

Intro to Linear Algebra

MAT 5230

Wm C Bauldry
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1. Algebraic Structures

Definition 1 A Group is a pair $\{X; \cdot\}$ such that

1. “ \cdot ” is closed on X .
 2. “ \cdot ” is associative on X .
 3. There is an identity $e \in X$ (w.r.t. “ \cdot ”).
 4. Every element $a \in X$ has an inverse a^{-1} (w.r.t. “ \cdot ”).
-

Definition 2 A Ring is a triple $\{X; +, \cdot\}$ such that

1. $\{X; +\}$ is an Abelian group.
2. $\{X; \cdot\}$ is a semigroup (lacks identity and inverses).
3. “ \cdot ” distributes over “ $+$ ”.

Algebraic Structures

Definition 3 A Field is a triple $\{X; +, \cdot\}$ such that

1. $\{X; +, \cdot\}$ is a ring.
 2. $\{X^\#; \cdot\}$ is an Abelian group where $X^\# = X - \{0\}$.
-

Definition 4 A Vector Space is an Abelian group $\{X; +\}$ over a field $\{F; +, \cdot\}$ with a scalar product $F \times X \rightarrow X$. For $\alpha, \beta \in F$ and $x, y \in X$,

1. $\alpha(x + y) = \alpha x + \alpha y$
2. $(\alpha + \beta)x = \alpha x + \beta x$
3. $(\alpha\beta)x = \alpha(\beta x)$
4. $1x = x$

Field

Definition 3 (Field) Let $F \neq \emptyset$ be a set with addition “+”: $X \times X \rightarrow X$ and multiplication “.”: $F \times X \rightarrow X$. Then $\{F; +, \cdot\}$ with the operations forms a field if the following axioms are satisfied:

1. $x + y = y + x, x \cdot y = y \cdot x$ commutative laws
2. $x + (y + z) = (x + y) + z, x \cdot (y \cdot z) = (x \cdot y) \cdot z$ associative laws
3. \exists unique element 0 satisfying $0 + x = x$ additive identity
4. To each x, \exists a unique $-x$ so that $x + (-x) = 0$ additive inverse
5. There is a unique element 1 satisfying $1 \cdot x = x$ mult. identity
6. To each $x \neq 0, \exists$ a unique x^{-1} so that $x \cdot x^{-1} = 1$ mult. inverse
7. $x \cdot (y + z) = x \cdot y + x \cdot z$ “.” over “+” distributive law

Examples of Fields

1. \mathbb{Q} , \mathbb{R} , and \mathbb{C} are fields.
2. \mathbb{Z} is *not* a field. (*Why?*)
3. Let p be a prime. Then \mathbb{Z}_p is a p -element field.
4. $\mathbb{Q}[\sqrt{2}] = \{a + b\sqrt{2} \mid a, b \in \mathbb{Q}\}$ is a field.
5. $\mathbb{Z}[\sqrt{2}] = \{a + b\sqrt{2} \mid a, b \in \mathbb{Z}\}$ is *not* a field. (*Why?*)
6. $\mathbb{Q}[\sqrt[3]{3}] = \{a + b\sqrt[3]{3} + c\sqrt[3]{3^2} \mid a, b, c \in \mathbb{Q}\}$ is a field.
7. $\mathbb{Z}_p[i]$, p is prime, is a field (with p^2 elements).

Vector Space

Definition 4 (Vector Space) *Let $X \neq \emptyset$ be a set (vectors) and F be a field (scalars) with vector addition “+”: $X \times X \rightarrow X$ and scalar multiplication “.”: $F \times X \rightarrow X$. Then X and F with the operations forms a vector space (or linear space), “ X is a vector space over F ,” if the following axioms are satisfied:*

1. $x + y = y + x$ commutative law
2. $x + (y + z) = (x + y) + z$ associative law
3. *There is a unique vector 0 satisfying $0 + x = x$* ‘zero vector,’ identity
4. $\alpha(x + y) = \alpha x + \alpha y$ scalar “.” over vector “+” distributive law
5. $(\alpha + \beta)x = \alpha x + \beta x$ scalar “+” over scalar “.” distributive law
6. $(\alpha\beta)x = \alpha(\beta x)$ scalar homogeneity
7. $0x = 0$ scalar-vector additive identity relation (*implied by 5.*)
8. $1x = x$ scalar-vector multiplicative identity relation

Examples of Vector Spaces

1. Let $n \in \mathbb{Z}^+$. Then \mathbb{Q}^n , \mathbb{R}^n , and \mathbb{C}^n are vector spaces.
2. Let $n \in \mathbb{Z}^+$. Then \mathbb{P}^n , the polynomials (real or complex) of degree less than or equal to n , forms a vector space.
3. $\mathbb{Z}_2 \times \mathbb{Z}_2 \times \mathbb{Z}_2$ is a vector space.
4. Let F be a field and $n \in \mathbb{Z}^+$. Then F^n is a vector space.
5. Let $M_{m \times n}$ be the $m \times n$ matrices with entries in a field F with componentwise addition and scalar multiplication.
6. Let $K \subseteq \mathbb{R}$ be a closed interval. Then $C(K)$, the continuous real-valued functions on K form a vector space.
7. Let $O \subseteq \mathbb{R}$ be an open interval. Then $C^1(O)$, the continuously differentiable real-valued functions on O , form a vector space.

Homomorphisms

Definition 5 (Group Homomorphism) *Let $\{X; +_X\}$ and $\{Y; +_Y\}$ be two groups with $\rho : X \rightarrow Y$. Then ρ is a homomorphism iff*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2)$$

Definition 6 (Ring Homomorphism) *Let $\{X; +_X, \cdot_X\}$ and $\{Y; +_Y, \cdot_Y\}$ be two rings with $\rho : X \rightarrow Y$. Then ρ is a homomorphism iff*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2)$$

$$\rho(x_1 \cdot_X x_2) = \rho(x_1) \cdot_Y \rho(x_2)$$

Vector Space Homomorphism

Definition 7 (Linear Transformation) *Let X and Y be vector spaces over the same field F . Then the relation $\rho : X \rightarrow Y$ is a linear transformation if and only if for every $\alpha \in F$ and $x_1, x_2 \in X$, it follows that:*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2) \quad (1)$$

$$\rho(\alpha \cdot x_1) = \alpha \cdot \rho(x_1) \quad (2)$$

Linear Transformation

$$\begin{array}{ccc} [x_1, x_2] & \xrightarrow{+} & x_1 + x_2 \\ \rho \downarrow & & \rho \downarrow \\ [\rho(x_1), \rho(x_2)] & \xrightarrow{+} & \rho(x_1 + x_2) = \\ & & \rho(x_1) + \rho(x_2) \end{array} \quad (1)$$

$$\begin{array}{ccc} [\alpha, x_1] & \xrightarrow{\cdot} & \alpha \cdot x_1 \\ \rho \downarrow & & \rho \downarrow \\ [\alpha, \rho(x_1)] & \xrightarrow{\cdot} & \rho(\alpha \cdot x_1) = \\ & & \alpha \cdot \rho(x_1) \end{array} \quad (2)$$

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2. Properties of Finite Fields

Theorem 1 \mathbb{Z}_p is a field if and only if p is prime.

Theorem 2 Let p be a prime and $n \in \mathbb{Z}^+$. Then there exists a finite field F with p^n elements.

Theorem 3 For any prime p and $n \in \mathbb{Z}^+$, there is (essentially) only one field with p^n elements.
(The splitting field of $x^{p^n} - x$ over the field \mathbb{Z}_p .)

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4. Properties of Vector Spaces

Theorem 4 *Let X be a vector space over the field F . Let $x, y, z \in X$ and $\alpha, \beta \in F$. Then*

1. *if $\alpha x = \alpha y$ and $\alpha \neq 0$, then $x = y$;*
2. *if $\alpha x = \beta x$ and $x \neq 0$, then $\alpha = \beta$;*
3. *if $x + y = x + z$, then $y = z$;*
4. $\alpha \cdot 0 = 0$;
5. $\alpha(x - y) = \alpha x - \alpha y$ where $-y \triangleq (-1) \cdot y$;
6. $(\alpha - \beta)x = \alpha x - \beta x$;
7. $x + y = 0$ implies that $x = -y$.

More Examples of Vector Spaces

Sequence Vector Spaces

- \mathbb{R}^∞ and \mathbb{C}^∞
- Finitely non-zero real (or complex) sequences
- Null real (or complex) sequences
- Bounded real (or complex) sequences
- Convergent real (or complex) sequences

Function Vector Spaces

- $\mathbb{P} = \{\text{polynomials with real (or complex) coefficients}\}$
- $C([a, b]) = \{f \mid f : [a, b] \rightarrow \mathbb{R} \text{ is continuous}\}$ over \mathbb{R}
- $L_1([a, b]) = \{f \mid \int_a^b |f(t)| dt < \infty\}$ over \mathbb{R}

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5. Homomorphisms

Definition 5 (Group Homomorphism) *Let $\{X; +_X\}$ and $\{Y; +_Y\}$ be two groups with $\rho : X \rightarrow Y$. Then ρ is a homomorphism iff*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2)$$

Definition 6 (Ring Homomorphism) *Let $\{X; +_X, \cdot_X\}$ and $\{Y; +_Y, \cdot_Y\}$ be two rings with $\rho : X \rightarrow Y$. Then ρ is a homomorphism iff*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2)$$

$$\rho(x_1 \cdot_X x_2) = \rho(x_1) \cdot_Y \rho(x_2)$$

Vector Space Homomorphism

Definition 7 (Linear Transformation) *Let X and Y be vector spaces over the same field F . Then the relation $\rho : X \rightarrow Y$ is a linear transformation if and only if for every $\alpha \in F$ and $x_1, x_2 \in X$, it follows that:*

$$\rho(x_1 +_X x_2) = \rho(x_1) +_Y \rho(x_2) \quad (3)$$

$$\rho(\alpha \cdot x_1) = \alpha \cdot \rho(x_1) \quad (4)$$

Examples

1. Set $\phi : \mathbb{R}^2 \rightarrow \mathbb{R}^4$ by $\phi(x, y) = (x, 0, 0, y)$.
2. Set $\psi : \mathbb{R}^2 \rightarrow \mathbb{C}$ by $\psi(x, y) = x + i y$.

Linear Transformation

$$\begin{array}{ccc} [x_1, x_2] & \xrightarrow{+} & x_1 + x_2 \\ \rho \downarrow & & \rho \downarrow \\ [\rho(x_1), \rho(x_2)] & \xrightarrow{+} & \rho(x_1 + x_2) = \\ & & \rho(x_1) + \rho(x_2) \end{array} \quad (1)$$

$$\begin{array}{ccc} [\alpha, x_1] & \xrightarrow{\cdot} & \alpha \cdot x_1 \\ \rho \downarrow & & \rho \downarrow \\ [\alpha, \rho(x_1)] & \xrightarrow{\cdot} & \rho(\alpha \cdot x_1) = \\ & & \alpha \cdot \rho(x_1) \end{array} \quad (2)$$

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6. Subspace of a Vector Space

Definition 8 (Subspace) *Let X be a vector space over F and let $\emptyset \neq V \subseteq X$. Then V is a subspace of X iff*

1. $\forall u, v \in V$, we have $u + v \in V$ (closed under addition)
 2. $\forall \alpha \in F, \forall u \in V$, we have $\alpha u \in V$ (closed under scalar mult.)
-

Theorem 5 *A subspace of a vector space is itself a vector space.*

Proof. Let V be a subspace of X . V is closed under vector addition and scalar multiplication by definition. All remaining vector space properties — with the exception of $0 \in V$ — are inherited from X . Let $v \in V$ (because $V \neq \emptyset$). Since $0 \in F$, then $0v = 0 \in V$. Thus V is a vector space. \square

Note. Every vector space has at least 2 subspaces. What are they?

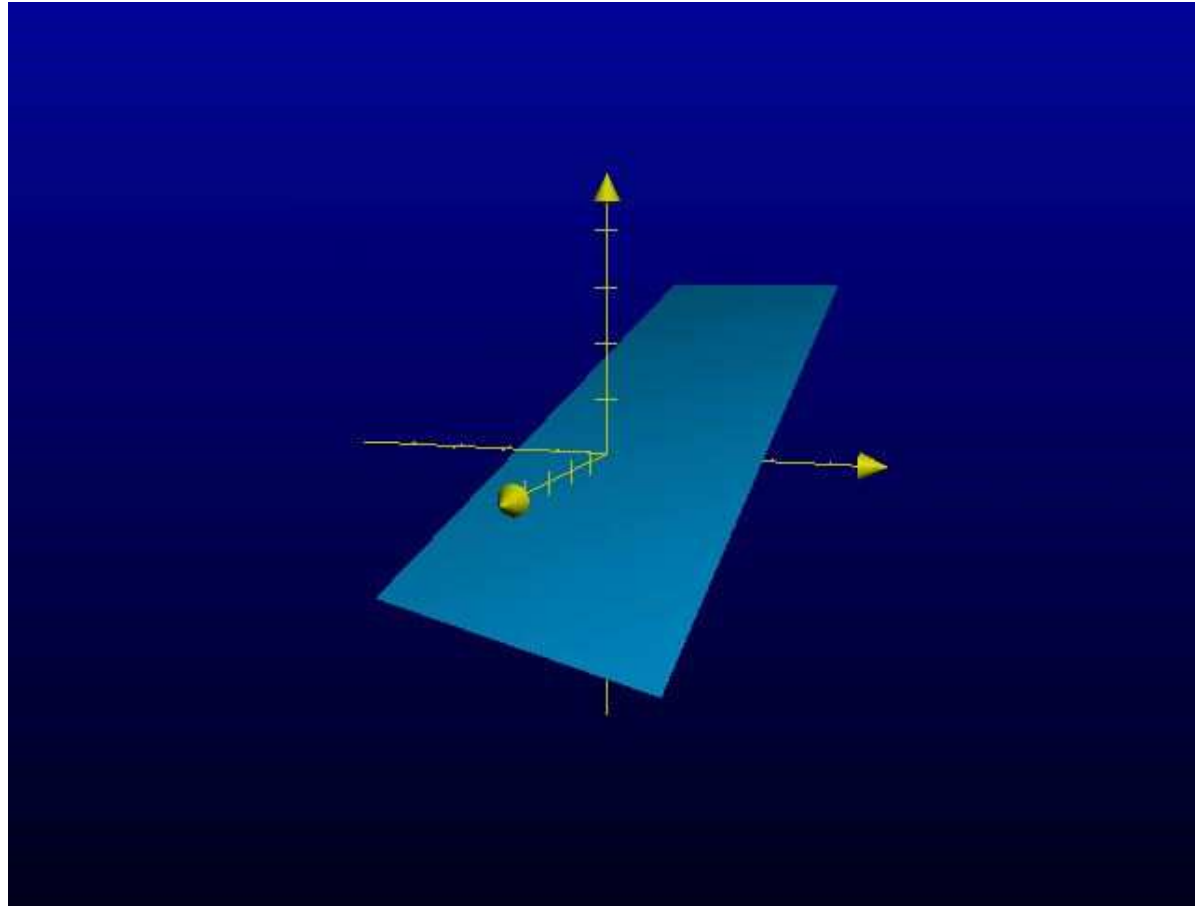
Examples of Subspaces

- $\{0\}$ and X are always subspaces of X
- \mathbb{R}^2 is a subspace^a of \mathbb{R}^3 , \mathbb{C}^2 is a subspace of \mathbb{C}^3 .
- For $m < n$, we have that \mathbb{R}^m is a subspace of \mathbb{R}^n
- For $m < n$, we have that \mathbb{P}^m is a subspace of \mathbb{P}^n
- Is
 - $V_1 = \{(x, 1) \mid x, y \in \mathbb{R}\}$ a subspace of \mathbb{R}^2 ?
 - $V_2 = \{(x, y, x + y, 0) \mid x, y \in \mathbb{R}\}$ a subspace of \mathbb{R}^4 ?
 - $V_3 = \{(x, y, x + y + 2, 0) \mid x, y \in \mathbb{R}\}$ a subspace of \mathbb{R}^4 ?

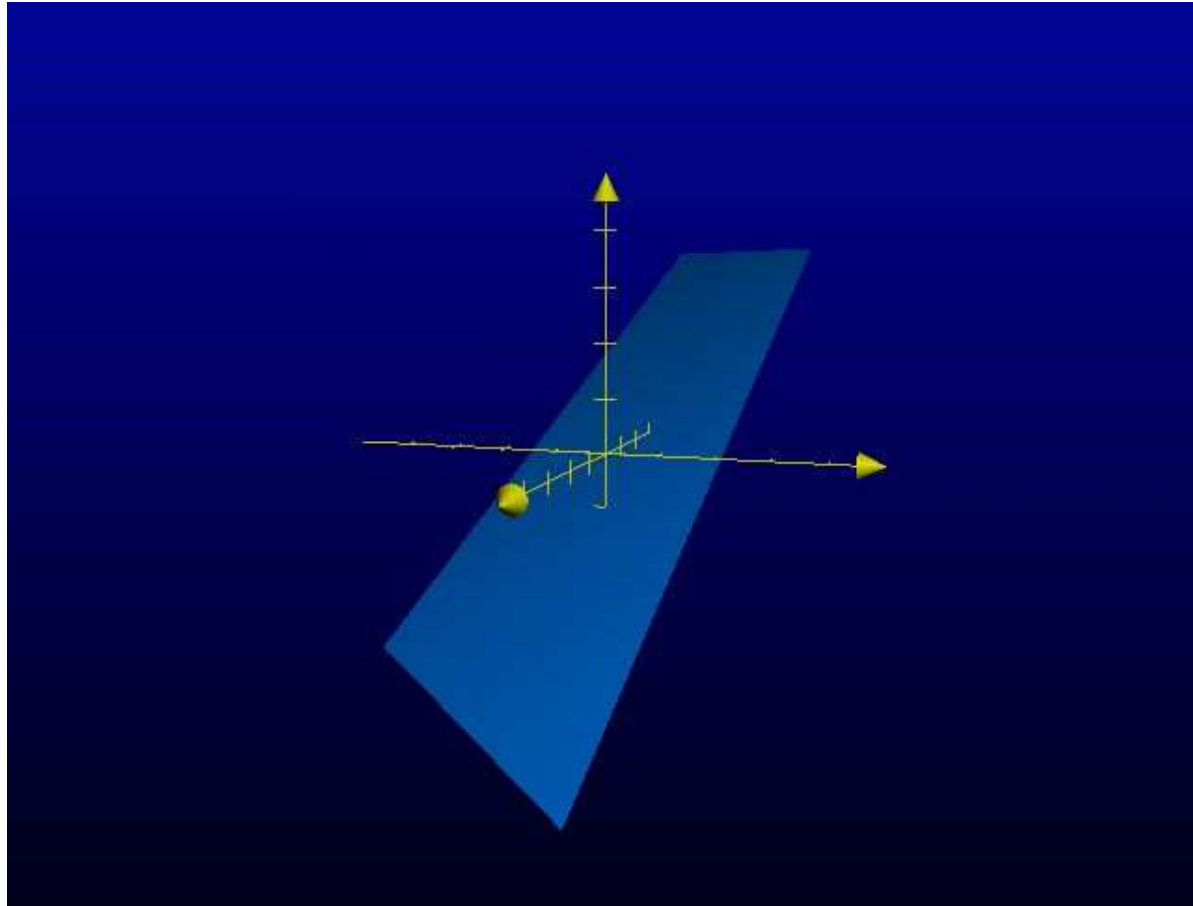
^a Thinking of \mathbb{R}^2 as a subset such as $\{(x, y, 0) \mid x, y \in \mathbb{R}\}$, &c., of \mathbb{R}^3 .
Formally, \mathbb{R}^2 is isomorphic to a subspace of \mathbb{R}^3 .

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Is This a Subspace?



Is This a Subspace?



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7. Operations with Subspaces

Theorem 6 *Let X be a vector space over F and let V_1 and V_2 be subspaces of X . Then $V = V_1 \cap V_2$ is a subspace.*

Pf. (Exercise.)

Theorem 7 *Let X be a vector space over F and let X_i for $i \in I$ be subspaces of X where I is some index set. Then*

$V = \bigcap_{i \in I} X_i$ is a subspace.

Pf. (Easy closure calculations.)

NB: Unions (usually) or complements of subspaces do not form new subspaces.

Direct Sum

Definition 9 (Direct Sum) *Let X_1, X_2, \dots, X_r be subspaces of X . The set $X_1 + X_2 + \dots + X_r$ forms the direct sum $X_1 \oplus X_2 \oplus \dots \oplus X_r$ iff for every x in the sum, there is a unique set of $x_i \in X_i$ such that $x = \sum_{i=1}^r x_i$.*

Theorem 8 $X_1 + X_2 = X_1 \oplus X_2$ if and only if $X_1 \cap X_2 = \{0\}$.

Pf. Based on: Let $0 \neq v \in X_1 \cap X_2$. Then $v = v + 0 = 0 + v$ is two different ways to write v .

Note. $X_1 + X_2$ is a subspace; $X_1 \oplus X_2$ is a subspace that 'looks like' a direct product.

Subspaces of \mathbb{R}^2 and \mathbb{R}^3

Example 1 Set $X = \mathbb{R}^2$. Let X_1 be given by the line $y = x$ and X_2 by the line $y = -x$. Then

$$\begin{array}{ccccccc} \{0\} = X_1 \cap X_2 & \subseteq & X_1 \cup X_2 & \subseteq & X_1 + X_2 & = & X_1 \oplus X_2 = \mathbb{R}^2 \\ \text{subsp} & & \neg\text{subsp} & & \text{subsp} & & \end{array}$$

Example 2 Set $X = \mathbb{R}^3$. The subspaces of \mathbb{R}^3 are:

- $\{0\}$
- A line L through the origin.
- The direct sum of two distinct lines through the origin $L_1 \oplus L_2$ yields a plane.
- The direct sum of three distinct non-coplanar lines through the origin $L_1 \oplus L_2 \oplus L_3$ yields \mathbb{R}^3 .

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8. Linear Combinations

Note: From now on, α_i , etc., will be elements of the base field F and x_i, y_i , etc., will be vectors from the space X .

Definition 10 (Finite Linear Combination) *Let $Y \subseteq X$. A vector $x \in X$ is a (finite) linear combination of vectors in Y iff there is a finite set of vectors $\{y_i\} \subseteq Y$ and scalars $\{\alpha_i\}$ such that*

$$x = \sum_{i=1}^n \alpha_i y_i$$

Note: The sum is not required to be unique. (Unlike \oplus .)

Example 3 *Let $Y = \{(1, 0), (1, 1), (0, 1)\} \subset \mathbb{R}^2$. Then the vector $x = (2, 3)$ can be written as $x = 2(1, 0) + 3(0, 1)$ or as $x = 2(1, 1) + 1(0, 1)$ or as $x = -1(1, 0) + 3(1, 1)$.*

Generated Subspace & Span

Theorem 9 *Let $\emptyset \neq Y \subseteq X$. Define*

$$V(Y) \triangleq \{\text{all linear combinations from } Y\}.$$

Then $V(Y)$ is a subspace of X and is called the subspace generated by Y .

Definition 11 (Span) *Y spans X if and only if $V(Y) = X$.*

Example 4 *Let $Y = \{(1, 0), (1, 1), (0, 1)\}$. Then Y spans \mathbb{R}^2 . (Exercise.)*

Example 5 *Let $Z = \{(1, 1, 0), (1, 0, 1), (0, 1, 1), (1, 1, 1)\}$. Does the set Z span \mathbb{R}^3 ?*

Dependence and Independence

Definition 12 (Linear Dependence) *Let $\{x_1, x_2, \dots, x_m\}$ be a nonempty subset of X . If there exists a set of scalars $\{\alpha_i\}$, not all zero, such that $\alpha_1 x_1 + \alpha_2 x_2 + \dots + \alpha_m x_m = 0$, then $\{x_1, x_2, \dots, x_m\}$ is linearly dependent.*

Definition 13 (Linear Independence) *If the nonempty subset $\{x_1, x_2, \dots, x_m\}$ of X is not linearly dependent, then $\{x_1, x_2, \dots, x_m\}$ is linearly independent.*

Example 6 *Y and Z from the previous examples are both linearly dependent.*

Example 7 *Let $W = \{(1, 1, 0), (1, 0, 1), (0, 1, 1)\}$. Then W is linearly independent.*

More Examples

Example 8 Let $V = \{(1, 1, 0, 0), (1, 0, 1, 0), (1, 1, 1, 0)\}$. Is V linearly independent? Does V span \mathbb{R}^4 ?

Example 9 Let $U = \{(0, 0, 0), (1, 0, 0), (0, 1, 0)\}$. Is U linearly independent?

Example 10 Let $\mathcal{P} = \{1, x, x^2, x^3, \dots\}$. Then $V(\mathcal{P}) = \mathbb{P}$, the set of all real polynomials; i.e., \mathcal{P} spans \mathbb{P} . Is \mathcal{P} linearly independent? Yes! But how do we show this? Consider

$$p(x) = \sum_{i=0}^n \alpha_i x^i = 0$$

and note that the only n th degree polynomial with $n + 1$ roots, is $p(x) \equiv 0$.

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9. Linear Independence

Theorem 10 (Uniqueness) *Let $Y = \{x_1, x_2, \dots, x_m\}$ be a linearly independent set of vectors. If $\sum_{i=1}^m \alpha_i x_i = \sum_{i=1}^m \beta_i x_i$, then $\alpha_i = \beta_i$ for $i = 1..m$.*

Pf. Simple calculation.

Theorem 11 *A set Y is linearly dependent if and only if some vector $x \in Y$ can be written as a linear combination of other vectors in Y .*

- Add any number of vectors to a dependent set, it will still be dependent.
- Add one vector to an independent set, it may or may not stay independent.

Infinite Example

Example 11 Let $\mathcal{P} = \{1, x, x^2, x^3, \dots\}$. Then $V(\mathcal{P}) = \mathbb{P}$, the set of all real polynomials; i.e., \mathcal{P} spans \mathbb{P} . Is \mathcal{P} linearly independent? Yes! But how do we show this? Let $p(x) \in \mathbb{P}$. Then, for some n ,

$$p(x) = \sum_{i=0}^n \alpha_i x_i = 0.$$

Note that the only n th degree polynomial with $n + 1$ roots, is $p(x) \equiv 0$. Hence all α_i are 0.

Unique Expression

Theorem 12 (Uniqueness of Expression) *A finite nonempty set Y is linearly independent if and only if, for each nonzero $y \in V(Y)$, there exists a unique subset $\{x_1, \dots, x_m\}$ of Y and a unique set of scalars $\{\alpha_1, \dots, \alpha_m\}$ such that $y = \sum_{i=1}^m \alpha_i x_i$.*

Assignment:

1. Prove Theorem 11
2. Prove Theorem 12

Theorem 13 *Y is linearly independent if and only if $Z \subsetneq Y$ implies $V(Z) \neq V(Y)$.*

Pf. Exercise.

Basis of a Vector Space

Definition 14 (Hamel basis) *A (finite) set $Y \subseteq X$ is a Hamel basis (or just a basis) if and only if*

- 1. Y is linearly independent*
- 2. $V(Y) = X$*

Id est, Y is a (finite) linearly independent spanning set.

Theorem 14 *If Y is linearly independent, then Y is a basis for $V(Y)$.*

Pf. Exercise.

Note: The theorem *Every vector space has a basis* is a result of the *Axiom of Choice*.

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10. Basis of a Vector Space

Recall:

Definition 15 (Hamel Basis) *A set $Y \subseteq X$ is a Hamel Basis (or just a basis) if and only if*

1. *Y is linearly independent*
2. *$V(Y) = X$*

Note: The theorem «*Every vector space has a basis*» is a result of the *Axiom of Choice*.

Exempli gratia

- $\{(0, 1), (1, 2)\}$ is a basis of \mathbb{R}^2
- $\{(1, 1, 0), (1, 0, 1), (0, 1, 1)\}$ is a basis of \mathbb{R}^3
- $\{(1, 1, 0), (1, 2, 0), (2, 1, 0)\}$ is *not* a basis of \mathbb{R}^3

Basis Properties

Theorem 15 (Uniqueness of Scalars) *Let $\{x_1, x_2, \dots, x_n\}$ be a basis for X . Then for each vector $x \in X$, there is a unique set of scalars $\{\alpha_1, \alpha_2, \dots, \alpha_n\}$ such that*

$$x = \alpha_1 x_1 + \alpha_2 x_2 + \cdots + \alpha_n x_n$$

Pf. Standard calculation.

Theorem 16 (Maximum Independent Set Size) *Suppose that $B = \{x_1, x_2, \dots, x_n\}$ is a basis of X with n finite and $Y = \{y_1, y_2, \dots, y_m\}$ is a set of linearly independent vectors. Then $m \leq n$.*

Note: n is finite is necessary.

Proof of Theorem 16 - Outline

Proof Outline.

1. Assume $m > n$.
2. Write y_1 as a linear combination of the x_i . At least one coefficient can't be 0, say the coefficient of x_n (reindex x 's if necessary).
3. Replace x_n in B with y_1 . Show B still is a basis for X .
4. Start over with y_2 and the "new" B . Replace x_{n-1} by y_2 .
5. Continue the process until y_n replaces x_1 .
6. B - still a basis - now is $\{y_1, y_2, \dots, y_n\}$.
7. Thus y_{n+1} can be written as as linear combination from B contradicting the linear independence of Y . Hence $m \leq n$.

Dimension

Theorem 17 *If $B = \{x_1, x_2, \dots, x_N\}$ is a basis of X for some $N < \infty$, then every basis of X contains exactly N vectors.*

Pf. • Let B_1 be a basis with n vectors and B_2 be a basis with m vectors.

- Apply Theorem 16 with B_1 as the basis and B_2 as the linearly independent set. Therefore $m \leq n$.
- Now apply Theorem 16 with B_2 as the basis and B_1 as the linearly independent set. Therefore $n \leq m$.
- Since $m \leq n$ and $n \leq m$, it follows that $m = n$.

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11. Dimension of a Vector Space

Definition 16 (Dimension) *If X has a finite basis of n vectors, then X is finite dimensional and has dimension $\dim(X) = n$. If X is not finite dimensional, then X has infinite dimension and $\dim(X) = \infty$.*

Example 12 *Several standard spaces:*

- $\dim(\mathbb{R}^n) = n$
- $\dim(\mathbb{P}^n) = n + 1$
- $\dim(\mathbb{R}^\infty) = \infty$ *The space of real sequences is large (but it's a “small ∞ ”)*
- $\dim(\mathbb{P}) = \infty$ *(another “small ∞ ,” isomorphic to \mathbb{R}^∞)*

Examples

Example 13 *Infinite dimensional spaces*

- $\dim(\mathcal{C}[0, 1]) = \infty$ *The space of continuous functions on $[0, 1]$ is very large (a “big ∞ ”)*
- $\dim(\mathcal{B}(\mathbb{R})) = \infty$ *with $\mathcal{B}(\mathbb{R}) = \{ \text{bounded real functions} \}$*
- *Is the following true:
Let Z be an arbitrary set and X an arbitrary vector space over F . The space of all functions from Z to X , written X^Z , is a vector space over F with dimension $\dim(X^Z) = \dim(X)^{|Z|}$*

Basis & Dimension Facts

Basis Facts

- Every vector space has a basis (requires the [Axiom of Choice](#))
- Every linearly independent set can be extended to a basis
- A linearly independent set can be no larger than a basis
- A set containing more vectors than a basis must be linearly dependent
- Any two bases for a vector space contain the same number of vectors (finite dimensional case)
- If X has a set with n linearly independent vectors and every set of $n + 1$ vectors is dependent, then $\dim(X) = n$
- If Y is a subspace of X , then $\dim(Y) \leq \dim(X)$.

“Two Out of Three Ain’t Bad”

Theorem 18 *Suppose X is a vector space with $\dim(X) = n$ and $Y \subseteq X$. If any two of the following hold, then the third also holds.*

1. Y spans X
2. Y is linearly independent
3. Y contains exactly n vectors

Theorem 19 *Suppose that $\dim(X) < \infty$ and that $X = Y \oplus Z$. Then $\dim(X) = \dim(Y) + \dim(Z)$.*

Nota Bene: Recall that \oplus is the “interior analogue” of \times and that if $X = Y \times Z$, then $\dim(X) = \dim(Y) \times \dim(Z)$.

“Sum of Dimensions” Proof

Proof of Theorem 19 (3.3.43).

Since $\dim(X) < \infty$, so are $\dim(Y)$ and $\dim(Z)$. Therefore there are bases of Y and Z : $\mathcal{B}_Y = \{y_1, \dots, y_n\}$ and $\mathcal{B}_Z = \{z_1, \dots, z_m\}$. Set $\mathcal{B} = \mathcal{B}_Y \cup \mathcal{B}_Z$. Let

$$0 = \sum_{i=1}^n \alpha_i y_i + \sum_{i=1}^m \beta_i z_i$$

be a linear combination from \mathcal{B} . Since representation of vectors is unique in $X = Y \oplus Z$, we have that $0 = \sum_{i=1}^n \alpha_i y_i$ and $0 = \sum_{i=1}^m \beta_i z_i$. Therefore $0 = \alpha_i = \beta_j$ for all i and j as \mathcal{B}_Y and \mathcal{B}_Z are independent. I.e., \mathcal{B} is linearly independent.

Since $X = Y \oplus Z$, it is clear that \mathcal{B} spans X . Hence,

$$|\mathcal{B}| = n + m = \dim(X).$$

(Go to TOC)

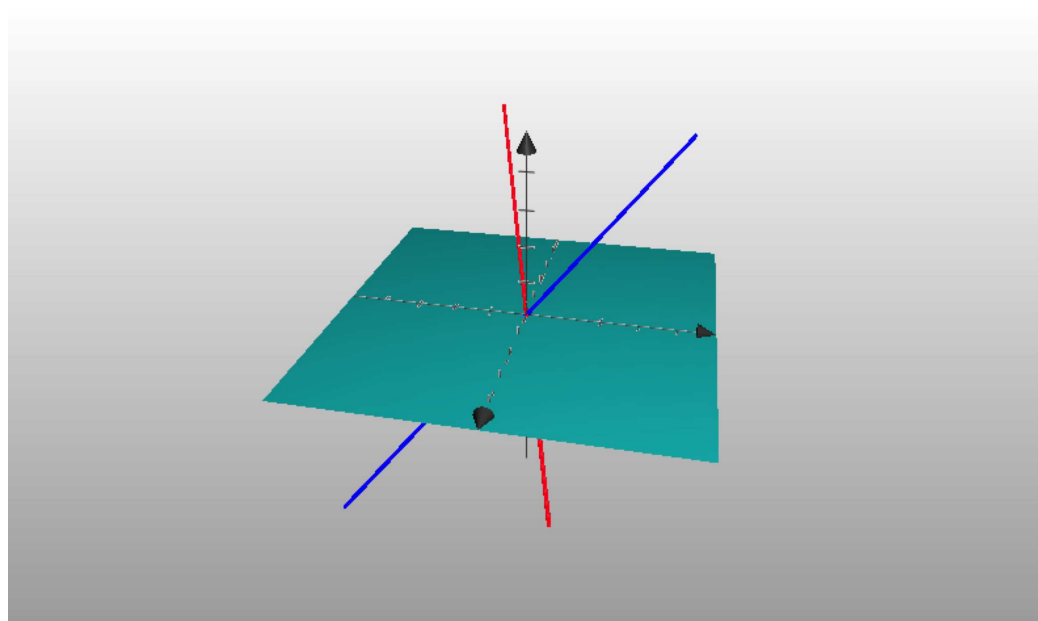
12. Subspaces and Direct Sums

The theorem *Every linearly independent set can be extended to a basis* has:

Corollary 20 *Suppose X is an n -dimensional vector space with an m -dimensional subspace Y . Then there exists a subspace Z of dimension $(n - m)$ such that $X = Y + Z$.*

Pf. (Sketch) Take bases \mathcal{B}_X for X and \mathcal{B}_Y for Y . Eliminate the portion of \mathcal{B}_X dependent on \mathcal{B}_Y . The remaining vectors form a basis for Z .

Note: Z need not be unique. ($Z =$ red or blue)



Linear Transformations

Definition 17 (Linear Transformation) *A mapping T from a vector space X into a vector space Y , both spaces over the field F , is a linear transformation, written as $T \in L(X, Y)$, if and only if for all $x \in X$, $y \in Y$, and $\alpha \in F$, we have*

1. $T(x + y) = T(x) + T(y)$

2. $T(\alpha x) = \alpha T(x)$

A nonlinear transformation is a mapping that is not linear.

Theorem 21 (Superposition Principle) *$T \in L(X, Y)$ if and only if*

$$T \left(\sum_{i=1}^m \alpha_i x_i \right) = \sum_{i=1}^m \alpha_i T(x_i)$$

Examples of Linear Transformations

Example 14

- $T : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ **by** $T([x, y]) = [2x + 3y, x - y]$
- $T : \mathbb{R}^2 \rightarrow \mathbb{R}^1$ **by** $T([x, y]) = [x]$
- $D : \mathbb{P}^n \rightarrow \mathbb{P}^{n-1}$ **by** $D(p) = \frac{d}{dx} p(x)$
- $I : \mathcal{C}[0, 1] \rightarrow \mathbb{R}$ **by** $I(f) = \int_0^1 f(t) dt$
- **Let** $k \in \mathcal{C}[a, b] \times \mathcal{C}[a, b]$ **such that for any** $x \in \mathcal{C}[a, b]$,

$$\hat{x}(s) = \int_a^b x(t)k(s, t) dt \in \mathcal{C}[a, b]$$

Then $\hat{\cdot} : \mathcal{C}[a, b] \rightarrow \mathcal{C}[a, b]$ **is a linear transformation.**^a

^a**Fredholm Integral Equation** of the First Type *or* a kernel transform

13. Examples of Linear Transformations

Example 15

- Let $\mathcal{L}_1^c = \{f : \mathbb{R} \rightarrow \mathbb{C} \mid f \in \mathcal{C}(\mathbb{R}) \text{ and } \int_{\mathbb{R}} |f| < \infty\}$. Now define the **Fourier transform** $\mathcal{F}(f) \in \mathcal{L}_1^c$ by

$$\mathcal{F}(f)(s) = \int_{\mathbb{R}} f(t) e^{-ist} dt$$

Then $\mathcal{F} : \mathcal{L}_1^c \rightarrow \mathcal{L}_1^c$ is a linear transformation.

- Let $z \in \mathbb{C}$. Then \bar{z} = (the complex conjugate of z) is a nonlinear transformation.
- Let $|\cdot|$ be the absolute value function on \mathbb{R} . Is $|\cdot|$ a linear transformation from \mathbb{R} to \mathbb{R} ?

Null Space and Range Space

Definition 18 *Let $T \in L(X, Y)$. Then the*

1. *null space $\mathcal{N}(T)$ (or kernel $\ker(T)$) is the set*

$$\mathcal{N}(T) = \{x \in X \mid T(x) = 0\},$$

2. *range space $\mathcal{R}(T)$ (or image space) is the set*

$$\mathcal{R}(T) = \{y \in Y \mid y = T(x) \text{ for some } x \in X\} = T(X).$$

Theorem 22 *Let $T \in L(X, Y)$. Then*

1. *$\mathcal{N}(T)$ is a subspace of X ,*
2. *$\mathcal{R}(T)$ is a subspace of Y .*

Pf. Exercise (3.4.20)

Range & Dimension

Theorem 23 *If $T \in L(X, Y)$, then $\dim(\mathcal{R}(T)) \leq \dim(X)$.*

Pf. Assume $X \neq \{0\} \neq \mathcal{R}(T)$, otherwise the result is trivial. Set $n = \dim(X) > 0$. Choose $\{y_1, \dots, y_{n+1}\} \subseteq \dim(\mathcal{R}(T))$. For each i , find x_i such that $T(x_i) = y_i$. Since $\dim(X) = n$, we know that there are scalars α_i so that

$$\alpha_1 x_1 + \cdots + \alpha_{n+1} x_{n+1} = 0$$

Applying T to this linear combination yields

$$\alpha_1 y_1 + \cdots + \alpha_{n+1} y_{n+1} = 0$$

Since the y_i were arbitrary, every subset of $\dim(\mathcal{R}(T))$ with $n + 1$ vectors is linearly dep. Thence $\dim(\mathcal{R}(T)) \leq n$.

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14. The Dimension Theorem

Theorem 24 *The inverse image of a basis under a linear transformation is linearly independent. I.e., Let $T \in L(X, Y)$ and let $\mathcal{B}_Y = \{y_i\}$. For each i , choose an x_i such that $T(x_i) = y_i$. Then the set $\{x_i\}$ is linearly independent.*

Pf. Exercise (3.4.24)

Theorem 25 (The Dimension Theorem) *Let $T \in L(X, Y)$ with $\dim(X) < \infty$. Then*

$$\dim(\mathcal{R}(T)) + \dim(\mathcal{N}(T)) = \dim(X).$$

Pf. Set $\dim(X) = n$ and $\dim(\mathcal{N}(T)) = s$ and set $r = n - s$.
(Need to show: $\dim(\mathcal{R}(T)) = r = n - s$.)

The Dimension Theorem Proof

Pf. Find a basis for $\mathcal{N}(T)$ labeling the vectors $\{e_1, \dots, e_s\}$. Extend this set to a basis for X by adding r vectors to have $\mathcal{B} = \{x_1, \dots, x_r, e_1, \dots, e_s\}$. Since \mathcal{B} is a basis, then $T(\mathcal{B})$ spans $\mathcal{R}(T)$. Since $T(e_i) = 0$, then $T(\{x_1, \dots, x_r\})$ spans $\mathcal{R}(T)$. Set $y_i = T(x_i)$; so $\{y_1, \dots, y_r\}$ spans $\mathcal{R}(T)$. Suppose a linear combination $\alpha_1 y_1 + \dots + \alpha_r y_r = 0$. Then because $\sum_r \alpha_i T(x_i) = T(\sum_r \alpha_i x_i)$, we have that $\sum_r \alpha_i x_i \in \mathcal{N}(T)$, thus $\sum_r \alpha_i x_i = \sum_s \gamma_i e_i$ which can be written as

$$\alpha_1 x_1 + \dots + \alpha_r x_r - \gamma_1 e_1 - \dots - \gamma_s e_s = 0$$

which implies each $\alpha_i = 0$. Hence $\dim(\mathcal{R}(T)) = r$.

– *What about the cases $s = 0$ and n ?*

(Group-Project time!)

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“Your Turn”

The Setup. Define $\mathcal{D} : \mathbb{R}^4 \rightarrow \mathbb{R}^4$ by

$$\mathcal{D}([x_1, x_2, x_3, x_4]) = [x_2, 2x_3, 3x_4, 0]$$

The Project.

1. Is \mathcal{D} a linear transformation?
2. What is $\mathcal{R}(T)$?
3. Find $\dim(\mathcal{R}(T))$.
4. What is $\mathcal{N}(T)$?
5. Find $\dim(\mathcal{N}(T))$.
6. Calculate $\dim(\mathcal{R}(T)) + \dim(\mathcal{N}(T))$.

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15. Rank & Nullity

Definition 19 (Rank and Nullity of a Linear Transformation)

Let $T \in L(X, Y)$.

- The rank ρ of T is the dimension of the range space;
 $\rho(T) = \dim(\mathfrak{R}(T))$
- The nullity ν of T is the dimension of the nullspace;
 $\nu(T) = \dim(\mathfrak{N}(T))$

Corollary 26 (Fundamental Theorem of Linear Algebra)

Let $T \in L(X, Y)$ where $\dim(X) = n$. Then

$$\rho(T) + \nu(T) = n$$

Pf. ✓

“Affine Nullspace”

Corollary 27 *Let $T \in (X, Y)$ where $\dim(X) < \infty$, and let $\mathcal{B} = \{x_1, \dots, x_s\}$ be a basis for $\mathfrak{N}(T)$ so that $\dim(\mathfrak{N}(T)) = s$. Then*

- 1. a vector $x \in X$ satisfies $T(x) = 0$ iff there is a unique set of scalars α_i s.t. $x = \sum_{i=1}^s \alpha_i x_i$,*
- 2. a vector $y_0 \in Y$ is in $\mathfrak{R}(T)$ iff there is at least one vector $x \in X$ s.t. $y_0 = T(x)$,*
- 3. if vectors $x_0 \in X$ and $y_0 \in Y$ are s.t. $T(x_0) = y_0$, then $x \in X$ satisfies $T(x) = y_0$ iff there is a unique set of scalars β_i s.t. $x = x_0 + \sum_{i=1}^s \beta_i x_i$.*

Pf. ✓

Inverses

Theorem 28 *Let $T \in L(X, Y)$.*

- 1. T^{-1} exists iff $T(x) = 0$ implies $x = 0$; i.e., $\mathfrak{N}(T) = \{0\}$.*
- 2. If T^{-1} exists, then $T^{-1} \in L(\mathfrak{R}(T), X)$.*

Pf. 1. (\Leftarrow) Assume $\mathfrak{N}(T) = \{0\}$. Then $T(x_1) = T(x_2) \Leftrightarrow T(x_1) - T(x_2) = 0 \Leftrightarrow T(x_1 - x_2) = 0 \Leftrightarrow x_1 - x_2 \in \mathfrak{N}(T) \Leftrightarrow x_1 = x_2$.

(\Rightarrow) Now assume that T^{-1} exists and that $T(x) = 0$. Since $T(0) = 0$, then $T(x) = T(0)$. Whence $x = 0$.

2. Assume that T is nonsingular and that $T(x_1) = y_1$, $T(x_2) = y_2$. Then $T^{-1}(y_1 + y_2) = T^{-1}(T(x_1) + T(x_2)) = T^{-1}(T(x_1 + x_2)) = x_1 + x_2 = T^{-1}(y_1) + T^{-1}(y_2)$. For $\alpha \in F$, $T^{-1}(\alpha y_1) = T^{-1}(\alpha T(x_1)) = T^{-1}(T(\alpha x_1)) = \alpha x_1 = \alpha T^{-1}(y_1)$.

Examples

Example Set 16

- Let $T([a, b]) = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} [a, b]$. Show T is nonsingular.
- Let $S([a, b]) = \begin{bmatrix} 6 & 3 \\ 2 & 1 \end{bmatrix} [a, b]$. Show T is singular.
- $\mathcal{D} : \mathbb{P} \rightarrow \mathbb{P}$ defined by $\mathcal{D}(p) = \frac{dp}{dx}$ is singular.
- Is $\mathcal{I} : \mathbb{P} \rightarrow \mathbb{P}$ defined by $\mathcal{I}(p) = \int p \, dx$ nonsingular?
- Is $T([a, b]) = [a + b, 0, a - b, 0, 0]$ invertible?

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Project Solution

The **Group-Project** solution is much easier when looking at the spaces from a different “dimension.”

The Setup. Define $\mathcal{D} : \mathbb{R}^4 \rightarrow \mathbb{R}^4$ by

$$\mathcal{D}([x_1, x_2, x_3, x_4]) = [x_2, 2x_3, 3x_4, 0]$$

A Solution. Consider $\mathcal{T} : \mathbb{P}^3 \rightarrow \mathbb{P}^3$ with $\mathcal{T}(p) = p'$. ($\mathbb{P}^3 \cong \mathbb{R}^4$)

- $\mathfrak{R}(T) = \{\text{polynomials of degree } 2\} \cong \mathbb{R}^3$
- $\mathfrak{N}(T) = \{\text{constant polynomials}\} \cong \mathbb{R}^1$
- $4 = 3 + 1 \Rightarrow \mathbb{R}^4 \cong \mathbb{P}^3 = \{p \in \mathbb{P}^3 \mid p(0) = 0\} \oplus \mathfrak{N}(T)$

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16. Singular and Nonsingular Examples

Example Set 17

- Let $T([a, b]) = \begin{bmatrix} 1 & 2 \\ 1 & 0 \end{bmatrix} [a, b]$. Show T is nonsingular.
- Let $S([a, b]) = \begin{bmatrix} 6 & 3 \\ 2 & 1 \end{bmatrix} [a, b]$. Show T is singular.
- $\mathcal{D} : \mathbb{P} \rightarrow \mathbb{P}$ defined by $\mathcal{D}(p) = \frac{dp}{dx}$ is singular.
- Is $\mathcal{I} : \mathbb{P} \rightarrow \mathbb{P}$ defined by $\mathcal{I}(p) = \int p \, dx$ nonsingular?
- Is $T([a, b]) = [a + b, 0, a - b, 0, 0]$ invertible?

“Inverse Results”

Theorem 29 *Let $T \in L(X, Y)$ with $\dim(X) < \infty$. Then T is invertible if and only if $\rho(T) = \dim(X)$. T is said to have “full rank.”*

Pf. ✓

Theorem 30 *Let $T \in L(X, Y)$ with $\dim(X) = \dim(Y) = n$ where $n < \infty$. Then T is invertible if and only if $\mathfrak{R}(T) = Y$.*

Pf. (\Rightarrow) T invertible implies that $\dim(\mathfrak{R}(T)) = n = \dim(Y)$. Since $\mathfrak{R}(T)$ is a subspace of Y , then $\mathfrak{R}(T) = Y$.

(\Leftarrow) Choose a basis $\mathcal{B} = \{y_1, \dots, y_n\}$ for $\mathfrak{R}(T) = Y$. Then, since $T^{-1}(\mathcal{B})$ is an independent set of size n , it forms a basis for X . Hence the only set of scalars for which $\sum_i \alpha_i x_i = 0$ is $\alpha_i = 0$. Whence $\mathfrak{N}(T) = \{0\}$, so T is invertible.

Collected Results, I

Theorem 31 (Invertible Linear Transformations) *Let X and Y be vector spaces over F and let $T \in L(X, Y)$. TFAE:*

1. *T is invertible or nonsingular*
2. *T is injective or 1-1*
3. *$T(x) = 0$ implies $x = 0$; i.e., $\mathfrak{N}(T) = \{0\}$*
4. *For each $y \in Y$, \exists a unique $x \in X$ such that $T(x) = y$*
5. *If $T(x_1) = T(x_2)$, then $x_1 = x_2$*
6. *If $x_1 \neq x_2$, then $T(x_1) \neq T(x_2)$,*

If X is finite dimensional, then TFAE:

7. *T is injective*
8. *$\rho(T) = \dim(X)$*

Collected Results, II

Theorem 32 (Surjective Linear Transformations) *Let X and Y be vector spaces over F and let $T \in L(X, Y)$. TFAE:*

1. *T is surjective or onto*
2. *For $y \in Y$, there is at least one $x \in X$ such that $T(x) = y$*

If X and Y are finite dimensional, then TFAE:

3. *T is surjective*
4. *$\rho(T) = \dim(Y)$*

Pf. ✓

Collected Results, III

Theorem 33 (Bijective Linear Transformations) *Let X and Y be vector spaces over F and let $T \in L(X, Y)$. TFAE:*

1. *T is bijective or onto*
2. *For $y \in Y$, there is a unique $x \in X$ such that $T(x) = y$*

If X and Y are finite dimensional, then TFAE:

3. *T is surjective*
4. *$\rho(T) = \dim(X) = \dim(Y)$*

Theorem 34 (Common Finite Dimension) *Let X and Y be vector spaces over F with finite dimension n and $T \in L(X, Y)$. Then*

$T : \text{injective} \Leftrightarrow T : \text{surjective} \Leftrightarrow T : \text{bijective} \Leftrightarrow T : \text{invertible}$

Transformation Spaces

Definition 20 For S and T in $L(X, Y)$ and α in F , define

1. $S + T$ by $(S + T)(x) \triangleq S(x) + T(x)$

2. αS by $(\alpha S)(x) \triangleq \alpha S(x)$

3. $S \circ T$ by $(S \circ T)(x) \triangleq S(T(x))$

Theorem 35 $L(X, Y)$ is a vector space over F (using 1 & 2)

Theorem 36 $L(X, X)$ is an associative algebra with identity over F (using 1, 2, & 3, and identity $I(x) = x$)

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17. Transformation Spaces

Definition 21 For S and T in $L(X, Y)$ and α in F , define

1. $S + T$ by $(S + T)(x) \triangleq S(x) + T(x)$
2. αS by $(\alpha S)(x) \triangleq \alpha S(x)$
3. ST by $(ST)(x) \triangleq S(T(x))$ **when** $\text{range}(T) \subseteq \text{dom}(S)$

Theorem 37 Let $S, T, U \in L(X, X)$. Then

1. If $ST = US = I$, then S is bijective and $S^{-1} = T = U$.
2. If S is bijective, then $(S^{-1})^{-1} = S$.
3. If S and T are bijective, then $(ST)^{-1} = T^{-1}S^{-1}$.
4. If S is bijective and $\alpha \neq 0$, then $(\alpha S)^{-1} = (1/\alpha) \cdot S^{-1}$.

Polynomials of Transforms

Theorem 38 $L(X, X)$ is an associative algebra^a with identity over F (using 1, 2, & 3, and identity $I(x) = x$). $L(X, X)$ is usually noncommutative.

Definition 22 (Powers of Transforms) Let $T \in L(X, X)$. Then set $T^0 = I$ and, for $n > 0$, define $T^{(n)} \triangleq T \cdot T^{(n-1)}$ and $T^{(-n)} \triangleq (T^{-1})^n$.

Definition 23 Let $p \in \mathbb{P}^n$, so that $p(\lambda) = a_0 + a_1\lambda + \cdots + a_n\lambda^n$. For $T \in L(X, X)$, define

$$p(T) = a_0 I + a_1 T + \cdots + a_n T^n = \sum_{i=0}^n \alpha_i T^i.$$

^a “Vector space plus multiplication.” See pg. 56 and 104 of the text.

Finite Dimension Structure Theorem

Definition 24 X is isomorphic to Y , written $X \cong Y$, if and only if there is a bijection $T \in L(X, Y)$.

Theorem 39 (Structure Theorem) Every n -dimensional vector space X over the field F is isomorphic to F^n .

Pf. Choose a basis $\mathcal{B} = \{e_1, \dots, e_n\}$ for X . Then define $T \in L(X, F^n)$ by

$$T \left(\sum_{i=1}^n \alpha_i e_i \right) = [\alpha_1, \alpha_2, \dots, \alpha_n]$$

Corollary 40 Let F be a field and n be a positive integer. There is exactly one vector space of dimension n over F .

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18. Linear Functionals

Definition 25 *Let X be a vector space over F . Then $f \in L(X, F)$ is called a linear functional.*

Example Set 18

- *Let $f \in \mathcal{C}[a, b]$. Then $F(f) = \int_a^b f(t) dt$ is a linear functional.*
- *Let $f \in \mathcal{C}[a, b]$ and choose $k \in \mathcal{C}[a, b]$. Then $F_k(f) = \int_a^b f(t)k(t) dt$ is a linear functional.*
- *Let $f \in \mathcal{C}[a, b]$ and $x_0 \in [a, b]$. Is $\frac{df}{dt}(x_0)$ a linear functional?*
- *Let F be a field. The mappings $\text{proj}_i : F^n \rightarrow F$ for $i = 1..n$ given by $\text{proj}_i([\alpha_1, \alpha_2, \dots, \alpha_n]) = \alpha_i$ are linear functionals. $\phi = \sum \alpha_i \text{proj}_i$ is also a linear functional.*

Vector Space of Linear Functionals

Definition 26 Let X be a vector space over F . Define $X^f = L(X, F)$. When $f \in X^f$ is evaluated at the vector $x \in X$, we use the notation $f(x) \triangleq \langle x, f \rangle$. Using x' in place of $f \in X^f$, we see

$$\begin{aligned}(f_1 + f_2)(x) &= \langle x, x'_1 + x'_2 \rangle \triangleq \langle x, x'_1 \rangle + \langle x, x'_2 \rangle \\ &= f_1(x) + f_2(x)\end{aligned}$$

and

$$\begin{aligned}(\alpha f)(x) &= \langle x, \alpha x' \rangle \triangleq \alpha \langle x, x' \rangle \\ &= \alpha f(x)\end{aligned}$$

Theorem 41 $X^f = L(X, F)$ is a vector space over F called the algebraic conjugate of X .

Algebraic Conjugate Basis

Theorem 42 *Let X be a vector space with basis $\mathcal{B} = \{e_1, \dots, e_n\}$ and let $\{\alpha_1, \dots, \alpha_n\}$ be a set of arbitrarily chosen scalars. Then there is a unique linear functional $x' \in X^f$ such that $\langle e_i, x' \rangle = \alpha_i$ for $i = 1..n$.*

Pf. (\exists) For every $x \in X$, we have unique scalars ξ_i such that $x = \sum_n \xi_i e_i$. Define $x' \in X^f$ by $\langle x, x' \rangle = \sum_n \alpha_i \xi_i$. If $x = e_i$ for some i , then $\xi_i = 1$ and $\xi_j = 0$ for every $j \neq i$. Hence $\langle x, x' \rangle = \alpha_i$; i.e., $\langle e_i, x' \rangle = \alpha_i$.

(!) Suppose $\langle e_i, x'_1 \rangle = \alpha_i$ and $\langle e_i, x'_2 \rangle = \alpha_i$ for $i = 1..n$. Then $\langle e_i, x'_1 \rangle - \langle e_i, x'_2 \rangle = 0$ for $i = 1..n$, and so $\langle e_i, x'_1 - x'_2 \rangle = 0$ for $i = 1..n$. This implies that $x'_1 = x'_2$.

Definition 27 (Kronecker Delta) Set $\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$.

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19. Conjugate Dimension Theorem

Theorem 43 *Let X be a finite dimensional vector space with basis $\mathcal{B} = \{e_1, \dots, e_n\}$. Then there exists a unique basis $\mathcal{B}' = \{e'_1, \dots, e'_n\}$ for X^f such that $\langle e_i, e'_j \rangle = \delta_{ij}$; we call \mathcal{B}' the dual basis of \mathcal{B} . Further $\dim(X) = n = \dim(X^f)$.*

Pf. There exists a unique set of linear functionals $\mathcal{B}' = \{e'_j\}$ such that $\langle e_i, e'_j \rangle = \delta_{ij}$ for $i, j = 1..n$ which are found by applying the previous theorem to the sets $A_j = \{\delta_{ij} | j = 1..n\}$.

(\mathcal{B}' is linearly independent) Since $\sum \beta_i e'_i = 0$ implies

$$0 = \left\langle e_j, \sum_i \beta_i e'_i \right\rangle = \sum_i \beta_i \langle e_j, e'_i \rangle = \sum_i \beta_i \delta_{ij} = \beta_j$$

Conjugate Dimension Theorem, II

(Pf.) (\mathcal{B}' spans X^f) Let $x' \in X^f$ and define $\alpha_i = \langle e_i, x' \rangle$. (This form is often called a *projection*.) For $x \in X$, there are scalars so that $x = \sum_i \xi_i e_i$. Then

$$\langle x, x' \rangle = \left\langle \sum_i \xi_i e_i, x' \right\rangle = \sum_i \langle \xi_i e_i, x' \rangle = \sum_i \xi_i \langle e_i, x' \rangle = \sum_i \xi_i \alpha_i$$

It also follows that $\langle x, e'_j \rangle = \sum_i \xi_i \langle e_i, e'_j \rangle = \xi_j$. Combine these two results to obtain

$$\langle x, x' \rangle = \sum_i \alpha_i \langle x, e'_i \rangle = \left\langle x, \sum_i \alpha_i e'_i \right\rangle$$

which gives us $x' = \sum_i \alpha_i e'_i$.

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20. Algebraic Transpose

Definition 28 (Algebraic Transpose) Let $S \in L(X, Y)$. Then $S^T : Y^f \rightarrow X^f$ given by $\langle x, S^T y' \rangle = \langle Sx, y' \rangle$ is the algebraic transpose of S .

Example 19 Let $X = \mathbb{R}^3$ and $Y = \mathbb{R}^2$. Define $S \in L(\mathbb{R}^3, \mathbb{R}^2)$ by $y = S(x) = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$ and $y' \in Y^f$ by $\langle y, y' \rangle = [1, 1] \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$. Then $x' = S^T(y')$ is found by

$$\begin{array}{l|l} \langle x, x' \rangle = \langle x, S^T y' \rangle = \langle Sx, y' \rangle & x'(x) = (S^T(y'))(x) \\ \langle x, x' \rangle = \langle \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}, y' \rangle & x'(x) = y'(S(x)) \\ \langle x, x' \rangle = \langle \begin{bmatrix} x_1+x_2 \\ x_2+x_3 \end{bmatrix}, y' \rangle & x'(x) = y'(\begin{bmatrix} x_1+x_2 \\ x_2+x_3 \end{bmatrix}) \\ \langle x, x' \rangle = x_1 + 2x_2 + x_3 & x'(x) = x_1 + 2x_2 + x_3 \end{array}$$

The Space of Algebraic Transposes

Theorem 44 *Let S^T be the algebraic transpose of S where $S \in L(X, Y)$. Then $S^T \in L(Y^f, X^f)$.*

Pf. (Calculation.)

1. $S^T(y'_1 + y'_2) = S^T(y'_1) + S^T(y'_2)$:

$$\begin{aligned}\langle x, S^T(y'_1 + y'_2) \rangle &= \langle Sx, (y'_1 + y'_2) \rangle = \langle Sx, y'_1 \rangle + \langle Sx, y'_2 \rangle \\ &= \langle x, S^T y'_1 \rangle + \langle x, S^T y'_2 \rangle\end{aligned}$$

2. $S^T(\alpha y') = \alpha S^T(y')$:

$$\begin{aligned}\langle x, S^T(\alpha y') \rangle &= \langle Sx, \alpha y' \rangle = \alpha \langle Sx, y' \rangle \\ &= \alpha \langle x, S^T(y') \rangle = \langle x, \alpha S^T(y') \rangle\end{aligned}$$

Algebra of Algebraic Transposes

Theorem 45 *Let I be the identity transform of $L(X, X)$. Then I^T is the identity transform of $L(X^f, X^f)$.*

Theorem 46 *Let 0 be the zero transform of $L(X, Y)$. Then 0^T is the zero transform of $L(Y^f, X^f)$.*

Theorem 47 *Let $R, S \in L(X, Y)$ and $T \in L(Y, Z)$ and let R^T , S^T , and T^T be the respective transposes. Then*

1. $(R + S)^T = R^T + S^T$
2. $(TS)^T = S^T T^T$

Exercise 3.52.32 (Pg. 113.) *Prove the theorems.*

[\(Go to TOC\)](#)

21. Bilinear Functionals

Recall: We have $\overline{a + bi} = a - bi$ for any **complex number**.

Definition 29 (Conjugate Functional) *Let X be a vector space over \mathbb{C} . A mapping $g : X \rightarrow \mathbb{C}$ is a conjugate functional iff $g(\alpha_1 x_1 + \alpha_2 x_2) = \overline{\alpha_1} g(x_1) + \overline{\alpha_2} g(x_2)$ for all $x_i \in X$ and $\alpha_i \in \mathbb{C}$*

Definition 30 (Bilinear Form) *Let X be a vector space over \mathbb{C} . A mapping $g : X \times X \rightarrow \mathbb{C}$ is a bilinear form or bilinear functional iff for all x, x_i and $y, y_i \in X$ and $\alpha_i, \beta_i \in \mathbb{C}$*

$$1. \quad g(\alpha_1 x_1 + \alpha_2 x_2, y) = \alpha_1 g(x_1, y) + \alpha_2 g(x_2, y)$$

$$2. \quad g(x, \beta_1 y_1 + \beta_2 y_2) = \overline{\beta_1} g(x, y_1) + \overline{\beta_2} g(x, y_2)$$

That is, g is linear in the first variable and conjugate linear in the second variable.

Examples

Example Set 20

1. Let $X = \mathbb{C}^2$ and g be given by

$$g(z_1, z_2) = \Re(z_1)\Re(z_2) + \Im(z_1)\Im(z_2).$$

2. Let $X = \mathbb{R}^2$ and h be given by

$$h(x, y) = \vec{x} \cdot \vec{y} = x_1y_1 + x_2y_2.$$

3. Let X be a vector space over \mathbb{C} and let $P, Q \in X^f$.

Then $k(x_1, x_2) = P(x_1)\overline{Q(x_2)}$ is a bilinear functional.

4. The conjugate of a bilinear functional is also a bilinear functional. I.e., $h(x, y) = \overline{g(x, y)}$.

Definitions

Definition 31 Let X be a vector space over \mathbb{C} and g be a bilinear functional on X . Then for all $x, y \in X$,

- g is symmetric iff $g(x, y) = \overline{g(y, x)}$.
- g is positive iff $g(x, x) \geq 0$.
- g is strictly positive iff $g(x, x) > 0$ whenever $x \neq 0$.
- $\tilde{g}(x) = g(x, x)$ is the quadratic form induced by g .

Example 21 For $h : \mathbb{R}^2 \rightarrow \mathbb{R}$ of Example Set 20, No 2, the induced quadratic form is $\tilde{h}(x) = \tilde{h}([x_1, x_2]) = x_1^2 + x_2^2$.

(Go to TOC)

22. Quadratic Forms & Inner Products

Theorem 48 *Let g be a bilinear functional. Then*

$$\frac{g(x, y) + g(y, x)}{2} = \tilde{g}\left(\frac{x + y}{2}\right) - \tilde{g}\left(\frac{x - y}{2}\right)$$

Theorem 49 (Polarization) *Let X be a vector space over \mathbb{C} and g be a bilinear functional on X . Then*

$$g(x, y) = \left[\tilde{g}\left(\frac{x + y}{2}\right) - \tilde{g}\left(\frac{x - y}{2}\right) \right] \\ + i \left[\tilde{g}\left(\frac{x + iy}{2}\right) - \tilde{g}\left(\frac{x - iy}{2}\right) \right]$$

Pfs. ✓

“Symmetry is Real”

Theorem 50 *Let g and h be bilinear functionals on the complex vector space X . If $\tilde{g} = \tilde{h}$, then $g = h$.*

Theorem 51 *A bilinear functional g on a complex vector space X is symmetric iff \tilde{g} is real.*

Pf. (\Rightarrow) Let g be symmetric, then $g(x, y) = \overline{g(y, x)}$ so that $\tilde{g}(x) = \overline{\tilde{g}(x)}$. Hence \tilde{g} is real.^a

(\Leftarrow) If \tilde{g} is real, set $h(x, y) = \overline{g(y, x)}$. Then $\tilde{h}(x) = \overline{\tilde{g}(x, x)} = g(x, x) = \tilde{g}(x)$; i.e., $\tilde{h} = \tilde{g}$. By the previous theorem, $h = g$, and hence $g(x, y) = \overline{g(y, x)}$. That is g is symmetric.

^a $z = \bar{z} \Rightarrow x + iy = x - iy \Rightarrow y = 0 \Rightarrow z \in \mathbb{R}$.

Inner Product

Ex. Work through example 3.6.18 on pg. 117.

Definition 32 (Inner Product) *A bilinear functional g is an inner product iff*

1. *g is strictly positive* $g(x, x) > 0$ whenever $x \neq 0$
2. *g is symmetric* $g(x, y) = \overline{g(y, x)}$

Definition 33 (Inner Product) (Alternate Definition) *A function $(\cdot, \cdot) : X \times X \rightarrow \mathbb{C}$ is an inner product iff*

1. $(x, x) > 0$ whenever $x \neq 0$ and $(0, 0) = 0$
2. $(x, y) = \overline{(y, x)}$
3. $(\alpha x + \beta y, z) = \alpha(x, z) + \beta(y, z)$
4. $(x, \alpha y + \beta z) = \bar{\alpha}(x, y) + \bar{\beta}(x, z)$

Inner Product Space

Definition 34 *A complex vector space with an inner product is an inner product space. A subspace of an inner product space with the restricted inner product is an inner product subspace.*

Definition 35 *Let X be an inner product space. Two vectors x and y are orthogonal, written as $x \perp y$, iff $(x, y) = 0$. If x is orthogonal to every vector in a set $A \subseteq X$, then $x \perp A$.*

Example Set 22

1. *Let $X = \mathbb{R}^2$ and let $(x, y) = x_1y_1 + x_2y_2$. Then $\{X; (\cdot, \cdot)\}$ is a real inner product space.*
2. *Let $X = \mathbb{C}^n$ and let $(u, v) = \sum_n u_i \bar{v}_i$. Then $\{X; (\cdot, \cdot)\}$ is a complex inner product space.*

(Go to TOC)

23. Inner Product Space Examples

Example 23 Let $X = C_{\mathbb{C}}[0, 1]$ and set $(f, g) = \int_0^1 f(t)\overline{g(t)} dt$.

1. $(t^2 + it, 1 - it) = \int_0^1 (t^2 + it)(1 + it)dt = \frac{3}{4}i$

2. $(t^2 + it, 36t + (2t - 25)i) = 0$, *thence it follows that*
 $(t^2 + it) \perp (36t + (2t - 25)i)$.

3. $(e^{2\pi kit}, e^{2\pi nit}) = \int_0^1 e^{2\pi(k-n)it} dt = \frac{i}{2\pi(n-k)} e^{-2\pi i(n-k)t} \Big|_0^1$

So $(e^{2\pi kit}, e^{2\pi nit}) = \delta_{kn}$. Thus $\mathcal{E} = \{e^{2\pi nit} : n \in \mathbb{Z}\}$ forms a set of mutually orthogonal functions.

Orthogonal Polynomials

Example 24 Let $X = \mathcal{C}_{\mathbb{R}}[0, 2\pi]$ and define the inner product

$$(f, g) = \int_0^{2\pi} f(t)g(t) dt.$$

1. $(t^2 + t, 1 - t) = \int_0^{2\pi} (t^2 + t)(1 - t)dt = 2\pi^2(1 - 2\pi^2)$

2. $(\cos(kt), \cos(nt)) = \int_0^{2\pi} \cos(kt) \cos(nt)dt = \frac{\pi}{2} \delta_{kn}$. So $\{\cos(nt) : n = 0.. \infty\}$ is a mutually orthogonal set.

3. Set $\cos(t) = x$. Then $\cos(nt) = \cos(n \arccos(x))$ becomes a polynomial in x . The inner product becomes

$$(f, g) = \frac{2}{\pi} \int_{-1}^{+1} f(t)g(t) \frac{1}{\sqrt{1-t^2}} dt$$

Orthogonal Polynomials, II

Example 24

(3.) Set $T_n(x) = \cos(n \arccos(x))$. Then $(T_k, T_n) = \delta_{kn}$, so that $\{T_n, n = 0..∞\}$ forms an orthogonal set of polynomials. The first few **Chebyshev polynomials** are $T_0(x) = 1$ and

$$T_1(x) = x$$

$$T_2(x) = 2x^2 - 1$$

$$T_3(x) = 4x^3 - 3x$$

$$T_4(x) = 8x^4 - 8x^2 + 1$$

$$T_5(x) = 16x^5 - 20x^3 + 5x$$

$$T_6(x) = 32x^6 - 48x^4 + 18x^2 - 1$$

[\(Go to TOC\)](#)

24. Projections

Definition 36 *Let $X = X_1 \oplus X_2$ and let $x = x_1 + x_2$ be the unique representation of $x \in X$ relative to $X_1 \oplus X_2$. Then define the mapping P by $P(x) = x_1$. We call P the projection on X_1 along X_2 .*

Theorem 52 *Let $X = X_1 \oplus X_2$ and P be the projection on X_1 along X_2 . Then*

1. $P \in L(X, X)$ and $P \in L(X, X_1)$
2. $\mathfrak{R}(P) = X_1$
3. $\mathfrak{N}(P) = X_2$

Pf. ✓

Example 25 *Let $X = \mathbb{R}^2$ and $P([x_1, x_2]) = x_2$.*

Projections, II

Example 26 Let $X = \mathbb{P}^3$ and $P(\sum_{i=0}^3 \alpha_i x^i) = \alpha_0 + \alpha_2 x^2$.

Theorem 53 Let $P \in L(X, X)$. Then P is a projection on $\mathfrak{R}(P)$ along $\mathfrak{N}(P)$ iff $P^2 = P$.

Pf. (\Rightarrow) Suppose that P is the projection on $\mathfrak{R}(P)$ along $\mathfrak{N}(P)$. Then $X = \mathfrak{R}(P) \oplus \mathfrak{N}(P)$. Let $x = x_1 + x_2$. Then $P^2(x) = P(P(x_1 + x_2)) = P(x_1) = x_1$. Hence $P^2 = P$.

(\Leftarrow) Now suppose that $P^2 = P$. (i) Let $y \in \mathfrak{R}(P)$. Then $\exists x \in X$ so that $P(x) = y$. Whence $P(P(x)) = P(y)$. But $P^2 = P$, so $P(P(x)) = P(x) = y$; i.e. $P(y) = y$. If y is also in $\mathfrak{N}(P)$, then $P(y) = 0$ which implies that $y = 0$. Hence $\mathfrak{R}(P) \cap \mathfrak{N}(P) = \{0\}$. (ii) For $x \in X$, $x = P(x) + (I - P)(x)$. Set $x_1 = P(x)$ and $x_2 = (I - P)(x) = x - x_1$. Thence X is equal to $X_1 \oplus X_2$ with P being the projection on X_1 along X_2 .

Projection “Symmetry”

Definition 37 $P \in L(X, X)$ is idempotent iff $P^2 = P$.

Theorem 54 P is a projection on X_1 along X_2 iff $(I - P)$ is a projection on X_2 along X_1 .

Corollary 55 If P is projection, then $X = \mathfrak{R}(P) \oplus \mathfrak{N}(P)$

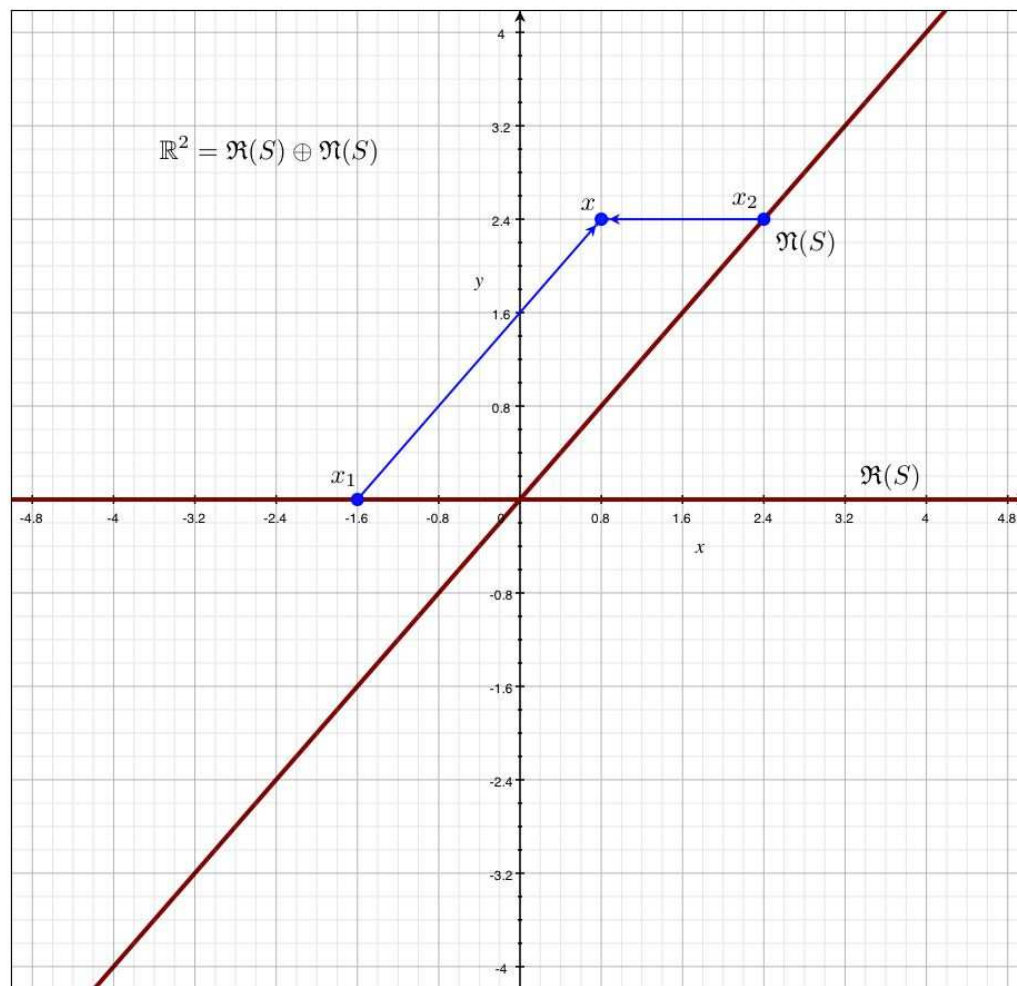
Example Set 27 Let $X = \mathbb{R}^2$.

- Set $R\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ x_2 \end{bmatrix}$. Is R a projection?
- Set $S\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 - x_2 \\ 0 \end{bmatrix}$. Is S a projection?
- Set $T\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} 0 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 2x_2 \end{bmatrix}$. Is T a projection?

Definition 38 P is an orthogonal projection on an inner product space iff $\mathfrak{R}(P) \perp \mathfrak{N}(P)$.

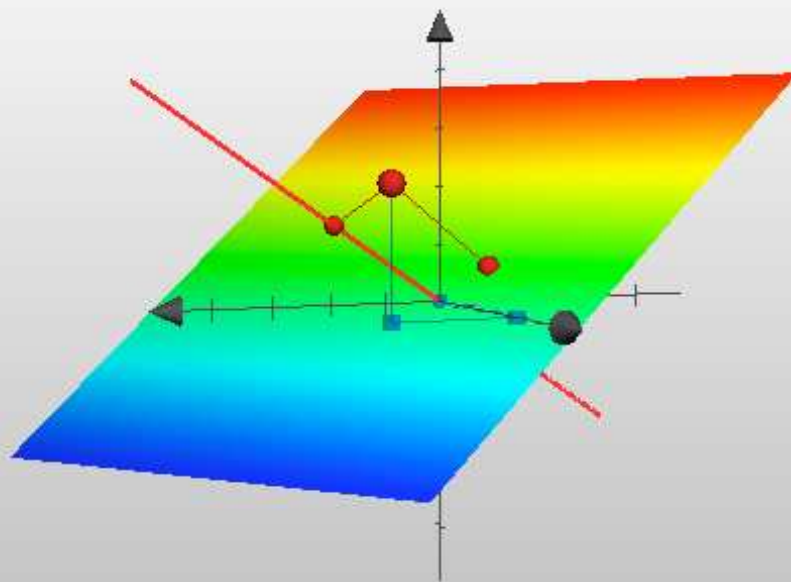
Projection Example S

(Eg.) In \mathbb{R}^2 , set $S\left(\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\right) = \begin{bmatrix} 1 & -1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 - x_2 \\ 0 \end{bmatrix}$.



Projection Example in \mathbb{R}^3

(Eg.) In \mathbb{R}^3 , set $X_1 = \left\{ \begin{bmatrix} -(r+t) \\ r+1 \\ t-1 \end{bmatrix} \right\}$ and $X_2 = \left\{ \begin{bmatrix} 2t \\ 2t \\ t \end{bmatrix} \right\}$.



(Go to TOC)

25. Eigenvalues

Definition 39 *Let $T \in L(X, X)$, where X is an n -dimensional vector space over F . A scalar λ such that $T(x) = \lambda x$ for some nonzero x is called an eigenvalue of T .*

Theorem 56 *Let $T \in L(X, X)$ and let $\lambda \in F$. Then $\mathfrak{N}_\lambda = \{x \mid T(x) = \lambda x\}$ is a subspace of X . This subspace is equal to $\mathfrak{N}(\lambda I - T)$ and, if nontrivial, is called an eigenspace.*

Pf. ✓

Background: Let X be an n -dimensional vector space over F . Then $X \cong F^n$. Every linear transformation $T \in L(X, X)$ can be described by its action on a basis. Choosing a basis, allows T to be represented as matrix multiplication (in F). Using the “right” bases gives T as a diagonal matrix greatly simplifying everything.

Eigenvalues, II

- Eigenvalue notes from Luke
- Eigenvalues and differential equations notes from Celes

[\(Go to TOC\)](#)

26. Vector Spaces & Matrices

Background. Let X be a vector space over the field F and let $\dim(X) = n < \infty$.

- Then $X \cong F^n$
- Then, given a basis \mathcal{B}_X , each $x \in X$ can be written as $x = [\alpha_1, \dots, \alpha_n]_{\mathcal{B}_X}$ in “basis order” (row or col format ^a)
- Let $T \in L(X, Y)$. T 's action on \mathcal{B}_X , i.e., the set $T(\mathcal{B}_X)$, completely determines $T(x)$ for any $x \in X$.
- Let \mathcal{B}_Y be a basis for Y . Then there is a *matrix* T based on \mathcal{B}_X and \mathcal{B}_Y , so that

$$y = T(x) = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \dots & \dots & \dots & \dots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \times \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}$$

^a “Column” and “row” vectors are artifices to aid the arithmetic.

Examples and $\mathbf{T} = [T]$

Example Set 28

1. Let $X = \mathbb{R}^2$. Then $[1, 2]_{\{[1,0],[0,1]\}} = [-1, 1]_{\{[1,1],[2,3]\}}$.
2. Let $X = \mathbb{P}^2$ with the “standard basis” $\{e_i = t^i\}$.
 $x = [1, 2, 3] = 1 + 2t + 3t^2$
3. Let $D : \mathbb{P}^3 \rightarrow \mathbb{P}^3$ be differentiation. Then, with the standard basis $\{1, t, t^2, t^3\}$,

$$D \left(\begin{bmatrix} \alpha \\ \beta \\ \gamma \\ \delta \end{bmatrix} \right) = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 3 \\ 0 & 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} \alpha \\ \beta \\ \gamma \\ \delta \end{bmatrix} = \begin{bmatrix} \beta \\ 2\gamma \\ 3\delta \\ 0 \end{bmatrix}$$

Definition 40 (The matrix of T) If $\mathcal{B}_X = \{e_j\}$ and $\mathcal{B}_Y = \{f_i\}$, then $\mathbf{T} = [a_{ij}]$ where $a_{ij} = \text{proj}_i(T(e_j))$ with $\text{proj}_i : Y \rightarrow Y$ being the projection on the i th coordinate of Y w.r.t. \mathcal{B}_Y .

The Matrix of T

Example Set 29 Let $T \in L(\mathbb{R}^2, \mathbb{R}^2)$ given by $T([x_1, x_2]) = [x_1 - x_2, x_1 + x_2]$.

1. Use the standard basis for both. Then $\mathbf{T} = \begin{bmatrix} +1 & -1 \\ +1 & +1 \end{bmatrix}$.

2. Use $\mathcal{B}_X = \{[1, 1], [2, 3]\}$ and $\mathcal{B}_Y = \{[1, 2], [4, 3]\}$. Then $\mathbf{T} = \begin{bmatrix} \frac{12}{5} & -\frac{2}{5} \\ \frac{37}{5} & -\frac{2}{5} \end{bmatrix}$.

—We now return you to the regularly scheduled program.—

Definition 41 (Coordinate representation) Let $x \in X$ and let $\mathcal{B} = \{e_1, \dots, e_n\}$ be a basis for X . Then there are unique scalars ξ_j such that $x = \sum_j \xi_j e_j$. Write x in coordinate

representation with respect to the basis \mathcal{B} as $x = \begin{bmatrix} \xi_1 \\ \vdots \\ \xi_n \end{bmatrix}_{\mathcal{B}}$.

The Transition Matrix

Example 30 Let $\mathcal{B} = \{e_1, \dots, e_4\}$ be the standard basis for \mathbb{R}^4 . Set $\mathcal{B}^* = \{[1, 2, 1, 0], [3, 3, 3, 0], [2, -10, 0, 0], [-2, 1, -6, 2]\}$. Then, for $x \in \mathbb{R}^4$, define $T_{\mathcal{B}^* \rightarrow \mathcal{B}}$ by $[e_1 \dots e_4]$ so

$$[x]_{\mathcal{B}} = \begin{bmatrix} 1 & 3 & 2 & -2 \\ 2 & 3 & -10 & 1 \\ 1 & 3 & 0 & -6 \\ 0 & 0 & 0 & 2 \end{bmatrix} \times [x]_{\mathcal{B}^*}$$

Hence

$$[x]_{\mathcal{B}^*} = \begin{bmatrix} 1 & 3 & 2 & -2 \\ 2 & 3 & -10 & 1 \\ 1 & 3 & 0 & -6 \\ 0 & 0 & 0 & 2 \end{bmatrix}^{-1} \times [x]_{\mathcal{B}} = \begin{bmatrix} 5 & 1 & -6 & -\frac{27}{2} \\ -\frac{5}{3} & -\frac{1}{3} & \frac{7}{3} & \frac{11}{2} \\ \frac{1}{2} & 0 & -\frac{1}{2} & -1 \\ 0 & 0 & 0 & \frac{1}{2} \end{bmatrix} \times [x]_{\mathcal{B}}$$

Query: How is a vector in \mathcal{B}_1 coordinates expressed in \mathcal{B}_2 coordinates? Can of cake: use

$$T_{\mathcal{B}_1 \rightarrow \mathcal{B}_2} = T_{\mathcal{B}_2 \rightarrow \mathcal{B}}^{-1} \times T_{\mathcal{B}_1 \rightarrow \mathcal{B}}$$

(Go to TOC)

27. Rank of a Matrix

Theorem 57 *Let $T \in L(X, Y)$ where $\dim(X) = n$ and $\dim(Y) = m$. The $\rho(T) = r$ iff there are bases \mathcal{B}_X and \mathcal{B}_Y such that*

$$\mathbf{T} = \left[\begin{array}{c|c} \overbrace{\begin{matrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 1 \end{matrix}}^r & \begin{matrix} 0 & \dots & 0 \\ 0 & & \\ \dots & & \\ 0 & \dots & 0 \end{matrix} \\ \hline \begin{matrix} 0 & \dots & 0 \\ 0 & & \\ \dots & & \\ 0 & \dots & 0 \end{matrix} & \begin{matrix} 0 & \dots & 0 \\ 0 & & \\ \dots & & \\ 0 & \dots & 0 \end{matrix} \end{array} \right] \left. \vphantom{\begin{matrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & \dots & 0 & 1 \end{matrix}} \right\} m = \dim(Y)$$

$n = \dim(X)$

The Rank Theorem Examples

Example Set 31

1. Consider $T \in L(\mathbb{R}^3 \rightarrow \mathbb{R}^2)$. Then \mathbf{T} must have one of the forms below (assuming proper choice of bases):

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Explain why.

2. Consider $T \in L(\mathbb{R}^3 \rightarrow \mathbb{R}^4)$. Then \mathbf{T} must have one of the forms below (assuming proper choice of bases):

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Explain why.

The Rank Theorem Proof

Theorem 57 Let $T \in L(X, Y)$. Then $\rho(T) = r$ iff $\mathbf{T} = \begin{bmatrix} Id & 0 \\ 0 & 0 \end{bmatrix}$.

Pf. (\Leftrightarrow) Let $r = \rho(T)$. Choose a basis for $\mathfrak{N}(T)$ of $n - r$ vectors listing it as $\{e_{r+1}, e_{r+2}, \dots, e_n\}$. Extend this basis to all of X as $\mathcal{B}_X = \{e_1, e_2, \dots, e_r, e_{r+1}, \dots, e_n\}$. Calculate $\mathcal{F} = \{T(e_i) \mid i = 1..r\}$ which forms a basis for $\mathfrak{R}(T)$. (Thm 3.4.25) Extend \mathcal{F} to a basis \mathcal{B}_Y by adding vectors $\{f_{r+1}, \dots, f_m\}$. (Thm 3.3.44) Then

$$f_1 = \mathbf{T}e_1 = (1)f_1 + (0)f_2 + \dots + (0)f_r + (0)f_{r+1} + \dots + (0)f_m$$

$$f_2 = \mathbf{T}e_2 = (0)f_1 + (1)f_2 + \dots + (0)f_r + (0)f_{r+1} + \dots + (0)f_m$$

...

$$f_r = \mathbf{T}e_r = (0)f_1 + (0)f_2 + \dots + (1)f_r + (0)f_{r+1} + \dots + (0)f_m$$

$$0 = \mathbf{T}e_{r+1} = (0)f_1 + (0)f_2 + \dots + (0)f_r + (0)f_{r+1} + \dots + (0)f_m$$

...

$$0 = \mathbf{T}e_n = (0)f_1 + (0)f_2 + \dots + (0)f_r + (0)f_{r+1} + \dots + (0)f_m$$

[\(Go to TOC\)](#)

28. Rank & Algebra of Matrices

Definition 42 Let $A \in \mathfrak{M}_{mn}$ be the matrix of $A \in L(X, Y)$ w.r.t. the bases \mathcal{B}_X and \mathcal{B}_Y . The rank of A is the largest number of linearly independent columns in A .

Theorem 58 Let A, B , and C be comparable/conformal matrices and let $\alpha, \beta \in F$. Then

1. $(A + B)C = AC + BC$
2. $A(B + C) = AB + AC$
3. $A(BC) = (AB)C$
4. $(\alpha + \beta)A = \alpha A + \beta A$
5. $\alpha(A + B) = \alpha A + \alpha B$
6. $(\alpha A)(\beta B) = (\alpha\beta)(AB)$
7. $A + B = B + A$
8. $(A + B) + C = A + (B + C)$

Algebra of Matrices

Theorem 59

1. *The zero matrix $\mathbf{0} = [0_{ij}]$ represents the zero transform $0(x) = 0$ for every basis.*
2. *The identity matrix $\mathbf{I} = [\delta_{ij}]$ represents the identity transform $I(x) = x$ for every basis.*
3. *The matrix \mathbf{A} is nonsingular iff the transform A is nonsingular.*
4. *If \mathbf{A} is nonsingular, then \mathbf{A}^{-1} is unique.*
5. *If \mathbf{A}_n and \mathbf{B}_n are nonsingular, then $(\mathbf{AB})^{-1} = \mathbf{B}^{-1}\mathbf{A}^{-1}$.*
6. *$\text{rank}(\mathbf{A}_n) = n$ if and only if $(\mathbf{A}_n x = 0 \Leftrightarrow x = 0)$.*
7. *For $\mathbf{A} \in \mathfrak{M}_n$, set $\mathbf{A}^m = \underbrace{\mathbf{A} \cdot \mathbf{A} \cdots \mathbf{A}}_m$ & $\mathbf{A}^{-m} = (\mathbf{A}^{-1})^m$.*

Partitioned Vectors & Matrices

Partitioning a vector or matrix can be very useful and is natural in direct sums. E.g.,

$$\begin{bmatrix} x_1 \\ x_2 \\ \hline x_3 \end{bmatrix}, \quad \begin{bmatrix} a_{11} & a_{12} & | & b_{11} \\ a_{21} & a_{22} & | & b_{21} \\ \hline c_{11} & c_{12} & | & d_{11} \end{bmatrix}, \quad \begin{bmatrix} \mathbf{A}_{11} & | & \mathbf{A}_{12} & | & \mathbf{A}_{11} \\ \hline \mathbf{A}_{21} & | & \mathbf{A}_{22} & | & \mathbf{A}_{21} \end{bmatrix}$$

Theorem 60 *Let $P \in L(X, X)$ be a projection and $\dim(X) = n$. Then there is a basis for $X = \mathfrak{R}(P) \oplus \mathfrak{N}(P)$ s.t.*

$$\mathbf{P} = \begin{bmatrix} 1 & 0 & \cdots & 0 & | & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 & | & 0 & \cdots & 0 \\ \cdot & \cdot & \cdots & \cdot & | & \cdot & \cdots & \cdot \\ 0 & 0 & \cdots & 1 & | & 0 & \cdots & 0 \\ \hline 0 & 0 & \cdots & 0 & | & 0 & \cdots & 0 \\ \cdot & \cdot & \cdots & \cdot & | & \cdot & \cdots & \cdot \\ 0 & 0 & \cdots & 0 & | & 0 & \cdots & 0 \end{bmatrix}$$

(Go to TOC)

29. Similarity & Equivalence

Ab hinc: X and Y are vector spaces over F with $\dim X = n$ and $\dim(Y) = m$.

Theorem 61 Let $\mathcal{B}_X = \{e_1, \dots, e_n\}$ be a basis for X and let $\mathbf{P} = [p_{ij}]$ be an $n \times n$ matrix. Set $e'_k = \sum_j p_{jk} e_j$. Then $\mathcal{B}'_X = \{e'_1, \dots, e'_n\}$ is a basis for X iff \mathbf{P} is nonsingular.

Pf. Calculation based on the linear independence of \mathcal{B}_X .

Definition 43 Let \mathbf{P} be the matrix of Thm 61, then \mathbf{P} is the matrix of \mathcal{B}'_X w.r.t \mathcal{B}_X .

Theorem 62 \mathbf{P} is the matrix of \mathcal{B}'_X w.r.t \mathcal{B}_X iff \mathbf{P}^{-1} is the matrix of \mathcal{B}_X w.r.t \mathcal{B}'_X .

Pf. Exercise.

Similarity of Matrices

Theorem 63 *Let P be the matrix of \mathcal{B}'_X w.r.t \mathcal{B}_X and Q be the matrix of \mathcal{B}''_X w.r.t \mathcal{B}'_X . Then PQ is the matrix of \mathcal{B}''_X w.r.t \mathcal{B}_X .*

Pf. *Exercise.*

Theorem 64 *Let P be the matrix of \mathcal{B}'_X w.r.t \mathcal{B}_X and let $x \in X$ be \mathbf{x} in \mathcal{B}_X coordinates. Then $P\mathbf{x}' = \mathbf{x}$ gives x in \mathcal{B}'_X coordinates.*

Pf. *Exercise.*

$$\begin{array}{ccc} \mathbf{x} = P\mathbf{x}' & \xrightarrow{A} & \mathbf{y} = A\mathbf{x} \\ \uparrow P & & \downarrow Q \\ \mathbf{x}' & \xrightarrow{A'} & \mathbf{y}' = Q\mathbf{y} \\ & & = QAP\mathbf{x}' \end{array}$$

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30. Equivalence of Transformations

Theorem 65 Let $A \in L(X, Y)$ where

- A has matrices $A_{\mathcal{B}_X \rightarrow \mathcal{B}_Y}$, and $A'_{\mathcal{B}'_X \rightarrow \mathcal{B}'_Y}$, resp.
- P is the matrix of \mathcal{B}'_X w.r.t. \mathcal{B}_X and Q of \mathcal{B}'_Y w.r.t. \mathcal{B}_Y

Then $A' = QAP$.

Pf.

$$\begin{aligned} Ae'_i &= A \cdot \sum_k p_{ki} e_k = \sum_k p_{ki} Ae_k = \sum_k p_{ki} \left(\sum_l a_{lk} f_l \right) \\ &= \sum_k p_{ki} \left(\sum_l a_{lk} \left[\sum_j q_{jl} f'_j \right] \right) = \sum_k \sum_l \sum_j q_{jl} a_{lk} p_{ki} \cdot f'_j \end{aligned}$$

Whence

$$a'_{ij} = \sum_l \sum_k q_{il} a_{lk} p_{kj}$$

Definition of Equivalence

Definition 44 Two $m \times n$ matrices A and A' are equivalent iff there are nonsingular square matrices P_n and Q_m such that $A' = Q_m \cdot A \cdot P_n$. Equivalence is written as $A' \sim A$.

Theorem 66 Matrix equivalence is an equivalence relation. I.e., \sim is reflexive, symmetric, and transitive.

Pf. Exercise.

Theorem 67 Let A and $B \in \mathfrak{M}_{m,n}$. Then

1. A is equivalent to $\left[\begin{array}{c|c} I_r & 0 \\ \hline 0 & 0 \end{array} \right]$ where $r = \text{rank}(A)$.
2. $A \sim B$ iff $\text{rank}(A) = \text{rank}(B)$.

Equivalence Example

Example 32 Consider $A \in L(\mathbb{R}^4, \mathbb{R}^5)$.

$$\text{Suppose } \mathbf{A} = \begin{bmatrix} 7 & -9 & 5 & -4 \\ 7 & 3 & -8 & -5 \\ 4 & 9 & 5 & 6 \\ 11 & 0 & 10 & 2 \\ 0 & 12 & -13 & -1 \end{bmatrix} \text{ and } \mathbf{A}' = \begin{bmatrix} 1 & 13 & 0 & 12 \\ -21 & -31 & 8 & 6 \\ 13 & 14 & -7 & 15 \\ -1 & 21 & 3 & 0 \\ 11 & -46 & -10 & -21 \end{bmatrix}.$$

$$\text{Then } \mathbf{P} = \begin{bmatrix} -1 & 1 & 1 & 0 \\ 1 & 0 & -1 & -1 \\ 1 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \text{ and } \mathbf{Q} = \begin{bmatrix} -1 & 0 & -1 & 1 & -1 \\ 0 & 1 & -1 & -1 & 0 \\ 1 & -1 & 1 & -1 & -1 \\ 1 & -1 & 0 & 1 & 1 \\ -1 & 0 & 0 & -1 & 1 \end{bmatrix}.$$

1. Show that $\mathbf{A}' = \mathbf{QAP}$.

2. Find the matrix $\begin{bmatrix} I_r & \vdots & 0 \\ \vdots & & \\ 0 & \vdots & 0 \end{bmatrix}$ equivalent to both \mathbf{A} and \mathbf{A}' .

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31. Determinants: “Work Day”

Exercise. Use an undergraduate text on Linear Algebra to:

1. Define the *determinant of a matrix*.
2. List the main properties/theorems on determinants.
3. Choose the five most important properties.
4. Give a numerical example demonstrating each important property listed.
5. Discuss the relation between *determinant of a matrix* and *nonsingularity of a linear transformation*.

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32. Determinants & Invariants

Recall the following

Theorem 68 *Let $A \in L(X, X)$.*

- $|A| \neq 0$ *iff* A is nonsingular
- $|A \cdot B| = |A| \cdot |B|$
- $|A^{-1}| = |A|^{-1}$
- $|\alpha A| = \alpha^n |A|$ *where* $n = \dim(A)$
- $|A| = 0$ *iff*
 - A has a row/column of zeros
 - A has two identical rows/columns
 - A has a row/column that is a linear combination of other rows/columns
 - $A\mathbf{x} = \mathbf{b}$ has nonunique solutions

Eigenvalue & Eigenvector

Definition 45 Let $A \in L(X, X)$. A scalar λ such that there is a nonzero $x \in X$ for which $Ax = \lambda x$ is an eigenvalue and the corresponding x is an eigenvector.

Definition 46 The polynomial $p(\lambda) = |A - \lambda I|$ is the characteristic polynomial of A .

Theorem 69 (Cayley-Hamilton) Let $A \in L(X, X)$. Then $p(A) = 0$. (NB: Also $p(0) = \prod \lambda_i$. See Zhou^a)

Definition 47 Let $A \in L(X, X)$. Then the subspace Y is an invariant subspace under A iff $A(Y) \subseteq Y$; i.e., $\forall y \in Y$, we have $Ay \in Y$.

Definition 48 Set $\mathfrak{N}_\lambda(A) = \mathfrak{N}_\lambda = \mathfrak{N}(A - \lambda I)$.

^a “Intro. to Symmetric Polynomials & Symmetric Functions”

Reduced Linear Transformation

Theorem 70 *Let $A \in L(X, X)$. Then X , $\mathfrak{N}(A)$, $\mathfrak{R}(A)$, and $\{0\}$ are all invariant subspaces under A .*

Example 33 *Let $A : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ be given by $\begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$. Then $\{0\}$, $\mathfrak{N}(A) = \langle \begin{bmatrix} 2 \\ -1 \end{bmatrix} \rangle$, $\mathfrak{R}(A) = \langle \begin{bmatrix} 1 \\ 2 \end{bmatrix} \rangle$, and \mathbb{R}^2 are all invariant.*

Example 34 *(Exercise.) Let $B : \mathbb{R}^3 \rightarrow \mathbb{R}^3$ be given by $\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 1 \\ 1 & 2 & 0 \end{bmatrix}$. Then $\{0\}$, $\mathfrak{N}(B) = \langle ? \rangle$, $\mathfrak{R}(B) = \langle ? \rangle$, and \mathbb{R}^3 are all invariant.*

Theorem 71 *Let λ be an eigenvalue of $A \in L(X, X)$. Then \mathfrak{N}_λ is invariant. (Exercise.)*

Definition 49 *Let $X = Y \oplus Z$ be such that both Y and Z are invariant subspaces under $A \in L(X, X)$. Then A is reduced by Y and Z and A can take form $\begin{bmatrix} A_1 & 0 \\ 0 & A_2 \end{bmatrix}$.*

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33. Eigenvalues & Diagonalization

Ab hinc: X is an n -dimensional vector space over F .

Theorem 72 *Let $\{\lambda_i \mid i = 1..p\}$ be a set of distinct eigenvalues of $A \in L(X, X)$ with corresponding nonzero eigenvectors $\mathcal{E} = \{e'_i \mid i = 1..p\}$. Then \mathcal{E} is linearly independent.*

Pf. Assume \mathcal{E} is dependent. Choose the smallest set of vectors from \mathcal{E} such that $0 = \sum_{i=1}^r \alpha_i e'_i$ (reordering the $r \leq p$ vectors as needed). Then $0 = A(0) = A(\sum_{i=1}^r \alpha_i e'_i)$ which gives $0 = \sum_{i=1}^r (\lambda_i \alpha_i e'_i)$ (*). Now $0 = \lambda_r 0 = \lambda_r \sum_{i=1}^r \alpha_i e'_i$, or $0 = \sum_{i=1}^r \lambda_r \alpha_i e'_i$ (**). Subtract (*) from (**) to obtain $0 = \sum_{i=1}^{r-1} (\lambda_r - \lambda_i) \alpha_i e'_i$ which contradicts r being minimal. Hence \mathcal{E} is linearly independent.

“Eigenbasis”

Theorem 73 *If $A \in L(X, X)$ has n distinct eigenvalues, then there is a basis of eigenvectors $\mathcal{B}_e = \{e'_i \mid i = 1..n\}$ such that the matrix of A is $\text{diag}(\lambda_1, \dots, \lambda_n)$.*

Pf. *Exercise.*

Corollary 74 *If $A \in L(X, X)$ has n distinct eigenvalues, then every matrix for A is similar to a diagonal matrix.*

Pf. Collect the eigenvectors $\mathcal{E} = \{e'_i \mid i = 1..n\}$. Set $P = [e'_1, \dots, e'_n]$. Then $\text{diag}(\lambda_1, \dots, \lambda_n) = P^{-1}AP$.

Example 35 See the [Maple worksheet](#). (To see what happens without a “cooked” example, enter the following in Maple: `with(LinearAlgebra):
A := RandomMatrix(5,5, generator=rand(-3..3)); Eigenvectors(A);`)

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34. “Eigen-Basis” Examples

Example 36

1. Let $A = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \in L(\mathbb{R}^3, \mathbb{R}^3)$. Then $p(\lambda) = \lambda^3 - 2\lambda^2 + \lambda$ (and $m(\lambda) = \lambda^2 - \lambda$) which indicates that A has eigenvalues: 0, 1, 1. The corresponding eigenvectors come from $\mathfrak{N}_\lambda = \mathfrak{N}(A - \lambda I)$. So $\mathfrak{N}_0 = \langle \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \rangle$ and $\mathfrak{N}_1 = \langle \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \rangle$.
- (Found by solving $\begin{bmatrix} 1-\lambda & 0 & 0 \\ 1 & -\lambda & 0 \\ 0 & 0 & 1-\lambda \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0$ with $\lambda = 0$ and 1, respectively.)
- (a) Define P and find P^{-1} .
- (b) Calculate the diagonal matrix $P^{-1}AP$ without using matrix multiplication.

“Eigen-Basis” Examples, II

Example 37

1. Let $B = \begin{bmatrix} 1 & 1 & 2 \\ 1 & 1 & 2 \\ 1 & 0 & 1 \end{bmatrix} \in L(\mathbb{R}^3, \mathbb{R}^3)$. Then $p(\lambda) = \lambda^3 - 3\lambda^2$ (and $m(\lambda) = \lambda^3 - 3\lambda^2$) which indicates that B has eigenvalues: 0, 0, and 3. The corresponding eigenvectors come from $\mathfrak{N}_\lambda = \mathfrak{N}(B - \lambda I)$. So $\mathfrak{N}_0 = \langle \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix} \rangle$ and $\mathfrak{N}_3 = \langle \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} \rangle$.

(Found by solving $\begin{bmatrix} 1-\lambda & 1 & 2 \\ 1 & 1-\lambda & 2 \\ 1 & 0 & 1-\lambda \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = 0$ with $\lambda = 0$, and 3, respectively.)

(a) Explain why P (and so P^{-1}) doesn't exist.

(b) Can B be diagonalized? Why or why not?

(Solution.)

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35. Geometric Multiplicity

Definition 50 Let λ be an eigenvalue of $A \in L(X, X)$. Then

- the algebraic multiplicity of λ is the multiplicity as a root of the characteristic polynomial $p(\lambda)$;
- the geometric multiplicity of λ is the dimension of the nullspace $\mathfrak{N}_\lambda = \mathfrak{N}(A - \lambda I)$.

Example 38 Let $X = \mathbb{R}^3$. Each matrix below has characteristic polynomial $p(\lambda) = -(\lambda - 2)^3$.

$$\begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\text{alg} = 3, \text{geo} = 3$$

$$\text{iev} = \{e_1, e_2, e_3\}$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\text{alg} = 3, \text{geo} = 2$$

$$\text{iev} = \{e_1, e_3\}$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\text{alg} = 3, \text{geo} = 1$$

$$\text{iev} = \{e_1\}$$

Reduction Partition

Theorem 75 *Let $X = X_1 \oplus X_2$ be a direct sum that reduces $A \in L(X, X)$; i.e., A is invariant on X_1 and X_2 . Then there is a basis \mathcal{B} for X such that*

$$A_{\mathcal{B}} = \left[\begin{array}{c|c} A_1 & 0 \\ \hline 0 & A_2 \end{array} \right]$$

Theorem 76 *Let $X = X_1 \oplus \cdots \oplus X_p$ be a direct sum that reduces $A \in L(X, X)$; i.e., $A_k = A|_{X_k}$ is invariant on X_k for $k = 1..p$. Then there is a basis \mathcal{B} for X such that*

$$A_{\mathcal{B}} = \left[\begin{array}{cccc} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & A_p \end{array} \right] \quad \text{and} \quad |A_{\mathcal{B}}| = \prod_{k=1}^p |A_k|$$

Minimal Polynomial

Example 39 *If $A \in L(X, X)$ has n distinct eigenvalues in F , then $X = \mathfrak{N}_{\lambda_1} \oplus \cdots \oplus \mathfrak{N}_{\lambda_n}$ and $A = \text{diag}(\lambda_1, \dots, \lambda_n)$.*

Definition 51 *Let $A \in L(X, X)$. Then there is a monic polynomial $m(\lambda)$, the minimal polynomial, such that*

- $m(A) = 0$
- any polynomial m' with $m'(A) = 0$ has $\deg(m) \leq \deg(m')$

Example 40 *The three matrices of Example 38 have*

$$\begin{bmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 1 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$$

$$m(\lambda) = (\lambda - 2) \quad m(\lambda) = (\lambda - 2)^2 \quad m(\lambda) = (\lambda - 2)^3$$

Properties of the Minimal Polynomial

Theorem 77 *The minimal polynomial $m(\lambda)$ is unique.*

Theorem 78 *Let $q(\lambda)$ be a polynomial such that $q(A) = 0$. Then $m(\lambda) \mid q(\lambda)$.*

Corollary 79 *The minimal polynomial divides the characteristic polynomial; i.e., $m(\lambda) \mid p(\lambda)$.*

Theorem 80 *The characteristic polynomial divides a power of the minimal polynomial: $p(\lambda) \mid [m(\lambda)]^n$ where $n = \dim(X)$.*

Corollary 81 $m(\lambda) \mid p(\lambda) \mid [m(\lambda)]^n$.

Proofs. Exercises.

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36. Jordan Canonical Form

Definition 52 Let $A \in L(X, X)$. If there is a power k such that $A^k = 0$, but $A^{k-1} \neq 0$, then A is nilpotent of index k .

NB: For a nilpotent matrix A of index k , $m_A(\lambda) = \lambda^k$.

Definition 53 Define $N_k \in \mathfrak{M}_{k \times k}$ to be

$$N_k = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 1 \\ 0 & 0 & \cdots & 0 & 0 \end{bmatrix}$$

Then N_k is nilpotent of index k .

Definition 54 Define $J_k(\lambda_i) = N_k + \lambda_i I$. The matrix $J_k(\lambda_i)$ is a Jordan block.

Jordan Blocks

Theorem 82 *Let $J_k(\lambda_i)$ be the Jordan block matrix of size k (with eigenvalue λ_i). Then*

- $p(\lambda) = (\lambda - \lambda_i)^k$

- $m(\lambda) = (\lambda - \lambda_i)^k$

Pf. Consider $J_k(\lambda_i) - \lambda I$. For $\lambda = \lambda_i$, we see

$$J_k(\lambda_i) - \lambda_i I = N_k$$

which is nilpotent of index k . Hence $p(\lambda) = (\lambda - \lambda_i)^k$. Since $m \mid p$ and no lower power of N_k than k gives 0, it follows that we also have $m(\lambda) = (\lambda - \lambda_i)^k$.

Jordan Form

Theorem 83 *Let $A \in L(X, X)$ with*

$$p(\lambda) = \prod_{i=1}^r (\lambda - \lambda_i)^{n_i} \quad \text{and} \quad m(\lambda) = \prod_{i=1}^r (\lambda - \lambda_i)^{m_i}$$

Then there is a block-diagonal matrix for A with blocks $J(\lambda_i)$. For each λ_i the blocks $J(\lambda_i)$ have the properties:

- 1. There is at least one block $J_{m_i}(\lambda_i)$; all others have order $\leq m_i$.*
- 2. The sum of the orders of the blocks for $J(\lambda_i)$ is n_i .*
- 3. The number of blocks $J(\lambda_i)$ equals the geometric multiplicity of λ_i .*
- 4. A uniquely determines the number of blocks $J(\lambda_i)$.*

JCF Example, I

Example 41 Let $A = \begin{bmatrix} 1 & 2 & 1 & 0 \\ 0 & 3 & 1 & 0 \\ 1 & 1 & 2 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$. (A is not diagonalizable.)

First $p(\lambda) = (4 - \lambda)(1 - \lambda)^3$. Hence, $m(\lambda) = (4 - \lambda)(1 - \lambda)^k$ where $k = 1, 2$, or 3 . Testing, we determine that $m(\lambda) = (4 - \lambda)(1 - \lambda)^2$. Thus there are Jordan blocks $J_1(4)$ and $J_2(1)$ from the factor powers in $m(\lambda)$. Since the sum of the block's indices must be 4, the last block is $J_1(2)$. We have determined that

$$JCF(A) = \text{diag}(J_1(4), J_2(1), J_1(1)) = \begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

Now we compute the transition matrix P that converts $JCF(A) = P^{-1}AP$. The first eigenvalue 4 has one independent eigenvector: $\mathfrak{N}_4 = \langle [1, 1, 1, 0]^T \rangle$. The second

JCF Example, II

Example 41 (continued) eigenvalue 1 has geometric multiplicity 2; i.e., $\dim(\mathfrak{N}_1) = 2$, and has only 2 independent eigenvectors. $\mathfrak{N}_1 = \langle [0, 0, 0, 1]^T, [1, 1, -2, 0]^T \rangle$. We need another independent vector for P . Set $\mathfrak{N}_{1,2} = \mathfrak{N}((A - 1I)^2) = \langle [0, 0, 0, 1]^T, [-3, 0, 1, 0]^T, [-5, 1, 0, 0]^T \rangle$. Let $N_\lambda = A - \lambda I$, then $x_1, x_2 = N_1 x_1, \dots, x_j = N_1 x_{j-1}$ can form an independent chain of vectors. Try $x_1 = [-5, 1, 0, 0]^T$, then $x_2 = N_1 x_1 = [2, 2, -4, 0]^T$ and $x_3 = N_1 x_2 = 0$. We have 4 independent vectors with which to construct P .

$$P = [\mathfrak{N}_4[1], \mathfrak{N}_1[1], x_2, x_1] = \begin{bmatrix} 1 & 0 & 2 & -5 \\ 1 & 0 & 2 & 1 \\ 1 & 0 & -4 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 4 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} = P^{-1}AP$$

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37. JCF Examples

We will consider a 3×3 matrix A over \mathbb{R} ; i.e., $A \in L(\mathbb{R}^3, \mathbb{R}^3)$.

Example 42 Let $A = \begin{bmatrix} 4 & 4 & 1 \\ 0 & 2 & 4 \\ 0 & 0 & 2 \end{bmatrix}$. The characteristic polynomial is $p(\lambda) = (4 - \lambda)(2 - \lambda)^2$. The minimal polynomial is found to be the same: $m(\lambda) = (4 - \lambda)(2 - \lambda)^2$. We can directly write the Jordan canonical form $JCF(A) = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$. (Explain why.)

We construct the transition matrix P from eigen- and generalized eigenvectors. Set $N_4 = (A - 4I)$. The nullspace of N_4 is $\langle [1, 0, 0]^T \rangle$. Set $v_1 = [1, 0, 0]^T$. Now consider $N_2 = (A - 2I)$. The nullspace of N_2 is $\langle [-2, 1, 0]^T \rangle$. This space is “too small,” since the algebraic multiplicity of $\lambda = 2$ is 2. Consider $N_{2,2} = (A - 2I)^2$. The nullspace of $N_{2,2}$ is $\langle [-2, 1, 0]^T, [-9/2, 0, 1]^T \rangle$. Set $x_2 = [-9/2, 0, 1]^T$. This choice

JCF Examples, II

Example 42 (continued) gives $x_2 \in \mathfrak{N}(N_{2,2}) - \mathfrak{N}(N_2)$, and then define $x_1 = N_2 x_2 = [-8, 4, 0]^T$. Let P be the matrix $[v_1, x_1, x_2]$. Then

$$P = \begin{bmatrix} 1 & -8 & -9/2 \\ 0 & 4 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad P^{-1} = \begin{bmatrix} 1 & 2 & 9/2 \\ 0 & 1/4 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Whence

$$JCF(A) = P^{-1} A P = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}.$$

JCF Finite Field Example

We will consider the same 3×3 matrix A , but now over \mathbb{Z}_5 ; i.e., $A \in L(\mathbb{Z}_5^3, \mathbb{Z}_5^3)$. Proceed as before, but calculate in \mathbb{Z}_5 .

Example 43 Let $A = \begin{bmatrix} 4 & 4 & 1 \\ 0 & 2 & 4 \\ 0 & 0 & 2 \end{bmatrix}$. The characteristic polynomial is $p(\lambda) = (4 - \lambda)(2 - \lambda)^2$. The minimal polynomial is found to be the same: $m(\lambda) = (4 - \lambda)(2 - \lambda)^2$. We can directly write the Jordan canonical form $JCF(A) = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix}$. (Explain why.)

We again construct the transition matrix P from eigen- and generalized eigenvectors. Set $N_4 = (A - 4I) = (A + 1I) \pmod{5}$. The nullspace of N_4 is $\langle [1, 0, 0]^T \rangle$. Set $v_1 = [1, 0, 0]^T$. Now consider $N_2 = (A - 2I) = (A + 3I) \pmod{5}$. The nullspace of N_2 is $\langle [3, 1, 0]^T \rangle$. This space is “too small,” since the algebraic multiplicity of $\lambda = 2$ is 2.

JCF Finite Field Example, II

Example 43 (continued) Consider $N_{2,2} = (A - 2I)^2 = (A + 3I)^2 \pmod{5} = \begin{bmatrix} 4 & 3 & 3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$. The nullspace of $N_{2,2}$ is $\langle [3, 1, 0]^T, [3, 0, 1]^T \rangle$. Set $x_2 = [3, 0, 1]^T$ as this choice gives $x_2 \in \mathfrak{N}(N_{2,2}) - \mathfrak{N}(N_2)$, and then define $x_1 = N_2 x_2 = [2, 4, 0]^T$. Let P be the matrix $[v_1, x_1, x_2]$. Then

$$P = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 4 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad P^{-1} = \begin{bmatrix} 1 & 2 & 2 \\ 0 & 4 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Whence

$$JCF(A) = P^{-1} A P = \begin{bmatrix} 4 & 40 & 25 \\ 0 & 32 & 16 \\ 0 & 0 & 2 \end{bmatrix} = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 2 & 1 \\ 0 & 0 & 2 \end{bmatrix} \pmod{5}.$$

JCF Exercise

Exercise. Set $A = \begin{bmatrix} 0 & -1 & 0 & 2 \\ -1 & 0 & 0 & 2 \\ 0 & 0 & 1 & 0 \\ -1 & 1 & 0 & 1 \end{bmatrix}$.

Find

1. $p(\lambda)$
2. $m(\lambda)$
3. the transition matrix P
4. $JCF(A)$

THE END

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