 2, \dots, k$). Let S span V .

Plan: extend B to basis of V , show $T(\text{extra vector}) = \text{basis of Im}$.

By theorem 20-1, there exists $E \subseteq S$ such that $B \cup E$ is a basis of V .

Denote

$$E = \{v_{k+1}, \dots, v_n\} \quad (\text{note } n = \dim V, |E| = n - k)$$

Claim $T(E)$ is basis for $\text{Im } T$.

(i) $T(E)$ spans $\text{Im } T$

(a) " \subseteq " is clear since $T(E) \subseteq \text{Im } T$ by definition. So $\text{span } T(E) \subseteq \text{Im } T$ ($\text{Im } T \subseteq W$)

(b) " \supseteq " Let $w \in \text{Im}(T)$, ie $w = T(v)$, some $v \in V$. Since $B \cup E$ is a basis, $v = \sum_{i=1}^n a_i v_i$. Then,

$$\begin{aligned} w &= T\left(\sum_{i=1}^n a_i v_i\right) \\ &= \sum_{i=1}^n a_i T(v_i) && (T \text{ linear}) \\ &= \sum_{i=k+1}^n a_i v_i && (\text{Since } T(v_i) = 0 \text{ for } i = 1, 2, \dots, k) \end{aligned}$$

Hence $w \in \text{span}(T(E))$, since $E = \{v_{k+1}, \dots, v_n\}$

(ii) $T(E)$ is linearly independent. Suppose

$$\sum_{i=k+1}^n b_i T(v_i) = \vec{0} \quad (\text{linear comb vectors in } T(E))$$

So by linearity of T ,

$$T\left(\sum_{i=k+1}^n b_i v_i\right) = \vec{0}$$

So $\sum_{i=k+1}^n b_i v_i \in \text{Ker } T$, ie is linear comb of B

So $\sum_{i=k+1}^n b_i v_i = \sum_{i=1}^k b_i v_i$

ie $\sum_{i=1}^k (-b_i) v_i + \sum_{i=k+1}^n b_i v_i = \vec{0}$ is linear comb of v_1, \dots, v_n (ie $B \cup E$) but these independent. So all $b_i = 0$, hence $T(E)$ independent.

Conclude $T(E)$ basis of $\text{Im } T$. So,

$$\dim \text{Im } T = |T(E)| = |E| = n - k$$

So,

$$n = k + n - k$$

$$\dim V = |B| + |T(E)| = \dim \text{Ker } T + \dim \text{Im } T$$

□

Why is $|T(E)| = |E|$? True unless

$$T(v_i) = T(v_j) \quad (\text{for some } i, j \geq k+1, i \neq j)$$

If so,

$$T(v_i) - T(v_j) = 0$$

$$T(v_i - v_j) = 0 \quad (\text{so } v_i - v_j \in \text{Ker } T)$$

Hence $v_i - v_j = \sum_{l=1}^n a_l v_l$, dep relation on v_1, \dots, v_n . Impossible. □

Problem For $T : P_2 \rightarrow \mathcal{M}_{2 \times 2}$,

$$T(f(x)) = \begin{pmatrix} f(1) - f(2) & 0 \\ 0 & f(0) \end{pmatrix}$$

Find basis for $\text{Ker } T$.

Sol Already know $\dim \text{Im } T = 2$ (last ex). So

$$\dim P_2 = \dim \text{Ker } T + \dim \text{Im } T$$

$$3 = \dim \text{Ker } T + 2$$

So $\text{Ker } T$ is 1-dimensional. Only need to find *one* non-zero $f(x)$ s.t.

$$T(f(x)) = \begin{pmatrix} f(1) - f(2) & 0 \\ 0 & f(0) \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

ie need $f(1) = f(2)$ and $f(0) = 0$. For example, $f(x) = x^2 - 3x$ works. So $\{x^2 - 3x\}$ is a basis for $\text{Ker } T$ (or, $f(x) = ax^2 + bx + c$, $f(1) = a + b + c = f(2) = 4a + 2b + c$, $f(0) = 0 = c$, solve)

February 20th 2019

Comments on dimension theorem

$T : V \rightarrow W$, linear.

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

Left-hand part of the sum: Dimensions that are preserved ("saved") by T . Right-hand part: dimensions that are "lost" when you apply T .

Dimension: Subspaces are *infinite* sets (except $\{\vec{0}\}$). Dimension gives a way to compare the *sizes* of subspaces.

Injective/surjective transformation (ch. 5.5.)

Def Let $f : X \rightarrow Y$ be a *function* (X, Y sets).

(i) f is *surjective* ("onto") if

$$\forall y \in Y \quad \exists x \in X \quad f(x) = y$$

(equivalently, the image of f is Y)

(ii) f is called *injective* (or "on-to-one") if

$$\forall x_1, x_2 \in X (x_1 \neq x_2 \rightarrow f(x_1) \neq f(x_2))$$

(equivalently, $\forall x_1, x_2 \in X \quad (f(x_1) = f(x_2) \rightarrow x_1 = x_2)$)

Theorem 28. ("How to check if T inj/surj") Let $T : V \rightarrow W$. Then,

(i) T *injective* $\iff \text{Ker}(T) = \{\vec{0}\}$ (*nullity* (T) = 0)

(ii) T *surjective* $\iff \dim (\text{Im } T) = \dim W$ (*rank*(T) = $\dim W$)

(i) *Proof.* By direct proof.

(1) " \Rightarrow " Assume T inj. (know $\{\vec{0}\} \leq \text{Ker } T$). Let $v \in \text{Ker } (T)$. So $T(v) = \vec{0}$. But also $T(\vec{0}) = \vec{0}$, so $T(v) = T(\vec{0})$ hence $v = \vec{0}$ since T is injective.

(2) " \Leftarrow " Assume $\text{Ker } T = \{\vec{0}\}$. Let $v_1, v_2 \in V$. Suppose $T(v_1) = T(v_2)$ (prove $v_1 = v_2$).

$$\begin{aligned} T(v_1) - T(v_2) &= \vec{0} \\ T(v_1 - v_2) &= \vec{0} \end{aligned} \quad (\text{linear})$$

So $v_1 - v_2 \in \text{Ker } T = \{\vec{0}\}$. So $v_1 - v_2 = \vec{0}$, $v_1 = v_2$.

□

(ii) *Proof.* By direct proof.

- (1) " \Rightarrow " Assume T is surjective, that is $\text{Im } T = W$. Hence $\dim \text{Im } T = \dim W$.
- (2) " \Leftarrow " Assume $\dim \text{Im } T = \dim W$. But $\text{Im } T \leq W$, hence $\text{Im } T = W$ (by thm 20-2)

□

Problem Define $T : P_2(\mathbb{R}) \rightarrow \mathbb{R}$ by

$$T(f(x)) = \int_0^1 f(x) dx$$

(Exercise: T is linear). Is T injective? Surjective?

Sol *Dim Thm:*

$$\begin{aligned} \dim P_2 &= \dim \text{Im } T + \dim \text{Ker } T \\ 3 &= \dim \text{Im } T + \dim \text{Ker } T \end{aligned}$$

Hence $\text{Im } T \leq \mathbb{R}^1$, so $\text{Im } T = \{\vec{0}\}$ or \mathbb{R} . It is not $\{\vec{0}\}$ since $\int_0^1 1 dx = 1 \neq 0$, $T(1) \neq 0$. Hence $\text{Im } T = \mathbb{R}$ so

$$3 = 1 + \dim \text{Ker } T$$

So $\dim \text{Ker } T = 2$. $\text{Ker } T \neq \{\vec{0}\}$ not injective. $\text{Im } T = \mathbb{R}$ is surjective.

Theorem 29. ("shortcut when dim same") $T : V \rightarrow W$ linear, and $\dim V = \dim W$. Then,

$$T \text{ injective} \iff T \text{ surjective}$$

Proof. *Dim Thm:*

$$\dim W = \dim V = \dim \text{Im } T + \dim \text{Ker } T$$

If T inj, $\dim \text{Ker } T = 0$. So

$$\dim W = \dim \text{Im } T + 0$$

So T surjective (thm 28). If T surj, $\dim \text{Im } T = \dim W$ (thm 28), so

$$\dim W = \dim W + \dim \text{Ker } T$$

So $\dim \text{Ker } T = 0$ so $\text{Ker } T = \{\vec{0}\}$

□

Problem $T : P_2(\mathbb{R}) \rightarrow \mathbb{R}^3$, defined by

$$T(f(x)) = \begin{pmatrix} f(0) \\ f(1) \\ f(2) \end{pmatrix}$$

Is T injective? Surjective?

Sol Same $\dim (= 3)$. Check only one. Check surjective directly from def surj:

Let $\begin{pmatrix} a \\ b \\ c \end{pmatrix} \in \mathbb{R}^3$. Is $\begin{pmatrix} a \\ b \\ c \end{pmatrix} = T(f(x))$, some $f(x) \in P_2$?

That is, given $a, b, c \in \mathbb{R}$, is there a degree 2 polynomial such that $f(0) = a, f(1) = b, f(2) = c$? By Lagrange Interpolation, $f(x)$ exists ($\deg = 1$, less than # of points). So T surj, so also inj.

Isomorphism and coordinates (ch 5.5, 4.11 and 4.12)

Def: (Isomorphism)

- (1) If $T : V \rightarrow W$ (linear) is injective and surjective, it is called an *isomorphism*.
- (2) If V, W vector spaces and *there exists* an isomorphism $T : V \rightarrow W$, we say V and W are *isomorphic* and write $V \simeq W$

Note A function that is injective and surjective is called *bijective*.

Ex $T : P_2(\mathbb{R}) \rightarrow \mathbb{R}^3, T(f(x)) = \begin{pmatrix} f(0) \\ f(1) \\ f(2) \end{pmatrix}$ is an isomorphism (last ex.)

so $P_2(\mathbb{R}) \simeq \mathbb{R}^3$

Ex Prove that

$$T(ax^2 + bx + c) = \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

is isomorphism $P_2 \rightarrow \mathbb{R}^3$.

Sol T is linear : let $f(x), g(x) \in P_2(\mathbb{R}), d \in \mathbb{R}$. Then,

$$\begin{aligned} T(df + g) &= T(c(a_1x^2 + b_1x + c_1) + (a_2x^2 + b_2x + c_2)) \\ &= T((da_1 + a_2)x^2 + (db_1 + b_2)x + (dc_1 + c_2)) \\ &= \begin{pmatrix} da_1 + a_2 \\ db_1 + b_2 \\ dc_1 + c_2 \end{pmatrix} \\ &= d \begin{pmatrix} a_1 \\ b_1 \\ c_1 \end{pmatrix} + \begin{pmatrix} a_2 \\ b_2 \\ c_2 \end{pmatrix} \\ &= dT(f) + T(g) \end{aligned}$$

So T linear. Same $\dim (= 3)$. Check surj. Let $\begin{pmatrix} a \\ b \\ c \end{pmatrix} \in \mathbb{R}^3$. Then

$$T(ax^2 + bx + c) = \begin{pmatrix} a \\ b \\ c \end{pmatrix}, \text{ hence surj., hence inj., hence isomorphism.}$$

February 22nd 2019

Notes about functions

- (1) If $f : X \rightarrow Y$, then f injective and surjective $\iff f$ is invertible,
ie $\exists f^{-1} : Y \rightarrow X$ such that $\forall x \in X, y \in Y$ $f^{-1}(f(x)) = x$ and
 $f(f^{-1}(y)) = y$
- (2) If $g : Y \rightarrow Z$, you can compose f and g to get $g \cdot f : X \rightarrow Z$, defined
by $(g \cdot f)(x) = g(f(x))$ $x \xrightarrow{f} y \xrightarrow{g} z$

Theorem 30. Let $T : V \rightarrow W$ be an isomorphism (ie T linear, inj, surj.).
Then T has an inverse $T^{-1} : W \rightarrow V$ which is also a linear transformation.

Proof. Fact that T^{-1} exists is since T inj and surj. Prove T^{-1} is linear.
Let $w_1, w_2 \in W, c \in K$. Since T surjective, $w_1 = T(v_1), w_2 = T(v_2)$ for
some $v_1, v_2 \in V$. Also, $T^{-1}(w_1) = T^{-1}(T(v_1)) = v_1$ and $T^{-1}(w_2) =$
 v_2 . Then

$$\begin{aligned} T^{-1}(cw_1 + w_2) &= T^{-1}(cT(v_1) + T(v_2)) \\ &= T^{-1}(T(cv_1 + v_2)) && (T \text{ linear}) \\ &= cv_1 + v_2 \\ &= cT^{-1}(w_1) + T^{-1}(w_2) \end{aligned}$$

So T^{-1} linear. □

Ex

$$T : P_2(\mathbb{R}) \rightarrow \mathbb{R}^3, T(ax^2 + bx + c) = \begin{pmatrix} a \\ b \\ c \end{pmatrix}$$

$$T^{-1} : \mathbb{R}^3 \rightarrow P_2(\mathbb{R}), T^{-1} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = (ax^2 + bx + c)$$

Point Once you know $V \simeq W$ (isomorphic) you can go back and forth between them, do vector space operations in either V or W . That is, V and W have exactly the same *structure* (as far as addition and scalar multiplication are concerned), even though “vectors” look different.

Proposition 31. *If $V \simeq W$, both finite-dimensional, then $\dim V = \dim W$*

Proof. $V \simeq W$ so $\exists T : V \rightarrow W$, T inj and surj (bijective), linear. So
Dim Thm,

$$\dim V = \dim \operatorname{Im} T + \dim \operatorname{Ker} T$$

and T inj., so $\dim \operatorname{Ker} T = 0$, and T surj., so $\operatorname{Im} T = W$, so

$$\dim V = \dim W + 0$$

□

Theorem 32. *Let $B = \{v_1, v_2, \dots, v_n\}$ be a basis of V . For any $v \in V$, you can write*

$$v = \sum_{i=1}^n a_i v_i$$

Then,

- (a) *The numbers (a_1, a_2, \dots, a_n) are unique and are called the coordinates of v relative to B , denoted*

$$[v]_B = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix}$$

- (b) *The function $C_B : V \rightarrow K^n$ defined by*

$$C_B(v) = [v]_B = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} \quad (\text{"find coordinates"})$$

is an isomorphism

Hence, if $\dim V = n$ then $V \simeq K^n$

Proof. By direct proof.

- (a) Assume v can also be written as

$$v = \sum_{i=1}^n b_i v_i \quad (\text{as well as } \sum_{i=1}^n a_i v_i = v)$$

Then

$$\begin{aligned}\vec{0} &= v - v = \left(\sum_{i=1}^n a_i v_i\right) - \left(\sum_{i=1}^n b_i v_i\right) \\ \vec{0} &= \sum_{i=1}^n (a_i - b_i) v_i\end{aligned}$$

Since $\{v_1, \dots, v_n\}$ independent (B = basis) all $a_i - b_i = 0$ ($i = 1, 2, \dots, n$) so $a_1 = b_1$. Hence representation is *unique*.

(b) Let $v = \sum_{i=1}^n a_i v_i, u = \sum_{i=1}^n b_i v_i$ be in $V, c \in K$. Then,

$$\begin{aligned}C_B(cv + u) &= C_B\left(\sum_{i=1}^n (ca_i + b_i) v_i\right) \\ &= \begin{pmatrix} ca_1 + b_1 \\ ca_2 + b_2 \\ \vdots \\ ca_n + b_n \end{pmatrix} \\ &= c \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} + \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix} \\ &= C_B(v) + C_B(u)\end{aligned}$$

Hence C_B is linear. To check C_B inj. and surj., since $\dim V = n = \dim K^n$, need only check on (other will follow). We will prove surj.

Let $\begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} \in K^n$. Then let $v = \sum_{i=1}^n a_i v_i$, so $C_B(v) = \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix}$

□

Remarks

- (1) We need the coords to be *unique* in order for $C_B : V \rightarrow K^n$ to be a (well-defined) function.
- (2) If you use a different basis, or even same basis but in different order, you get different coords and also different isomorphism.

Always infinitely many isomorphisms

Lemma 33. Let $T : V \rightarrow W, S : W \rightarrow U$ be a linear transformation. Then

(a) $S \cdot T : V \rightarrow U$ ($V \xrightarrow{T} W \xrightarrow{S} U$) is linear

(b) If T, S both injective (surjective), then $S \cdot T$ is also injective (surjective)

Proof. Exercise. □

Theorem 34. Let V, W be finite-dimensional vector spaces over field K . Then,

$$V \simeq W \iff \dim V = \dim W$$

That is, as far as vector space ops go, only the dimension really matters.

Proof. By direct proof.

- “ \Rightarrow ” Prop 31.
- “ \Leftarrow ” $\dim V = \dim W = n$. By Thm 32, $V \simeq K^n$, $W \simeq K^n$, using $C_{B_1} : V \rightarrow K^n$, $C_{B_2} : W \rightarrow K^n$. Then $C_{B_2}^{-1} : K^n \rightarrow W$ is an isomorphism (Thm 30), so

$$C_{B_2}^{-1} \cdot C_{B_1} : V \rightarrow W \quad (V \xrightarrow{C_{B_1}} K^n \xrightarrow{C_{B_2}^{-1}} W)$$

is linear, injective, surjective by lemma 33 so it is an isomorphism. □

February 25th 2019

Recall $V \simeq W \iff \dim V = \dim W$ (proved for finite-dim vector spaces only).

Note: If $T : V \rightarrow W$ isomorphism, $T^{-1} : W \rightarrow V$ is also an isomorphism.

Examples of isomorphisms:

- $P_n(K) \simeq K^{n+1}$
- $\mathcal{M}_{m \times n} \simeq K^{mn}$
- $K^n \simeq K^m \iff n = m$

Question If $n = \dim V$, then $V \simeq K^n$, why bother studying vector spaces other than K^n ?

Answer If you only want to know about addition and scalar multiplication, only K^n matters *but* the “vectors” P_n , $\mathcal{M}_{n \times m}$ etc... have other properties not always related to vector space operations.

For example, in $P_2(\mathbb{R})$ we can evaluate polynomials $f(x)$ at say $x = 3$,

$$\begin{aligned} f(x) &= ax^2 + bx + c \\ f(3) &= 9a + 3b + c \end{aligned}$$

If we consider $P_2(\mathbb{R}) \simeq \mathbb{R}^3$, "eval at $x = 3$ " is a linear transformation:

$$T : \mathbb{R}^3 \rightarrow \mathbb{R}$$

$$T(a, b, c) = 9a + 3b + c$$

Computations related to linear transformation

Theorem 35 (T is determined by its value on a basis). *Let V, W be vector spaces, $\{v_1, v_2, \dots, v_n\}$ basis V .*

Let $w_1, w_2, \dots, w_n \in W$ be any vectors (need not be distinct). Then there is one linear transformation $T : V \rightarrow W$ s.t. $T(v_i) = w_i$

Idea of proof If you want to calculate $T(v)v \in V$ (arbitrary element), write v uniquely in terms of basis

$$v = \sum_{i=1}^n a_i v_i$$

Then since T is supposed to be linear, compute

$$\begin{aligned} T(v) &= T\left(\sum a_i v_i\right) \\ &= \sum a_i T(v_i) \\ &= \sum a_i w_i \end{aligned}$$

Problem Suppose $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ is linear and

$$T\begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{bmatrix} -2 \\ 1 \end{bmatrix}, \quad T\begin{pmatrix} 1 \\ -1 \end{pmatrix} = \begin{bmatrix} 1 \\ 3 \end{bmatrix}$$

Find $T\begin{pmatrix} 3 \\ 4 \end{pmatrix}$.

Solution $\left\{ \begin{bmatrix} -2 \\ 1 \end{bmatrix}, \begin{bmatrix} 1 \\ 3 \end{bmatrix} \right\} = \text{basis } \mathbb{R}^2$, should have enough info to know what T is. Need to find

$$\begin{aligned} \begin{bmatrix} 3 \\ 4 \end{bmatrix} &= x \begin{bmatrix} 1 \\ 1 \end{bmatrix} + y \begin{bmatrix} 1 \\ -1 \end{bmatrix} \\ \begin{bmatrix} 1 & 1 & 3 \\ 1 & -1 & 4 \end{bmatrix} &\rightarrow \begin{bmatrix} 1 & 0 & \frac{7}{2} \\ 0 & 1 & -\frac{1}{2} \end{bmatrix} \end{aligned}$$

So

$$\begin{aligned} T\begin{pmatrix} 3 \\ 4 \end{pmatrix} &= T\left(\frac{7}{2}\begin{pmatrix} 1 \\ 1 \end{pmatrix} - \frac{1}{2}\begin{pmatrix} 1 \\ -1 \end{pmatrix}\right) \\ &= \frac{7}{2}T\begin{pmatrix} 1 \\ 1 \end{pmatrix} - \frac{1}{2}T\begin{pmatrix} 1 \\ -1 \end{pmatrix} \\ &= \frac{7}{2}\begin{bmatrix} -2 \\ 1 \end{bmatrix} - \frac{1}{2}\begin{bmatrix} 1 \\ 3 \end{bmatrix} \end{aligned}$$

*Row, column, nullspace of a matrix***Def** $A \in \mathcal{M}_{m \times n}(K)$

1. The row space, $\text{row}(A)$ is the span of the rows of A . Subspace of K^n
2. The column space, $\text{col}(A)$ is span of columns. Subspace of K^m
3. $\text{Nullspace}(\ker)$, is the solution set to the homogeneous system $Ax = \vec{0}$. Subspace of K^n

Proposition 36. Let $A \in \mathcal{M}_{m \times n}(K)$. Then

- (1) $A_{ei} = \text{column } i \text{ of } A$
- (2) If $B \in \mathcal{M}_{n \times p}(K)$ then column i of AB is Ab_i , $b_i = \text{column } i \text{ of } B$

Proof. Proof by picture! □

i)
$$\begin{pmatrix} x & a_{12} & x & x & x \\ x & a_{22} & x & x & x \end{pmatrix} \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \begin{pmatrix} a_{12} \\ a_{22} \\ \vdots \\ a_{n2} \end{pmatrix}$$

$$e_2$$

ii)
$$\begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix} \begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix} = \begin{pmatrix} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{pmatrix}$$

$$A \quad B \quad (b_i, c)$$

Proposition 37. Let $A \in \mathcal{M}_{m \times n}(K)$, so $L_A : K^n \rightarrow K^m$.

- (1) $\ker(A) = \text{Ker}(L_A)$
- (2) $\text{col}(A) = \text{Im}(L_A)$
- (3) $\text{row}(A) = \text{Im}(L_{A^T})$

Proof. By direct proof.

(1)

$$\begin{aligned}
\text{Ker}(A) &= \{x \in K^n \mid A_x = \vec{0}\} \\
&= \{x \in K^n \mid L_A(x) = \vec{0}\} \\
&= \text{Ker}(A)
\end{aligned}$$

(2) Take basis $\{e_1, e_2, \dots, e_n\}$ for K^n . Then by prop 26,

$$e_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, e_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \dots$$

$$L_A(e_1) \dots L_A(e_n) \text{ spans } \text{Im}(L_A)$$

But $L_A(e_1) = A_{e_1} = \text{column } 1 \text{ of } A$, ie columns of A span $\text{Im}(L_A)$
hence $\text{col}(A) = \text{Im}(L_A)$

(3) $\text{col}(A) = \text{col}(A^T) = \text{Im}(L_{A^T})$ by (2)

□

Def: Rank of $A \in \mathcal{M}_{m \times n}(K)$ is number of non-zero rows in RREF.**Proposition 38.** Let $A \in \mathcal{M}_{m \times n}(K)$, $R = \text{RREF}(A)$. Then,

$$(i) \text{ rank}(A) = \text{rank}(A^T)$$

$$(ii) \text{ rank}(A) = \dim \text{row}(A)$$

$$(iii) \dim \text{row}(A) = \dim \text{col}(A)$$

$$(iv) \text{ There is an invertible matrix } B \in \mathcal{M}_{m \times n}(K) \text{ s.t. } BA = R$$

Proof(iii) We have:

$$\begin{aligned}
\dim \text{row}(A) &= \text{rank}(A) && \text{(by (ii))} \\
&= \text{rank}(A^T) && \text{(by (i))} \\
&= \dim \text{row}(A^T) && \text{(by (ii))} \\
&= \dim \text{col}(A) && \text{(by (iii))}
\end{aligned}$$

□