

Review Functions & Equivalence

- Injective / One-to-One: Every output is only hit once
 - Surjective / Onto: Range = Codomain
 - Bijective/Invertible: Injective & Surjective \Leftrightarrow
 - $\Leftrightarrow f: X \rightarrow Y, f^{-1}: Y \rightarrow X$ s.t. $f \circ f^{-1} = \text{id}_Y$ & $f^{-1} \circ f = \text{id}_X$
 - Restriction: For $X' \subseteq X$, $f|_{X'}: X' \rightarrow Y$, $f|_{X'}(x) = f(x)$ for $x \in X'$
 - Equivalence Relation (\sim) is symmetric, reflexive, & transitive.
 - Equivalence class of $x \in X$ is $E_x = \{y \in X \mid y \sim x\}$
 - Equivalence classes partition the set X .

An equivalence relation for example is $x \sim y \Leftrightarrow x = y \text{ mod } N$ for $x, y \in \mathbb{Z}$

Fields

A field is a set w/ 0 & 1 & operations $a+b$, $a-b$, ab , a/b ($b \neq 0$).

Example: $\mathbb{Q}, \mathbb{R} \subset \mathbb{Q}(\sqrt{2}) = \{a + b\sqrt{2} \mid a, b \in \mathbb{Q}\} \subset \mathbb{R}$, $\mathbb{Q}(i) \subset \mathbb{C}$

$$i) \mathbb{Q}(\sqrt{-2}) = \{a + b\sqrt{-2} \mid a, b \in \mathbb{Q}\} \subset \mathbb{R}, \quad \mathbb{Q}(i) \subset \mathbb{C}$$

(iii) $\mathbb{Z}_p = \{0, 1, \dots, p-1\}$ w/ \oplus , \cdot mod p & p is prime Galois Field!

A characteristic $n \geq 0$ is the smallest integer s.t. $1+1+\dots+1 = 0$. If there is no such n , then the characteristic is 0.

(i) & (ii) have characteristic 0 & (iii) has characteristic p

Thm: For some field F , $\text{char}(F) = 0 \Leftrightarrow \mathbb{Q} \subseteq F$

Systems of Linear Equations

To solve linear systems we want to simplify the system using operations which do not change the solutions to the system. We simplify by eliminating variables

$$\begin{aligned} 2x_1 - x_2 + x_3 &= 0 \Rightarrow -2x_2 \Rightarrow -7x_2 - 7x_3 = 0 \\ x_1 + 3x_2 + 4x_3 &= 0 \\ \Rightarrow x_2 + x_3 &= 0 \Rightarrow x_2 + x_3 = 0 \\ x_1 + 3x_2 + 4x_3 &\leq 0 \Rightarrow 3x_2 + 4x_3 \leq 0 \end{aligned}$$

$\Rightarrow x_1 = x_2 = -x_3$ of the solution is $(c, c, -c)$

normally normalize this system by reducing matrices to REF.

Def: Equivalence of Linear Systems

Two systems of linear eqns are equivalent iff each eqn of the 1st system is a l.c. of the 2nd & vice versa.

This is an equivalence relation.

(Also if they have the same AREF)

Thm: Equivalent systems have the same set of solutions.

Pf:

Showing that 2 systems are l.c.'s of each other uses operations which do not change the solution set.

Matrices

$$\begin{cases} 2x_1 - x_2 + x_3 = 0 \\ x_1 + 3x_2 + 4x_3 = 0 \end{cases} \Leftrightarrow \left[\begin{array}{ccc|c} 2 & -1 & 1 & 0 \\ 1 & 3 & 4 & 0 \end{array} \right] \left[\begin{array}{c} x_1 \\ x_2 \\ x_3 \end{array} \right] = \left[\begin{array}{c} 0 \\ 0 \end{array} \right]$$

(1,1) entry
↓
(2,3) entry

We can do the same transformations (elementary row operations) on the augmented coefficient matrix (coefficient matrix w/ solutions)

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

Elementary Row Operations

- Multiply a row by a scalar $\neq 0$
- Multiply a row by a scalar $\neq 0$ & add it to another row
- Switch two rows

These operations are invertible.

Def: Row Equivalence

A matrix A is row equivalent to a matrix B iff B can be obtained from A by a sequence of elementary row operations

This is an equivalence relation

Thm:

Row-equivalent matrices correspond to equivalent (homogeneous w/ RHS=0) systems of linear eqns, meaning they have the same solutions.

Row Reduced Form

Def:

A m x n matrix R is row-reduced iff

- 1st $\neq 0$ entry (called pivot) in each $\neq 0$ row is 1
- In a column containing a pivot, all other entries = 0.

Def: RREF

R is a row-reduced echelon matrix iff

i) & iii) it is row-reduced

iii) All zero rows are below any non-zero row

iv) If a pivot is below another pivot, then it is to its right

Any ^{matrix} can be made a RREF matrix by reordering the rows

Thm:

All matrices are row-equivalent to a row-reduced echelon matrix

Cor: Corollary

All undetermined homogeneous system (#eqns < # unknowns) always has non-trivial solutions

Cor:

A homogeneous system w/ n eqns & n unknowns ($A\bar{x} = \bar{0}$ where A square) has only the trivial solution $\bar{x} = 0$
 \Leftrightarrow A's RREF is equivalent to the identity matrix ($A = I$)

Matrix Multiplication

For $A \in M_{m,n}$ & $B \in M_{n,p}$, $AB \in M_{m,p}$.

To find c_{ij} of $AB = C$ and $c_{ij} =$
 $\sum_{k=1}^n c_{ik} \cdot b_{kj}$ \leftarrow row_i(A) \times col_j(B)

Properties:

i) $I_m A = A$ & $A I_n = A \quad \forall A \in M_{m,n}$

ii) $(AB)C = A(BC)$

iii) $AB \neq BA$ in general

Def: Elementary Matrix

An elementary matrix is a matrix obtained from the identity matrix I by a single row operation

Examples:

i) $\begin{bmatrix} 1 & 0 \\ 0 & c \end{bmatrix}, \begin{bmatrix} c & 0 \\ 0 & 1 \end{bmatrix} \quad c \neq 0$

ii) $\begin{bmatrix} 1 & c \\ 0 & 1 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ c & 1 \end{bmatrix}$

iii) $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

Let e be an elementary row operation & $E = e(I_m)$ be an elementary matrix.

Then $\forall A \in M_{m,n}$, $e(A) = EA$

Cor: B is row-equivalent to $A \Leftrightarrow B = PA$ where P = product of elementary matrices

Example:

$$i) A = \begin{bmatrix} x & z \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \xrightarrow{\text{R}_1 \leftrightarrow R_2} \begin{bmatrix} cx & cz \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} c & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x & z \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = EA$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \xrightarrow{\text{R}_2 \leftarrow R_2 - cR_1} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = E$$

$$ii) A = \begin{bmatrix} x & z \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \xrightarrow{\text{C}_2 \leftarrow C_2 + tC_1} \begin{bmatrix} x & cy \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & c \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x & z \\ y & t \\ 1 & 0 \\ 0 & 1 \end{bmatrix} = EA$$

$$I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \xrightarrow{\text{C}_2 \leftarrow C_2 + tC_1} \begin{bmatrix} 1 & c \\ 0 & 1 \end{bmatrix} = E$$

Invertible Matrices

Consider $N \times N$ (square) matrices

Def:

A left inverse of A is B s.t. $BA = I$
A right inverse of A is C s.t. $AC = I$

If $BA = I = AC$ then $B = C$

Def:

If $\exists A^{-1}$, then A^{-1} is a unique matrix s.t. $AA^{-1} = A^{-1}A = I$

A is called invertible iff \exists such A^{-1} .

Prop:

$$(A^{-1})^{-1} = A$$

$$(AB)^{-1} = B^{-1}A^{-1}$$

Thm: $R \xrightarrow{\text{row-equiv}} I$ iff R is a product of elementary operations

Ex:

$R = PA$ where P is the product of elementary matrices.

When $AP = I$, $R = P I = P$ means R is row-equivalent to I

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Elementary Matrices & Their Inverses (Continuing)

Every elementary operation $e(A)$ is invertible, that is, $e^{-1}(e(A)) = A$
 $(\exists E^{-1} \text{ s.t. } e(e^{-1}(A)) = e^{-1}(e(A)) = A)$

Likewise every elementary matrix E is invertible, that is
 $\exists E^{-1} \text{ s.t. } E E^{-1} = E^{-1} E = I$

We can expand this to products of elementary matrices, so

$$\text{Let } P = E_1 E_2 \dots E_n$$

$$\exists P^{-1} \text{ s.t. } P P^{-1} = P^{-1} P = I$$

In particular $P^{-1} = E_n^{-1} E_{n-1}^{-1} \dots E_1^{-1}$. Intuitively, this means you are applying the inverses of the elementary operations in the reverse order.
 $\xrightarrow{\text{to}}$ what you originally did.

Vector Spaces

Def:

A vector space over a field F is a set V w/ operations

$$+ : V \times V \rightarrow V, (u, v) \mapsto u + v, \text{ vector addition}$$

$$\cdot : F \times V \rightarrow V, (\alpha, v) \mapsto \alpha v, \text{ scalar multiplication}$$

Subject to the axioms

$$i) \bar{u} + \bar{v} = \bar{v} + \bar{u} \quad \text{commutativity}$$

$$ii) (\bar{u} + \bar{v}) + \bar{w} = \bar{u} + (\bar{v} + \bar{w}) \quad \text{associativity}$$

$$iii) \exists 0 \in V \text{ s.t. } \bar{v} + \bar{0} = \bar{v} \quad \forall \bar{v} \in V \quad \text{additive identity}$$

$$iv) \forall v \in V \quad \exists -v \in V \text{ s.t. } v + (-v) = 0 \quad \cancel{v + v} \quad (p-1)v = 3v$$

$$v) 1v = v \text{ for } 1 \in F \quad \cancel{1=2} \rightarrow \mathbb{Z}_p$$

$$vi) (\alpha \beta)v = \alpha(\beta v) \quad \cancel{\beta=2}$$

$$vii) \alpha(u+v) = \alpha u + \alpha v \quad \cancel{\alpha+\beta v}$$

$$\begin{array}{c|cc|c} & 1 & 2 & \dots \\ \hline 1 & 1 & 1 & \dots \\ 2 & 1 & 2 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{array}$$

$$\begin{array}{c|cc|c} & 1 & 2 & \dots \\ \hline 1 & 1 & 1 & \dots \\ 3 & 1 & 3 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{array}$$

$$\begin{array}{c|cc|c} & 1 & 2 & \dots \\ \hline 2 & 2 & 1 & \dots \\ 3 & 3 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{array}$$

$$\begin{array}{c|cc|c} & 1 & 2 & \dots \\ \hline 1 & 1 & 1 & \dots \\ 4 & 1 & 4 & \dots \\ \vdots & \vdots & \vdots & \ddots \end{array}$$

Rem: Remark

$$i) \alpha \bar{0} = \bar{0} = 0 \bar{v} \quad \forall \alpha \in F, \bar{v} \in V$$

$$ii) (-1)v = -v \quad \alpha \neq 0$$

(In the context of a finite field \mathbb{Z}_p , $-1 \in p-1$)

$$iii) \alpha \neq 0, v \neq 0 \Rightarrow \alpha v \neq 0$$

Examples of Vector Spaces

$$i) F^n = \left\{ \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \mid x_i \in F \right\}$$

ii) $F^{m \times n} = \text{space of } m \times n \text{ matrices w/ entries in } F$ ← generalization of above

Def: $V = \{f: S \rightarrow F\}$ w/ pointwise operations, that is function maps indices to entries

$$(f+g)(s) = f(s) + g(s) \quad \& \quad (cf)(s) = c f(s) \text{ for } c \in F, f, g \in V$$

v) $F[x] =$ polynomials w/ coefficients in F

$$F[x]_{\deg n} = \left\{ \sum_{k=0}^n a_k x^k \mid a_k \in F \right\}$$

v) $F \subset K$ - field extension $\Rightarrow K$ is a vector space over F

Def: Linear Combination

A linear combination of $v_1, \dots, v_n \in V$ is

$$v = c_1 v_1 + c_2 v_2 + \dots + c_n v_n \in V \text{ where } c_i \in F$$

Let $\text{span}\{v_1, \dots, v_n\} =$ set of all linear combinations of v_1, \dots, v_n

We can extend this to work w/ infinite sets:

$\forall \text{set } S \subseteq V, \text{span}(S) =$ set of all linear combinations of elements in S

Thm:

$\text{span}(S)$ is closed under vector addition & scalar multiplication \uparrow should be fairly intuitive

$$(a_1 v_1 + \dots + a_n v_n) + (b_1 v_1 + \dots + b_n v_n) = (a_1 + b_1) v_1 + \dots + (a_n + b_n) v_n$$

$$c(a_1 v_1 + \dots + a_n v_n) = (ca_1) v_1 + \dots + (ca_n) v_n$$

Subspaces

Def: Sub

A subspace of a vector space V is the subset U which is itself a vector space under the operations of V . (after they've been restricted)

In other words, U is closed under vector addition & scalar multiplication

$$\begin{aligned} &\forall u, v \in U \quad u + v \in U \\ &\forall c \in F, u \in U \quad cu \in U \end{aligned}$$

Equivalently, $+|_U: U \times U \rightarrow U$ & $\cdot|_U: F \times U \rightarrow U$ are well-formed.

Thm:

A subset is a subspace \Leftrightarrow it is closed under all linear combinations,

In essence, linear combinations are the "essence" of $+ \& \cdot$.

Rem:

All subspaces must contain the zero vector (by the axioms) & b/c $0v = \vec{0} \quad \forall v \in V$ where V is any vector space. By the field axioms $0 \in F$ for all fields F .

Examples of Subspaces:

i) $\{\vec{0}\} \subseteq V$ is a trivial subspace *TOPOR key had more notes

$$\text{ii) } F^n \subset F^n \text{ subspace} \Rightarrow \begin{bmatrix} x_1 \\ \vdots \\ x_{n-1} \\ 0 \end{bmatrix}$$

iii) $\forall A \in F^{m \times n}$, its nullspace $\text{null}(A) = \{x \in F^n \mid Ax = \vec{0}\}$ is a subspace of F^n . This is b/c $Ax + Ay = \vec{0} + \vec{0} = \vec{0}$ & $cAx = c\vec{0} = \vec{0}$

iv) $\text{span}(S)$ where $S \subseteq V$ is a subspace.

Thm:

\forall subspaces $W_i \subseteq V$, then $\bigcap W_i$ is a subspace.

IT doesn't work for union!

This falls out b/c if you're in W_i , then you are closed under W_j . This means that if you're in the intersection, you are closed under all W_i , meaning you can't escape $\bigcap W_i$.

Rem:

For a subset $S \subseteq V$, $\text{span}(S) = \min$ subspace of V containing $S = \bigcup_{S \subseteq W} W$

Spanning set: a set of vectors in V such that $\bigcup_{S \subseteq W} W = V$

Notation:

$$\text{span}(S) = \langle S \rangle$$

Take subspaces $[W_1, W_2] \subset V$ & consider $\langle W_1 \cup W_2 \rangle$

$$\begin{aligned} \langle W_1 \cup W_2 \rangle &= \{ \underbrace{c_1 v_1 + \dots + c_k v_k}_{W_1} + \underbrace{c_{k+1} v_{k+1} + \dots + c_n v_n}_{W_2} \mid v_i \in V, v_i \in W_1 \text{ & } v_{k+1}, \dots, v_n \in W_2 \} \\ &= \{ w_1 + w_2 \mid w_1 \in W_1, w_2 \in W_2 \}. \end{aligned}$$

We use this to define addition of subspaces. (Space of subspaces!)

Def:

$$W_1 + W_2 = \{w_1 + w_2 \mid w_1 \in W_1 \text{ & } w_2 \in W_2\} \xrightarrow{\text{Trivially expanded to}} \sum W_i$$

In \mathbb{R}^2 , take w_1 & w_2 to be two lines through 0 (where $w_1 \neq w_2$).

Then $w_1 \cap w_2 = \{0\}$ & $w_1 + w_2 = \mathbb{R}^2$

Basis & Dimension

Def: Basis

A subset $B \subset V$ is a basis for V iff $\forall v \in V \exists!$ l.c. of elements of B .

This is split in two parts, existence (i) & uniqueness (ii)

i) $\text{span}(B) = V \Leftrightarrow \forall v \in V, \text{span}(B) \nsubseteq \text{literally } V \subseteq B$, but we know $B \subseteq V$ by definition
 $\Leftrightarrow B$ spans V

ii) No vector $v \in B$ can be expressed as a l.c. of other vectors in V .

In particular, we know $0 = 0x \in \text{span}(B)$ by the axioms.

Suppose also $0 = \sum c_i v_i$ $\forall i \in B$. This is unique iff all coefficients are zero ($c_i = 0$). This means uniqueness is satisfied iff $c_i = 0$ is the only solution to $\sum c_i v_i = 0$

Def: Linearly Independent (l.i.)

Vectors are linearly independent iff there are no non-trivial solution to $c_1 v_1 + \dots + c_n v_n = 0$. (Trivial where $c_1 = \dots = c_n = 0$)

A basis B of a vector space V is a linearly independent spanning set of V .

Def: Linearly Dependent

Not l.i. or there exist non-trivial solution to $c_1 v_1 + \dots + c_n v_n = 0$.

Def: Dimension

The dimension of v.s. V is the cardinality of some basis B of V .

$$\dim(V) = |B|$$

We say $\dim(V)$ is infinite iff there is no finite basis.

We need to show that the dimension of V doesn't depend on the specific basis B chosen.

Example: Standard

\mathbb{R}^n has a basis $B = \{e_1 = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix}, \dots, e_n = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}\}$

b/c $\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = x_1 e_1 + \dots + x_n e_n$, so every $v \in \mathbb{R}^n$ is a unique l.c. of B .

Standard basis of a v.s.
 V where $\dim(V) = n$ is $\{e_1, \dots, e_n\}$

Example:

The space of polynomials $F[x]$ has a standard basis $B = \{1, x, \dots, x^n\}$.
 $\dim(F[x]) = \infty$.

Example:

$\mathbb{R} \subset \mathbb{C}$ subfield $\Rightarrow \mathbb{C}$ is a v.s. over \mathbb{R}

$$\dim_{\mathbb{R}} \mathbb{C} = 1 \quad B = \{1\}$$

$$\dim_{\mathbb{R}} \mathbb{C} = 2 \quad B = \{1, i\}$$

$$\dim_{\mathbb{R}} \mathbb{C} = \infty$$

Rem:

The basis of the trivial space $V = \{0\}$ is $B = \emptyset$.

By definition, $\dim(V) = \dim(\{0\}) = |\emptyset| = |\emptyset| = 0$.

Now it's time to prove that choice of basis doesn't matter for dimension. (We'll actually go more general w/ the Fundamental theorem of _____)

QUESTION: Does it matter to dimension?

Thm:

Let V be a vector space spanned by m vectors.
Any set of $n > m$ vectors is linearly dependent.

PF:

$V = \text{Span}\{w_1, \dots, w_m\}$. Consider $\{v_1, \dots, v_n\}$.
Since $v_j \in V$, $v_j = \sum_{i=1}^m a_{ij} w_i \quad \forall j \quad 1 \leq j \leq n$.

For $x_1, \dots, x_n \in F$

TOD: Take from notes

Cor:

If V is a finite v.s., then any two basis has the same cardinality.

PL:

Assume v.s. V has basis $B_1 = \{w_1, \dots, w_m\}$.

Take any other basis B_2 .

If $|B_2| \geq m$, then B is linearly dependent, so $|B_2| \leq m$.

Swapping the roles of B_1 & B_2 gives you $|B_1| \leq m$. \leftarrow Also if $|B_2| < m$, then B_2 doesn't span V .
Therefore $|B_1| = |B_2|$

Thm/Cor:

Let $\dim(V) = m$ where m is finite.

Let $S \subseteq V$, $|S| \leq n$.

If $n > m \Rightarrow S$ is linearly dependent (From above)

If $n < m \Rightarrow S$ is not a spanning set of V . $\langle S \rangle \neq V$.

This means $\dim(V) = \max \# \text{ of l.i. vectors} = \min \# \text{ vectors in a spanning set}$.

Thm:

Let S be a l.i. subset of v.s. V where $v \in V$ & $v \notin \langle S \rangle$.
Then $S \cup \{v\}$ is linearly independent.

PF:

Suppose $x_0 v + \sum_i x_i v_i = 0$ for $v_i \in S$.

Suppose $x_0 \neq 0$ for contradiction. Then

$$v = -\frac{1}{x_0} \sum_i x_i v_i \in \langle S \rangle$$

This contradicts $v \notin S$, so $x_0 = 0$ must be true. Since S is l.i.

$$\sum_i x_i v_i = 0$$

only when $\forall x_i = 0$.

By repeated use of the above theorem, we can prove.

Thm:

Let V be a finite dimensional v.s.

Any l.i. subset of V can be extended to a basis.

Cor:

Let W be a subspace of a finite dimensional v.s. V .

Any basis of W can be extended to a basis for V (since the basis of W is a l.i. subset of V).

Cor:

If subspaces $W \subseteq V$, $\dim(W) \leq \dim(V)$ w/ $\dim(W) = \dim(V)$ iff $W = V$.

Thm:

Let V be a v.s. where $\dim(V) = n < \infty$.

Any n l.i. vectors form a basis. \leftarrow they imply each other.

Any n spanning vectors form a basis. \leftarrow

This follows from the theorem that we can add vectors to l.i. set to get a basis & you can remove vectors from a spanning set to get a basis.

Example:

Consider $v_1 = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}$, $v_2 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$, $v_3 = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \in \mathbb{R}^3$

$$b = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = x_1 v_1 + x_2 v_2 + x_3 v_3 = \begin{bmatrix} x_1 + x_2 + x_3 \\ 2x_1 + x_2 + 3x_3 \\ 2x_1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ 2 & 1 & 3 \\ 2 & 0 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

This is true for some b & x iff $Ax=0$ has only one solution x , which is true iff A is invertible, which is true iff $\det(A) \neq 0$.

Thm:

Let W_1 & W_2 be subspaces of V where $\dim(V) < \infty$.

$$\text{Then } \dim(W_1 + W_2) = \dim(W_1) + \dim(W_2) - \dim(W_1 \cap W_2)$$

Recall: $W_1 + W_2 = \langle W_1 \cup W_2 \rangle$

Like inclusion
exclusion principle
for sets

Pf.

Let \hat{B}_1 be a basis for $W_1 \cap W_2$.

Since $W_1 \subseteq W_1 \cap W_2$, we can extend \hat{B}_1 to be a basis B_1 for W_1 . Likewise we get B_2 basis for W_2 .

We claim $B_1 \cup B_2$ is a basis for $W_1 + W_2$. In that case
 $|B_1 \cup B_2| = |B_1| + |B_2| - |B_1 \cap B_2| = \dim(W_1) + \dim(W_2) - \dim(W_1 \cap W_2)$
 $\Leftrightarrow \dim(W_1 + W_2) = \dim(W_1) + \dim(W_2) - \dim(W_1 \cap W_2)$

Now we show $B_1 \cup B_2$ is a basis for $W_1 + W_2$.

Let

$$B = \{v_1, \dots, v_k\}$$

$$B_1 = \{v_{1,000}, v_{k,000}, u_{1,000}, u_{m,000}\}$$

$$B_2 = \{v_{1,000}, v_{k,000}, w_{1,000}, w_{n,000}\}$$

$$B_1 \cup B_2 = \{v_{1,000}, v_{k,000}, u_{1,000}, u_{m,000}, w_{1,000}, w_{n,000}\}$$

\forall vector $= x + y$ $x \in V_1, y \in V_2$

$$x = \sum a_i v_i + \sum b_i u_i$$

$$y = \sum c_i v_i + \sum d_i w_i$$

$$x + y = \sum (a_i + c_i) v_i = \sum b_i u_i + \sum d_i w_i$$

Therefore, $B_1 \cup B_2$ spans $W_1 + W_2$.

$$\begin{aligned} \sum a_i v_i + \sum b_i w_i + \sum c_i w_i &= 0 \\ \underbrace{\sum a_i v_i + \sum b_i w_i}_{\in W_1 \cap W_2} &= -\sum c_i w_i \end{aligned}$$

$\in W_1$ $\in W_2$

So $\forall i, b_i = 0$ & $\forall c_i = 0$.

Since B is a basis for $W_1 \cap W_2$, $\sum a_i v_i = 0$ iff $a_i = 0$.
Therefore B, VB_2 is l.i.

Thus B, VB_2 is a basis for $W_1 \cap W_2$, so
 $\dim(W_1 \cap W_2) = \dim(W_1) + \dim(W_2) - \dim(W_1 \cup W_2)$

Coordinates

Ex:

Let $V = \mathbb{R}^2$ w/ standard basis $B = \{e_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}\}$.
 $\forall v \in V, v = x e_1 + y e_2 = \begin{bmatrix} x \\ y \end{bmatrix} = v$.

Let's consider another basis $B' = \{v_1, v_2\}$.
 $v = x_1 v_1 + y_2 v_2$.

This gives you another set of coordinates x & y .

This is the idea of using any basis to create a coordinate system for your v.s. Really, you need an ordered basis b/c otherwise you wouldn't know which coordinate goes to which vector $v \in B$.

Thm: Coordinate Vector

Let V be a v.s. over field F where $\dim(V) = n$.

Fix some ordered basis $B = \{v_1, \dots, v_n\}$ for V .
Then $\forall v \in V \exists! v = x_1 v_1 + \dots + x_n v_n$ where $x_i \in F$

This means there is some unique coordinate vector w.r.t. B

$$[v]_B = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in F^n$$

We say x_1, \dots, x_n are the coordinates of v w.r.t. B

Recall Isomorphisms are bijections b/w vector spaces that preserves the properties of $+ \& \cdot$.

Rem:

The map $V \rightarrow F^n, v \mapsto [v]_B$ is a bijection b/c you can easily go back & forth. This map is an isomorphism.

This means all n -dimension vector spaces V over F are isomorphic w/ F^n .

Change of Basis

Let $B = \{v_1, v_2, \dots, v_n\}$ & $B' = \{v'_1, v'_2, \dots, v'_n\}$ be 2 ordered bases for V .

$$(i) v = \sum_i x_i v_i \Leftrightarrow [v]_B = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = X$$

$$(ii) v = \sum_j x'_j v'_j \Leftrightarrow [v]_{B'} = \begin{bmatrix} x'_1 \\ \vdots \\ x'_n \end{bmatrix} = X'$$

We want algorithm that can transform b/w $[v]_B$ & $[v]_{B'}$
 for any basis B & B' of V & any vector $v \in V$. We do this by
defining a linear transformation from B to B' . For this it is
 sufficient to write every element of B' as a linear combination
 of B . We can then be clever & make this a linear transformation
 from B' to B & thus as a matrix $P \in F^{n \times n}$ such that V
 $\forall v \in V \quad [v]_B = P[v]_{B'}$. We call P the transition matrix.

Since $\forall j \forall i \in V$, we know

$$(iii) v_j \cdot v'_j = \sum_i p_{ij} v_i \text{ for some scalar } p_{ij} \in F \Leftrightarrow v'_j = \begin{bmatrix} p_{1,j} \\ \vdots \\ p_{n,j} \end{bmatrix} \text{ j-th column of } P$$

We then plug (iii) into (i)

$$v = \sum_j x'_j v'_j = \sum_j \left(x'_j \sum_i (p_{ij} v_i) \right) \Leftrightarrow$$

TODD: Look at lecture notes

conversely, we have the following theorem.

Theorem

Let $B = \{v_1, v_2, \dots, v_n\}$ be a basis for V .

Let $P \in \mathbb{F}^{n \times n}$ be an invertible matrix, $P = (P_{ij})$.

$$v'_j = \sum_{i=1}^n P_{ij} v_i \quad \forall j \quad 1 \leq j \leq n$$

Then $B' = \{v'_1, \dots, v'_n\}$ is a basis.

Example

$$\text{Let } V = \mathbb{R}^3, \quad v_1 = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}, \quad v_2 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \quad v_3 = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}$$

Let $x \in V$

$$v = x_1 v_1 + x_2 v_2 + x_3 v_3$$

$$= [v_1 \ v_2 \ v_3] \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$= Ax$$

To solve $AX = v$, we make an augmented matrix $[A | v]$ & row-reduce to $[I | w]$.

$AX = v \Leftrightarrow RX = w$. If $R = I$, then solution is $v = w$.

In general, we can make our work more general by solving $[A | I]$ into $[I | A^{-1}]$. That way we can do

$$AX = v \Leftrightarrow X = A^{-1}v \Leftrightarrow X = A'$$

In this way we transform any vector V into a coordinate vector w.r.t. $B = \{v_1, v_2, v_3\}$.

In particular $[e_i]_B$ is the 1st col of A^{-1} , $[e_2]_B$ the 2nd, $[e_3]_B$ the 3rd.

Functions/ Mappings

TODO: Move to MA407

Def:

Let $f: A \rightarrow B$ be a function from A to B .
 $A = \text{Dom}(f) = \text{domain of } f$
 $B = \text{Codom}(f) = \text{codomain of } f$
 $\text{Rng}(f) \subseteq \text{Codom}(f)$ is the range of f .

Examples:

Let $\mathbb{Q}^+ = \left\{ \frac{m}{n} : m, n \in \mathbb{Z} \right\}$ be the set of positive rational numbers.

We define a function $f: \mathbb{N} \times \mathbb{N} \rightarrow \mathbb{Q}^+$ as
 $f(m, n) = \frac{m}{n}$

Suppose $(m_1, n_1) = (m_2, n_2)$. We show $f((m_1, n_1)) = f((m_2, n_2))$
 $f(m_1, n_1) = \frac{m_1}{n_1} = \frac{m_2}{n_2} = f(m_2, n_2)$

Now define $g: \mathbb{Q}^+ \rightarrow \mathbb{N} \times \mathbb{N}$, let's define $g\left(\frac{m}{n}\right) = (m, n)$.
 Is g a function? No. g tries to be f^{-1} but f^{-1} is not injective.

We show that $a = b \Rightarrow g(a) = g(b)$ does not hold.
 $\frac{3}{2} = \frac{6}{4}$ but $g\left(\frac{3}{2}\right) \neq g\left(\frac{6}{4}\right) \Leftrightarrow (3, 2) \neq (6, 4)$

Def: Image

Let $f: A \rightarrow B$.

Let $C \subseteq A$.

$f(C) = \{f(c) : c \in C\}$ is called the image of C under f .

Let $D \subseteq B$.

We're not assuming f^{-1} exists!

$f^{-1}(D) = \{a \in A : f(a) \in D\}$ is called the inverse image of D under f .

The image of A under f is $\text{Rng}(f)$ TODO: are these right?

The inverse image of B under f is $\text{Dom}(f)$

vw pale

Def: Row Space

For $A \in F^{m \times n}$

its row space $\text{row}(A)$ is the span of the row vectors of A .
 $\text{row}(A) = \text{span} \{ \text{row vectors of } A \} \subseteq F^{m \times 1}$ (subspace of possible row vectors)

Rem:

Let $A \in F^{m \times n}$. The transpose matrix $A^T \in F^{n \times m}$ where
 $(A^T)_{ij} = A_{ji}$ (switch rows & cols)

In this case $\text{row}(A) = \text{col}(A^T)$ & $\text{col}(A) = \text{row}(A^T)$

Def: Rank

The rank of $A \in F^{m \times n}$ is $\text{rank}(A) = \dim(\text{row}(A))$, that is the dimension of the row space.

Rem:

Since $\text{row}(A) \subseteq F^{m \times 1}$, $\text{rank}(A) \leq m$.

You can actually replace row & col
& it is equivalent, meaning $\text{rank}(A) \leq \min(m, n)$

Notes:

For $A \in F^{n \times n}$, A is invertible iff $\text{rank}(A) = n$, (proof later)

Thm:

i) Iff $A, B \in F^{m \times n}$ are row equivalent, then $\text{row}(A) = \text{row}(B)$.

ii) If R is a row-reduced matrix, then its non-zero rows form a basis for $\text{row}(R)$.

PF:

i) Let $A \in F^{m \times n}$. $A \xrightarrow{e} A_r = e(A)$ where e is elem. operations. All rows of A_r are l.c.s of A . Thus, the rows are in $\text{row}(A)$, so $\text{row}(A_r) \subseteq \text{row}(A)$. We do the same in the reverse direction (elem. ops. are invertible) to show $\text{row}(A) \subseteq \text{row}(A_r)$.

Thus $\text{row}(A) = \text{row}(A_r)$. We can apply this transitively to get the theorem.

ii) Let r_1, \dots, r_k be the non-zero rows of R .
 $\text{row}(R) = \text{span} \{ r_1, \dots, r_k \}$ by def.
We want to show ii.

$$\forall f_i = (0, 0, \dots, 1, *, *, \dots, *)$$

{ Basically, eliminate the redundant vectors }

$$R = \begin{bmatrix} & 0 \\ 0 & 1 & \dots & * \\ & 0 \end{bmatrix} + f_i$$

b-th column

$$\sum_{j=1}^k c_j f_j = (*, 0, 0, \underset{\text{k-th column}}{c_i}, *, 0, 0, *)$$

b/c it is c_i times 1 in the k-th column

This sum is only zero if all c_i are zero. Thus there are no non-trivial solutions & R is l.i.

Example:
Let

$$\begin{aligned}v_1 &= (1, 1, 1, 1) && \leftarrow \text{could write vertically} \\v_2 &= (2, 3, -1, -1) \\v_3 &= (3, 2, 1, 1) \\v_4 &= (3, 6, -1, -1)\end{aligned}$$

be vectors in \mathbb{R}^4 .

We form a basis for $V = \text{span}\{v_1, v_2, v_3, v_4\}$ by defining a matrix

$$A = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{bmatrix}$$

might be proper subset

Note here $\text{row}(A) = \text{span}\{v_1, v_2, v_3, v_4\} = V \subseteq \mathbb{R}^4$

To find a basis for V , we row-reduce A .

$$\begin{aligned}A &= \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 3 & -1 & -1 \\ 3 & 2 & 1 & 1 \\ 3 & 6 & -1 & -1 \end{bmatrix} \xrightarrow{R_2 - 2R_1} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 3 & 2 & 1 & 1 \\ 3 & 6 & -1 & -1 \end{bmatrix} \xrightarrow{R_3 - 3R_1} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 0 & -1 & -2 & -2 \\ 3 & 6 & -1 & -1 \end{bmatrix} \xrightarrow{R_3 + R_2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & -1 & -1 \\ 3 & 6 & -1 & -1 \end{bmatrix} \xrightarrow{R_4 - 3R_1} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & -1 & -1 \\ 0 & 3 & -4 & -4 \end{bmatrix} \xrightarrow{R_4 - 3R_2} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & -1 & -1 \\ 0 & 0 & 5 & 5 \end{bmatrix} \xrightarrow{R_3 \div (-1)} \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 5 & 5 \end{bmatrix} \xrightarrow{R_1 - 4R_3} \begin{bmatrix} 1 & 0 & 4 & 4 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 5 & 5 \end{bmatrix} \xrightarrow{R_4 - 5R_3} \begin{bmatrix} 1 & 0 & 4 & 4 \\ 0 & 1 & -3 & -3 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \\&\quad \xrightarrow{x_1, x_2, x_3, x_4}\end{aligned}$$

By the theorem, a basis for V is

$$w_1 = (1, 0, 0, 0)$$

$w_2 = (0, 1, 0, 0)$ non-zero entries of the row-reduced matrix

$$w_3 = (0, 0, 1, 1)$$

By def, $\{w_1, w_2, w_3\}$ spans V & trivially they are l.i.

We can use $\{w_1, w_2, w_3\}$ to rewrite V as

$$V = \{(x_1, x_2, x_3, x_4) \mid x_3 = x_4 = 0\}$$

Linear Transformations

Linear transformations are functions/maps that preserve linearity. That is they preserve the properties of linear combinations in a sense.

Def:

Let V & W be vector spaces over F .

A linear transformation/map from V to W is a function $T: V \rightarrow W$ s.t.

$$T: V \rightarrow W \text{ s.t.}$$

$$T(v_1 + v_2) = T(v_1) + T(v_2) \quad \forall v_1, v_2 \in V$$

$$T(cv) = cT(v) \quad \forall v \in V, c \in F$$

When $V=W$, we say T is a linear operator.

Equivalently, image of a linear combination is the linear combination of images

$$T(\sum c_i v_i) = \sum c_i T(v_i)$$

(We use b/c linear transformations are homomorphisms of vector spaces)

Notation:

$L(V, W) = \text{Hom}(V, W) = \text{Hom}_F(V, W)$ is the set of linear transformations from V to W over field F .

$L(V, V) = \text{End}(V) = \text{End}_F(V)$ is the set of all linear maps from V to V over field F , or equivalently an endomorphism on V .

These are both actually vector spaces themselves.

Examples: Linear Maps

i) $\frac{d}{dx}$ (derivative) is a linear map \leftarrow & actually a linear operator

$$(f+g)' = f' + g' \quad \& \quad (cf)' = cf' \quad c \in F \quad f, g \in C^\infty(F)$$

continuous functions on field F

or $f, g \in F[x]$ or $f, g \in F[x]$ \downarrow polynomials

ii) ODE $a_n(x)\left(\frac{d}{dx}\right)^n f + a_{n-1}(x)\left(\frac{d}{dx}\right)^{n-1} f + \dots + a_1(x)\frac{d}{dx} f + a_0(x)f = T(f) = 0$

where T is a linear operator is a linear map. (extension of i))

iii) Definite integrals are linear maps. \leftarrow Indefinite integrals aren't b/c they aren't functions b/c of $+C$

$$(T(f))(x) = \int_0^x f(y) dy$$

iv) Let $A \in F^{m \times n}$, $X \in F^n$. $\leftarrow T: F^n \rightarrow F^m$ $T(X) = AX$ is a linear map

$$T(X+Y) = A(X+Y) = AX + AY \quad \& \quad T(cx) = A(cx) = c(AX) \quad \forall X, Y \in F^n, c \in F$$

We will later show F^n is the canonical form of any v.s. V where $n = \dim(V)$. Likewise $F^{m \times n}$ is the canonical form of any linear transformation $T \in L(V, W)$ where $n = \dim(V)$ & $m = \dim(W)$. We do this by defining a bijection b/w them that is actually itself a linear map.

Thm:

Let $V \times W$ be vector spaces & B be a basis for V .

For any map $f: B \rightarrow W$, there is a unique linear map $T: V \rightarrow W$ that is an extension of f (i.e. $T|_B = f$). In other words, every linear transformation is uniquely determined by its action on the basis.

Pf:

Let $v \in V$. Since B is a basis,

$$\exists! v = \sum x_i v_i \quad x_i \in F, v_i \in B.$$

We define the linear map extension as T (that is $T|_B = f$)

$$T(v) = T\left(\sum x_i v_i\right) = \sum x_i T(v_i) = \sum x_i f(v_i)$$

We have thus shown T exists & is unique.

In order to apply T , we break the vector into coordinates/a l.c. of the basis, apply T (or f) to the basis, & then do the l.c.

Rem: T is $\sum c_i v_i \mapsto \sum c_i f(v_i)$

Let $v, w \in V$ where $B = \{b_1, \dots, b_n\}$ is an ordered basis for V . Then

$$[v+w]_B = [v]_B + [w]_B \quad \& \quad [cv]_B = c[v]_B$$

This means the map $V \rightarrow F^n$, $v \mapsto [v]_B$ is a linear map.

In fact, it is a bijection.

Since $v \mapsto [v]_B$ is a bijective linear map, it is an isomorphism.

Def: Isomorphism

An isomorphism (of vector spaces) is (that is V & F^n are "equivalent") a bijective linear map. That means in that we can rename them to we can freely switch b/w the two spaces.

We write $V \cong W$ iff \exists isomorphism $V \rightarrow W$.

Rem:

i) \cong (\exists isomorphism) is an equivalence relation

ii) $V \cong W \Leftrightarrow \dim(V) = \dim(W)$ ← yes! both ways

This is b/c (as shown above) $V \cong F^n$, $n = \dim(V)$.

How do we identify an isomorphism? It needs to be a linear map, surjective, & injective.

Def: Image of Map

Let $T: V \rightarrow W$ be a linear map. The image of T is $\text{Im}(T) = T(V) = \{T(v) : v \in V\} \subseteq W$. or range

$$\text{Im}(T) = T(V) = \{T(v) : v \in V\} \subseteq W.$$

also called range

T is surjective iff $T(v) = w$.

Rem:

$\forall T \in \text{Hom}(V, W)$, we have $T(0) = 0$. If this wasn't the case, T wouldn't be a linear map.

Thm:

Let $T \in \text{Hom}(V, W)$. T is injective iff $T(v) = 0$ only when $v = 0$.

Pf:

Let $v_1, v_2 \in V$ where $v_1 \neq v_2$. (so $v_1 - v_2 \neq 0$).

$$T(v_1) = T(v_2) \Leftrightarrow T(v_1) - T(v_2) = 0 \Leftrightarrow T(v_1 - v_2) = 0$$

Thus $T(v') = 0$ where $v' \neq 0$ implies T is injective & vice versa.

Def:

The kernel (or null space) of $T: V \rightarrow W$ is

$$\text{Ker}(T) = \text{Null}(T) = \{v \in V : T(v) = 0\} \subseteq V,$$

Prop:

$\forall T \in \text{Hom}(V, W)$, we have

i) $\text{Ker}(T) \subseteq V$ (subspace)

ii) $\text{Im}(T) \subseteq W$ (subspace)

iii) T is injective iff $\text{Ker}(T) = \{0\}$. \leftarrow from above proof

iv) T is surjective iff $\text{Im}(T) = W$. \leftarrow def of surjective

We can thus measure how close a linear map is to being injective ($\dim(\text{Ker}(T))=0$) & how close to being surjective ($\dim(\text{Im}(T))=\dim(W)$).

Def:

Let $T: V \rightarrow W$ be a linear map.

The nullity of T is $\text{nullity}(T) = \dim(\text{Ker}(T))$

The rank of T is $\text{rank}(T) = \dim(\text{Im}(T))$

(Note A_{ei} is i -th column of A)

Example:

Let $A \in F^{m \times n}$. We define a linear map $T_A: F^n \rightarrow F^m$ as $T_A(x) = Ax$. Then

$$\text{Ker}(A) = \{x \in F^n : Ax = 0\} = \text{null space of } A$$

$$\text{Im}(A) = \{Ax : x \in F^n\} = \text{column space of } A$$

Thm: Rank-Nullity Theorem

Let $V \neq W$ be v.s. where $\dim(V) < \infty$.

Let $T \in \text{Hom}(V, W)$.

Then

$$\begin{array}{c} \text{rank}(T) + \text{nullity}(T) = \dim(V) \\ \uparrow \quad \uparrow \\ \dim(\text{Im}(T)) \quad \dim(\text{Ker}(T)) \end{array}$$

PF:

We know $\text{Ker}(T) \subseteq V$ subspace.

Since $\dim(V) < \infty$, we know $\dim(\text{Ker}(T)) = \text{nullity}(T) < \infty$.

Pick a basis $\{v_1, \dots, v_n\}$ be a basis for $\text{Ker}(T)$
 & extend it to be a basis for V $\{v_1, \dots, v_k, \dots, v_n\}$.
 Since $\text{Ker}(T) \subseteq V$, $k \leq n$.

$$\begin{aligned} \forall v \in V \exists! v = \sum_{i=1}^n x_i v_i \quad (x_i \in F) \\ T(v) = T\left(\sum_{i=1}^n x_i v_i\right) = \sum_{i=1}^n x_i T(v_i) \end{aligned}$$

We split this sum to be using v_1, \dots, v_k & v_{k+1}, \dots, v_n .

$$T(v) = \sum_{i=1}^k x_i T(v_i) + \sum_{i=k+1}^n x_i T(v_i) = 0 + \sum_{i=k+1}^n x_i T(v_i) \quad v_1, \dots, v_n \text{ basis for } \text{ker}(T)$$

$$\text{Thus } \text{Im}(T) = \{T(v) \mid v \in V\} = \text{span}\{T_{k+1}, \dots, T_n\}.$$

We show $\{T_{k+1}, \dots, T_n\}$ is l.i., meaning it's a basis for $\text{Im}(T)$.

$$\text{Suppose } \sum_{i=k+1}^n x_i T(v_i) = 0 = T\left(\sum_{i=k+1}^n x_i v_i\right) \text{ for some } x_i,$$

$$\Rightarrow \sum_{i=k+1}^n x_i v_i \in \text{Ker}(T)$$

This would mean v_1, \dots, v_k, v_n would be linearly dependent, which violates the assumption that they are a basis.

This implies $\{T(v_{k+1}), \dots, T(v_n)\}$ is a basis for $\text{Im}(T)$, meaning

All this means

$$\dim(\text{Ker}(T)) = \text{nullity}(T) = k$$

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

$$\dim(V) = n$$

This is the equality we want. \square

Def: $\forall A \in F^{m \times n}$, $\text{rowrank}(A) = \text{column rank}(A)$.

Let $T_A: F^n \rightarrow F^m$, $T_A(X) = AX$ be a linear map.

$\text{nullity}(A) = \text{nullity}(T_A)$ & $\text{columnrank}(A) = \text{rank}(T_A)$ is known from earlier work.
 $n = \text{nullity}(T_A) + \text{rank}(T_A)$ by the rank-nullity theorem.

On the other hand, $\text{nullity}(A)$ & $\text{rowrank}(A)$ aren't changed by elementary row operations.

We can apply a series of row operations to row-reduce A . We can see

$$A = \begin{bmatrix} 1 & 0 & 0 & * & * \\ 0 & 1 & 0 & * & * \\ 0 & 0 & 1 & * & * \end{bmatrix} \underbrace{\quad}_{n} \left\{ m \right\}$$

$$\text{nullity}(A) = \# \text{ free variables} = n - \# \text{ pivots}$$

$$\text{rowrank}(A) = \# \text{ non-zero rows} = \# \text{ pivots} = \text{columnrank}(T)$$

We have thus shown row rank & column rank are equivalent. We call it simply rank.

Linear Transformations \simeq Matrices

If we have $A \in F^{m \times n}$, we can define $T_A: F^n \rightarrow F^m$ $T_A(X) = AX$ easily. What about the reverse direction?

(Given a linear map $T: F^n \rightarrow F^m$, we find $A \in F^{m \times n}$ such that $T(X) = AX$.)

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \sum_{i=1}^n x_i e_i \in F^n$$

standard basis vectors

(This process can be applied to any basis, not just the standard basis.)

$$T(X) = T\left(\sum_{i=1}^n x_i e_i\right) = \sum_{i=1}^n x_i T(e_i) = \sum_{i=1}^n A_i x_i = AX$$

where $A = [A_1 \dots A_n] \in F^{m \times n}$ & $A_i = T(e_i)$. That is, create a matrix where the columns are the results of T applied to the basis vectors.

We have thus shown any linear transformation can be made into a matrix & vice versa.

Algebra of Linear Maps

Here we will show the set of linear maps is a vector space, making them nice, consistent & meta.

Def:

Let V, W be vector spaces.

Let $T, U \in \text{Hom}(V, W)$ = set of linear maps $T: V \rightarrow W$ & $c \in F$.

$$(T+U)(v) = T(v) + U(v)$$

$$(cT)(v) = cT(v)$$

We won't show it now but here vector addition & scalar multiplication follow the vector space axioms so $\text{Hom}(V, W)$ is a vector space.

Thm:

Let V, W, Z be vector spaces.

Let $T \in \text{Hom}(V, W)$ & $S \in \text{Hom}(W, Z)$.

The composition $S \circ T = ST : V \rightarrow Z$ is a linear map (i.e., $ST \in \text{Hom}(V, Z)$)

PF:

Let $u, v \in V$ & $c \in F$.

$$\begin{aligned} (ST)(u+v) &= S(T(u+v)) \\ &= S(T(u)+T(v)) \\ &= S(T(u))+S(T(v)) \\ &= (ST)(u)+(ST)(v) \end{aligned}$$

$$\begin{aligned} (ST)(cv) &= S(T(cv)) \\ &= S(cT(v)) \\ &= cS(T(v)) \\ &= c(ST)(v) \quad \square \end{aligned}$$

Def:

The identity operator $I : V \rightarrow V$ on vector space V

$$I(v) = v \quad \forall v \in V$$

$I \in \text{Hom}(V, V) = \text{Endo}(V)$ trivially. (not proved here)

Prop:

i) $I \circ T = T$ & $T \circ I = T$

ii) $S(T_1 + T_2) = ST_1 + ST_2$ & $(S + S_2)T = S_1T + S_2T$

iii) $c(ST) = (cS)T = S(cT), \forall c \in F$

iv) $T_1(T_2T_3) = (T_1T_2)T_3$

All these properties combined means that $\text{Endo}(V)$ is an associative algebra over field F . (this idea isn't important here)

Recall: A function $T: V \rightarrow W$ is invertible iff $\exists S = T^{-1}: W \rightarrow V$ such that $ST = I_V$ & $TS = I_W$ (or $ST = TS = I$ as abuse of notation or generic composition)

We already know T is invertible iff T is bijective.

Thm: If $T \in \text{Hom}(V, W)$ & T is invertible, then $T^{-1} \in \text{Hom}(W, V)$ \leftarrow T^{-1} linear transformation

Def: An isomorphism $T: V \rightarrow W$ is an invertible/bijective linear map.

Prop:

- i) The inverse of an isomorphism is an isomorphism. (symmetric)
- ii) The composition of an isomorphism is an isomorphism (transitive)
- iii) All vector spaces are isomorphic to themselves by the identity (reflexive)

Def: We say V isomorphic to W iff $\exists T: V \rightarrow W$ s.t. T is an isomorphism.

By the above properties, we can see this defines an equivalence relation.

Thus, if V is isomorphic to W , we write

$$V \cong W.$$

Def: Let $T \in \text{Hom}(V, W)$.

We say T is non-singular iff $\text{Ker}(T) = \text{Null}(T) = \{0\}$, that is its kernel is trivial.

T non-singular
 $\Leftrightarrow T$ injective
 $\Leftrightarrow \text{nullity}(T) = 0$

Prop:

i) T injective
 $\Leftrightarrow \text{Ker}(T) = \{0\}$
 $\Leftrightarrow T$ is non-singular
 $\Leftrightarrow \text{nullity}(T) = 0$.

ii) T surjective
 $\Leftrightarrow \text{Img}(T) = W$
 $\Leftrightarrow \text{rank}(T) = \dim(W)$

Recall:

By the rank-nullity theorem, $\text{nullity}(T) + \text{rank}(T) = \dim(V)$

Thm:

Let $T \in \text{Hom}(V, W)$ where $\dim(V) = \dim(W) < \infty$.

T isomorphism

$\Leftrightarrow \exists T^{-1}$

$\Leftrightarrow T$ bijective

$\Leftrightarrow T$ injective $\Leftrightarrow T$ non-singular $\Leftrightarrow \text{Nullity}(T) = 0$

$\Leftrightarrow T$ surjective $\Leftrightarrow \text{Img}(T) = W \Leftrightarrow \text{rank}(T) = W$

Thm:

Let $T \in \text{Hom}(V, W)$.

T is non-singular iff T sends any linearly independent subset of V to a linearly independent subset of W .

Pf: \Rightarrow

Assume T is non-singular.

Let $A \subseteq V$ be a linearly-independent subset of V .

Suppose for contradiction that $T(A) = B$ is lin. dep.

This means for some

$$c_1 T(v_1) + \dots + c_k T(v_k) = 0$$

for some non-trivial $c_i \in F$, $v_i \in A$.

$$\Rightarrow T(c_1 v_1 + \dots + c_k v_k) = 0$$

$$\Rightarrow c_1 v_1 + \dots + c_k v_k = 0$$

Since A is linearly independent

$$c_1 = \dots = c_k = 0$$

This contradicts our assumption that c_i is trivial, so

$B = T(A)$ is time ind.

□

Pf: \Leftarrow

Take $v \in V$ $v \neq 0$, thus $\{v\}$ is lin. ind.

This means $\{T(v)\}$ is linearly independent.

This means $T(v) \neq 0$, so

$$\text{Ker}(T) = \text{Null}(T) = 0.$$

Thm:

$T \in \text{Hom}(V, W)$ is an isomorphism iff T sends a basis to a basis.

This is an extension of the above theorem.

Col V: $V \cong W$ iff $\dim(V) = \dim(W)$

Recall: A lin. map $T: V \rightarrow W$, where V has basis B , is uniquely determined by the restriction of T w/ B . $T|_B: B \rightarrow W$ $\xrightarrow{\text{You pick } T|_B: B \rightarrow W \text{ arbitrarily}}$

Linear Transformation & Matrices

This is review & extension of earlier work.

Let $B = \{v_1, \dots, v_n\}$ be an ordered basis for V .

Since B is a basis

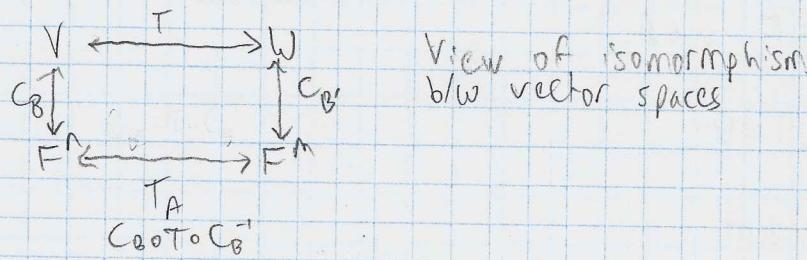
$$\forall v \in V \quad \exists! v = \sum_{j=1}^n x_j v_j$$

We can rewrite this as a coordinate vector

$$[v]_B = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in F^n$$

We earlier showed the map $C_B: V \rightarrow F^n$ s.t.
 $C_B(v) \in [v]_B$
is an isomorphism.

Let $B' = \{w_1, \dots, w_m\}$ be an ordered basis for W .
Let $T \in \text{Hom}(V, W)$.



This means $T_A(X) = AX$ for some matrix $A \in F^{m \times n}$

For $v \in V$,

$$[T(v)]_{B'} = A[v]_B \quad \leftarrow \text{summarizes graph as equality}$$

Summarizing everything,

$$[v]_B = x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \Rightarrow v = \sum_{j=1}^n x_j v_j$$

Then

$$T(v) = T\left(\sum_{j=1}^n x_j v_j\right) = \sum_{j=1}^n x_j T(v_j) \Rightarrow [T(v)]_{B'} = \sum_{j=1}^n x_j \underbrace{[T(v_j)]_{B'}}_{A_j \in F^m} = [A_1 \dots A_n] \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = AX$$

where $A \in F^{m \times n}$ where $A_j = [T(v_j)]_{B'}$

Def:

use all the above items,
 A is the matrix of T relative to basis B, B' .

We

$$\boxed{A = [T]_{B'}^{B'}}$$

(map B to B')sometimes we elide B & B'
if they're understoodThm:Let $T \in \text{Hom}(V, W)$, $\forall v \in V$

$$\boxed{[T(v)]_{B'} = [T]_{B'}^{B'}[v]_B}$$

where the j -th column of $[T]_{B'}^{B'}$ is $[T(v_j)]_B$ where $B = \{v_1, \dots, v_n\}$.Thm:If we fix basis B for V & B' for W ,
then the map

$$\begin{aligned} \text{Hom}(V, W) &\rightarrow F^{m \times n} = F^n \rightarrow F^m \\ T &\mapsto [T]_{B'}^{B'} \end{aligned}$$

is a vector space isomorphism.

That is we can transform
lin. transforms to other
lin. transforms.Coro:

$$\dim(\text{Hom}(V, W)) = \dim(V) \dim(W) = mn$$

The basis for $\text{Hom}(V, W)$ is $\{E_{ij}\}$ where $1 \leq i \leq m$ & $1 \leq j \leq n$.

$$E_{ij}(v_j) = w_i$$

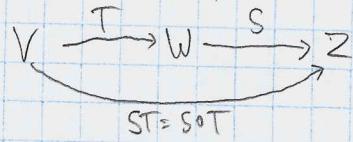
where

 $B = \{v_1, \dots, v_n\}$ basis for V & $B' = \{w_1, \dots, w_m\}$ basis for W .Let us define vector addition, scalar multiplication, & composition
of linear maps in terms of how they relate linear maps & matricesThm: Vector Addition & Scalar Multiplication are sameLet $T, S \in \text{Hom}(V, W)$ & $c \in F$. B basis V & B' basis W .

$$T + S = T(v) + S(v) \iff [T]_{B'}^{B'} + [S]_{B'}^{B'}$$

$$cT = cT(v) \iff c[T]_{B'}^{B'}$$

composition is matrix multiplication
Let $T \in \text{Hom}(V, W)$, $S \in \text{Hom}(W, Z)$.



where $ST \in \text{Hom}(V, Z)$.

Choose ordered basis B, B', B'' for V, W, Z resp.

Then

note we elide basis decorations

$$[ST] = [S][T]$$

PF:

$\forall v \in V$ we have

$$\begin{aligned} [ST][v] &= [(ST)(v)] \\ &= [S(T(v))] \\ &= [S][T(v)] \\ &= [S][T][v] \end{aligned}$$

Thus $[ST] = [S][T]$.

Recall:

the identity operator $I \in \text{End}(V) = \text{Hom}(V, V)$.

Then

$$[I]_B^B = \text{identity matrix} = I = \begin{bmatrix} 1 & 0 & \dots \\ 0 & 1 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

for all basis B for V . \leftarrow must be same basis for this to hold.

Now consider two ordered basis B, B' for V .

$$[v]_{B'} = [I]_{B'}^{B'} [v]_B \quad \forall v \in V$$

Here $P = [I]_B^B$ is the transition matrix from B to B' .
We know P is invertible & $P^{-1} = [I]_{B'}^{B}$.

$[v]_{B'}$ & $[v]_B$ are non-zero for non-zero v .

Example:

$V = F[x]_{\deg \leq 2}$ has standard basis $B = \{1, x, x^2\}$.

Consider $B' = \{x+1, x^2+1, x^2+x\}$.

We find the transition matrix $A = [I]_{B'}^B$,

$$[v]_B = [I]_B^B [v]_B = P [v]_{B'}$$

We now do this for v_1, v_2, v_3

In general v_j basis vector in B'

$$[v_j]_B = P[v_j]_{B'} = Pe_j = j\text{-th column in } P$$

Here $[v_j]_B$ is the coordinates of v_j in standard basis, which is easy to find.

$$[v_1]_B = [x+1]_B = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$[v_2]_B = [x^2+1]_B = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

$$[v_3]_B = [x^2+x]_B = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

This means P is matrix w/ above 3 columns

$$P = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 1 \end{bmatrix}$$

Cool! So $P = [I]_{B'}^B$ is trivial to find.

To find the opposite transition, we do

$$[I]_{B'}^B = P^{-1}$$

which is easy (enough) since P is trivial.

Consider vector space V w/ basis B .

For all linear operators $T \in \text{End}(V) \Leftrightarrow F^{n \times n}$ ($n \times n$ matrices)

$$[T]_B^B = [T]_B = \text{matrix of } T \text{ relative to } B$$

$$[T(v)]_B = [T]_B [v]_B \quad \forall v \in V$$

Now consider basis B'

$$[T(v)]_{B'} = [T]_{B'} [v]_{B'} \quad \forall v \in V$$

Let $P = [t]_{B'}^B$ be the transition matrix from B to B'

$$[v]_{B'} = P[v]_B \quad \forall v \in V$$

We can relate $[T]_B$ & $[T]_{B'}$ using P . (See next page)

using P we get

$$[T(v)]_B = P[T(v)]_{B'} = P[T]_{B'} [v]_{B'} = [T]_{B'} [v_B] = [T]_{B'} P[v]_B$$

Cancelling $[v]_B$ we get

$$P[T]_{B'} = [T]_{B'} P$$

Thm:

Let $T \in \text{End}(V)$ where V has basis B & B' .

$$\text{Let } P = [I]_{B'}^B$$

$$\boxed{[T]_B = P^{-1}[T]_{B'} P}$$

We say $[T]_B$ & $[T]_{B'}$ are conjugate or similar matrices.

Defn:

Two $n \times n$ matrices A & B are similar iff \exists invertible matrix P s.t.

$$\boxed{B = P^{-1}AP} \quad \text{Symmetric relation should be obvious}$$

This relation is

i) symmetric $B = P^{-1}AP \Rightarrow A = PBP^{-1} = P^{-1}BP$

ii) reflexive $A = I^{-1}AI$

iii) transitive $B = P^{-1}AP \quad C = Q^{-1}BQ \Rightarrow C = Q^{-1}P^{-1}APQ = (PQ)^{-1}A(PQ)$

Therefore similarity is an equivalence relation.

Example:

$$V = F[x]_{deg \leq 2}, \quad B = \{e_1, e_2, e_3\}, \quad B' = \{v_1, v_2, v_3\}$$

$$\text{Let } D \in \text{End}(V) \text{ where } D(v) = \frac{d}{dx} v$$

We apply D to B

$$D(e_1) = D(1) = 0, \quad D(e_2) = D(x) = 1, \quad D(e_3) = 2x$$

$$[D]_B = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

We apply D to B'

$$D(v_1) = D(1+x) = 1 \quad D(v_2) = D(1+x^2) = 2x, \quad D(v_3) = D(x+x^2) = 1+2x$$
$$= 1/2(v_1 + v_2 - v_3) \quad = v_1 - v_2 + v_3 \quad = 3/2v_1 - 1/2v_2 + 1/2v_3$$

$$[D]_{B'} = \begin{bmatrix} 1/2 & 1/2 & 3/2 \\ 1/2 & -1 & -1/2 \\ -1/2 & 1 & 1/2 \end{bmatrix}$$

Linear Functionals

It's a function on functions, so functional!

Def:

A Linear functional on V is a linear map $V \rightarrow F$.

where V is a vector space over field F .

The space $\text{Hom}(V, F) = V^*$ is called the dual space of V .

Examples:

i) Let $V = C([a, b])$ = space of continuous functions $f: [a, b] \rightarrow \mathbb{R}$.

$$\text{Let } L(f) = \int_a^b f(x) dx \quad \forall f \in V.$$

L is a linear functional on V , that is $L \in V^*$.

ii) Let $V = F^{n \times n}$.

The trace, the sum of the diagonal,

$$\text{tr}(A) = \sum_{i=1}^n a_{ii} \quad \text{where } A = [a_{ij}] \quad \forall A \in V.$$

is a linear functional.

iii) Let $V = F^n$ w/ the standard basis $\{e_1, \dots, e_n\}$. That is

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = \sum_{i=1}^n x_i e_i.$$

Like all linear maps

Key: All linear functionals isomorphic to F^n

Any $f \in V^* \cong \text{Hom}(V, F)$ is uniquely determined by
 $a_i = f(e_i) \in F$ where a_1, \dots, a_n arbitrary.

To find $f(x)$, we find the linearity of f .

$$f(x) = f\left(\sum_{i=1}^n x_i e_i\right) = \sum_{i=1}^n x_i f(e_i) = \sum_{i=1}^n x_i a_i = Ax$$

Then $f \mapsto A = [a_1, \dots, a_n] \in F^{n \times n}$ is an isomorphism.

Let $B = \{v_1, \dots, v_n\}$ be a basis for V .

Any linear functional $f \in V^*$ is uniquely determined by its action on B
 $a_i = f(v_i) \in F \quad \forall v_i \in B$ & a_1, \dots, a_n can be arbitrary

B/c B is a basis

$$v = \sum_{i=1}^n x_i v_i \quad \forall v \in V$$

$$\Rightarrow f(v) = f\left(\sum_{i=1}^n x_i v_i\right) = \sum_{i=1}^n x_i f(v_i) = \sum_{i=1}^n x_i a_i$$

This generalizes to any finite dimensional space

$v_i \in V$ be such that

$f_i(v) = x_i \leftarrow$ take i -th coordinate

$$\Leftrightarrow f_i(v_j) = \delta_{ij} = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{else} \end{cases}$$

Kronecker delta. It's named bc it's super common

These f_1, \dots, f_n actually give a basis for V^* called the dual basis as

$$f(v) = \sum x_i f_i(v) = \sum x_i a_i = \sum f_i(v) a_i$$

$$\text{Thus } f = \sum a_i f_i$$

Thm:

Let $S = \{v_1, \dots, v_n\} \subseteq V$ be a subset of V .

Let $S^* = \{f_1, \dots, f_n\} \subseteq V^*$ be a subset of V^* s.t.

$$f_i(v_j) = \delta_{ij} = \begin{cases} 1 & \text{if } i=j \\ 0 & \text{else} \end{cases}$$

The sets S & S^* are linearly independent.

PF:

$$\text{Suppose. } v = \sum_{j=1}^n x_j v_j \in \text{Span}(S).$$

$$f(v) = \sum_{j=1}^n x_j f_i(v_j) = x_i$$

$x_i = f_i(v) = 0 \iff v = 0$. Thus S is lin. independent.

Similarly, suppose $f = \sum_{j=1}^n c_j f_i \in \text{Span}(S^*)$.

$$f(v_j) = \sum_{i=1}^n c_i f_i(v_j) = c_j$$

$c_j = f(v_j) = 0 \iff f = 0$. Thus S^* is lin. independent.

Thm:

Let V be a vector space $\dim(V) = n < \infty$.

Let $B = \{v_1, \dots, v_n\} \subseteq V$ & $B^* = \{f_1, \dots, f_n\} \subseteq V^*$ s.t.

$$f_i(v_j) = \delta_{ij}.$$

Then

i) B is a basis for V

ii) B^* is a basis for V^* (dual basis of V)

iii) $v = \sum_{j=1}^n x_j v_j = \sum_{j=1}^n f_j(v) v_j \quad \forall v \in V \leftarrow \text{Find } v \text{ from evaluating } B^* \text{ on } v$

iv) $f = \sum_{i=1}^n c_i f_i = \sum_{i=1}^n f(v_i) f_i \quad \forall f \in V^* \leftarrow \text{Find } f \text{ from evaluating } f \text{ on } B$

These fall as an extension of the earlier theorem.

Pf:

i) By the earlier theorem B is linearly independent. Since $|B| = \dim(V) = n$
 B is a basis.

ii) By the earlier theorem B^* is linearly independent. Since $|B^*| = \dim(V^*) = n$
 B^* is a basis.
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Alternatively, every $f \in V^*$ is uniquely determined by $f(v_1), \dots, f(v_n)$
& use iv to see $f \in \text{span}(B^*) = \langle B^* \rangle$

iii) & iv) Done in the earlier theorem.

Example:

$$V = F[x]_{\deg \leq n-1} \quad \text{so } \dim(V) = n$$

w/ standard basis

$$B = \{1, x, \dots, x^{n-1}\}$$

We find $B^* = \{f_0, f_1, \dots, f_{n-1}\}$ dual basis.

By definition -
 $f_i(v_j) = \delta_{ij}$

evaluation is linear map

$$f_0(a_0 + a_1x + \dots + a_{n-1}x^{n-1}) = a_0 \Leftrightarrow f_0(p(x)) = p(0) \quad \forall p(x) \in V$$

$$f_1(a_0 + a_1x + \dots + a_{n-1}x^{n-1}) = a_1 \Leftrightarrow f_1(p(x)) = \frac{d}{dx} p(0) = p'(0) \quad \forall p(x) \in V$$

cancel out power rule exponents

$$f_i(p(x)) = \frac{1}{i!} \left(\frac{d}{dx} \right)^i p(0) = \frac{1}{i!} p^{(i)}(0) \quad \forall p(x) \in V \quad \text{is the general rule.}$$

$$\text{Thus } B^* = \left\{ f_i : i \in \{0, \dots, n-1\}, \right. \\ \left. f_i(p(x)) = \frac{1}{i!} p^{(i)}(0) \right\}$$

Thus $\forall p(x) \in V$

$$p(x) = \sum_{i=0}^{n-1} f_i(p(x)) x^i = \sum_{i=0}^{n-1} \frac{1}{i!} p^{(i)}(0) x^i \quad \text{by Taylor Formula}$$

You can expand this to all polynomials $F[x]$ to get Taylor Series!

Example:

We can do the same as above but for

$$B = \{1, x-b, \dots, (x-b)^{n-1}\}$$

where $b \in F$ fixed.

This gives us

$$B^* = \{f_i : i \in \{0, \dots, n-1\}, f_i(p(x)) = \sum_{i=0}^{n-1} p^{(i)}(t) x^i\}$$

Then $\forall p \in F$

$$p(x) = \sum_{i=0}^{n-1} \frac{1}{i!} p^{(i)}(t) x^i$$

(Here we get into duality & dual basis. More on that later.)

We call this the evaluation of p at t .

Example:

Now fix $t_1, \dots, t_n \in F$, $t_i \neq t_j$ Viz & consider $L_i(p(x)) = p(t_i)$.

$$B^* = \{L_1, \dots, L_n\} \subseteq V^*$$

$V = F[x]_{\text{deg} \leq n}$ (same as above)

We want to find $B = \{p_1, \dots, p_n\} \subseteq V$ s.t.

$$L_i(p_j) = p_j(t_i) = \delta_{ij}.$$

We define p_j as

$$p_j(x) = \prod_{\substack{1 \leq k \leq n \\ k \neq j}} \frac{x - t_k}{t_j - t_k}$$

The fact that these are polynomials & not any function is unimportant.

Here it is easy to see $p_j(t_i) = \begin{cases} 1 & i=j \\ 0 & \text{o/w} \end{cases}$.

Using this B we get

$$p(x) = \sum_{j=1}^n L_j(p) p_j(x) = \sum_{j=1}^n p(t_j) p_j(x) \leftarrow \text{Lagrange Interpolation Formula}$$

This says every polynomial of degree strictly less than n can be uniquely determined by evaluating it on n unique values.

Thm:

Fix $f \in V^*$. $\text{Img}(f) \subseteq F$ by definition of $V^* = \text{Hom}(V, F)$.

$$\text{rank}(f) = \dim(\text{Img}(f)) = \begin{cases} m & \text{if } f \neq 0 \\ 0 & \text{if } f = 0 \end{cases} \quad \text{b/c } f \text{ is 1D, any vector output being non-zero means whole space covered.}$$

By the rank-nullity theorem

$$\text{nullity}(f) = \dim(\text{Ker}(f)) = \dim(V) - \text{rank}(f) \quad \text{or} \quad \dim(V) = \text{nullity}(f) + \text{rank}(f).$$

If $f=0$, then $\text{Ker}(f)=V$.

If $f \neq 0$, then $\text{Ker}(f) \subset V$ subspace where $\dim(\text{Ker}(f)) = \dim(V) - 1 \Rightarrow \text{codim}(\text{Ker}(f)) = 1$

Def:

Let $W \subseteq V$ be a subspace of V . The codimension of W is $\text{codim}(W) = \dim(V) - \dim(W)$.

Essentially how much the subspace loses.

Def:

A hyperspace of vector space V, W (subspace W) where V is $\text{codim}(W)=1$.

This is the maximal proper subspace.
Essentially V with the subspace W .

Thm:

i) $\forall f \in V^*$, $f \neq 0$ $\text{Ker}(f) = N_f$ is a hyperspace.

ii) $\forall W \subseteq V$ where $\text{codim}(W) \neq 1$ (W hyperspace) $\exists f \in V^*$ s.t. $W = \text{Ker}(f)$

Pf:

i) We proved this in an earlier "theorem".

ii) Pick a basis $\{v_1, \dots, v_{n-1}\}$ for W & extend it to a basis for $V \setminus \{v_1, \dots, v_n\}$.

Define $f \in V^*$ by $f(v_i) = 0$ $1 \leq i \leq n-1$, $f(v_n) = 1$. \leftarrow actually f_n of dual basis!

Here f is an $f \in V^*$ s.t. $\text{Ker}(f) = W$.

Def:

For subset $S \subseteq V$, its annihilator is $S^\circ = \{f \in V^* \mid f(v) = 0 \ \forall v \in S\}$.

If $S = \{\}$, then $S^\circ = V$

Note that S° is a subspace of V^* .

Closed Under Addition: $f(v) + g(v) = 0 + 0 = 0$

Closed Under Multiplication: $c f(v) = c(0) = 0$

Thm:

Let $W \subseteq V$ be a subspace of V where $\dim(V) < \infty$.

Then $\dim(W^\circ) = \text{codim}(W) = \dim(V) - \dim(W)$

This is b/c $\text{codim}(W) = \dim(\text{Ker}(f)) = \text{nullity}(f)$.

Def:

Pick a basis $\{v_1, \dots, v_n\}$ for W & extend it to basis $B = \{v_1, \dots, v_n\}$ for V .

The dual basis B^* for V^* is $B^* = \{f_1, \dots, f_n\}$.

By the definition of dual basis

$$f_i(v_j) = \delta_{ij}$$

Take $1 \leq j \leq k$ & $k+1 \leq i \leq n$. Then $i \neq j$. Thus $f_i(v_j) = 0$.

Then $f_i \in W^0$.

Recall $\forall f \in V^*$

$$f = \sum_{j=1}^n f(v_j) f_j.$$

Then $f \in W^0 \Leftrightarrow f(v_j) = 0 \quad \forall 1 \leq j \leq k \Leftrightarrow \text{span}\{f_{k+1}, \dots, f_n\} \subseteq$

This gives us

$$W^0 = \text{span}\{f_{k+1}, \dots, f_n\} \quad (\text{As } \{f_{k+1}, \dots, f_n\} \text{ is a basis for } W).$$

Coro: $W = N_{f_{k+1}} \cap \dots \cap N_{f_n}$.

PF:

$$\text{Let } v \in V, v = \sum_{i=1}^n x_i v_i, \text{ then } v \in N_{f_j} \Leftrightarrow x_j = 0 \quad \& \quad x_j = f_j(v).$$

Double Dual

Def:

Let V be a vector space over F .

$V^* = \text{Hom}(V, F)$ is the dual space.

$V^{**} = (V^*)^* = \text{Hom}(V^*, F)$ is the double dual (space).

We want to find symmetry b/w $V \& V^*$ via double duals.

$\forall v \in V$, there is a linear functional $L_v: V^* \rightarrow F$ i.e. $L_v \in (V^*)^* = V^{**}$

$L_v(f) = f(v) \quad \text{for } f \in V^*$. This is called the evaluation of f on v .

Also works for $\dim(V) = \infty$

Lemma:

The map $v \mapsto L_v$ where $v \in V$ & $L_v \in V^{**}$ is a linear map.

PF:

We first assert L_v is closed under addition & multiplication.

$$L_v(f+g) = L_v(f) + L_v(g) \quad \& \quad L_v(cf) = cL_v(f) \quad f, g \in V^* \quad c \in F. \quad \text{you can check yourself}$$

Thus $L_v \in V^{**}$

Further

$$L_{v+w} = L_v + L_w \quad \& \quad L_cv = cL_v \quad v, w \in V, c \in F.$$

Thus $v \mapsto L_v$ is linear.

Suppose $v \in V$ s.t. $L_v = 0$. Then

$$L_v(f) = f(v) = 0 \quad \forall f \in V^*$$

If $v \neq 0$, then \exists basis for V containing v , so then there is a linear functional $f \in V^*$ s.t. $f(v) \neq 0$.

In this case where $L_v = 0$, $v \neq 0$. Thus the map is injective.

\cap f_i are elements in dual basis that vanish at v

In general, $\dim(\text{Hom}(V, W)) = \dim(V) \dim(W)$.

Thus $\dim(V^*) = \dim(\text{Hom}(V, F)) = \dim(V) \dim(F) = \dim(V)$.
 Likewise $\dim(V^{**}) = \dim(V)$.

Thm:

The map $v \in V \rightarrow L_v \in V^{**}$, where V is a finite-dimensional vector space, is a vector space isomorphism $V \rightarrow V^{**}$.

Example:

This theorem breaks down for infinite dimension V 's.

Let $V = F[x]$ w/ basis $\{1, x, x^2, \dots\}$.

Let $f \in V^*$ be defined as

$$a_i = f(x^i) \in F \text{ where } i \in \{0, 1, 2, \dots\}$$

For an arbitrary vector $x \in F[x]$,

$$f(x) = \sum_{i=0}^{\infty} a_i x^i$$

Since polynomials must be finite $f(x) \notin F[x]$ in general.

Instead $f(x)$ can be infinite, so we say

$$f(x) \in F[[x]], \text{ a power series}$$

$$\text{Thus } F[x]^* \cong F[[x]]$$

Notation:

For all linear functionals $f \in V^*$ & vectors $v \in V$, we write the evaluation of f & v as

$$\langle f, v \rangle = f(v) \in F$$

This gives a map from $V^* \times V \rightarrow F$. We call this map bilinear b/c it is linear in both arguments when one is fixed.

This notation is nice b/c it makes the relationship more symmetric seeming, giving intuition for L_v .

$$\langle L_v, f \rangle = \langle f, v \rangle = \langle v, f \rangle$$

if we identify $v \in V$ w/ $L_v \in V^{**}$

Let $B = \{v_1, \dots, v_n\}$ basis for V .

Let $B^* = \{f_1, \dots, f_n\}$ basis for V^* , dual basis for V .

Then the dual basis of V^* (i.e. B^{**} for V^{**}) is
 $B^{**} = \{L_{v_1}, \dots, L_{v_n}\}$ basis for V^{**} , dual basis for V^* .

Rem: The isomorphism $V \rightarrow V^{**}$ is natural, unlike the isomorphism $V \rightarrow V^*$.

By natural we mean

- i) it doesn't depend on a choice of basis
- ii) it behaves well wrt linear maps.

Informally,
The mapping $f: S \rightarrow S^{**}$ transforms
to $f: T \rightarrow T^{**}$ where all properties hold.

In other words, its a functor on the category of vector spaces.

Recall:

The annihilator W^0 of $W \subseteq V$ is
 $W^0 = \{f \in V^* \mid f(w) = 0 \forall w \in W\} \subseteq V^*$ subspace

Thm:

Let $W \subseteq V$ subspace w/ $\dim(V) < \infty$.

isomorphism $b: V \rightarrow V^{**}$

Then $W^{00} = (W^0)^0 \subseteq V^{**}$ corresponds to W under $V^{**} \cong V$.

P.F:

Recall $V^{**} \cong V$ is given by $v \mapsto L_v: V \rightarrow V^{**}$, where $L_v(f) = f(v) \forall f \in V^*$.

Take $v \in W$ & $f \in W^0$. Then $f(v) = 0$ by definition.

By the definition of L_v

$$L_v(f) = f(v) = 0$$

Then $L_v \in W^{00}$.

a subspace of

Therefore W is sent to W^{00} under $V \xrightarrow{\cong} V^{**}$.

We want to show W & W^{00} are equal. We'll go thru two ways one w/ dimension & the other w/ basis.

First, let's use dimension.

$$\dim(W^0) = \text{codim}(W) = \dim(V) - \dim(W)$$

$$\dim(W^{00}) = \dim(V^*) - \dim(W^0) = \dim(V) - (\dim(V) - \dim(W)) = \dim(W)$$

We have $W \subseteq W^{00}$ but $\dim(W) = \dim(W^{00})$, so $W = W^{00}$. \square

Next, let's use basis.

Pick a basis $\{v_1, \dots, v_k\}$ for W .

Extend it to a basis $\{v_1, \dots, v_n\}$ where $k \leq n$ for V .

Take the dual basis $\{f_1, \dots, f_n\}$ for V^* .

This (on next page)
is a full proof.

The basis for W^0 is $\{f_{k+1}, \dots, f_n\}$ b/c

$$f_i(v_j) = \delta_{ij} = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$$

b/c $\forall i, j \in \mathbb{Z}, k+1 \leq j \leq n \quad 1 \leq i \leq k \iff f_i$.

Now we do the same for $W^0 \subseteq V^{**}$.

Start w/ basis $\{f_{k+1}, \dots, f_n\}$ for W^0 .

Extend it to basis $\{f_1, \dots, f_n\}$ for V^* (from earlier).

Take the basis $\{L_{v_1}, \dots, L_{v_n}\}$ for V^{**} (dual basis for V).

By $V^{**} \cong V$, $\{v_1, \dots, v_n\}$ is a basis for V .

Hence a basis for W^{00} is $\{L_{v_1}, \dots, L_{v_n}\}$ by similar logic.

This is the basis for W identified by $V^{**} \cong V$.

Therefore $W^{00} = W$. \square

Matrix Coefficients of a Linear Map

Let $T \in \text{Hom}(V, W)$ where V, W are vector spaces.

In order to represent T by a matrix, we need basis

$B = \{v_1, \dots, v_m\}$ for V & $B' = \{w_1, \dots, w_n\}$ for W .

Then $A = [T]_{B'}^B \in F^{m \times n}$ is the matrix of T relative to B, B' .

The j -th column of $A = [T] = (a_{ij})$ is $[T v_i]$ we ellide parens
ellide $\rightarrow T v_j = \sum_{i=1}^m a_{ij} v_i$ $\forall j \in \{1, \dots, n\}$

Consider the dual basis $(B')^*$ of B' .

$(B')^* = \{g_1, \dots, g_m\}$ basis for W^*

where $g_k(w_i) = \delta_{ki}$

Then

Then

$$a_{ij} = g_i(T v_j) = \langle g_i, T v_j \rangle$$

These are called the matrix coefficients of the linear map T .

Transpose of Linear Transform

Let $T \in \text{Hom}(V, W)$.

Take $g \in W^*$ & $v \in V$.

$T v \in W$, so it makes sense to apply g . That is

$$g(T v) = \underbrace{\langle g, T v \rangle}_{\text{linear in } g}$$

We can view this as a bilinear map $W^* \times V \rightarrow F$. That is it is linear in g & fixed v & linear in v & fixed g .

This gives us a linear functional $S_g: V \rightarrow F$ where

$$S_g v = g(T v) \text{ where } S_g \in V^*$$

This means $\forall g \in W^*$, there is a linear functional $S_g \in V^*$.

depends really on g , so we can think of S (not applied to any g) as $S: W^* \rightarrow V^*$

where

$$Sg = S_g \text{ where } S_g \in$$

$$\text{So, } (Sg)(v) = g(Tv) \Leftrightarrow \langle Sg, v \rangle = \langle g, Tv \rangle$$

where $Sg \in V^*$ & $v \in V$.

I like to think of this as S_g where we have a "slot" for $g \in W^*$ which returns V^* .

We call S the transpose of T

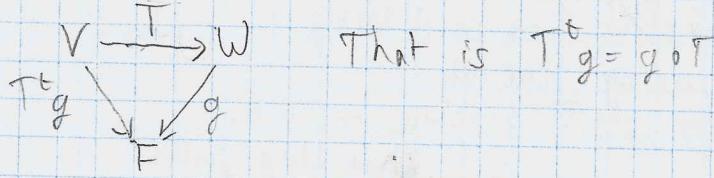
Def:

or adjoint of T

$S = T^t$ is the transpose of $T: V \rightarrow W$ where $S: W^* \rightarrow V^*$ this is called a contravariant function defined by

$$(T^t g)(v) = \underbrace{\underbrace{g(Tv)}_{W^*} \underbrace{v}_{V}}_{V^*}, \Leftrightarrow \langle T^t g, v \rangle = \langle g, Tv \rangle$$

We can visualize this w/ the following diagram



Thm:

Let $T \in \text{Hom}(V, W)$. Then, $T^t \in \text{Hom}(W^*, V^*)$.

$[T^t]$ corresponds to $[T]^t$.

PF:

Let the following be basis

$$B = \{v_1, \dots, v_n\} \text{ for } V,$$

$$B' = \{w_1, \dots, w_m\} \text{ for } W,$$

$$B^* = \{f_1, \dots, f_n\} \text{ for } V^* \text{ dual basis to } B, \text{ where } f_i(v_j) = \delta_{ij}$$

$$B'^* = \{g_1, \dots, g_m\} \text{ for } W^* \text{ dual basis to } B', \text{ where } g_i(w_j) = \delta_{ij}$$

$[T]_B^{B'} \in F^{m \times n}$ matrix T wrt B, B' .

$[T^t]_{B'^*}^{B^*} \in F^{n \times m}$ matrix T^t wrt B'^*, B^* .

We show $[T]_B^{B'}$ & $[T^t]_{B'^*}^{B^*}$ are transpose of each other.

To do this we use our matrix coefficients from earlier.

Last time we found the (i, j) -th entry of $[T]$ is $g_i(Tv_j)$.

By the definition of T^t

$$g_i(Tv_j) = (T^t g_i)(v_j)$$

If we identify $V \cong V^{**}$ we get

$$g_i(Tv_j) = (T^t g_i)(v_j) = \sum_{i,j} (T^t g_i)_j v_j$$

This is the (j, i) -th entry of $[T^t]$.

Thus $[T]_B^{B'} = [T^t]_{B'^*}^{B^*}$.

Prop:

Many of these come directly from the properties of matrix transpose.

$$\text{i)} (ST)^t = T^t S^t \text{ where } T \in \text{Hom}(V, W), S \in \text{Hom}(W, U)$$

$$\text{ii)} (T^t)^t = T \text{ if we identify } V \cong V^{**} \text{ & } W \cong W^{**}$$

Thm:

Let $T \in \text{Hom}(V, W)$. Then $\text{not assuming } \dim(V) < \infty \text{ or } \dim(W) < \infty$

$$\text{i)} \text{Ker}(T^t) = (\underbrace{\text{Img}(T)}_{\subseteq W})^\circ$$

$$\text{ii)} \underbrace{\text{Img}(T^t)}_{V^*} \subseteq (\underbrace{\text{Ker}(T)}_{\subseteq V})^\circ. \text{ This is equal if } \dim(V) < \infty \text{ & } \dim(W) < \infty$$

Pf:

i) We use the definition of T^t
 $(T^t g)_v = g(Tv) \quad g \in W^*, v \in V$

$g \in \text{Ker}(T^t) \iff T^t g = 0 \in V^*$.

$0 \in V^*$ is the functional such that $0(v) = 0 \quad \forall v \in V$. Thus

$$g \in \text{Ker}(T^t) \Leftrightarrow T^t g = 0 \in V^*$$

$$\Leftrightarrow T^t g = 0 \in V^*$$

$$\Leftrightarrow (T^t g)(v) = 0 \quad \forall v \in V$$

$$\Leftrightarrow g(Tv) = 0 \quad \forall v \in V$$

$$\Leftrightarrow g(w) = 0 \quad \forall w \in \text{Img}(T)$$

$$\Leftrightarrow g \in (\text{Img } T)^\circ$$

ii) We try to do something similar, but if we go both directions we fail (if non-finite).

We want to show $\forall f \in \text{Img}(T^t), f \in (\text{Ker}(T))^\circ$.

Take any $f = T^t g \in \text{Img}(T^t)$ for some $g \in W^*$. We show f "vanishes" on the kernel of f . Let $v \in \text{Ker}(T)$

$$f(v) = (T^t g)(v) = g(Tv) = g(0) = 0.$$

Thus $f \in (\text{Ker } T)^\circ$, so $\text{Img}(T^t) \subseteq (\text{Ker}(T))^\circ$.

we now take on the finite dimensional case. To do that we show their dimensions are equal. We do this w/ the rank-nullity theorem,

$$\begin{aligned} \text{rank}(T^t) &= \text{nullity}(T^t) = \dim(\text{Dom}(T^t)) \\ \Rightarrow \text{rank}(T^t) &= \dim(\text{Dom}(T^t)) - \text{nullity}(T^t) \\ \Rightarrow \dim(\text{Img}(T^t)) &= \dim(W) - \dim(\text{Ker}(T^t)) = \dim(W) - \dim(\text{Img}(T)) \\ \therefore \dim(\text{Img}(T^t)) &= \dim(W) - \dim(\text{Img}(T)) \end{aligned}$$

From part (i), $\text{Ker}(T^t) = (\text{Img}(T))^{\circ}$. $\dim((\text{Img}(T))^{\circ}) = \text{codim}(\text{Img}(T)) = \dim(W) - \dim(\text{Img}(T))$

$$\begin{aligned} \dim(\text{Img}(T^t)) &= \dim(W) - \dim((\text{Img}(T))^{\circ}) \\ \Rightarrow \dim(\text{Img}(T^t)) &= \dim(\text{Img}(T)) = \text{rank}(T) \\ &= \text{rank}(T^t) \\ &= \dim(V) - \dim(\text{Ker}(T)) \leftarrow \\ &= \text{codim}(\text{Ker}(T)) \\ &= \dim((\text{Ker}(T))^{\circ}) \end{aligned}$$

Thus $\dim(\text{Img}(T^t)) = \dim((\text{Ker}(T))^{\circ})$ & $\text{Img}(T^t) \subseteq (\text{Ker}(T))^{\circ}$, so

$\text{Img}(T^t) = (\text{Ker}(T))^{\circ}$
when $\dim(V) < \infty$ & $\dim(W) < \infty$.

Coro:

$\forall T \in \text{Hom}(V, W)$ where $\dim(V) < \infty$ & $\dim(W) < \infty$,

$$\underline{\text{rank}(T) = \text{rank}(T^t)}$$

This is the same as $\forall A \in M$

$$\text{rowrank}(A) = \text{colrank}(A)$$

Chapter 5: Determinants

(The previous section was chapters 1-3) | 1

Recall:

$$\text{i)} \det \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc \leftarrow \begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

- ii) $\forall A \in M_n, \det(A) \neq 0 \Leftrightarrow A$ invertible

Def:

The determinant $\det: F^{m \times n} \rightarrow F$ is a function from $m \times n$ matrixes to their field.

We can decompose or view the determinant as

$$D: \underbrace{F^n \times \dots \times F^n}_{m \text{ times}} \rightarrow F. \quad \text{also works for rows}$$

That is a function of the columns of the matrix

Properties:

i) The determinant D is n -linear, that is linear in each column if we keep the other $n-1$ columns fixed.

$$\therefore D(A_1, \dots, B_i + C_i, \dots, A_n) \quad (\text{that is make } A_i = B_i + C_i) \\ = D(A_1, \dots, A_{i-1}, B_i, A_{i+1}, \dots, A_n) \\ + D(A_1, \dots, A_{i-1}, C_i, A_{i+1}, \dots, A_n)$$

same for columns

$$\therefore D(A_1, \dots, \lambda A_i, \dots, A_n) \Rightarrow D(A_1, \dots, A_i, \dots, A_n) \quad \forall \lambda \in F$$

$$\therefore D(\lambda A) = \lambda^n D(A)$$

ii) D is an alternating function. That is it changes sign when we swap two columns

$$D(A_1, \dots, A_i, \dots, A_j, \dots, A_n) \quad i < j \\ = -D(A_1, \dots, A_j, \dots, A_i, \dots, A_n)$$

$$\therefore A_i = A_j \text{ for any } i \neq j \Rightarrow D(A) = 0 \quad (\text{Given characteristic}(F) \neq 2).$$

iii) $D(I) = 1$ where $I =$ identity matrix \leftarrow this is required to uniquely determine determinant b/c o/w you'd have scalar multiples.

Normalization

Defn: \exists n-linear alternating function $\det: F^{n \times n} \rightarrow F$ where $\det(I) = 1$.

That is any n-linear alternating function $D: F^{n \times n} \rightarrow F$ can be written as $D(A) = D(I) \det(A)$ $\forall A \in F^{n \times n}$. Shows \det is unique.

PF:

We construct such a $\det: F^{n \times n} \rightarrow F$ where $\det(I)$ exists & then we show it is unique.

We define \det as

$$\det(A) = \sum_{\sigma \in S_n} \text{sgn}(\sigma) a_{1,\sigma(1)} a_{2,\sigma(2)} \cdots a_{n,\sigma(n)} \quad \forall A = (a_{ij}) \in F^{n \times n}$$

permutations of
1..n
↑
↓
sgn (± 1) of
 σ , depending
on σ

where

$\sigma: \{1, \dots, n\} \rightarrow \{1, \dots, n\}$ bijection (thus permutation) b/c $S_n = \{f: 1..n \rightarrow 1..n\}$ & bijective

$$\text{sgn}(\sigma) = (-1)^m \text{ if } \sigma = \text{product of } m \text{ transpositions}$$

well defined b/c $m \pmod 2$ invariant b/c
any extra swap is pair

sgn(σ) makes the alternating clear. Every entry appears exactly once in sum/products & every column only appears once in a product so it is n-linear. \det is normal b/c only the diagonal entries are non-zero, so only one entry (where $\sigma = \text{identity}$) is non-zero & in particular if it is 1, so $\det(I) = 1$.

We now show uniqueness by showing any n-linear alternating function

$D: F^{n \times n} \rightarrow F$ can be written as

$$D(A) = D(I) \det(A) \quad \forall A \in F^{n \times n}$$

or similarly row operations

To do this we use elementary column operations.

i) multiply column by scalar & add it to another

$$\text{if } j \rightarrow D(\dots, cA_i + A_j, \dots) = c D(\dots, A_i, \dots) + D(\dots, A_j, \dots) = D(A_1, \dots, A_n)$$

$c @ \text{idx}=j$
 $\text{old} \xrightarrow{\text{add}}$
 $\text{has } A_i @ \text{idx}=i,$
 $\text{so } D(\dots) = 0 \text{ w/}$
 duplicate columns

$\therefore D$ stays the same

ii) Multiply column by non-zero scalar

$$D(A_1, \dots, cA_i, \dots, A_n) = c D(A_1, \dots, A_n)$$

i^{th}
 col

$\therefore D$ multiplied by same scalar $c \neq 0$

iii) Swap two columns

from axioms / def of D

$$D(A_1, \dots, A_j, \dots, A_i, \dots, A_n) = -D(A_1, \dots, A_n)$$

$\therefore D$ changes sign

Note that for each elementary column operation, D is multiplied by a non-zero scalar.

↙ like row
reduce

With these column operations, we column reduce the matrix
 $A \rightarrow \dots \rightarrow R \leftarrow$ reduced matrix

When reduced, R will either be the identity matrix or have a zero column.

When $R = I$, $D(R) = D(I)$. When R has zero column, $D(R) = 0$.
 \det has the same property but $\det(I) \neq 1$.

Hence

$$D(A) = c D(R) \quad \& \quad \det(A) = c \det(R) \quad \text{for some } c \in F$$

so

$$D(A) = D(I) \det(A)$$

Properties of Determinant:

- i) $\det(A^T) = \det(A)$
- ii) $\det(AB) = \det(A) \det(B)$
- iii) $\det(P^{-1}AP) = \det(A)$

(Determinant of two similar matrices is equal)

- iv) $\det[A \ B] = \det(A) \det(C)$

$\begin{pmatrix} A & C \\ 0 & B \end{pmatrix}$
 block triangular
 matrix

$$\begin{aligned} D(A) &= c D(R) = \frac{c D(I)}{c \det(R)} \\ &\Rightarrow D(A) = D(I) \det(A) \end{aligned}$$

This comes from division (case where $R \neq I$)

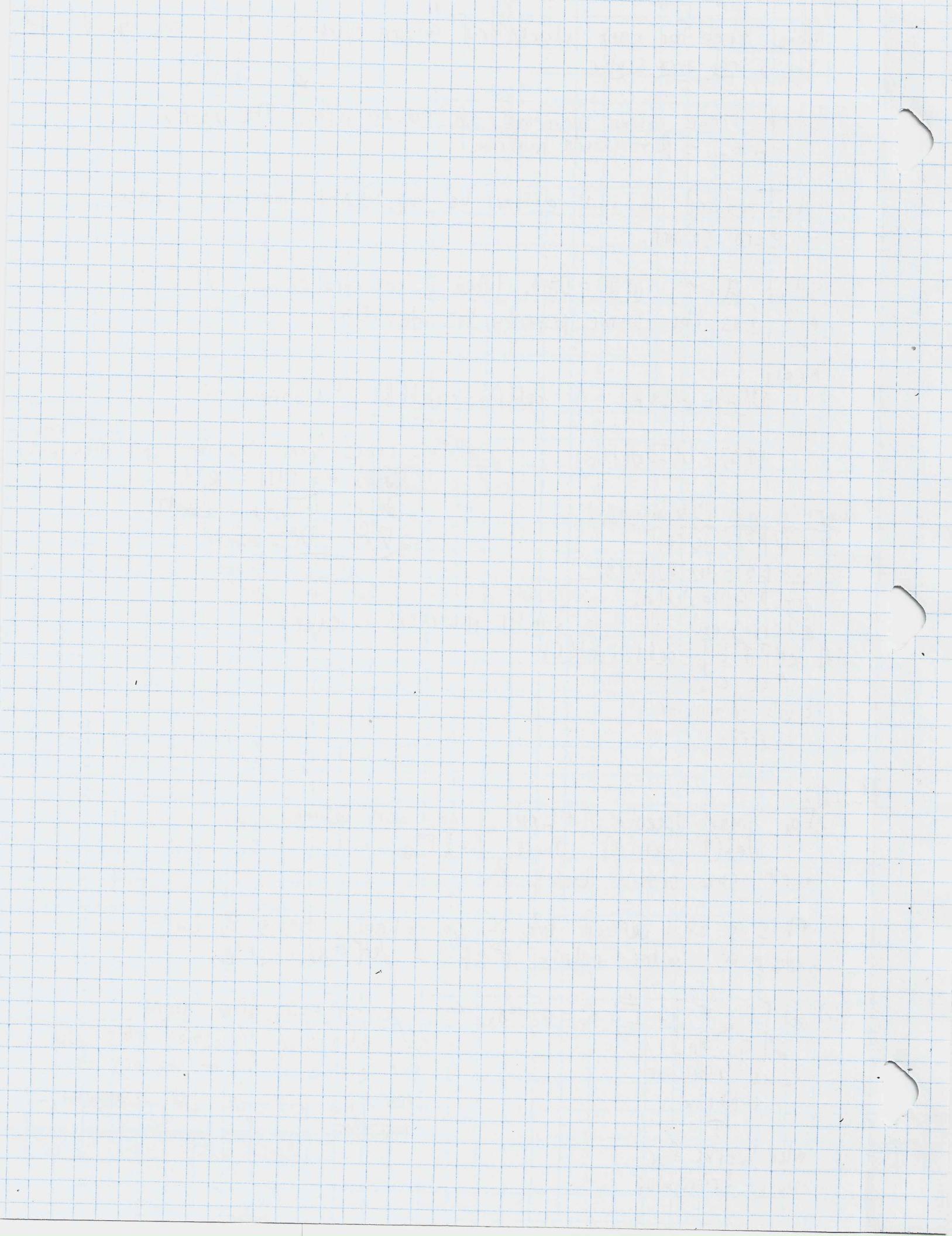
Coro:

- i) For linear operator $T \in \text{End}(V)$ we can define $\det(T) = \det(A)$ where $A = [T]_B$ wrt some ordered basis B .

This is well defined b/c if we change basis B , we get a similar matrix ' $P^{-1}AP$ ' & $\det(P^{-1}AP) = \det(A)$.

- ii) $\det \begin{bmatrix} a_1 & * \\ \vdots & \ddots \\ 0 & a_n \end{bmatrix} = \prod_{i=1}^n a_i = a_1 \cdots a_n$ ← nice for computation along w/ elementary operations b/c you can get a string of things to multiply until you get a triangular matrix

$\begin{pmatrix} a_1 & * \\ \vdots & \ddots \\ 0 & a_n \end{pmatrix}$
 upper triangular
 matrix
 also works for
 lower triangular



Chapter 1 from MA 720: Quotient Space A Tensor Products

Def: \mathbb{F} can be infinite dimensional

Let V be a vector space w/ $W \subseteq V$ subspace. The quotient space/factor space V/W is the set of all cosets W in V .

The $V/W = \{v + W \mid v \in V\}$ s.t. $V/W \subseteq V$ and $|V/W| = |V|/|W|$

Recall:

A coset of v in W is the following for some $v \in V$.

$$v + W = \{v + w \mid w \in W\} \subseteq V \text{ subset.}$$

We call $v \in V$ the representative of the coset $v + W$.

The representative is not unique.

Two cosets w/ representatives $v, v' \in V$ are equal iff $v - v' \in W$

$v + W = v' + W \Leftrightarrow v - v' \in W \leftarrow$ you could reach v' from v using only elements of W .

$$(v + w) + W = v + W \quad \forall w \in W.$$

For V/W to be a vector space, we need to define operations on cosets.

Vector Operations on Cosets:

Let $v, v' \in V$ & $c \in \mathbb{F}$.

$$\text{i)} (v + W) + (v' + W) = (v + v') + W$$

$$\text{ii)} c(v + W) = (cv) + W$$

The zero vector in V/W is $0 + W = W$. ($w + W = 0 + W \quad \forall w \in W$).

All vector space properties fall from V .

Thus V/W is a vector space.

$$b/c \quad w - 0 = w \in W$$

Thm:

Let $\{v_1, \dots, v_m\}$ be a basis for W . & extend it to a basis $\{v_1, \dots, v_n\}$ for V .

Then $\{v_{m+1} + W, \dots, v_n + W\}$ is a basis for V/W . (
 $(v_i + W, \dots, v_n + W)$ are all $0 + W$ b/c $v_1, \dots, v_m \in W$)

Rem:

$$\dim(V/W) = \dim(V) - \dim(W)$$

Isomorphism theorem

For all linear transformation $T \in \text{Hom}(V, U)$, we have a vector space isomorphism

$$V/\text{Ker}(T) \cong \text{Img}(T). \quad \text{This gives another way to prove rank-nullity!}$$

This is given by $V + \text{Ker}(T) \rightarrow T(V)$ b/c $\forall v \in \text{Ker}(T) \quad Tv = 0$.

Tensor Products

Informally, tensor products are what happen when you try to multiply two vector spaces. We could do cartesian product of two vector spaces but that is no longer a vector space & lacks nice properties like distributivity. The tensor product is similar to the cartesian product but "fixes" these issues.

Let V, W be vector spaces (can be infinite) over F . We want the following properties for the tensor product \otimes

$$\begin{aligned} (cv) \otimes w &= c(v \otimes w) = v \otimes (cw) \\ (v+v') \otimes w &= v \otimes w + v' \otimes w \\ v \otimes (w+w') &= v \otimes w + v \otimes w' \end{aligned} \quad \left\{ \begin{array}{c} \\ \\ \star \end{array} \right.$$

That is we want the tensor product \otimes to be bilinear.

Def:

Let V, W be vector spaces. We construct the tensor product \otimes .

We start w/ the cartesian product $V \times W$ & construct a vector space S consisting of all formal linear combinations such that $V \times W$ is a basis. (This is huge b/c $V \times W$ is huge & the basis).

We impose relations on S by taking the quotient space S/K where K is the vector space spanned by the properties mentioned in \star . That is K 's elements have the following

$$\begin{aligned} c(v, w) - (cv, w) &= 0 \\ c(v, w) - (v, cw) &= 0 \\ (v+v', w) - (v, w) - (v', w) &= 0 \\ (v, w+w') - (v, w) - (v, w') &= 0 \end{aligned} \quad \left\{ \begin{array}{c} \\ \\ \\ \end{array} \right.$$

$$\forall c \in F \quad v, v' \in V \quad w, w' \in W.$$

The tensor product of V & W is

$V \otimes W = S/K$ where $S = V \times W$ & K subspace of S spanned by linearity relations & for $v \in V$ $w \in W$, their tensor product is

$$v \otimes w = (v, w) + K$$

More Quotient Spaces

Ihm:

Let V be a vector space w/ $W \subseteq V$ subspace. Let U be another vector space.

Then there is a natural isomorphism

$$\text{Hom}(V/W, U) \cong \{T \in \text{Hom}(V, U) \mid Tw = 0 \quad \forall w \in W\} \quad \begin{array}{l} \xrightarrow{\uparrow} \text{annihilator } W^0 \text{ where} \\ \text{U is field} \end{array}$$

$$\text{or } W \subseteq \text{Ker}(T) \Rightarrow \text{Null}(T)$$

connected to

PF:

where $Tv = 0 \nLeftarrow$ critical

Given $T \in \text{Hom}(V, W)$, we get an induced map $\bar{T}: V/W \rightarrow U$, where
 $\bar{T}(v+W) = Tv \quad \forall v \in V$

This is an isomorphism b/c we can define T given \bar{T} .

This is well defined b/c if we choose v' where $v-v'=w \in W$

Then by the definition of cosets

$$\bar{T}(v+W) = \bar{T}(v'+W)$$

We can do the same
in reverse

This is true b/c if we rewrite v' as $v' = v-w$, we get

$$T(v) = T(v-w) = T(v) - T(w) = T(v').$$

Thus $\bar{T}(v+W) = \bar{T}(v'+W) \Leftrightarrow v = v' + w \in W$ must be true in both cases. \square

Coro:

If $U = F$, then $(V/W)^* \cong W^0$.

Thm:

There is a natural isomorphism $\tau: V \rightarrow V/W$ where
 $\tau(v) \in v+W$.

Here $W = \text{Ker } (\tau)$

The tensor product turns a
bilinear function into a
linear one

or $\text{Ker } (\tau)$

Thm:

F U vectorspace

$$\begin{aligned} \text{Hom}(V \otimes W, U) &= \text{Hom}(S/K, U) \cong \{T \in \text{Hom}(S, U) \mid T(K) = 0\} \\ &\cong \{f: V \times W \rightarrow U \mid f \text{ bilinear}\}. \end{aligned}$$

A linear map $T: S \rightarrow U \Leftrightarrow$ function $T: V \times W \rightarrow U$. That is
 $T(v, w) \in U \quad \forall v \in V, w \in W$

The condition $T(K) = 0$ means

$$T(c(v, w) - (cv, w)) = 0 \Leftrightarrow T(c(v, w)) = T(cv, w)$$

$$T(c(v, w) - (v, cw)) = 0 \Leftrightarrow T(c(v, w)) = T(v, cw)$$

$$T((v+v', w) - (v, w) - (v', w)) = 0 \Leftrightarrow T(v+v', w) = T(v, w) + T(v', w)$$

$$T((v, w+w') - (v, w) - (v, w')) = 0 \Leftrightarrow T(v, w+w') = T(v, w) + T(v, w')$$

that is T is bilinear.

This means $\text{Hom}(V \otimes W, U)$ is the space of bilinear maps
 $T: V \times W \rightarrow U$.

Any bilinear map $T: V \times W \rightarrow V$ induces a linear map $\tilde{T}: V \otimes W \rightarrow V$ given by $\tilde{T}(v \otimes w) = T(v, w) \quad \forall v \in V, w \in W$.

Remark:

$V \otimes W$ is spanned by all pure tensors $v \otimes w$.

We will use the above theorem for the tensor product b/c it is equivalent to the quotient space construction & more useful.

We can actually generalize the tensor product to n spaces.

Def:

We can actually generalize the tensor product to n spaces.

We use associativity

$$V_1 \otimes V_2 \otimes V_3 \otimes \dots \stackrel{?}{=} ((V_1 \otimes V_2) \otimes V_3) \otimes \dots \cong V_1 \otimes (V_2 \otimes (V_3 \otimes \dots))$$

or switch to n-tuples.

Coro:

Then an n -linear map $V_1 \times \dots \times V_n \rightarrow U \cong$ a linear map $V_1 \otimes \dots \otimes V_n \rightarrow U$.

Example:

Let $V = F$. Find $a \otimes w$ where $a \in F = V$ & $w \in W$ where W is a vector space
 $a \otimes w = (a \cdot 1) \otimes w = a(1 \otimes w)$

Thus $F \otimes W$ is spanned by vectors $1 \otimes w$ where $w \in W$.

$$F \otimes W = \{1 \otimes w \mid w \in W\}$$

Take $w, w' \in W$, then $1 \otimes w + 1 \otimes w' = 1 \otimes (w + w')$.
So $F \otimes W \cong W$.

Consider the bilinear map $T: F \times W \rightarrow W$, where $T(a, w) = aw$.
This induces the linear map $\tilde{T}: F \otimes W \rightarrow W$ & it's an isomorphism

Example:

Let V & W be vector spaces,

$\forall g \in V^*$ & $h \in W^*$ we have a bilinear map $T: V \times W \rightarrow F$ where

$$T(v, w) = g(v) h(w)$$

T is bilinear b/c g & h are linear & the product of two linear maps (given independent values) is bilinear.

This gives an induced linear map $\tilde{T}: V \otimes W \rightarrow F$ where
 $\tilde{T}(v \otimes w) = g(v) h(w)$

Here $\tilde{T} \in (V \otimes W)^*$

Def:

Let V, V', W, W' be vector spaces.

Let $T: V \rightarrow V'$ & $S: W \rightarrow W'$ be vector spaces.

This gives us a bilinear map $F: V \times W \rightarrow V' \otimes W'$

$$F(v, w) \mapsto (Tv) \otimes (Sw)$$

normally this is anonymous

This bilinear map gives us an induced linear map

$$T \otimes S = F: V \otimes W \rightarrow V' \otimes W'$$

where

$$(T \otimes S)(v \otimes w) = F(v \otimes w) = (Tv) \otimes (Sw)$$

This defines the tensor product of linear maps.

Remark: \otimes is not commutative

This tensor product of linear maps naturally gives us the Kronecker product of matrices.

Thm:

we use index set rather than $\mathbb{N} \times \mathbb{N}$ b/c
this applies in infinite dimensional cases.

Let $\{v_i\}_{i \in I}$ be a basis for V ,

Likewise $\{w_j\}_{j \in J}$ for W .

Then $\{v_i \otimes w_j\}_{i \in I, j \in J}$ is a basis for $V \otimes W$

$$\& \dim(V \otimes W) = \dim(V) \dim(W).$$

PF:

We show $\{v_i \otimes w_j\}_{i \in I, j \in J}$ is a basis for $V \otimes W$. The dimension property falls from that trivially.

First we show $\{v_i \otimes w_j\}_{i \in I, j \in J}$.

By definition $V \otimes W = \text{span}\{v \otimes w \mid v \in V, w \in W\}$

Since $\{v_i\}_{i \in I}$ is a basis for V , we can rewrite v as (likewise w)

$$v = \sum_i a_i v_i \quad \& \quad w = \sum_j b_j w_j.$$

Thus

$$v \otimes w = \left(\sum_i a_i v_i \right) \otimes \left(\sum_j b_j w_j \right)$$

by the linearity & distributivity of the tensor product, we can rewrite this as

$$v \otimes w = \sum_i \sum_j a_i b_j (v_i \otimes w_j).$$

b/c we wrote $v \otimes w$ as l.c. of $\{v_i \otimes w_j\}_{i \in I, j \in J}$

$$\therefore V \otimes W = \text{span}\{v_i \otimes w_j \mid i \in I, j \in J\}, \{v_i \otimes w_j\}_{i \in I, j \in J}$$

Thus $\{v_i \otimes w_j\}_{i \in I, j \in J}$ spans $V \otimes W$.

Now we show $\{v_i \otimes w_j\}_{i \in I, j \in J}$ is linearly independent. To do this, we show $\sum_{i,j} a_{ij} \cdot (v_i \otimes w_j) = 0$ if & only if $\forall a_{ij} = 0$.

To do this we use the dual basis for $V^* \otimes W$ given by $v \in V$ where $v = \sum_i a_i v_i$. We can rewrite a_i (& thus v) as applications of dual basis on v_i . So $\{v_i\}_{i \in I}$ is just a basis for V & $\{v^*\}_{i \in I}$ is just a basis for V^* . Generally true.

$$a_i = f_i(v)$$

$$\Leftrightarrow v = \sum_i f_i(v) v_i$$

Let $\{g_i\}_{i \in I}$ be the dual basis to $\{v_i\}_{i \in I}$ & $\{h_j\}_{j \in J}$ be the dual basis to $\{w_j\}_{j \in J}$. So $g_k(v_i) = \delta_{ki}$ & $h_l(w_j) = \delta_{lj}$.

Then $g_k \otimes h_l \in (V \otimes W)^*$

$$(g_k \otimes h_l)(v_i \otimes w_j) = g_k(v_i) h_l(w_j) = \delta_{ki} \delta_{lj} = \begin{cases} 1 & \text{if } (k, l) = (i, j) \\ 0 & \text{o/w} \end{cases}$$

By the definition of $(g_k \otimes h_l)$ & the nature of dual bases, $\forall v, w$

$$v \otimes w = \sum_{i,j} (g_i \otimes h_j) \underbrace{(v_i \otimes w_j)}_{V \otimes W} = \sum_{i,j} a_{ij} (v_i \otimes w_j)$$

Applying this to $\sum_{i,j} a_{ij} (v_i \otimes w_j) = 0$, we get

$(g_i \otimes h_j)(0) = 0 \quad \forall i \in I, j \in J$ (b/c $\{g_i \otimes h_j\}_{i \in I, j \in J}$ is a basis for $(V \otimes W)^*$)

Thus

$$a_{ij} = 0 \quad \forall i \in I, j \in J$$

& $\{v_i \otimes w_j\}_{i \in I, j \in J}$ is linearly independent.

Thus $\{v_i \otimes w_j\}_{i \in I, j \in J}$ is a basis for $V \otimes W$. \square

Ihm:

If $\dim(V) < \infty$ & $\dim(W) < \infty$, we have a canonical/natural isomorphism $\varphi: V^* \otimes W \rightarrow \text{Hom}(V, W)$ where

$$(\varphi(f \otimes w))(v) = f(v)w \quad \text{dimensions match so this has a shot.}$$

Pf:

To have linear map $\varphi: V^* \otimes W \rightarrow \text{Hom}(V, W)$, we need a bilinear map $T: V^* \times W \rightarrow \text{Hom}(V, W)$.

Let $T(f, w) = T_{f,w}$ where $T_{f,w}(v) = f(v)w$. We show T is well-defined & bilinear.

First, $T_{f,w}$ is indeed a linear map $V \rightarrow W$ b/c all components are linear.

We now check T is bilinear. This is linear (if you saw it & believe) when you fix w & separately when you fix f . Thus T is bilinear & so is φ .

To show the map φ is an isomorphism, we show it sends a basis to a basis. (No need for bijective b/c this is sufficient.)

Pick basis $B = \{v_1, \dots, v_n\}$ for V . Pick the dual basis $B^* = \{f_1, \dots, f_n\}$ for V^* . Pick basis $B' = \{w_1, \dots, w_m\}$ for W .

For linear transformations $\text{Hom}(V, W)$, we have a basis $\{e_{ij}\}_{\substack{1 \leq i \leq n \\ 1 \leq j \leq m}}$ where $e_{ij}(v_k) = \delta_{jk} w_j$. $\xrightarrow{\text{keep same index ranges}}$

A basis for $V^* \otimes W$ is $\{f_i \otimes w_j\}_{\substack{1 \leq i \leq n \\ 1 \leq j \leq m}}$

Then $\phi(f_j \otimes w_i) = T_{f_j, w_i}$, $T_{f_j, w_i}(v_k) = f_j(v_k)w_i = e_{ij}(w)$
Thus $T_{f_j, w_i} = e_{ij}.$

Thus $\phi(f_j \otimes w_i) = e_{ij}$, meaning ϕ sends a basis to a basis,
meaning ϕ is an isomorphism. \square

Extension of Scalars (& Other Field Stuff)

closed

Let $F \subseteq K$ be a field extension. That is F is a subfield of K .

Let V be a vector space over F . Then Note $\otimes_F = \otimes$ of vector spaces
Then $K \otimes_F V$ is a vector space over K .

We now define scalar multiplication $K \otimes_F V$

$$a(b \otimes v) = (ab) \otimes v \quad \forall a, b \in K, v \in V$$

With this definition $K \otimes_F V$ is a vector space over K if
 $\{v_i\}_{i \in I}$ is a basis for V over F then $\{1 \otimes v_i\}_{i \in I}$ is a basis for
 $K \otimes_F V$ over K . In particular $\dim_K(K \otimes_F V) = \dim_F V$.

we "don't gain" anything
when scalars match

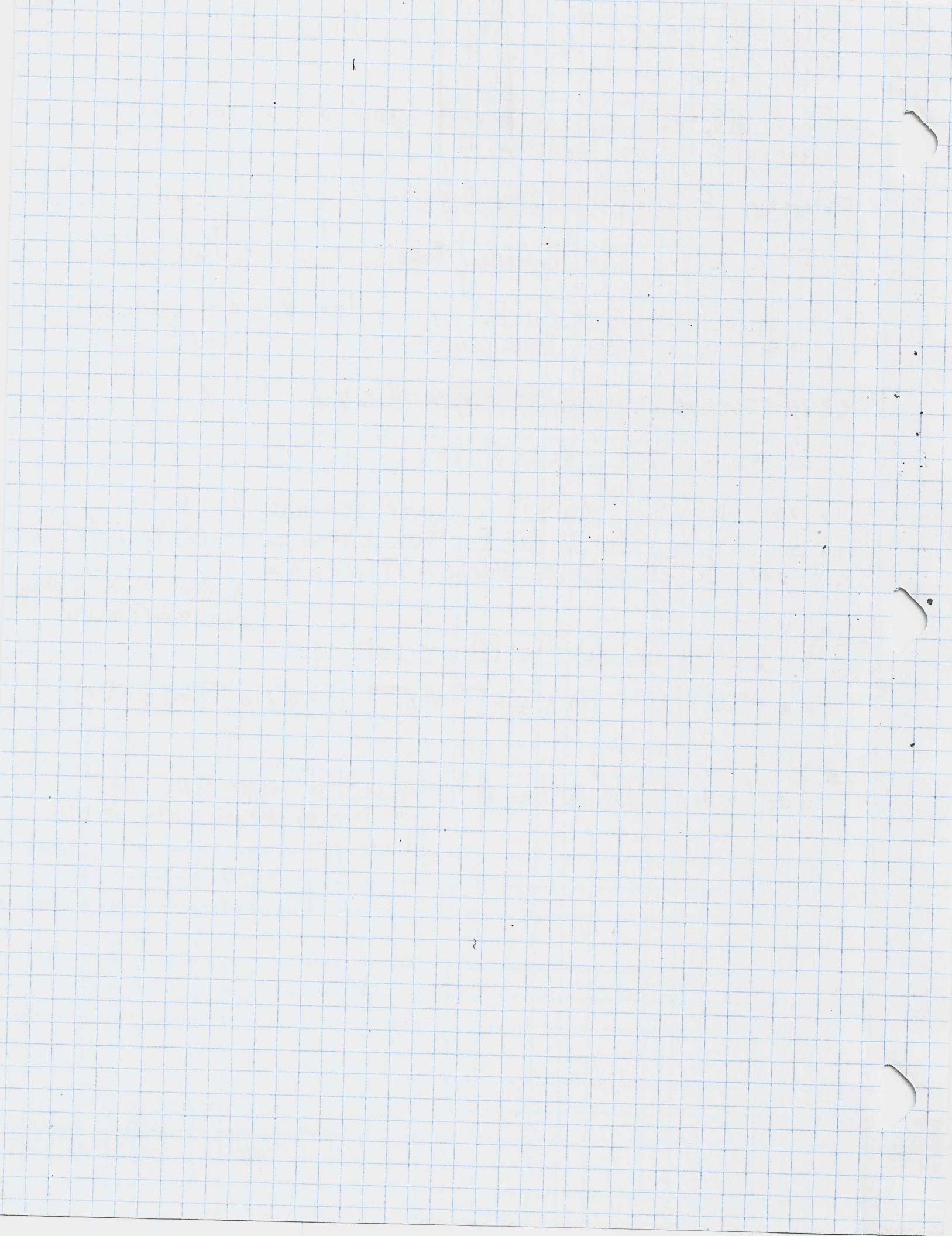
Examples:

Using this we get the following identities

$$\text{i)} K \otimes_F F^n \cong K^n \quad \text{ii)} K \otimes_F F^{m \times n} \cong K^{m \times n} \quad \text{iii)} K \otimes_F F[x] \cong K[x]$$

Rem:

$\dim_F(K \otimes_F V) = (\dim_F K)(\dim_F V)$ ← We get a larger space but
as long as scalars match no more dimension



Chapter 6: Elementary Canonical Forms

How do we represent linear operators? In particular, how do we represent them well?

Def:

Let V be a vector space over field F where $\dim(V) = n < \infty$. w/ linear operator $T \in \text{End}(V) = \text{Hom}(V, V)$.

or semi-simple

T is diagonalizable if $\exists B$ basis for V st the matrix of T wrt B $[T]_B$ is a diagonal matrix.

Let $B = \{v_1, \dots, v_n\}$.

We say $[T]_B = \text{diag}(\lambda_1, \dots, \lambda_n)$ iff

$$T = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & \cdots & \lambda_n \end{bmatrix}$$

The j -th column of $[T]_B$ is

$[Tv_j]_B$ = coordinate vector of Tv_j wrt B .

Since $[T]_B = \begin{bmatrix} \lambda_1 & 0 \\ & \ddots \\ 0 & \lambda_n \end{bmatrix}$, the j -th column is $\begin{bmatrix} 0 \\ \vdots \\ \lambda_j \\ \vdots \\ 0 \end{bmatrix} = \lambda_j e_j$. $\forall j = 1, \dots, n$

Thus $Tv_j = \lambda_j v_j$. $\forall j = 1, \dots, n$.

When you get such a vector like v_j , you call it an eigenvector & λ_j the eigenvalue.

In other words, there exists a basis of only eigenvectors for T . (more later)

or characteristic vector

& characteristic value

Def:

i) We say $v \neq 0$ an eigenvector for $T \in \text{End}(V)$ w/ eigenvalue λ (a scalar) iff

$$Tv = \lambda v \quad \& \quad v \neq 0.$$

We exclude 0 b/c then $Tv = \lambda v$ for all scalars λ , which isn't useful.

Likewise we say $\lambda \in F$ is an eigenvalue for $T \in \text{End}(V)$ w/ eigenvector $v \neq 0$ iff

$$Tv = \lambda v$$

The λ -eigenspace of $T \in \text{End}(V)$ is $\text{Ker}(T - \lambda I)$. More intuitively it is the set of all solutions v to $Tr = \lambda v$ (plus $v=0$) or the set of all eigenvectors w/ eigenvalue λ .

Thm:

Let $T \in \text{End}(V)$ where $\dim(V) < \infty$. Then

λ is an eigenvalue for T

$\Leftrightarrow T - \lambda I$ is singular (i.e. not invertible)

$\Leftrightarrow \text{Ker}(T - \lambda I) \neq \{0\}$

$\Leftrightarrow \det(T - \lambda I) = 0$ — The way we find all eigenvalues

$\wedge \det(\lambda I - T) = 0$ b/c $\det(T - \lambda I) = (-1)^n \det(\lambda I - T)$

Def:

i) The characteristic polynomial of T is

$f(\lambda) = \det(\lambda I - T)$ some write $\det(T - \lambda I)$, $\pm t$ may differ by sign

ii) This is indeed a polynomial $f(\lambda) \in F[\lambda]$ b/c it is a sum of linear factors.

iii) In particular it has degree n where $\dim(V) = n$ & is monic (i.e. its leading coefficient is one).

iv) We can explicitly write f as

$$f(\lambda) = \lambda^n - \text{tr}(T)\lambda^{n-1} + \dots + (-1)^n \det(T) \quad \text{where } \lambda=0 \text{ i.e. } f(0)$$

{ well defined for similar reasons to $\det(T)$ being well defined }

Hand wavy I know

Thm:

The roots of the characteristic polynomial (i.e. λ s.t. $\det(\lambda I - T) = 0$) are precisely the eigenvalues for T .

This theorem is how we find eigenvalues in practice.

Rem:

Eigenvalues/eigenvectors & all work above applies to matrices $A \in F^{n \times n}$ where you define $T \in \text{End}(F^n)$ $TV = Av$.

Note that $[T]_B = A$ where B is the standard basis.

(Hopefully this is intuitive)

Example:

Let $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$. Find the eigenvalues & eigenvectors.

To find the eigenvalues λ_1, λ_2 we solve the characteristic polynomial

$$f(\lambda) = \det(\lambda I - A) = \begin{vmatrix} \lambda & -1 \\ 0 & \lambda \end{vmatrix} = \lambda^2$$

Thus 0 is an eigenvalue.

The 0-eigenspace is $\text{Ker}(A - 0I) = \text{Ker}(A) = \{x \in F^2 \mid Ax = 0\}$.

$$\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow x_2 = 0$$

Thus $\text{Ker}(A) = \{ \begin{bmatrix} * \\ 0 \end{bmatrix} \mid x \in F \} = \text{Span}\{\mathbf{e}_1\}$. This gives us a unique (up to scalar multiplication) eigenvector $e_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$.

Note: $\det(T) = \det([T]_B)$

for $T \in \text{End}(V)$ where B basis for V . This is well defined b/c

$[T]_B, [T]_{B'}$ similar & determinant of similar matrices are equal.

Note that A is not diagonalizable. This is b/c it has eigenvector e_1 , which cannot be a basis for \mathbb{F}^2 . 2

Thm:

Let V be a vector space over \mathbb{F} w/ $\dim(V) = n < \infty$.
Let $T \in \text{End}(V)$ be an isomorphism.

T is diagonalizable (or semi-simple) if \exists basis for V of eigenvectors of T . That is

$$\begin{aligned}\exists \text{ basis } \{v_1, \dots, v_n\} \text{ st} \\ T v_i = \lambda_i v_i \quad \forall i \in \{1, \dots, n\}\end{aligned}$$

Thm:

Let $A \in \mathbb{F}^{n \times n}$ be an upper (or lower) triangular matrix.

$$A = \begin{bmatrix} \lambda_1 & * \\ & \ddots \\ 0 & \lambda_n \end{bmatrix}.$$

The eigenvalues of A are the entries on the diagonal $\lambda_1, \dots, \lambda_n$. \leftarrow it is not clear there are enough (unique) eigenvectors for A to be diagonalizable.

This is true b/c the determinant of a triangular matrix is the product of the entries on the main diagonal.

$$f(x) = \begin{vmatrix} x - \lambda_1 & * & & \\ & \ddots & & \\ 0 & & x - \lambda_n & \end{vmatrix} = (x - \lambda_1) \cdots (x - \lambda_n).$$

Thm:

Eigenvectors corresponding to distinct eigenvalues are linearly independent.

Coro:

If $T \in \text{End}(V)$ where $\dim(V) = n < \infty$ & T has n distinct eigenvalues, then T is diagonalizable.

This holds b/c if you have n linearly independent vectors from an n -dimensional space, they form a basis.

Pf:

This is for the above theorem (not corollary). This is continued on the next page.

We use the following lemma in this proof

Lemma: If $Tv = \lambda v$, then $g(T)v = g(\lambda)v$ for any $g(x) \in F[x]$.

Pf:

$$Tv = \lambda v \Rightarrow T^2v = T(Tv) = T(\lambda v) = \lambda(Tv) = \lambda\lambda v = \lambda^2 v.$$

We can continue on like this inductively to give us
 $T^k v = \lambda^k v \quad \forall k \geq 0.$

This applies for $k=0$ b/c $T^0 = I$, $T^0 v = v = \lambda^0 v$.

By linearity $(\sum_{k=0}^n a_k T^k)v = (\sum_{k=0}^n a_k \lambda^k)v$. \square

Now the main proof.

Let V be a vector space w/ $\dim(V) = n < \infty$.

Let $T \in \text{End}(V)$ be a linear operator on V w/ m distinct eigenvalues. That is
 $Tv_i = \lambda_i v_i \quad \forall i \in \{1, \dots, m\}$ where $\lambda_i = \lambda_j \iff v_i = v_j$.

Suppose $c_1 v_1 + \dots + c_m v_m = 0$ for some c_1, \dots, c_m . We want to show these c 's are trivial. That is $c_1 = \dots = c_m = 0$.

Here is one way. Consider repeated applications of T on $c_1 v_1 + \dots + c_m v_m = 0$.

$$c_1 v_1 + \dots + c_m v_m = 0$$

$$c_1 \lambda_1 v_1 + \dots + c_m \lambda_m v_m = 0$$

$$c_1 \lambda_1^{m-1} v_1 + \dots + c_m \lambda_m^{m-1} v_m = 0$$

This gives us the following ^{square} matrix w/ linearly independent rows (& columns) since all λ 's are distinct

$$\begin{bmatrix} 1 & \dots & 1 \\ \lambda_1 & \dots & \lambda_m \\ \vdots & \ddots & \vdots \\ \lambda_1^{m-1} & \dots & \lambda_m^{m-1} \end{bmatrix} \left\{ \text{Van der Monde matrix. } \det(\dots) = \prod_{i < j} (\lambda_i - \lambda_j) \right\}$$

Since this matrix is linearly independent, it is invertible, meaning the system of linear equations has one solution which is the trivial $c_1 = \dots = c_m = 0$.

Here is another way. Recall the Lagrange interpolation polynomials

$$L_j(x) = \prod_{\substack{i=1 \\ i \neq j}}^m \frac{x - \lambda_i}{\lambda_j - \lambda_i} \Rightarrow L_j(v_i) = b_{ij}.$$

Now apply $L_j(T)$ to $c_1 v_1 + \dots + c_m v_m = 0$.

$$0 = L_j(T)(c_1 v_1 + \dots + c_m v_m) = c_1 L_j(T)v_1 + \dots + c_m L_j(T)v_m$$

$$= c_1 L_j(\lambda_1)v_1 + \dots + c_m L_j(\lambda_m)v_m$$

$$= c_j v_j = 0$$

Thus $c_j = 0 \quad \forall j$ (b/c eigenvectors $v_i \neq 0$ by definition).

Therefore eigenvectors corresponding to distinct eigenvalues are linearly independent.

Thm:

Let V be a vector space w/ $\dim(V) = n < \infty$.

Let $T \in \text{End}(V)$ w/ (distinct) eigenvalues $\lambda_1, \dots, \lambda_m$ ($m \leq n$)
where $\lambda_i \neq \lambda_j \forall i \neq j$. Note that these eigenvalues may have some multiplicity.

Consider the eigenspaces W_i

$W_i \subseteq \text{Ker}(T - \lambda_i I) = \lambda_i$ eigenspace where
 $d_i = \dim(W_i)$.

In this case we know the following are equivalent statements

$\Leftrightarrow T$ is diagonalizable

$\Leftrightarrow f(x) = (x - \lambda_1)^{d_1} \cdots (x - \lambda_m)^{d_m}$ + characteristic polynomial factors

\Leftrightarrow the multiplicity of eigenvalues matches dimension of eigenspaces (no linearly dependent eigenvectors w/ same eigenvalue)

$$\Leftrightarrow \sum_{i=1}^m d_i = \dim(V) = n$$

Pf:

i) Suppose T is diagonalizable. Then there is basis of eigenvectors. Each eigenvector is in one of the eigenspaces W_i . Since all eigenvectors are linearly independent (as basis), the dimensions adds up to at least n : $d_1 + \dots + d_m = n$. Likewise the basis for V is given by a union of bases for W_1, \dots, W_m .

ii) Suppose $d_1 + \dots + d_m = n$. Then a union of bases W_1, \dots, W_m provides a basis for V (b/c each eigenspace has only $\{0\}$ in intersection & vectors w/ different eigenvalues are independent). Thus T is diagonal wrt this basis. Here

$$[T] = \begin{bmatrix} \lambda_1 & & & & & 0 \\ & \ddots & & & & \\ & & \lambda_2 & & & \\ & & & \ddots & & \\ & & & & \ddots & \lambda_m \\ 0 & & & & & \lambda_m \end{bmatrix}$$

applies to (i) to!

iii) Thus we can see the characteristic polynomial is

$$f(x) = (x - \lambda_1)^{d_1} \cdots (x - \lambda_m)^{d_m}$$

Rem:

In general, you can factor the characteristic polynomial as

$$f(x) = (x - \lambda_1)^{k_1} \cdots (x - \lambda_m)^{k_m}$$

However

$$k_i \geq d_i \text{ where } d_i = \dim(\text{Ker}(T - \lambda_i I))$$

Rem: If T is diagonalizable w/ (distinct) eigenvalues $\lambda_1, \dots, \lambda_m$ ($\lambda_i \neq \lambda_j$; $\forall i \neq j$), then

$$(T - \lambda_1 I) \circ \cdots (T - \lambda_m I) = f(T) = 0, \quad \text{minimal polynomial that annihilates } T$$

Thm: Cayley-Hamilton Theorem

$f(T) = 0$ for any linear operator T where $f(x)$ is the characteristic polynomial. (degree is $\dim V$)

Def:

A polynomial $g(x) \in F[x]$ is an annihilating polynomial of T iff $g(T) = 0$.

PF:

First we show such non-zero polynomials $g(x)$ exist.

Recall $\dim(\text{End}(V)) = n^2$. If you take $n^2 + 1$ linear operators, you get linearly dependent operators.

Take $I, T, T^2, \dots, T^{n^2}$. These are linearly dependent so there is some linear combination that is zero, which gives us a non-zero annihilating polynomial.

Now we show the Cayley-Hamilton theorem.

A ring is a group w/ multiplication as well

Let $J = \{\text{annihilating polynomials of } T\} = \{g(x) \in F[x] \mid g(T) = 0\}$. We just showed $J \neq \{0\}$. Note that J is closed under $+ \wedge \times$.

- i) $\forall g_1, g_2 \in J \Rightarrow g_1 + g_2 \in J$
- ii) $\forall g \in J \wedge \forall h \in F[x] \Rightarrow gh \in J$

This means J is an ideal of the ring $F[x]$, denoted $J \triangleleft F[x]$.

B/c polynomials are well studied as a ring we have a full description. Thus recall from abstract algebra the following theorem

Thm:

For every non-zero ideal in the ring of polynomials $J \triangleleft F[x], J \neq 0$, there exists a unique monic polynomial $p \in J$ of min degree.

Then $J = \{ph \mid h \in F[x]\}$ is just the set of multiples of p .

We call p the generator of the ideal J .

(Monic = leading coefficient is one)

• Proved by division w/ remainder (?)

Now w/ our $J = \{g(x) \in F[x] \mid g(T) = 0\}$ the monic generator of this ideal is called the minimal polynomial of T .

Def:

The minimal polynomial of linear operator T is a unique non-zero monic polynomial of minimum degree st $p(T) = 0$.

For $g(x) \in F[x]$, we have

$g(T) = 0 \Leftrightarrow p(x) \mid g(x)$ ($p(x)$ divides $g(x)$)

Recall that the characteristic polynomial for linear transformation T is

$$f(x) = \det(xI - T).$$

It has roots precisely equal to the eigenvalues of T .

Thm:

Let $p(x)$ be the minimal polynomial for T & $f(x)$ the characteristic polynomial.

$p(x)$ & $f(x)$ have the same roots. (w/ possibly diff multiplicities)

PF:

We want to show $p(\lambda) = 0$ ($\lambda \in F$) iff λ is an eigenvalue of T .

Assume $p(\lambda) = 0$ for some $\lambda \in F$. Then $p(x) = (x - \lambda)q(x)$.

B/c p is the minimal polynomial, that is the smallest polynomial st $p(T) = 0$, & q has degree 1 less than p ($\deg(q) = \deg(p) - 1$), we know $q(T) \neq 0$.

Thus $\exists v \neq 0$ st $q(T)v = w \neq 0$. Combining this w/ $p(T) = 0$, gives us $(T - \lambda I)w = (T - \lambda I)q(T)v = p(T)v = 0$.

Since $w \neq 0$, w is an eigenvector w/ eigenvalue λ . \square

Assume λ is an eigenvalue. Then $Tw = \lambda w$ for some $w \in W$ where $w \neq 0$.

Then $p(T)w = p(\lambda)w$. However, $p(T) = 0$ so $p(T)w = 0$.

Thus $p(\lambda)w = 0$ but since $w \neq 0$, $p(\lambda) = 0$.

Thus $p(\lambda) = 0$. \square

Invariants & Subspaces

Def:

A subspace W of V is called T -invariant iff

$$Tw \in W \quad \forall w \in W.$$

This means the restriction of T on W , $T|_W$ is still a linear transformation $T|_W: W \rightarrow W$, which can be useful for induction.

Example:

A 1-dimensional subspace $W = \text{span}\{w\} = Fw = \{cw \mid c \in F\}$ ($w \neq 0$) is T -invariant. That means

$Tw = \lambda w$ for some $\lambda \in F$. & choose λ to lead to eigenvalues, could be any letter

Thus we can see w is an eigenvector of T . & W is thus

an eigenspace of T .

Example:

Every eigenspace $\text{Ker}(T - \lambda I)$ is T -invariant. True.

You can see this by letting $w \in \text{Ker}(T - \lambda I)$. We know

$$Tw = 0 \quad b/c \quad w \in \text{Ker}(T - \lambda I).$$

We know the 0 vector is in all vector spaces, so we know

$$Tw = 0 \in \text{Ker}(T - \lambda I).$$

Example:

Let $S \in \text{End}(V)$ be a linear operator that commutes w/ $T \in \text{End}(V)$, that is $ST = TS$. \rightarrow image (think: range)

Then $\text{Ker}(S)$ & $\text{Im}(S)$ are T -invariant.

First we show $\text{Ker}(S)$ is T -invariant. Let $v \in \text{Ker}(S)$. Then

$$(TS)v = T(Sv) = T(0) = 0,$$

thus we know by $ST = TS$

$$0 = (ST)v = S(Tv) = 0$$

thus $Tv \in \text{Ker}(S)$ when $v \in \text{Ker}(S)$. Therefore $\text{Ker}(S)$ is T -invariant.

Now we show $\text{Im}(S)$ is T -invariant. Let $v \in \text{Im}(S)$. Then $\exists v' \in V$ s.t. $v = Sv'$.

Then we can write Tv as

$$Tv = T(Sv')$$

$= S(Tv')$ b/c S commutes.

Then $Tv = S(Tv')$ (where $Tv' \in V$), so $Tv \in \text{Im}(S)$ given $v \in \text{Im}(S)$.

Therefore $\text{Im}(S)$ is T -invariant.

Example:

If we have such a commuting $S, T \in \text{End}(V)$, we know $S = g(T) \wedge g(x) \in F[x]$.

What can we do with T -invariant subspaces?

Let B_w be a basis for W . Extend it to a basis B_v for V . Let $T \in \text{End}(V)$.
Let $m = \dim(W) \leq n = \dim(V)$.

We can represent T as a matrix. We know W is T -invariant iff A_3 is all zero

$$[T]_{B_v} = \begin{bmatrix} A_1 & A_2 \\ A_3 & A_4 \end{bmatrix}_{m \times n}$$

Further we know $[T]_{B_w} = A_1$.

In more detail, where $B_w = \{v_1, \dots, v_m\}$ & $B_v = \{v_{1000}, v_{m+100}, v_n\}$. The j -th column of $[T]_{B_v}$ is $[Tv_j]_{B_v}$.

$$Tv_j = \sum_{i=1}^n a_{ij} v_i \Rightarrow A = (a_{ij})$$

Then we know the entries of $[T]_{B_V}$

$$[T]_{B_V} = \left[\begin{array}{ccc|ccc} a_{11} & \dots & a_{1m} & a_{1,m+1} & \dots & a_{1,n} \\ \vdots & & & \vdots & & \vdots \\ a_{m1} & \dots & a_{mm} & a_{m,m+1} & \dots & a_{mn} \\ \hline a_{m+1,1} & \dots & a_{m+1,m} & a_{m+1,m+1} & \dots & a_{m+1,n} \\ \vdots & & \vdots & \vdots & & \vdots \\ a_{n1} & \dots & a_{nm} & a_{n,m+1} & \dots & a_{nn} \end{array} \right] = \begin{bmatrix} A_1 & A_2 \\ A_3 & A_4 \end{bmatrix}$$

Prop:

Here are some properties of minimal/characteristic polynomials we know from the determinant.

- i) The characteristic polynomial of $T|_W$ divides that of T .
- ii) The minimal polynomial of $T|_W$ likewise divides that of T .

PF:

- i) From our earlier work above we know

$$A = [T]_{B_V} = \begin{bmatrix} A_1 & A_2 \\ 0 & A_4 \end{bmatrix} \quad \& \quad [T|_W]_{B_W} = A_1.$$

Let $f(x)$ be the characteristic polynomial of T & $g(x)$ be that of $T|_W$

$$\begin{aligned} f(x) &= \det(xI - A) = \det \begin{bmatrix} xI - A_1 & -A_2 \\ 0 & xI - A_4 \end{bmatrix} \\ &= \det(xI - A_1) \det(xI - A_4). \\ &= g(x) \det(xI - A_4). \end{aligned}$$

Here it is clear that the characteristic polynomial of $T|_W$ $g(x)$ divides that of T $f(x)$.

- ii) Let $p(x)$ be the minimal polynomial of T & $q(x)$ be that of $T|_W$.

$$p(T) = 0 \Rightarrow p(T)v = 0 \quad \forall v \in V.$$

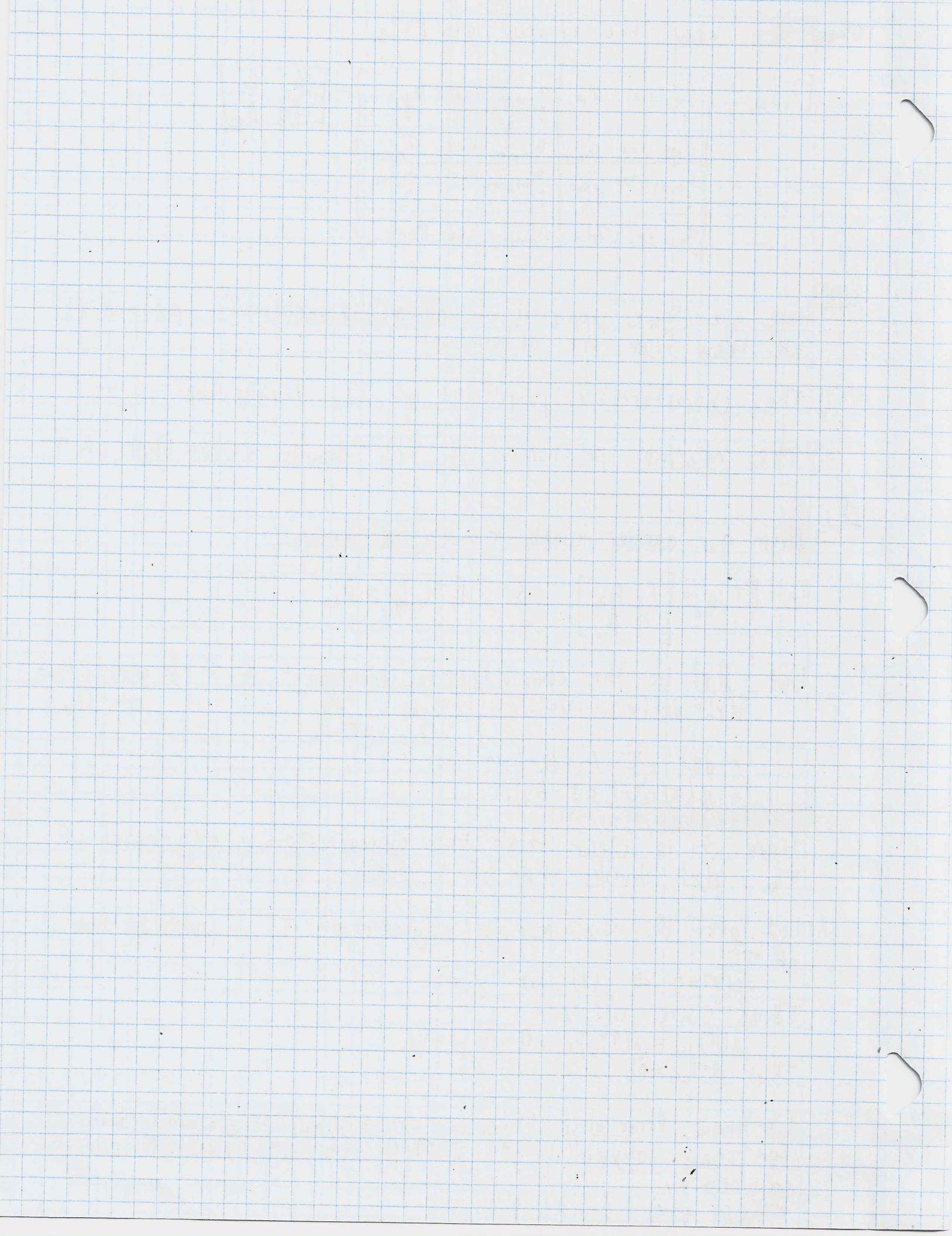
Thus since $w \in V$

$$p(T)w = p(T|_W)w = 0. \quad \forall w \in W.$$

$$\text{Thus } p(T|_W) = 0.$$

We know from our theorems on minimal polynomials that for some polynomial p^* $p^*(T^*) = 0$ iff A^* divides T^* 's minimal polynomial.

thus $q(x)$ divides $p(x)$. \square



Rem:

When W is T -invariant, T induces a linear operator \tilde{T} on the quotient space V/W defined as

$$\tilde{T}(v+W) = T_v + W \quad v \in V.$$

This is well defined b/c $w_1 + W = w_2 + W$ for all $w_1, w_2 \in W$. Since W is T -invariant we know $T_v \in W$ iff $v \in W$.

Rem:

A basis $B_{V/W}$ for V/W is

$$B_{V/W} = \{v_1 + W, \dots, v_m + W\}.$$

We remove v_1, \dots, v_m b/c $v_1, \dots, v_m \in W$. A $w + W$ is the zero vector for cosets & you don't include the zero vector in a basis.

In this case for $T \in \text{End}(V)$ where

$$[T]_{B_V} = \begin{bmatrix} A_1 & A_2 \\ 0 & A_3 \end{bmatrix} \quad \& \quad [T]_{B_W} = A_1$$

we know that the matrix for the induced linear operator

$B_{V/W}$ is

$$[T]_{B_{V/W}} = A_3$$

thus where we can write the minimal polynomial p_V of V as the product of that for W p_W & of V/W $p_{V/W}$

$$p_V(x) = p_W(x) p_{V/W}(x).$$

Def:

For a T -invariant subspace $W \subseteq V$ & $v \in V$, define I -conductor of v into W as

$$S(v; W) = \{g(x) \in F[x] \mid g(t) \in W\}.$$

This is an ideal in $F[x]$.

Thus since this is an ideal in $F[x]$ we know there exists a unique monic polynomial of minimum degree that generates it.

Thus $g \in S(v; W) \Leftrightarrow q_1 | g$. (q_1 divides g).

Rem:

i) The minimal polynomial $p(x)$ of T is in $S(v; W)$
 $p \in S(v; W)$.

Further $q_1 | p$.

For the zero subspace

$$S(V; \{0\}) = \{g(T) \in F[x] \mid g(T)v = 0\},$$

We call this the T -annihilator of v .

Example:

Consider an λ -eigenspace W of V . That is $W = \ker(T - \lambda I)$. By our properties of eigenspaces, we know W is T -invariant.

Notice that $T|_W = \lambda I_W$ where I_W is the identity operator of W .

The minimal polynomial of $T|_W$ is $x - \lambda \Rightarrow x - \lambda | p(x) \Rightarrow p(\lambda) = 0$, b/c $(\lambda - \lambda)^n = 0$.

Thus the characteristic polynomial of $T|_W$ is $(x - \lambda)^d$ where $d = \dim(W)$.
Thus $(x - \lambda)^d | f(x)$.

Triangulable Operators

A triangulable operator is an operator that can be expressed as a triangular matrix relative to some basis.

Recall:

A linear operator $T \in \text{End}(V)$ is diagonalizable if \exists basis B for V st $[T]_B$ is diagonal.

Def:

A linear operator $T \in \text{End}(V)$ is triangulable if \exists basis B for V st $[T]_B$ is triangular.

In this triangular case where

$$[T]_B = A = \begin{bmatrix} \lambda_1 & * \\ 0 & \ddots & \ddots \\ 0 & 0 & \lambda_n \end{bmatrix}$$

This is actually necessary & sufficient (theorem below).

We can easily find the characteristic polynomial $f(x)$ as

$$f(x) = (x - \lambda_1) \cdots (x - \lambda_n).$$

Notice that $\lambda_1, \dots, \lambda_n$ are our eigenvalues.

Thm:

A linear operator $T \in \text{End}(V)$ where $\dim(V) < \infty$ is triangulable iff the characteristic polynomial $f(x)$ is a product of linear factors. Likewise for the minimal polynomial $p(x)$.

Def:

A linear operator is called split if its minimal polynomial $p(x)$ can be written as / splits as a product of linear factors.

Cor:

Under an algebraically closed field (e.g. \mathbb{C}) which is one where all polynomials can be written as a product of linear factors, all linear operators are split & thus triangulable.

This is one reason why using complex numbers \mathbb{C} is so popular in practice.

Pf: Triangulable & Char./min. Polynomials pt. 1

Here we prove

(1) $T \in \text{End}(V)$ is triangulable

(2) \Leftrightarrow char. polynomial $f(x) = \text{product of linear factors}$

(3) \Leftrightarrow min. polynomial $p(x) = \text{product of linear factors}$

To show (1) \Leftrightarrow (2) \Leftrightarrow (3), we prove (1) \Rightarrow (2), (2) \Rightarrow (3), (3) \Rightarrow (1), thus giving us a circle which shows they are equivalent.

We have already shown (1) \Rightarrow (2). The proof was if $T \in \text{End}(V)$ is triangulable then

$$\begin{aligned} [T] &\stackrel{\sim}{=} \begin{bmatrix} x_1 & * \\ * & x_2 \\ \vdots & \ddots \\ 0 & x_n \end{bmatrix} \Rightarrow f(x) = \det(xI - [T]) = \det \begin{bmatrix} x-x_1 & \dots & 0 \\ \vdots & \ddots & x-x_n \\ 0 & \dots & 0 \end{bmatrix} \\ &= (x-x_1) \cdots (x-x_n). \end{aligned} \quad \underline{(1) \Rightarrow (2)}$$

We will show (2) \Rightarrow (3) using Cayley-Hamilton's theorem. However, we haven't proven that yet. As such, we will prove (3) \Rightarrow (1) next & then come back to (2) \Rightarrow (3) after a diversion to prove Cayley-Hamilton's

Now we show (3) \Rightarrow (1). Let $B = \{v_1, \dots, v_n\}$ be basis for V . Suppose the minimal polynomial $p(x)$ of T is a product of linear factors.

Let $A = (a_{ij})$ be the matrix for T relative to B , so

$$Tv_j = \sum_{i=1}^n a_{ij} v_i \quad \begin{array}{l} \text{Note: upper triangular} \\ \text{& lower} \\ \text{triangular equivalent} \end{array}$$

For the matrix A to be upper triangular iff

$$a_{ij} = 0 \quad \forall i > j$$

$$\Leftrightarrow Tv_j = \sum_{i=1}^j a_{ij} v_i \in \text{span}\{v_1, \dots, v_j\} = V_j. \quad \forall j \in \{1, \dots, n\}$$

Then

$$\begin{aligned} V_0 &= \{0\} \subseteq V_1 = \text{span}\{v_1\} \subseteq V_2 = \text{span}\{v_1, v_2\} \subseteq \dots \subseteq V_n = V \\ \dim(V_0) &= 0 \quad \dim(V_1) = 1 \quad \dim(V_2) = 2 \quad \dots \quad \dim(V_n) = n \end{aligned}$$

This sequence of subspaces V_0, \dots, V_n is called a Flag. (diversion)

Def:

A flag in vector space V is a increasing sequence of subspaces

$$V_0 = \{0\} \subset V_1 \subset \dots \subset V_n = V$$

such that

$$\dim(V_j) = j \quad \forall j \in \{1, \dots, n\}$$

Note: If you have a flag you can always choose basis $B = \{v_1, \dots, v_k\}$ s.t. $\{v_1, \dots, v_j\}$ is basis for V_j . You can prove this inductively by starting w/ the trivial basis for V_0 & repeatedly extending it to be a basis for V_{j+1} .

Idea:

A linear operator $T \in \text{End}(V)$ is triangulable iff it preserves some flag $V_0 \subset \dots \subset V_n$, that is each V_j is T -invariant.

Alright, we can almost restart our big proof. But first a lemma.

Lemma:

Let T be a split linear operator. Let $W \subset V$ be a T -invariant subspace. Then $\exists v \in V$ where $v \notin W$ w/ an eigenvalue λ s.t. $(T - \lambda I)v \in W$.

Pf:

Pick some $u \in V$ where $u \notin W$ (possible b/c $W \subset V$). Consider the T -conductor of u into W

$$S(u; W) = \{g(x) \in F[x] \mid g(T)u \in W\}.$$

Let $q(x)$ be a generator of the ideal $S(u; W)$. Then we know $q(x)$ divides the minimal polynomial $p(x)$ $q(x) | p(x)$. This is true b/c $p(x) \in S(u; W)$. We know this b/c $p(T) = 0$ & $0 \in W$ is always true.

Since T is a split linear operator we know $p(x)$ is a product of linear factors. Since $q(x)$ divides $p(x)$, we know $q(x) = \text{product of linear factors}$.

Thus $\exists \lambda \in F$ s.t. $q(\lambda) = 0$, b/c $q(x)$ is product of linear factors. Therefore we can factor out this λ to give us

$$q(x) = (x - \lambda) h(x) \text{ for some } h \in F[x].$$

Since $\deg(h) = \deg(q) - 1$, we know $h \notin S(u; W)$. We know this b/c since $q(x)$ is the generator of $S(u; W)$, it has minimal degree for polynomials in $S(u; W)$.

Since $h \notin S(u; W)$, we know $v = h(T)u \notin W$. We take this v & show $(T - \lambda I)v \in W$.

$$\begin{aligned} & (T - \lambda I)v \\ &= (T - \lambda I)h(T)u && (\text{Definition of } v) \\ &= q(T)u \in W && (\text{Definition of } q) \\ &\Rightarrow q(T)u \in W && (q(T)u \in S(u; W)) \end{aligned}$$

We have found a $v \in V$ where $v \notin W$ such that $(T - \lambda I)v \in W$.

Now we can finish $(3) \Rightarrow (1)$.

Pf: Triangulable $\&$ Char./Min. Polynomials pt. 2

(Continuing our work on $(3) \Rightarrow (1)$, we construct a T -invariant flag by induction.)

Start from $V_0 = \{0\}$. V_0 is trivially T -invariant. This is the base case.

Now inductively assume V_j -subspace is T -invariant & wr basis $\{v_1, \dots, v_j\}$. Then using our lemma we find a $v_{j+1} \in V$ where $v_{j+1} \notin V_j$ such that $(T - \lambda_{j+1} I)v_{j+1} \in V_j$ for some $\lambda_{j+1} \in F$.

Thus $Tv_{j+1} \in V_{j+1}$ where $V_{j+1} = V_j + FV_{j+1} = \text{Span}\{V_1, \dots, V_j, V_{j+1}\}$. 8

Rem:

For every split linear operator $T \exists$ basis $B = \{V_1, \dots, V_n\}$ st $[T]_B = \begin{bmatrix} \lambda_1 & * \\ \vdots & \ddots \\ 0 & \lambda_n \end{bmatrix}$.

If we take $V_j = \text{Span}\{V_1, \dots, V_j\} \quad j \in \{1, \dots, n\}$, we get $(T - \lambda_{j+1}I)v_{j+1} \in V_j \Rightarrow (T - \lambda_{j+1}I)v_i \in V_j \quad \forall i \in \{1, \dots, j+1\}$.

We will use this to prove Cayley-Hamilton's theorem.

Ihm: Cayley-Hamilton's Theorem (Again)

If you have a linear operator $T \in \text{End}(V)$, w/ characteristic polynomial $f(x)$. We know that the following holds for the corresponding matrix polynomial (again called $f(T)$)

$$f(T) = 0 + 0 \text{ matrix.}$$

pf:

We will prove this for only split linear operators.

What if the linear operator isn't split? If we extend to an algebraically closed field, then the linear operator must be split b/c we know we can factor the characteristic polynomial b/c we can completely factor all polynomials over an algebraically closed field (e.g. \mathbb{C}). We can always extend to an algebraically closed field b/c of topics in abstract algebra I haven't covered yet.

Let $T \in \text{End}(V)$ be a split linear operator. Then by our earlier part of the theorem, we know T is triangulable.

$$[T]_B = \begin{bmatrix} \lambda_1 & * \\ \vdots & \ddots \\ 0 & \lambda_n \end{bmatrix} \quad \text{w/ } B = \{V_1, \dots, V_n\}$$

Thus, the characteristic polynomial $f(x)$ is

$$f(x) = (x - \lambda_1) \cdots (x - \lambda_n)$$

Consider the following where $V_j = \text{Span}\{V_1, \dots, V_j\}$.

$(T - \lambda_j I)v_i \in V_{j-1} \Leftrightarrow (T - \lambda_j I)V_i \subseteq V_{j-1} \quad \forall 1 \leq i \leq j$ must be true, which you can convince yourself of by doing the subtraction.

(We use subspaces rather than vectors for simplicity below.)

Now we want to show $f(T)V=0$ to show $f(T)=0$, (R)

$$f(T)V = (T-\lambda_1 I) \cdots (\underbrace{T-\lambda_n I}_{\in V_{n-1}}) V_{n-1}$$

$$= (T-\lambda_1 I) \cdots (\underbrace{T-\lambda_{n-1} I}_{\in V_{n-1}}) V_{n-1} \\ \subseteq V_{n-2}$$

$$= \underbrace{(T-\lambda_1 I)}_{\subseteq V_0} V_1$$

$$= V_0 = \{0\} = 0$$

Thus $f(T)V=0$. Therefore $f(T)=0$. \square

Now with Cayley-Hamilton's Theorem proven we can finally tackle the last bit of our proof $(2) \Rightarrow (3)$.

DE: Triangulable & Char./Min. Polynomials pt. 3

We now show $(2) \Rightarrow (3)$. That is we show if the characteristic polynomial $f(x)$ of some linear operator T is split (i.e. factorable), then the minimal polynomial $p(x)$ of T is split.

If $f(x)$ is split then $p(x)$ is split b/c $p(x)$ divides $f(x)$ by Cayley-Hamilton's theorem.

We therefore conclude that

$T \in \text{End}(V)$ is triangulable

\Leftrightarrow char. polynomial $f(x) = \text{product of linear factors} / f(x) \text{ split}$

\Leftrightarrow min. polynomial $p(x) = \text{product of linear factors} / p(x) \text{ split}$

Diagonalizable Operators

Recall:

Linear operator $T \in \text{End}(V)$ is diagonalizable iff \exists basis $B = \{v_1, \dots, v_n\}$ s.t

$$[T]_B = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

By the definition of linear operators being applied wrt a basis, we know

$$Tv_j = \lambda_j v_j \quad \forall j \in \{1, \dots, n\}$$

Again by doing simple matrix subtraction we get $(T - \lambda_j I)v_j = 0$.

With such a T we know the characteristic polynomial $f(x)$ is

$$f(x) = (x - \lambda_1) \cdots (x - \lambda_n)$$

& by Cayley-Hamilton's theorem we get

$$f(T) = 0$$

& also by simple application of the definition of the characteristic polynomial $f(x)$ we get

$$f(T)v_j = 0 \quad \forall j \in \{1, \dots, n\} \Rightarrow f(T) = 0$$

Suppose $\lambda_1, \dots, \lambda_k$ are distinct ($\lambda_i \neq \lambda_j$ for $1 \leq i, j \leq k$). Reorder the list such that all λ_i 's copies are after λ_{i+1} 's.

Take the minimal polynomial $p(x)$ to be

$$p(x) = (x - \lambda_1) \cdots (x - \lambda_k)$$

Since we already have all unique diagonal entries, we know
 $p(T) = 0$ b/c $p(T)v_j = 0 \quad \forall j \in \{1, \dots, n\}$

We know this $p(x)$ is the minimal polynomial b/c all roots are distinct & if one root did not exist then $p(T) \neq 0$.

Thm:

A linear operator $T \in \text{End}(V)$ is diagonalizable if & only if its minimal polynomial $p(x)$ is a product of distinct linear factors.

PF:

Our earlier proof proves

T diagonalizable $\Rightarrow p(x)$ has distinct roots. \square

Now we prove

$p(x)$ has distinct roots $\Rightarrow T$ diagonalizable

Suppose $p(x) = (x - \lambda_1) \cdots (x - \lambda_k)$ where $\lambda_i \neq \lambda_j$ for $1 \leq i < j \leq k \leq n = \dim(V)$

Consider all eigenspace (W_j is λ_j -eigenspace)

$$W_j = \text{Ker}(T - \lambda_j I).$$

Take $W = W_1 + \cdots + W_k = \text{Span}$ of eigenvectors.

We want to show $W = V$ b/c then we have V is spanned by distinct eigenvectors of T , meaning T has n distinct eigenvectors, meaning T is diagonalizable (take basis of eigenvectors).

Assume for contradiction that $W \neq V$. By our earlier lemma we know $\exists v \in V$ where $v \notin W$ & an eigenvalue λ st $(T - \lambda I)v \in W$.

B/c $(T - \lambda I)v = w \in W$ & W is spanned by eigenvectors, we know we can write this as a sum (or linear combination) of eigenvectors

$$(T - \lambda I)v = w_1 + w_2 + \cdots + w_k \quad \text{where } w_1, \dots, w_k \text{ are eigenvectors}$$

$$\Leftrightarrow w_j \in W_j \quad \text{and} \quad Tw_j = \lambda_j w_j.$$

Likewise $\lambda = \lambda_i$ for some $i \in \{1, \dots, k\}$.

Now we can write the min. polynomial $p(x)$ as
 $p(x) = (x - \lambda_i) h(x)$ where $h(x) = \prod_{j \neq i} (x - \lambda_j)$

Thus using $w_i = (T - \lambda_i I)v$, we get
 $h(T)w = h(T)(T - \lambda_i I)v = p(T)v = 0$

Likewise since $w = w_1 + \dots + w_k$ we get
 $h(T)w = h(T)w_1 + \dots + h(T)w_k$
 $= h(\lambda_1)w_1 + \dots + h(\lambda_k)w_k$ (b/c $f(T)v = f(\lambda)v$ where λ eigenvalue for v under f)
 $= h(\lambda_i)w_i$ (definition of h)

Since $h(T)w = h(\lambda_i)w_i = 0$ & $h(\lambda_i) \neq 0$, we know $w_i = 0$.

Now consider $u = v - \sum_{j \neq i} \frac{w_j}{\lambda_j - \lambda_i}$

$$\begin{aligned} \text{Now apply } (T - \lambda_i I) \text{ to } u \text{ to get} \\ (T - \lambda_i I)u &= (T - \lambda_i I)v - \sum_{j \neq i} \frac{(T - \lambda_i I)w_j}{\lambda_j - \lambda_i} \\ &= (T - \lambda_i I)v - \sum_{j \neq i} \frac{(\lambda_j - \lambda_i)w_j}{\lambda_j - \lambda_i} \quad \text{replace } T \text{ w/ eigenvalue} \\ &= (T - \lambda_i I)v - w \\ &\in W - W \\ &= 0 \end{aligned}$$

B/c $(T - \lambda_i I)u = 0$, we know $u \in W_i$. However, that would mean
 $v \in W_i$ b/c of closure under vector addition.

This is a contradiction so $W = V$, V is spanned by $k = n$ distinct eigenvectors,
& thus T is diagonalizable.

Coro:

If T is diagonalizable & W is a T -invariant subspace, then
 $T|_W$ is also diagonalizable.

Def:

The minimal polynomial of $T|_W$ divides the minimal polynomial of T .

Thus if T 's min. polynomial is a product of linear factors then so is $T|_W$.

Simultaneous Diagonalization

Def

A set of linear operators $\mathcal{F} \subseteq \text{End}(V)$ can be simultaneously diagonalized
if \exists basis B for V st $[T]_B$ is diagonal for all $T \in \mathcal{F}$.

Recall that all diagonal matrices commute w/ each other.

Thm:

A set $\mathcal{F} \subset \text{End}(V)$ of linear operators is simultaneously diagonalizable iff

- Every $T \in \mathcal{F}$ is diagonalizable
- $\forall T, S \in \mathcal{F}, TS = ST$.

Pf: \Rightarrow

Suppose $B = \{v_1, \dots, v_n\}$ such that it diagonalizes all linear operators $T \in \mathcal{F}$ (i.e. $[T]_B$ diagonal $\forall T \in \mathcal{F}$).

Then for every $T \in \mathcal{F}$, B is a basis of eigenvectors, that is $Tv_i = \lambda_i v_i \quad \forall i \in \{1, \dots, n\}$. (Note that λ_i depends on T .)

Take some other $S \in \mathcal{F}$. Similarly,

$$Sv_i = \mu_i v_i \quad \forall i \in \{1, \dots, n\}.$$

We now show T & S commute by considering

$$(TS)v_i = T(Sv_i) = T(\mu_i v_i) = \mu_i T(v_i) = \mu_i \lambda_i v_i \quad \&$$

$$(ST)v_i = S(Tv_i) = S(\lambda_i v_i) = \lambda_i S(v_i) = \lambda_i \mu_i v_i.$$

Since $(TS)v_i = (ST)v_i$, we know TS & ST agree on a basis. Thus $TS = ST \quad \forall T, S \in \mathcal{F}$ (ii)

Trivially, we know every $T \in \mathcal{F}$ is diagonalizable b/c it's diagonalized by B . (i)

We've thus proven the forward direction.

Pf: \Leftarrow

Suppose every $T \in \mathcal{F}$ is diagonalizable & $TS = ST \quad \forall T, S \in \mathcal{F}$.

To prove that \mathcal{F} is simultaneously diagonalizable we use induction.

Pick some $T \in \mathcal{F}$. Since it is diagonalizable it has an eigenvalue $\lambda \in \mathbb{C}$ & a corresponding λ -eigenspace, $W = \text{Ker}(T - \lambda I)$.

In the case where $W = V$, then $T = \lambda I$, which is trivially diagonalizable in every basis.

In the case where $W \subset V$ is a proper subspace, then W is S -invariant $\forall S \in \mathcal{F}$. We know this b/c the operators commute.

Let us briefly show this. Let $w \in W = \ker(T - \lambda I)$

$$\begin{aligned} T_w &= 0 \\ \Rightarrow ST_w &= 0 \\ \Rightarrow TS_w &= 0 \\ \Rightarrow SW \in \ker(T - \lambda I) &= W \\ \Rightarrow W &\text{ is } S\text{-invariant} \end{aligned}$$

Consider the restrictions $S|_W$. Then $S|_W$ is diagonalizable b/c W is S -invariant & S is diagonalizable. (earlier proof)

Moreover, since all $S, R \in \mathcal{F}$ commute & are invariant on W , $S|_W$ & $R|_W$ commute $\forall S, R \in \mathcal{F}$.

By induction (or really recursion), there is a basis B_W for W st $[S]_{B_W}$ is diagonal $\forall S \in \mathcal{F}$.

Essentially, we keep going until we hit the trivial space. At each level we get an eigenvector $w \in W$.

Do this for every eigenspace of T . Since T is diagonalizable when we union all these bases, we get a basis for V in which all $S \in \mathcal{F}$ is diagonal. \square

Rem:

There is a similar result for simultaneous triangulation.

That is every set of commuting, triangulable/split linear operators can be made simultaneously triangular wrt to some basis.

Note: Commuting is sufficient but not necessary.

Direct Sums & Projections

Def:

Let W_1, \dots, W_k be subspaces of a vector space V . The sum of these subspaces is defined as

$$\sum_i W_i = W_1 + \dots + W_k = \{w_1 + \dots + w_k \mid w_i \in W_i\} = \text{span}(W_1, V, \dots, V, W_k).$$

We know $\sum_i W_i$ is a subspace of V (by closure)

Def:

Let $W = W_1 + \dots + W_k$ for some subspaces W_1, \dots, W_k of vector space V . We say W is a direct sum, denoted $W = W_1 \oplus \dots \oplus W_k$, iff there is a unique way to write $w \in W$ as $w = w_1 + \dots + w_k$ where $w_i \in W_i$.

$w = w_1 + \dots + w_k$ where $w_i \in W_i$
for all $w \in W$.

Equivalently iff W_1, \dots, W_k are independent in that $w_i A w_j = \underbrace{\text{for } i \neq j}_{0}$ or likewise

$w_1 + \dots + w_k = 0$ where $w_i \in W_i$ iff $w_1 = \dots = w_k = 0$.

Or likewise $\{w_1, \dots, w_k\}$ is linearly independent & $w_i \in W_i$ where $w_i \neq 0$.

Example:

Consider $B = \{v_1, \dots, v_n\} \subset V$. Let $W_i = \text{span}\{v_i\} = Fv_i$.

Let $W_i = \text{span}\{v_i\} = Fv_i$. Then B is a basis if & only if $V = W_1 \oplus \dots \oplus W_n$.

Example:

Let $\lambda_1, \dots, \lambda_k$ be distinct eigenvalues $T \in \text{End}(V)$.

Consider the eigen spaces $W_i = \ker(T - \lambda_i I)$.

Recall that if you have eigenvectors v_1, \dots, v_k w/ eigenvalues $\lambda_1, \dots, \lambda_k$ where all the eigenvalues are distinct, then the vectors are linearly independent.

Using this we know $W = W_1 \oplus \dots \oplus W_k$.

Note that $W = V$ if & only if T is diagonalizable (i.e. $k = \dim(V)$).

Example:

Consider $V = F^{n \times n}$.

Let $W_1 = \{A \in V \mid A \text{ is symmetric} \Leftrightarrow A^t = A\}$

Let $W_2 = \{A \in V \mid A \text{ is skew-symmetric} \Leftrightarrow A^t = -A\}$ { kinda like even & odd }

We show $V = W_1 \oplus W_2$.

Take some matrix $A \in V$. We want to write $A = B + C$ where $B \in W_1 \Leftrightarrow B^t = B$ & $C \in W_2 \Leftrightarrow C^t = -C$. We use these identities along w/ the properties of transpose to give us

$$A = B + C$$

$$A^t = B - C \quad \leftarrow (A^t = B^t + C^t)$$

We can then use elimination to give us

$$B = \frac{1}{2}(A + A^t)$$

$$C = \frac{1}{2}(A - A^t)$$

This assumes we can divide by 2, that is the characteristic of the field isn't two $\text{char}(F) \neq 2$.

We thus have shown how to write any matrix $A \in V$ as a sum of $B \in W_1$ & $C \in W_2$. By the definition of W_1 & W_2 we know $W_1 \cap W_2 = \{0\}$, so W_1 & W_2 are independent. (Work below.)

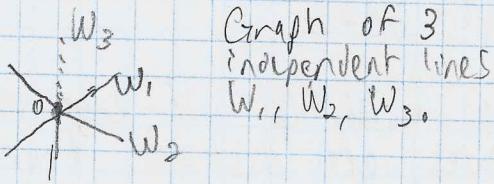
Thus we conclude $V = W_1 \oplus W_2$.

We again show that W_1 & W_2 are independent.

Suppose $B = B' + C$ for some $B, B' \in W_1$ & $C, C' \in W_2$. We show $B = B'$ & $C = C'$.
 Then $B - B' = C - C'$. Using the transpose we get
 $B - B' = C - C' \Rightarrow (B - B')^T = (C - C')^T \Rightarrow B - B' = C + C'$
 Therefore $B - B' = C + C' = 0$, so $B = B'$ & $C = C'$.
 Thus W_1 & W_2 are independent.

Example:

Consider $V = \mathbb{R}^3$ w/ 3 lines W_1, W_2, W_3 . We know $\dim(W_i) = 1$ & in particular $W_i = Fw_i$ where $w_i \in V$ & $w_i \neq 0$.



$$W_1 \cap W_2 = \{0\}$$

$\Leftrightarrow \{w_1, w_2\}$ are linearly independent

$\Leftrightarrow W_1 + W_2 = W_1 \oplus W_2$ is direct

$\Leftrightarrow W_1 \& W_2$ span a plane

Note that knowing every pair of lines is independent is not sufficient to show $\{W_1, W_2, W_3\}$ are independent b/c they may all fall w/in the same plane. That is

$$W_1 \oplus W_2 \& W_1 \oplus W_3 \& W_2 \oplus W_3 \not\Rightarrow W_1 \oplus W_2 \oplus W_3.$$

However, the converse is true

$$W_1 \oplus W_2 \oplus W_3 \Rightarrow W_1 \oplus W_2 \& W_1 \oplus W_3 \& W_2 \oplus W_3.$$

Note further than

$$W_1 \oplus W_2 \oplus W_3 \Leftrightarrow \{w_1, w_2, w_3\} \text{ basis for } V$$

Lemma:

\oplus is commutative & associative like you'd expect.

$$\text{Thus } W_1 \oplus W_2 \oplus W_3 = (W_1 \oplus W_2) \oplus W_3$$

Thm:

A sum $W_1 + \dots + W_k$ is direct if & only if $W_j \cap (W_1 + \dots + W_{j-1}) = \{0\} \quad \forall j = 2, \dots, k$

pf:

This is an application of $W_1 \oplus W_2 \oplus W_3 = (W_1 \oplus W_2) \oplus W_3$.

If this condition is equivalent to

$$W_1 \oplus W_2 \& (W_1 \oplus W_2) \oplus W_3, [(W_1 \oplus W_2) \oplus W_3] \oplus W_4, \text{ etc.}$$

If you use induction the proof falls as such.

Notation:

$$W = W_1 \oplus \dots \oplus W_k = \bigoplus_{i=1}^k W_i$$

(I also like $a_1 + \dots + a_n = \sum_{i=1}^n a_i$)

Thm:

Let B_i be a basis for $W_i \forall i \in \{1, \dots, k\}$ &
 $W = W_1 + \dots + W_k$. Then

Then $W = W_1 \oplus \dots \oplus W_k$ if & only if
 $B_i \cap B_j = \emptyset \forall i \neq j$ & B_1, \dots, B_k basis for W
which is equivalent to
the disjoint union $\bigsqcup_{i=1}^k B_i$ is a basis for W .

Coro:

Let V & W be independent spaces.

$$\dim(V \oplus W) = \dim(V) + \dim(W) \quad \text{From disjoint union of basis is basis}$$

Likewise $W = \bigoplus_{i=1}^r W_i$

$$\dim(\bigoplus_{i=1}^r W_i) = \sum_{i=1}^r \dim(W_i)$$

PF: \Rightarrow

Suppose $W = W_1 \oplus \dots \oplus W_k$. We show the B_i 's form a disjoint basis for W .

We show the bases are disjoint.

Suppose $v \in B_i \cap B_j$ for some $i \neq j$. Then $v \in W_i \cap W_j$. However W_i & W_j is independent, so $W_i \cap W_j = \{0\}$. Therefore $v = 0$. However no basis contains 0. This is a contradiction so the basis is disjoint.

We show the bases are a (disjoint) union for W .

Take $w \in W$. Then b/c W is a direct sum $\exists!$

$$\exists! w = w_1 + \dots + w_k \quad (w_i \in W_i)$$

Since $w_i \in W_i$, we know $w_i \in \text{span}(B_i)$. Thus b/c each $w_i \in W_i$, we know the sum w is in $\text{span}(B)$: $w \in \text{span}(B)$.

Now we show linear independence. For clarity index B_i by J_i . Then B is indexed by $J = \bigsqcup_{i=1}^k J_i$

Take $\sum_{j \in J} c_j v_j = 0$, where $B_i = \{v_j\}_{j \in J_i}$. We show $c_j = 0 \forall j \in J$.

We split this sum to basis for the corresponding subspaces.

$$\sum_{j \in J} c_j v_j = \left(\sum_{j \in J_1} c_j v_j \right) + \dots + \left(\sum_{j \in J_k} c_j v_j \right)$$

 W_1 W_k

Since W is a direct sum we know this sum of $\sum_{j \in J_i} c_j v_j \in W_i$ must be unique. Therefore

$$\sum_{j \in J_i} c_j v_j = 0 \quad \forall i \in \{1, \dots, k\}.$$

Thus $c_j = 0 \quad \forall j \in J$ & B is linearly independent.

Thus the disjoint union B forms a basis for W . \square

PF \square

Suppose the disjoint union $B = \bigsqcup_{i=1}^k B_i$ is a basis for $W = \sum_{i=1}^k W_i$ where B_i is a basis for W_i for all $i = 1, \dots, k$. We claim $W = \text{Span}(B) = \bigoplus_{i=1}^k W_i$.

We again index the B 's the same.

Take some $w \in W$. We know $w = \sum_{j \in J} c_j v_j$ b/c B is a basis for W .

Since B is a disjoint union of the B_i 's we know there is a unique way to write

$$w = \sum_{j \in J} c_j v_j = (\sum_{j \in J_1} c_j v_j) + \dots + (\sum_{j \in J_k} c_j v_j)$$

$$\in W_1 \quad \in W_k$$

b/c these summands are unique, we conclude $W = W_1 \oplus \dots \oplus W_k$.

projections

Let's start w/ a familiar example.

Example:

Consider $V = \mathbb{R}^2 = W_1 \oplus W_2$ where $W_1 = \mathbb{R}e_1$ & $W_2 = \mathbb{R}e_2$ where $e_1 = (1, 0)$ & $e_2 = (0, 1)$.

$\forall v = (x, y) \in \mathbb{R}^2 \quad v = x e_1 + y e_2$. Further this sum is unique,

We get our classic projections

$$v = (x, y) = (x, 0) + (0, y)$$

Projection Onto
x-axis / W_1 Projection Onto
y-axis / W_2

We can generalize this to any lines. Further we can do any vector space which is a direct sum of subspaces.

Def:

Let $V = W_1 \oplus \dots \oplus W_k$. Then $\forall v \in V \quad \exists ! v = w_1 + \dots + w_k$ where $w_i \in W_i$.

Define the projection of v onto W_i as

$$E_i(v) = w_i.$$

Thm:

E_1, \dots, E_k are linear operators on V w/ the properties

- i) $E_i^2 = E_i$ or E_i is idempotent $\forall i \in \{1, \dots, k\}$
- ii) $E_i \circ E_j = 0 \quad \forall i \neq j$ or likewise $E_i E_j = [0]$ $\forall i \neq j$ (as matrix)

i) $E_1 + \dots + E_k = I$ when E_i is defined as matrix wrt any basis 13
ii) $\text{Im}(E_i) = W_i$ (by definition)

Pf:

E_i is a linear operator on V . Let $v, v' \in V$ & $c \in F$.
B/c $\forall v, v' \in V$ we know that uniquely
 $v = w_1 + \dots + w_k$ & $v' = w'_1 + \dots + w'_k$

$$E_i(v+v') = w_i + w'_i = E(v) + E(v')$$

$$E_i(cv) = cw_i = cE(v). \quad \square$$

Thm:

Conversely if we have linear operators E_1, \dots, E_k that satisfy the previous theorems i, ii, & iii then $V = W_1 \oplus \dots \oplus W_k$ where $W_i = \text{Im}(E_i)$.

Pf:

Suppose we have some such linear operators E_1, \dots, E_k satisfying (i), (ii), & (iii).

Given property (iii), we write every $v \in V$ as

$$v = \sum_{i=1}^k v_i = (E_1 + \dots + E_k)v = E_1v + \dots + E_kv.$$

Thus we have a sum $v = w_1 + \dots + w_k$. We show this sum is direct by using (i) & (ii). $w_i \in W_i$

Consider $v = w_1 + \dots + w_k$. We show this is unique. B/c $\text{Im}(E_i) = W_i$, we know $\forall w_i \in W_i \quad w_i = E_i v_i$. We write

$$v = w_1 + \dots + w_k = E_1v_1 + \dots + E_kv_k$$

We apply E_i & use that

$$E_i w_j = E_i E_j v_j = 0 \quad \forall i \neq j \quad (\text{by (ii)})$$

$$E_i w_i = E_i E_i v_i = E_i v_i = w_i \quad (\text{by (i)})$$

Thus $w_i = E_i v_i$ is uniquely determined from v .

Thus the sum is unique & $V = W_1 \oplus \dots \oplus W_k$.

Example: Consider $\mathbb{R}^2 = \mathbb{R}e_1 \oplus \mathbb{R}e_2$ where $e_1 = (1, 0)$ & $e_2 = (0, 1)$.
Then $\forall v \in \mathbb{R}^2$

$$\Rightarrow \begin{cases} v = (x, y) = (x, 0) + (0, y) = xe_1 + ye_2 \\ E_1 v = E_1(x, y) = (x, 0) = xe_1 \\ E_2 v = E_2(x, y) = (0, y) = ye_2 \end{cases}$$

Example:

Consider $\mathbb{R}^2 = \mathbb{R}e_1 \oplus \mathbb{R}(e_1 + e_2)$.
Then $\forall v \in \mathbb{R}^2$

$$\Rightarrow \begin{cases} v = (x, y) = (x-y, 0) + (y, y) \\ E_1 v = E_1(x, y) = (x-y, 0) \\ E_2 v = E_2(x, y) = (y, y) \end{cases}$$

Notice that the spaces effect the other projections, even if the projecting space doesn't change.

Def:

A projection on a vector space V is a linear operator E such that
 $E^2 = E$,
That is an idempotent linear operator.

Lemma: Let E be a projection operator on V . Let $\overbrace{R = \text{Im}(E)}$ & $\overbrace{N = \text{Ker}(E)}$.
 R & N are subspaces of V . Then we know
 i) $V = R \oplus N$ (like rank nullity theorem),
 ii) $v = Ev + (I-E)v \quad \forall v \in V$. That is $(I-E)v \in N$,
 iii) $E|_R = I$ & $E|_N = 0$.
 iv) $I-E$ is a projection onto N . That is $\text{Im}(I-E) = N$ & $\text{Ker}(I-E) = R$
 This comes from solving the above equations.

Example:

Consider $V = F^{nm}$ & $T \in \text{End}(V)$ where $T(A) = A^t$.

Here you can easily see $T^2 = I$ b/c $(A^t)^t = A$. From this we get
 $(T-I)(T+I) = 0$

Which means the minimal polynomial of T divides $x^2 - 1$, so the eigenvalues are 1 & -1 .

Going further w/ these eigenvalues we see the eigenspaces are the symmetric matrices ($\lambda = 1$) & skew symmetric matrices ($\lambda = -1$).

$$W_1 = \{A \in V \mid A^t = A\} = \text{Ker}(T-I)$$

$$W_2 = \{A \in V \mid A^t = -A\} = \text{Ker}(T+I)$$

We earlier showed you can write every matrix as the sum of a symmetric matrix & skew symmetric matrix by doing
 $A = \frac{1}{2}(A + A^t) + \frac{1}{2}(A - A^t)$.

Thus we know $V = W_1 \oplus W_2$. Using this fact we can consider the projections onto symmetric & skew symmetric matrices by
 $E_1 = \frac{1}{2}(I+T)$ & $E_2 = \frac{1}{2}(I-T)$.

We can generalize this!

Prop:

Let V be a vector space (including ∞ dimensional). Let T be a linear operator of finite order, that is $T \in \text{End}(V)$ where $T^N = I$, for some $N \geq 1$.

Then the eigenvalues of T are the N th roots of 1 (unity).

$$\text{A: } V = W_0 \oplus \dots \oplus W_{N-1} \text{ where } W_j = \text{Ker}(T - e^{2\pi i j/N} I) \quad 0 \leq j \leq N-1.$$

The corresponding projections are

$$E_j = \frac{1}{N} \sum_{k=0}^{N-1} e^{-2\pi i j k/N} T^k. \quad \leftarrow \text{ kinda like averaging}$$

In particular T is diagonalizable b/c it has N eigenvalues.

Invariant Direct Sums

These are direct sums of subspaces that are all invariant under some linear operators. It is important for induction.

Thm:

A direct sum $V = W_1 \oplus \dots \oplus W_k$ is T -invariant if & only if each subspace W_i is T -invariant, that is $T w_i \in W_i \forall w_i \in W_i$.

This gives us the restriction operators

$$T_i = T|_{W_i} \in \text{End}(W_i).$$

Using this we can write T for V . Take some $v \in V$.

$$\text{B/C } V = W_1 \oplus \dots \oplus W_k, \exists! v = w_1 + \dots + w_k. \text{ Thus}$$

$$T v = T w_1 + \dots + T w_k = T_1 w_1 + \dots + T_k w_k$$

Using this definition we write $T = T_1 \oplus \dots \oplus T_k = (T_1, \dots, T_k)$. This gives us a (meta) linear map $T \mapsto T_1 \oplus \dots \oplus T_k$, which is in $\text{End}(W_1) \oplus \dots \oplus \text{End}(W_k)$.

Conversely, any k -tuple (T_1, \dots, T_k) where $T_i \in \text{End}(W_i)$ defines a $T \in \text{End}(V)$ such that $V = W_1 \oplus \dots \oplus W_k$ is T -invariant.

Lemma:

Let B_i be a basis for $W_i \quad \forall i = 1, \dots, k$. Then $B = \bigcup_{i=1}^k B_i$ is a basis for V .

If a direct sum is T -invariant then (Note: $[T]_B$ is block diagonal)

$$[T]_B = \begin{bmatrix} A_1 & & \\ & \ddots & \\ 0 & & A_k \end{bmatrix} \text{ where } [A_i] \equiv [T_i]_{B_i}$$

The direct sum of matrices A_1, \dots, A_k is defined as the block-diagonal matrix

$$A_1 \oplus \dots \oplus A_k = \begin{bmatrix} A_1 & & \\ & \ddots & \\ 0 & & A_k \end{bmatrix}$$

Recall that given $V = W_1 \oplus \dots \oplus W_k$ we get projection operators $E_1, \dots, E_k \in \text{End}(V)$ by

$$V = W_1 + \dots + W_k = E_1 V + \dots + E_k V, \text{ so } E_i v = w_i \quad \forall i=1..k.$$

These projections satisfy the necessary properties

- i) $E_i^2 = E_i \quad \forall i$
- ii) $E_i E_j = 0 \quad \forall i \neq j$
- iii) $E_1 + \dots + E_k = I$
- iv) $W_i = \text{Im}(E_i) \quad \forall i$

Recall further the direct sum decomposition $V = W_1 \oplus \dots \oplus W_k$ is T -invariant iff

- $\forall w_i \in W_i \quad \forall w_i \in W_i$
- $\forall w_i \in E_i v \quad T E_i v \in W_i = \text{Im}(E_i)$
- $\exists v \in V \text{ such that } T E_i v = E_i u \text{ for some } u \in W_i \quad \forall i$

This doesn't go anywhere

More clearly

$$\begin{aligned} V &= W_1 + \dots + W_k \quad \text{where } w_i = E_i v \in W_i; \\ \Rightarrow T v &= T w_1 + \dots + T w_k \quad \text{b/c subspaces } T\text{-invariant} \\ &\in W_1 + \dots + W_k \end{aligned}$$

Thus b/c W_i is T -invariant $T w_i = T E_i v = E_i T v$. This is actually sufficient to show W_i is T -invariant

Ihm: A direct sum is T -invariant iff T commutes w/ the corresponding projection operators E_1, \dots, E_k .

If you recall, all diagonal matrices commute. This gives some nice properties.

Diagonalizable Operators

Suppose T is diagonalizable w/ distinct eigenvalues $\lambda_1, \dots, \lambda_k$. This gives us eigenspaces $W_i = \text{Ker}(T - \lambda_i I)$.

B/c T is diagonalizable we know $V = W_1 \oplus \dots \oplus W_k$. Further $T|_{W_i} = \lambda_i I$.

In terms of matrices, the matrix of the operator is block diagonal

$$[T] = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ 0 & & \lambda_k \end{bmatrix}$$

where

$$A_i = [T|_{W_i}] = \begin{bmatrix} \lambda_i & 0 \\ 0 & \lambda_i \end{bmatrix}.$$

Thus the whole matrix is diagonal (duh).

This gives us minimal polynomial $p(x)$

$$p(x) = (x - \lambda_1) \cdots (x - \lambda_k)$$

B/C $V = W_1 \oplus \dots \oplus W_k$, we know $\exists! v = w_1 + \dots + w_k$. B/C the W_i 's are eigenspaces, we can simplify the calculation of Tv to $Tv = Tw_1 + \dots + Tw_k = \lambda_1 w_1 + \dots + \lambda_k w_k$.

We can generalize this to polynomials of the linear operator so for all $g(x) \in F[x]$

$$\begin{aligned} g(T)v &= g(T)w_1 + \dots + g(T)w_k \\ &= g(\lambda_1)w_1 + \dots + g(\lambda_k)w_k. \end{aligned}$$

We want to find the polynomials g_j such that $g_j(\lambda_i) = 1 \quad \forall i \quad \text{and} \quad g_j(\lambda_j) = 0 \quad \forall i \neq j$.

Recall:

To find these g_j 's we want the Lagrange interpolation polynomials

$$L_j(x) = \prod_{\substack{1 \leq i \leq k \\ i \neq j}} \frac{x - \lambda_i}{\lambda_j - \lambda_i}$$

By this definition of L_j ,

$$L_j(\lambda_i) = \delta_{ij}$$

Applying the Lagrange polynomials to our problem

$$\begin{aligned} L_j(T)v &= L_j(T)w_1 + \dots + L_j(T)w_k \\ &= L_j(\lambda_1)w_1 + \dots + L_j(\lambda_k)w_k \\ &= w_j = E_j v \end{aligned}$$

eigenspaces of T

Thus we have explicitly found the projections of $V = \underbrace{W_1 \oplus \dots \oplus W_k}$, so $E_j = L_j(T)$.

Ihm:

If the minimal polynomial of $T|End(V)$ is $p(x) = (x - \lambda_1) \cdots (x - \lambda_k)$ w/ $\lambda_i \neq \lambda_j \quad \forall i \neq j$

Then T is diagonalizable w/ eigenspaces

$$W_i = \ker(T - \lambda_i I).$$

So $V = W_1 \oplus \dots \oplus W_k$ w/ projections

$$E_i = L_i(T).$$

PF:

To prove $V = W_1 \oplus \dots \oplus W_k$, we check that $E_i = L_i(T)$ satisfy the earlier properties

i) $E_i^2 = E_i$

ii) $E_i E_j = 0 \quad \forall i \neq j$

iii) $E_1 + \dots + E_k = 0$

we can do this only using that $p(0)=0$.

First we show (i), that is $E_i^2 = L_i(T)^2 = E_i = L_i(T)$. Equivalently we show $L_i(T)^2 - L_i(T) = L_i(T)(L_i(T) - I) = 0$.

The polynomial $L_i(x)(L_i(x) - I) = 0$ for $x = \lambda_j$ $\forall j = 1, \dots, k$. This is b/c $L_i(\lambda_j) = 0 \forall i \neq j$ & $L_i(\lambda_i) = 1$.

b/c $L_i(x)(L_i(x) - I)$ has roots $\lambda_1, \dots, \lambda_k$, then we know the minimal polynomial $p(x)$ divides $L_i(x)(L_i(x) - I)$.

b/c $p(x)$ divides $L_i(x)(L_i(x) - I)$ & $p(T) = 0$, we know $L_i(T)(L_i(T) - I) = 0 \Leftrightarrow L_i(T)^2 = L_i(T)$. We do this for all i .

Now we show (ii). We show $E_i E_j = 0 \forall i \neq j$, or equivalently $L_i(T) L_j(T) = 0$. We know

$L_i(x) L_j(x) = 0$ for $x = \lambda_1, \dots, \lambda_k$
b/c at least one will be 0. b/c of this we know $p(x)$ divides $L_i(x) L_j(x)$. Since $p(T) = 0$, we know $L_i(T) L_j(T) = 0 \forall i \neq j$.

Now we show (iii). We show $E_1 + \dots + E_k = I$. Consider $L_i(x) + \dots + L_k(x) - I$. We know

$L_i(x) + \dots + L_k(x) - I = 0$ for $x = \lambda_1, \dots, \lambda_k$
Thus $L_i(x) + \dots + L_k(x) - I$ has roots $\lambda_1, \dots, \lambda_k$. Thus $p(x)$ divides it. Since $p(T) = 0$, we know $L_i(T) + \dots + L_k(T) = I$.

From (i), (ii), & (iii), it follows that $V = W_1 \oplus \dots \oplus W_k$ where $W_i = \text{Im}(L_i(T)) = \text{Im}\left(\prod_{\substack{j \in \{1, \dots, k\} \\ j \neq i}} T - \lambda_j I\right)$

To finish this off we just need to show $W_i = \text{Ker}(T - \lambda_i I)$. We do this by double set inclusion.

If $w \in \left(\prod_{j \neq i} T - \lambda_j I\right) v \in W_i$ then $(T - \lambda_i I)w = p(T)v = 0$. Thus $w \in \text{Ker}(T - \lambda_i I)$.

Conversely, take any $w \in \text{Ker}(T - \lambda_i I)$. We show $w \in W_i$. b/c $V = W_1 \oplus \dots \oplus W_k$ we know $w = w_1 + \dots + w_k$, thus

$Tw = Tw_1 + \dots + Tw_k = \lambda_1 w_1 + \dots + \lambda_k w_k = \lambda_i w$
But this should be

$$\lambda_i w = \lambda_i w_1 + \dots + \lambda_i w_k$$

Thus we get

$\lambda_1 w_1 = \lambda_i w_1, \lambda_2 w_2 = \lambda_i w_2, \dots, \lambda_k w_k = \lambda_i w_k$
But these should be distinct so we know $w_j = 0 \forall j \neq i$. Thus we conclude $w \in W_i$.

We have shown double set inclusion so $W_i = \text{Im}(E_i) = \text{Ker}(T - \lambda_i I)$ as claimed. \square

Remark:

For all $g(x) \in F[x]$, we have

$$g(T) = g(\lambda_1) E_1 + \dots + g(\lambda_k) E_k \quad \text{where } E_i = L_i(T).$$

Note: This is just the lagrange interpolation formula again.

In particular

$$f = \lambda_1 E_1 + \dots + \lambda_k E_k \xrightarrow{\text{Spectral decomposition of } T}$$

Primary Decomposition

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Example:

Consider $T = \begin{bmatrix} 2 & 0 & 0 \\ 1 & 2 & 0 \\ 0 & 0 & -1 \end{bmatrix}$ on \mathbb{R}^3 (wrt standard basis).

$$Te_1 = \begin{bmatrix} 2 \\ 1 \\ 0 \end{bmatrix} = 2e_1 + e_2$$

$$Te_2 = \begin{bmatrix} 0 \\ 2 \\ 0 \end{bmatrix} = 2e_2$$

$$Te_3 = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} = -e_3$$

You can see e_2 & e_3 are eigenvectors. If you find the characteristic polynomial $f(x)$ you get
 $f(x) = \det(xI - T) = (x-2)^2(x+1)$.

Thus we find eigenvalues 2 & -1. We find eigenspaces

$$\text{Ker}(T-2I) = \mathbb{R}e_2$$

$$\text{Ker}(T+I) = \mathbb{R}e_3.$$

Since the eigenspaces don't span \mathbb{R}^3 , T is not diagonalizable.

Consider $T-2I$. $(T-2I)e_2=0$ but $(T-2I)e_1=e_2$. However notice
 $(T-2I)^2e_1=0$. So
 $(T-2I)^2: e_1 \mapsto 0 \quad \& \quad e_2 \mapsto 0$.

Thus $\text{Ker}(T-2I)^2 = \text{span}\{e_1, e_2\}$. Now we can write \mathbb{R}^3 as
 $\mathbb{R}^3 = \text{span}\{e_1, e_2\} \oplus \text{span}\{e_3\}$
 $= \text{Ker}(T-2I)^2 \oplus \text{Ker}(T+I)$

We call $\text{Ker}(T-2I)^2$ a generalized eigenspace b/c it's kinda like an eigenspace.

Dfn:

The generalized λ -eigenspace of T is the set of all $v \in V$ st

$$(T-\lambda I)^m v = 0 \quad \text{for some } m \geq 1.$$

(We'll see later you can bound m)

What we're trying to do is break up the characteristic/minimal polynomials. We do this by describing how to factor them.

Lemma: Let $p(x) \in F[x]$ s.t. $p(x) = q_1(x)q_2(x)$ where $q_1(x)$ & $q_2(x)$ are relatively prime, i.e. $\gcd(q_1, q_2) = 1$.

Then $\exists h_1(x), h_2(x) \in F[x]$ s.t.
 $q_1h_1 + q_2h_2 = 1$

This is very similar to relative primality w/ the integers. It's just polynomials now.

PF:

Consider $J = \{q_1a_1 + q_2a_2 \mid a_1, a_2 \in F[x]\}$. J is an ideal of $F[x]$. That is it is closed under addition + of any two elements & multiplication by any $b \in F[x]$.

Here $J = \langle q_1, q_2 \rangle$ is the ideal generated by q_1 & q_2 . b/c J is an ideal

We know $J = \langle q \rangle$ can be generated by some $g \in F[x]$, that is $J = \{ga \mid a \in F[x]\}$.

But $q_1 \in J$ & $q_2 \in J$. Therefore g divides q_1 & q_2 .
 But since $\gcd(q_1, q_2) = 1$, we know g is constant. Thus $1 \in J$.

Thus $\exists h_1, h_2 \in F[x]$ s.t. $q_1h_1 + q_2h_2 = 1$.

b/c 1 is in the ideal, we actually know J is the whole ring
 $J = F[x]$.

Let V be a vector space over F . Consider $T \in \text{End}(V)$ w/ minimal polynomial $p(x) = q_1(x)q_2(x)$ where $\gcd(q_1, q_2) = 1$.

We again need another lemma.

Lemma:

Consider $T \in \text{End}(V)$ w/ minimal polynomial $p(x) = q_1(x)q_2(x)$. Then

- 1) $V = W_1 \oplus W_2$ where $W_i = \ker(T - q_i(T))$
- 2) the corresponding projections E_1 & E_2 are also polynomials of T .
- 3) the minimal polynomial of $T|_{W_i}$ is $q_i(x)$.

PF:

We want to find projections E_1 & E_2 s.t.

- i) $E_1^2 = E_1$ $\Leftrightarrow E_1^2 = E_1 \wedge E_2^2 = E_2$
- ii) $E_1 E_2 = 0 \quad \forall i \neq j \Leftrightarrow E_1 E_2 = E_2 E_1 = 0$ \nleftarrow here they're commutative
- iii) $E_1 + E_2 = I$
- iv) $W_i = \text{Im}(E_i) \Leftrightarrow W_1 = \text{Im}(E_1) \wedge W_2 = \text{Im}(E_2)$

Note in this case that $E_1 E_2 = E_2 E_1 = 0 \wedge E_1 + E_2 = I$ then
 $E_1 = E_1 I = E_1(E_1 + E_2) = E_1^2 + E_1 E_2 = E_1^2 \wedge E_2 = E_2^2$ by same logic

So we just show (i, ii) & (iii, iv).

We want explicitly $E_1 = q_1(T)$ & $E_2 = q_2(T)$, so

$$q_1(T)q_2(T) = 0$$

$$q_1(T) + q_2(T) = I$$

We want $W_1 = \text{Im}(E_1) = \text{Ker}(q_1(T))$, that is $E_1 v = q_1(T)v \in \text{Ker}(q_1(T))$. [7]
 Using the kernel requirement
 $q_1(T)g_1(T)v = 0 \quad \forall v \in V \Leftrightarrow q_1(T)g_1(T) = 0$.
 Similarly we want $q_2(T)g_2(T) = 0$. \downarrow
 $g_1(T)g_2(T) = 0$ [7]

Equivalently, we want p to divide $q_1g_1 - q_2g_2$, q_1g_2 , & $g_1 + g_2 - 1$.

Recall that $p = q_1q_2$ & $q_1h_1 + q_2h_2 = 1$ for some $h_1, h_2 \in F[x]$. \downarrow
 $q_1 + q_2 - 1 = 0$ b/c $q_1h_1 + q_2h_2 = 1$.

$$q_1(T) + q_2(T) = I$$

We let $g_1 = q_2h_2$ & $g_2 = q_1h_1$. Here we know

Likewise we can easily verify the products as $p = q_1q_2$.

Thus we have verified that p divides all the given polynomials
 b/c $q_1g_1 = q_1q_2h_2$, $q_2g_2 = q_2q_1h_1$, $q_1g_2 = q_1q_2h_1h_2$, $q_1 + q_2 - 1 = 0$.

Let

$$\text{Let } E_1 = q_1(T) = q_1(T)h_1(T) \quad \& \quad E_2 = q_2(T) = q_2(T)h_2(T)$$

We have already verified above that E_1 & E_2 satisfy the necessary properties to be projections. (2)

Thus $V = W_1 \oplus W_2$ where $W_i = \text{Im}(E_i)$. (1)

We now only need to show $W_i = \text{Ker}(q_i(T))$ & $q_i(x)$ is the minimal polynomial of $T|_{W_i}$. (3).

We already have shown $W_i \subseteq \text{Ker}(q_i(T))$. To reiterate the same $\forall v$.
 Then

$$E_i v = q_i(T)h_i(T)v \in \text{Im}(E_i)$$

So we know

$$q_i(T)E_i v = q_i(T)q_i(T)h_i(T)v = 0 \Rightarrow E_i v = w_i \in \text{Ker}(q_i(T))$$

$$p(T) = 0$$

Thus $w_i \in \text{Ker}(q_i(T))$. Likewise for W_2 .

Now we show $\text{Ker}(q_i(T)) \subseteq W_i$. Consider $v \in \text{Ker}(q_i(T))$.
 Then $q_i(T)v = 0$. Then

$$E_i v = q_i(T)h_i(T)v = h_i(T)q_i(T)v = 0$$

Since $E_i v = 0$, we know $E_i v = v$, so $v \in W_i$. Likewise for W_2 .

Thus $W_i = \text{Ker}(q_i(T))$. (1)

(1)

We now show (3). We show only for W_1 , but W_2 is shown similarly.

Take $w \in W_1 = \ker(q_1(T))$. Then $q_1(T)w = 0$. Since $w \in W_1$, we can rewrite this as where $T_1 = T|_{W_1}$.

$$q_1(T_1)w = 0 \Rightarrow q_1(T_1) = 0.$$

Since $q_1(T_1) = 0$, we know the minimal polynomial $p_1(x)$ of $T_1 = T|_{W_1}$ divides $q_1(x)$.

Consider some $h(T_1) = 0$. Then $h(T_1)w = 0 \quad \forall w \in W_1$. Since $w \in W_1$, we can write w as $w = E_1 v$.

Thus

$$h(T_1)w = h(T)w = h(T)E_1 v = h(T)q_2(t)h_2(t)v = 0 \quad \forall v \in V$$

Thus $h(T)q_2(t)h_2(t) = 0$. Thus p divides h_2 .

Since $q_1 h_1 + q_2 h_2 = 1$, it follows q_1 & $q_2 h_2$ are coprime, that is $\text{gcd}(q_1, q_2 h_2) = 1$.

Since $p = q_1 q_2$ divides h_2 , we conclude q_1 divides h_2 . Since q_1 & h_2 are coprime, q_1 divides h .

Since q_1 divides all polynomials $h(x) \in F[x]$ where $h(T_1) = 0$, we conclude (3) q_1 is the minimal polynomial of T_1 .

Thus our lemma is proven. \diamond

We can recursively/inductively apply this lemma which lets us factor our polynomials in two until we reach powers of irreducible polynomials.

This gives us our theorem.

Thm: Primary Decomposition Theorem

Let $T \in \text{End}(V)$ be a linear operator w/ minimal polynomial $p(x) = q_1(x) \cdots q_k(x)$ where $\text{gcd}(q_i, q_j) = 1 \quad \forall i \neq j$. Then

- 1) $V = W_1 \oplus \cdots \oplus W_k$ where $W_i = \ker(q_{i,i}(T))$
- 2) the corresponding projections E_1, \dots, E_k are polynomials of T
- 3) the minimal polynomial of $T|_{W_i}$ is $q_{i,i}(x)$.

PF:

Induction on k using the previous lemma.

We have thus shown we can write $p(x) = p_1(x)^{e_1} \cdots p_k(x)^{e_k}$ w/ irreducible $p_i(x)$. Then $q_{i,i}(x) = p_i(x)^{e_i}$ where $\text{gcd}(q_{ii}, q_{jj}) = 1 \quad \forall i \neq j$.

Example:

1) In $\mathbb{C}[x]$ the irreducible monic polynomials are $(x - \lambda)$ where $\lambda \in \mathbb{C}$.

2) In $\mathbb{R}[x]$ the irreducible monic polynomials are $(x - \lambda)$ where $\lambda \in \mathbb{R}$ or $(x - \lambda)(x - \bar{\lambda})$ where $\lambda \in \mathbb{C} \setminus \mathbb{R}$.

Split Linear Operators (aka Triangulable)

For a split linear operator T the minimal polynomial $p(x)$ is a product of linear operators

$$\text{B/C } p(x) = (x - \lambda_1)^{r_1} \cdots (x - \lambda_k)^{r_k}$$

B/C of this split we know

$$V = W_1 \oplus \cdots \oplus W_k \quad \text{where } W_i = \ker(T - \lambda_i I)^{r_i} = \text{generalized } \lambda_i\text{-eigen space}$$

Example:

Here we'll be solving ODEs w/ constant coefficients.

Consider $U = \text{space of smooth functions of } t$. Let $T = \frac{d}{dt} \in \text{End}(U)$.
Take some $p(x) = (x - \lambda_1)^{r_1} \cdots (x - \lambda_n)^{r_n} \in \mathbb{C}[x]$.

By our earlier theorem,

$V = \ker(p(T)) = \text{space of solutions to ODE } p(\frac{d}{dt})f(t) = 0$,
by definition

Then $p(T) = 0$ on V , so $V = W_1 \oplus \cdots \oplus W_k$ where $W_i = \ker(T - \lambda_i I)^{r_i}$
by our primary decomposition theorem.

Thus we've split up solving our potentially very complex polynomial
to solving linear factors which is very easy.

Solve the ODE

$$\left(\frac{d}{dt} - \lambda \right)^r f(t) = 0$$

Write $f(t) = e^{\lambda t} g(t)$. Then $\left(\frac{d}{dt} \right)^r g(t) = 0$ for some $g(t) \in \mathbb{C}[t]_{\deg \leq r-1}$.

Therefore, V (our space of solutions) has a basis of

$$\{ t^i e^{\lambda t} \mid 1 \leq i \leq k \wedge 0 \leq j \leq r_i - 1 \}$$

As expected $\dim(V) = r_1 + \cdots + r_k = \deg(p)$.

Now consider a split operator T w/ minimal polynomial

$$p(x) = (x - \lambda_1)^{r_1} \cdots (x - \lambda_n)^{r_n}$$

so $V = W_1 \oplus \cdots \oplus W_k$ where $W_i = \ker(T - \lambda_i I)^{r_i} = \text{generalized } \lambda_i\text{-eigen space}$.

Def: for diagonalized part of T

The semi-simple part of T is the linear operator D defined by

$$D|_{W_i} = \lambda_i I_{W_i} \quad \forall i = 1 \dots k. \quad \text{Thus}$$

$$D = \lambda_1 E_1 + \cdots + \lambda_k E_k$$

recall $W_i = \ker(T - \lambda_i I)^{r_i}$

Since $V = W_1 \oplus \cdots \oplus W_k$, for all $v \in V \exists! v = w_1 + \cdots + w_k$

$$v = v_{w_1} + \dots + v_{w_k} = \lambda_1 w_1 + \dots + \lambda_k w_k$$

Essentially we devise a linear operator N whose eigenspaces are the generalized eigenspaces.

By construction D is diagonalizable with $W_i \subseteq \text{Ker}(D - \lambda_i I)$.

Consider $N = T - D$ or $T = D + N$. Then on W_i we have $N^{r_i} = (T - \lambda_i I)^{r_i} = 0$. Thus $N^{r_i} w_i = 0 \quad \forall w_i \in W_i$.

If we take the largest r_i 's $r = \max(r_1, \dots, r_k)$, then $N^r w_i = 0 \quad \forall w_i \in W_i$.

Then $N^r = 0$ is nilpotent.

Def: the N defined above is the nilpotent part of T . It is unique.

Jordan-Chevalley Decomposition

The Jordan-Chevalley is our decomposition of linear operator T into $T = D + N$

where D is the semi-simple part of T & N the nilpotent one.

Thm:

Let T be a linear operator on a finite dimensional vector space V .
 T can be written uniquely as $T = D + N$

where D is diagonalizable/ semi-simple,
 N is nilpotent &
 $D \& N$ commute $DN = ND$.

Furthermore, there exist polynomials $g(x), h(x) \in F[x]$ st
 $D = g(T)$, $N = h(T)$, & $g(0) = h(0) = 0$.

Pf:

First we show such a D & N exist.

Assume $V = W_1 \oplus \dots \oplus W_n$ where $W_i \subseteq \text{Ker}(T - \lambda_i I)^{r_i}$ is generalized eigenspace for T .

By definition of D from earlier we know,

$D|_{W_i} = \lambda_i I_{W_i}$ b/c $W_i \subseteq \text{Ker}(D - \lambda_i I)$ is an eigenspace for D .

So D is diagonalizable.

Let $N = T - D$, then $N^{r_i}|_{W_i} = 0$, so $N^r = 0$ where $r = \max(r_1, \dots, r_k)$. Thus N is nilpotent.

By the definition of D & N we know $T = D + N$.

We know $\exists g(x) \in F[x]$ st $g(T) = D$ b/c

$D = \lambda_1 E_1 + \dots + \lambda_k E_k$

& E_i is a polynomial of T , thus $\exists g(x) \in F[x]$ st $g(T) = D$.

Consider $h(x) = x - g(x)$. Then $h(T) = T - g(T) = T - D = N$. Thus $\exists h(x) \in F[x]$ st $N = h(T)$.

B/c D & N are polynomials of T , we know they commute 19

$$DN = ND.$$

Now we just show that we can choose $g(x), h(x) \in F[x]$ s.t $g(D) = h(0) = 0$.

If it is sufficient to show $g(0) = 0$ b/c $h(0) = 0 - g(0) = 0$
if & only if $g(0) = 0$.

Note that $\lambda_1, \dots, \lambda_k$ are eigenvalues of T . Take some eigenvector $v \in V$ where $v \neq 0$ w/ $Tv = \lambda_i v$. Thus $v \in W_i$. Since $v \in W_i$ we know

$$Tv = \lambda_i v \Rightarrow g(T)v = g(\lambda_i)v$$

We have thus shown $g(\lambda_i) = \lambda_i$.

If some $\lambda_i = 0$, we can easily choose $g(0) = 0$.

Suppose however all eigenvalues are non-zero $\forall \lambda_i \neq 0$. Then the minimal polynomial of T is

$$p(x) = (x - \lambda_1)^{r_1} \cdots (x - \lambda_k)^{r_k}$$

Since all $\lambda_i \neq 0$, we know $p(0) \neq 0$.

Then we can replace $g(x)$ w/

$$\tilde{g}(x) = g(x) - \frac{g(0)}{p(0)} p(x).$$

Here we know

$$\tilde{g}(T) = g(T) - \frac{g(0)}{p(0)} p(T) = g(T) = D$$

$$\tilde{g}(0) = g(0) - \frac{g(0)}{p(0)} p(0) = 0$$

Thus such a D & N w/ polynomials $g(x)$ & $h(x)$ exist. (existence)

Now we show such a D & N are unique.

Suppose $T = D + N = D' + N'$ w/

D' diagonalizable

N' nilpotent, &

$$D'N' = N'D'$$

We show $D = D'$ & $N = N'$.

To do this we show $D'T = T D'$ & $N'T = TN'$.

$$D'T = D'(D' + N') = D'D' + D'N'$$

$$TN' = (D' + N')D' = D'D' + N'D'$$

Here we can see $V^T \cdot T^{-1} D = 0$, so $D^T = T D$. $N^T = TN'$ follows likewise.

By similar logic we know D' & N' commute w/ any polynomial of T . Since $D = g(T)$ & $N = h(T)$, we know $D'D = DD'$ & $N'N = NN'$.

Since both N & N' are nilpotent, there exists $m \in \mathbb{N}$ st $N^m = (N')^m = 0$.

B/c N & N' commute, we know $(N' - N)^{2m} = 0$.

as you can expand it w/ the usual binomial theorem & you'll always have at least one of N or N' have a power of at least m , so they are all 0.

Consider $D - D' = N - N'$. Since D & D' commute, they can be diagonalized simultaneously.

Recall: If you have some diagonalizable operators T_1, \dots, T_k that all commute. Then T_1, \dots, T_k can be diagonalized simultaneously.

Since D & D' can be diagonalized simultaneously, \exists basis of eigenvectors for D & D' . This same basis is a basis of eigenvectors for $D - D'$. Thus $D - D'$ is diagonalizable.

If for $v \neq 0$, $(D - D')v = \mu v = (N - N')v$, we know
 $(D - D')^{2m}v = N^{2m}v = (N - N')^{2m}v = 0$
 $\Rightarrow N^{2m}v = 0$
 $\Rightarrow \mu = 0$.

Thus $D - D' = N - N' = 0$ & $D = D'$ & $N = N'$. Thus the D & N are unique.

#Cyclic Subspaces

Def: Let V be a finite dimensional vector space w/ $T \in \text{End}(V)$. Pick some $v \in V$ & consider v, Tv, T^2v, T^3v, \dots

The T -cyclic subspace generated by v is $Z(v; T) =$

$$Z(v; T) = \text{span}\{v, Tv, T^2v, \dots\} = \{g(T)v \mid g(x) \in F[x]\}$$

This is the minimum subspace of V that contains v & is T -invariant. Sum of powers of T is polynomial

It is clearly a subspace b/c it's a span & it is clearly T -invariant. It is intuitive that it is minimum but not clear.

By the pigeonhole principle (valid b/c V is finite dimensional), \exists minimum $k \in \mathbb{N}$ st $w/ \forall v \in \text{span}\{v, Tv, \dots, T^{k-1}v\}$.

We say k is the max number such $\{v, Tv, \dots, T^{k-1}v\}$ is linearly independent. Thus we know $\{v, Tv, \dots, T^{k-1}v\}$ is a basis for $Z(v; T)$.

B/c $\{v, T v, \dots, T^{k-1} v\}$ is a basis for $Z(v; T)$, we know

$\forall r \in Z(v; T)$

$$r = c_0 v + c_1 T v + \dots + c_{k-1} T^{k-1} v = g(T) v \text{ where } g(t) \in F[x] \text{ deg } \leq k-1$$

In particular

$$T^m v \in \text{span}\{v, T v, \dots, T^{k-1} v\} = Z(v; T) \text{ for all } m \geq k.$$

We thus know $T^k v = g(T) v$. This is equivalent to $h(T)v = 0$ where

$$h(x) = x^k - g(x) = x^k - c_{k-1} x^{k-1} - \dots - c_1 x - c_0.$$

We can see $h(x)$ is a monic polynomial of degree k . In particular, $h(x)$ is the minimal polynomial s.t. $h(T)v = 0$.

Recall:

The T -annihilator of v is

$$S(v; \{0\}) = \{g(x) \in F[x] \mid g(T)v = 0\}$$

This is an ideal in $F[x]$ generated by the monic polynomial $p_v(x)$ of minimum degree called the T -annihilator (polynomial) of v .

Since $p_v(x)$ is the generator of $S(v; \{0\})$ we know that $g(T)v = 0$ iff $p_v(x)$ divides $g(x) \in F[x]$

Since the minimum polynomial $p(x)$ of T has $p(T) = 0$ by definition we know $p_v(x)$ divides $p(x)$.

Thm:

The cyclic subspace $Z(v; T)$ generated by $v \in V$ where $v \neq 0$ has a basis $\{v, T v, \dots, T^{k-1} v\}$ where $k = \deg(p_v(x))$.

Hence $\dim(Z(v; T)) = \deg(p_v(x))$.

Moreover $T|_{Z(v; T)}$ has minimal polynomial $p_v(x)$.

Let's try to find the matrix A of $T|_{Z(v; T)}$ relative to the ordered basis $\{v, T v, \dots, T^{k-1} v\}$.

$$A = \left[\begin{array}{cccc} 0 & 0 & \dots & 0 \\ 1 & 0 & \ddots & 0 \\ 0 & 1 & \ddots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{array} \right] \quad \left. \begin{array}{l} \text{Companion Matrix} \\ \text{of } p_v(x) \end{array} \right\}$$

This makes sense as we are finding $T(v + T v + \dots + T^{k-1} v)$. So

$$T(v + T v + \dots + T^{k-1} v) = T v + \dots + T^{k-1} v + T^k v = T v + \dots + T^{k-1} v + (c_0 v + c_1 T v + \dots + c_{k-1} T^{k-1} v)$$

where we get these cs? from the minimum polynomial / annihilator

$$p_V(x) = x^n - c_{k-1}x^{n-1} - \dots - c_1x - c_0.$$

We can construct such a matrix A from any monic polynomial h(x) of deg = k.
Here A is called the companion matrix of A.

Def:

If the cyclic subspace $Z(v; T)$ is the whole space V, that is
 $Z(v; T) = V$
then we say v is a cyclic vector.

Cor:

If v is a cyclic vector then

1) $p_V(x) = p(x) = f(x)$ where $p_V(x)$ is the T-annihilator of v,
 $p(x)$ is the minimum polynomial, &
 $f(x)$ is the characteristic polynomial,

2) If A is the companion matrix of a monic polynomial h(x) then
 $h(x) = \text{minimal polynomial} = \text{characteristic polynomial}.$

Theorem: Cyclic Decomposition Theorem $\& T \in \text{End}(V)$

For all finite dimensional subspaces $\exists v_1, \dots, v_r \in V$ st $p_{v_i}(x) = p_{v_i}(x)$
satisfy

& $A | p_1 | p_2 | p_3 | \dots | p_{r-1} | p_r$ (p_1 divides p_2, \dots)

$V = Z(v_1; T) \oplus \dots \oplus Z(v_r; T)$.

The number r & polynomials p_1, \dots, p_r are unique.

Def:

$p_1(x), \dots, p_r(x)$ are called the invariant factors of T.

Properties:

p_1, p_2, \dots, p_r all divide p_r , so p_r is the "largest." We know

1) $p_r(x) = p(x) = \text{min. polynomial of } T$

2) $p_1(x) \cdots p_r(x) = f(x) = \text{char. polynomial of } T$

Cor:

There is a cyclic vector of T if & only if $p(x) = f(x)$.

Background: Rational Form

Let $T \in \text{End}(V)$ be a T-invariant direct sum $V = W_1 \oplus \dots \oplus W_r$ if
 $T|_{W_i} \neq T|_{W_j}$. Pick basis B_i for W_i .

Then $B = \bigcup_{i=1}^r B_i$ is a basis for V.

Then $[T]_B$ is a block diagonal matrix where

$$[T]_B = \begin{bmatrix} A_1 & & \\ & \ddots & \\ 0 & & A_r \end{bmatrix} \text{ where } A_i = [T|_{W_i}]_{B_i}.$$

Then from the cyclic decomposition theorem

$$V = \mathbb{Z}(v_1; T) \oplus \dots \oplus \mathbb{Z}(v_r; T).$$

Ihm: Rational form

Let V be a vector space. Then \exists a basis B for V st

$$[T]_B = \begin{bmatrix} A_1 & & 0 \\ & \ddots & \\ 0 & & A_r \end{bmatrix}$$

where A_i is the companion matrix of $p_i(x)$ & $p_1(x), \dots, p_r(x)$ are the invariant factors of T .

This is a unique canonical form called the rational form

Def:

If $V = W \oplus W'$ we say subspace W' is complementary to W .

Let's prove the cyclic decomposition for a special case, nilpotent operators.

PF: Cyclic Decomposition for Nilpotent Operators

Let V be a vector space over field F w/ $\dim(V) = n$.

Let $N \in \text{End}(V)$ be a nilpotent operator, that is $N^k = 0$ for some $k \geq 1$.

Then the minimal polynomial $p(x)$ divides x^k . If you take the minimum k then $p(x) = x^k$ b/c then $p(T) = 0$ & $p(x) \in F[x]$ is the minimum degree polynomial to do so.

Suppose that the invariant factors $p_1(x), \dots, p_r(x)$ such that $p_i(x) = x^{k_i}$ where $k_1 \leq k_2 \leq \dots \leq k_r = k$.

Since $\dim(V) = n$ & N is nilpotent, the char. polynomial is $f(x) = x^n$.

The product of $p_1(x), \dots, p_r(x)$ is $x^{k_1 + k_2 + \dots + k_r}$. Since $p_1(x) \cdots p_r(x) = f(x)$ we know $k_1 + \dots + k_r = n$.

The companion matrix A_i of $p_i(x) = x^{k_i}$ is

$$A_i = \begin{bmatrix} 0 & \dots & 0 & 0 \\ 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & \dots & 0 & 1 \end{bmatrix} = [N|_{\mathbb{Z}(v_i; N)}]_{B_i}$$

annihilator of v_i

where $B_i = \{v_i, Nv_i, \dots, N^{k_i-1}v_i\}$ & $N^{k_i} = 0$ b/c $(p_{v_i}(x) = x^{k_i})$.

We expect $B = \bigcup_{i=1}^r B_i$ to be a basis for V .

We visualize the action of N on v_1, \dots, v_r as

$$\begin{array}{c} v_1 \xrightarrow[N]{Nv_1} \cdots \xrightarrow[N]{N^{k_1}v_1=0} k_1 \text{ vectors } \neq 0 \\ v_2 \xrightarrow[N]{Nv_2} \cdots \xrightarrow[N]{N^{k_2}v_2=0} k_2 \text{ vectors } \neq 0. \text{ Note } k_2 \geq k_1 \\ \vdots \\ v_r \xrightarrow[N]{Nv_r} \cdots \xrightarrow[N]{N^{k_r}v_r=0} k_r = k \text{ vectors } \neq 0 \end{array}$$

Here it should be obvious if the chains are a basis then for all $v \in V$

$N^k v = 0$. This is b/c in the largest case k_r , $k \geq k_r$. Thus the vector has "progressed" along the chain for enough for it to become 0. This is the

To prove the cyclic decomposition theorem for N . We have to show V has a basis B of such chains

$$B = \{v_1, Nv_1, \dots, N^{k_1-1}v_1, \dots, v_r, Nv_r, \dots, N^{k_r-1}v_r\}.$$

We prove this by induction on $\dim(V)$.

If $\dim(V) = 1$, then $V = Fv_1$ for any $v_1 \neq 0$. By the definition of N , we know

$Nv_1 = 0$. Thus B does have a basis $V = \{v_1\}$ b/c any non-zero vector forms a basis for a 1-dim space.

Now assume the statement is true for all spaces w/ $\dim < \dim(V)$. We want to find an N -invariant proper subspace of N .

Consider $\text{Im}(N)$ as our proper subspace. It is indeed proper by the rank-nullity theorem

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

Thus to show $\dim(\text{Im}(N)) < \dim(V)$, we show $\dim(\text{Ker}(N)) > 0$.

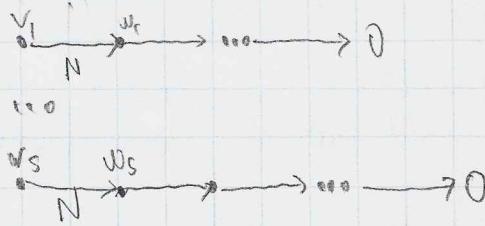
$\dim(\text{Ker}(N)) \neq 0$ b/c $N^k v = N(N^{k-1}v) = 0$ where $N^{k-1}v \neq 0$. Since there's a non-zero vector $N^{k-1}v$ in the kernel, the kernel is non-trivial & $\dim(\text{Ker}(N)) > 0$.

Thus $\text{Im}(N) \subset V$ & $\dim(\text{Im}(N)) < \dim(V)$. Since $\text{Im}(N)$ is an N -invariant subspace [b/c clearly $Nv \in \text{Im}(N) \iff v \in \text{Im}(N) \subset V$] & has smaller dimension than V , we use the inductive assumption.

That is $W = \text{Im}(N)$ has a basis of non-zero vectors from the chains

$$\begin{array}{c} w_1 \xrightarrow[N]{Nw_1} \cdots \xrightarrow[N]{N^{s-1}w_1=0} 0 \\ \vdots \\ w_s \xrightarrow[N]{Nw_s} \cdots \xrightarrow[N]{N^{s-1}w_s=0} 0 \end{array} \text{ where } s < r$$

Every such vector $w_i \in W = \text{Im}(N)$. Thus $w_i = Nv_i$ for some $v_i \in V$. Thus we can extend the chains (next page).



Now we need to show the vectors we added don't mess up the basis properties.

Claim: These vectors are (still) linearly independent

Proof:

Suppose

$$c_{10} v_1 + c_{11} Nv_1 + \dots + c_{1l_1} N^{l_1} v_1 + \dots + c_{s0} v_s + c_{s1} Nv_s + \dots + c_{sl_s} N^{l_s} v_s = 0$$

(probably should be using Σ notation)

Apply N to both sides. We're essentially moving everything along, giving us (use $w_i = Nv_i$)

$$c_{10} w_1 + c_{11} Nw_1 + \dots + c_{1l_1} N^{l_1} w_1 + \dots + c_{s0} w_s + c_{s1} Nw_s + \dots + c_{sl_s} N^{l_s} w_s = 0$$

Since $\{w_1, Nw_1, \dots, w_s, Nw_s, \dots\}$ forms a basis, we know

$$c_{10} = \dots = c_{1l_1-1} = \dots = c_{s0} = \dots = c_{sl_s-1} = 0$$

Thus all coefficients but the last are zero. That is we now must show

$$c_{1l_1} N^{l_1} v_1 + \dots + c_{sl_s} N^{l_s} v_s = c_{1l_1} N^{l_1} w_1 + \dots + c_{sl_s} N^{l_s} w_s = 0$$

Since $N^{l_1-1} w_1, \dots, N^{l_s-1} w_s$ is part of a basis for W , we know

$$c_{1l_1} = \dots = c_{sl_s} = 0$$

Since all c_i 's are zero, the vectors are linearly independent

Since the vectors $B' = \{v_1, Nv_1, \dots, v_s, Nv_s, \dots\}$ are linearly independent, B' is a candidate basis. (Note: It might not span V yet.)

We know we can extend B' to a basis for V . That is $\exists B'' \subset V$ st $B' \cup B''$ is a basis for V . Since $B \cup B''$ is a disjoint union, we know

$$V = W' \oplus W'' \text{ where } W' = \text{span}(B') \text{ & } W'' = \text{span}(B'')$$

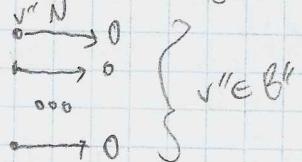
Note that W' is N -invariant. However, the complementary subspace might not be N -invariant. We need to show it is.

Consider some $v \in V$. Then $Nv \in \text{Im}(N) = W$ obviously. However, we have just shown that $Nv \in W$ if and only if $Nv = Nv'$.

Since $Nv = Nv'$, we know $Nv - Nv' = N(v - v') = 0$, so $v - v' \in \text{Ker}(N)$. If we replace v with $v - v'$ then $v - v'$ is still part of linearly independent set B'' st $B' \cup B''$ is a basis for V .

If we do this for all $v \in B''$ we get $B'' \subseteq \text{Ker}(N)$. Trivially then, W'' is n -invariant b/c all vectors go to 0.

Thus the basis $B = B' \cup B''$ is a union of chains from B' & B'' which consists of "single link chains" like



Remark:

$r = \dim(\text{Ker}(N)) = \text{Nullity}(N)$ & k_1, \dots, k_r are uniquely determined from N . In the above proof r is the number of chains.

Jordan (Canonical) Form

Consider some $T \in \text{End}(V)$ where $\dim(V) = n < \infty$ & T is a split linear operator. B/c T is split we know that the min. polynomial $p(x)$ & char. polynomial $f(x)$ can be written

$$p(x) = (x - \lambda_1)^{k_1} \cdots (x - \lambda_l)^{k_l}$$

$$f(x) = (x - \lambda_1)^{d_1} \cdots (x - \lambda_l)^{d_l}$$

where $\lambda_i \neq \lambda_j \forall i \neq j$ & $1 \leq k_i \leq d_i \forall i$.

(This always happens over the field $F = \mathbb{C}$)

By the primary decomposition theorem, we have

$V = W_1 \oplus \cdots \oplus W_l$ where $W_i = \ker(T - \lambda_i I)^{k_i}$ are the generalized eigenspaces. Note that $d_i = \dim(W_i)$. Clearly W_i is T -invariant on W_i .

Define N_i as $N_i = (T - \lambda_i I)|_{W_i} \in \text{End}(W_i)$. By construction N_i is nilpotent b/c $N_i^{k_i} = 0$. Thus, its min. polynomial is x^{k_i} .

We then use the rational form of N_i to get the Jordan form of the matrix.

Let B_i be a basis for W_i st $[N_i]_{B_i}$ is in rational form. Let $R_i = [N_i]_{B_i}$.

Notice $T|_{W_i} = N_i + \lambda_i I$ by the definition of N_i . Let $A_i = [T|_{W_i}]_{B_i} = \lambda_i I + R_i$.

The disjoint union $B = \bigcup_{i=1}^l B_i$ is a basis for V &

$$A = [T]_B = [A_1, \dots, A_l]$$

is block diagonal. This is the Jordan form of T .

The rational form R_i of the nilpotent operator N_i is itself block diagonal.

$$R_i = \begin{bmatrix} R_{i,1} & & \\ & \ddots & \\ & & R_{i,r_i} \end{bmatrix}$$

where each $R_{i,j}$ is

$$R_{i,j} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix}$$

The min. polynomial of N_i is x^{k_i} where k_i is the multiplicity of the eigenvalue λ_i as a root of the min. polynomial $p(x)$ of T . Thus the invariant factors of N_i are powers of x_i^k : $x_i^{k_{i1}} x_i^{k_{i2}}, \dots, x_i^{k_{ir}}$, where $1 \leq k_{i1} \leq \dots \leq k_{ir} = k_i$ & $k_{i1} + \dots + k_{ir} = d_i = \dim(W_i)$. 23

The number r_i is the nullity of N_i , that is $r_i = \dim(\ker(N_i))$, which is $\dim(\ker(T - \lambda_i I))$ or the dimension of the λ_i eigenspace. So $r_i = \dim(\ker(N_i)) = \dim(\ker(T - \lambda_i I))$.

The size of R_{ij} is $k_{ij} \times k_{rj}$.

By our earlier definition of A_i we get

$$A_i = \lambda_i I + R_i = \begin{bmatrix} J_{i,1} & & \\ & \ddots & \\ 0 & & J_{i,r_i} \end{bmatrix} \text{ where } J_{i,j} = \begin{bmatrix} \lambda_i & & 0 \\ 1 & \lambda_i & & \\ \vdots & 1 & \ddots & 0 \\ 0 & \cdots & 1 & \lambda_i \end{bmatrix}$$

We call $J_{i,j}$ a Jordan block & it is $k_{ij} \times k_{rj}$.

Since $A = [A_1 \ \dots \ A_r]$ & $A_i = [J_{i,1} \ \dots \ J_{i,r_i}]$, we have the diagonal of $A = [T]_B$ is made up of Jordan blocks.

Thm: Jordan Form

For every split linear operator $T \in \text{End}(V)$, there is a basis B for V s.t. the matrix $[T]_B$ is in Jordan form, that it is block diagonal w/ Jordan blocks on the diagonal. That is

$$A = [T]_B = \begin{bmatrix} J_{1,1} & & & & \\ & \ddots & & & \\ & & J_{1,r_1} & & \\ & & & \ddots & \\ 0 & & & & J_{r,r} \end{bmatrix}$$

We know that this matrix $A = [T]_B$ is unique if we order the blocks.

Note: You may ones above or below the diagonal in Jordan form. It is equivalent. (Reversing the basis switches b/w the two.)

Properties: Jordan Form

- 1) A linear transformation has only its eigenvalues $\lambda_1, \dots, \lambda_r$ along the main diagonal. Each λ_i appears d_i times which is the multiplicity of λ_i as a root of the char. polynomial $f(x)$.

See next page

3) The number r_i of Jordan blocks w/ eigenvalue λ_i is $r_i = \dim(W_i)$.

3) The largest Jordan block w/ eigenvalue λ_i has size k_i where k_i is the multiplicity of λ_i as root of min. polynomial $p(x)$.

Example:

Let $T = \begin{bmatrix} 1 & 2 & 3 \\ 0 & 1 & 2 \\ 0 & 0 & 1 \end{bmatrix} \in \text{End}(\mathbb{R}^3) = \mathbb{R}^{3 \times 3}$. Normally we would do \mathbb{C}^3 , but we do \mathbb{R}^3 b/c the char. polynomial factors over \mathbb{R} .

We find the char. polynomial $f(x)$ of T as $f(x) = (x-1)^3$.

We thus find k s.t. $N = T - I$ is nilpotent.

$$N = T - I = \begin{bmatrix} 0 & 2 & 3 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}, \text{ since } N^2 \neq 0 \text{ but } N^3 = 0.$$

Thus the min. polynomial $p(x)$ of T is $p(x) = (x-1)^3$.

Since $\text{Ker}(N) = \text{Ker}(T - I)$ has $\dim 1$ (i.e. the 1-eigenspace has $\dim 1$), we have 1 Jordan block $[I]_B$.

$$[TN]_B = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \Rightarrow [T]_B = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$

Notice $[TN]_B$ is also in rational form.

How do we find the rational form of N ? You need to pick some $v \in V$ s.t. $N^2 \neq 0$ b/c then we have chain

$$\underbrace{v \xrightarrow{Nr} N^2 v}_{\longrightarrow} 0$$

Then $B = \{v, Nv, N^2v\}$ is a basis of $V = \mathbb{R}^3$ s.t. N is in rational form, & thus T is in Jordan form.

Let's find the rational form of T . It is the companion matrix of the min. polynomial $p(x)$.

$$p(x) = (x-1)^3 = x^3 - 3x^2 + 3x - 1 = x^3 - (3x^2 - 3x + 1)$$

so the rational form of T is

$$[T]_B = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & -3 \\ 0 & 1 & 3 \end{bmatrix}$$

The basis B' that gives this rational form is

$$B' = \{v, v + T^2v\}$$

We can use the same vector $v \in V = \mathbb{R}^3$ as earlier, since $p_T(x) = (x-1)^3$. So $(T-I)^2v = N^2v = 0$. We do just need any $v \in V \subset \mathbb{R}^3$ s.t. $T^2v \neq 0$ tho.

To find $v \in V \subset \mathbb{R}^3$ just test it out when you find N^2 .

Example:

Let $T = \begin{bmatrix} -1 & 2 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \in \text{End}(\mathbb{R}^3) = \mathbb{R}^{3 \times 3}$. Again normally we'd take \mathbb{C}^3 , but \mathbb{R}^3 is enough to split T .

The char. polynomial $f(x)$ of T is thus $f(x) = (x+1)^3$.

We now find the min. polynomial $p(x)$ by finding a k st $N^k = 0$ where $N = T + I$ is the nilpotent operator.

$$N = T + I = \begin{bmatrix} 0 & -2 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow N^2 = 0 \Rightarrow p(x) = (x+1)^2$$

Since $k=2 < 3$, we know $V = \mathbb{R}^3$ isn't a cyclic space under T & instead there will be 2 subspaces.

Notice by inspection of N that

$$\text{Ker}(N) = \text{Ker}(T + I) = \text{span}\{e_1, e_3\}$$

so the nullity of N is 2 & thus the dimension of the -1 eigenspace is 2. Thus again we have 2 Jordan blocks,

Since there are only 2 Jordan blocks, the Jordan form of T must be

$$[T]_B = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad \text{or} \quad [T]_B = \begin{bmatrix} -1 & 0 & 0 \\ 1 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \quad \text{depending on order of Jordan blocks.}$$

We could if we allowed it, have the ones above the diagonal.

By this same B we get the rational form of N

$$[N]_B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

How do we find this basis $B = \{v_1, v_2, v_3\}$? By inspection of B , we need

$$\begin{aligned} Nv_1 &= 0 \\ Nv_2 &= v_3 \iff \begin{array}{c} \xrightarrow{N} 0 \\ \xleftarrow{N} v_3 \end{array} \\ Nv_3 &= 0 \end{aligned}$$

Note that the kernel of N has a basis $\{v_1, v_3\}$.

We have 2 ways to find $B = \{v_1, v_2, v_3\}$.

- Start from our earlier basis for $\text{Ker}(N)$, namely $\{e_1, e_3\}$. Then we search for $v_2 \in \text{Ker}(N)$ & find v_2 st $Nv_2 = v_3$.

Note that $\text{Im}(N) = \text{span}\{v_3\}$. Since $\text{Im}(N)$ is its column space,

$$\text{if } N = \begin{bmatrix} 0 & 2 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \text{ we know } v_3 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \text{ will work.}$$

If you look at the action of N on the basis you see
 $Nv_1=0$, $Nv_2=2e_1$, $Nv_3=0$

Thus we can see $v_1=e_3$, $v_2=e_2$, & $v_3=2e_1$ will work for B .

2) Find v_2 st $Nv_2 \neq 0$. Then let $v_3=Nv_2$.

Now let's find the rational form of T . We need to find the invariant factors. We know the number of invariant factors of T is 2 b/c that is the dimension of the eigenspace.

The invariant factors for T are polynomials $p_1(x)$, $p_2(x)$ st p_1 divides p_2 ,
 $p_2=p$ & $p_1p_2=f$.

B/c $p_2=p$, we know $p_2=(x+1)^2$. This leaves $p_1(x)=x+1$ as the only option.
By rewriting $p_1(x)$, & $p_2(x)$ we get the rational form, as

$$\begin{aligned} p_1(x) &= x - (-1) \\ p_2(x) &= x^2 - (-2)x - 1 \end{aligned}$$

$$\Rightarrow [T]_{B'} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & -2 \end{bmatrix}$$

To find $B'=\{u_1, u_2, u_3\}$ we need $Tu_1=-u_1$, $(T+I)u_1=0$,

$$Tu_1=-u_1, \quad (T+I)=U_1$$

$$Tu_2=u_3, \quad Tu_3=T^2u_2=-u_2-2Tu_2 \leftarrow \text{Come from } (T+I)^2u_2=0.$$

We want u_2 such that its annihilator is $p_{u_2}(x)=(x+1)^2$, but
 $(T+I)u_2 \neq 0$.

We can take $u_2=e_2$ b/c $Nv_2=(T+I)v_2=2e_1 \neq 0$. Then $Tu_2=Te_2=2e_1-e_2$
Then take $v_3=e_3$.

The cyclic decomposition of T is

$$V = Z(u_1; T) \oplus Z(u_2; T)$$

$$Z(v_1; N) = \text{span}\{e_3\}$$

$$Z(v_2; N) = \text{span}\{e_1, e_2\}$$

Bilinear Forms

Def:

Consider a vector space V . A bilinear form on V is a bilinear map $f: V \times V \rightarrow F$ which is bilinear (i.e. linear in each argument when the other is fixed). More explicitly for all $v, v', w, w' \in V$ & CEF

$$f(v+v', w) = f(v, w) + f(v', w)$$

$$f(cv, w) = cf(v, w) = f(v, cw)$$

$$f(v, w+w') = f(v, w) + f(v, w')$$

Recall our work on tensor products. Every bilinear map $V \times V \rightarrow F$ has a corresponding linear map on the tensor product $V \otimes V \rightarrow F$.

We can view this corresponding tensor form as a linear functional on $V \otimes V$.

The set of all bilinear forms is a vector space, as are all linear transformations. [25]

$$(f+g)(v, w) = f(v, w) + g(v, w)$$

$$(cf)(v, w) = c f(v, w)$$

This vector space is the dual of $V \otimes V$, that is $(V \otimes V)^*$.

Example:

Consider $V = \mathbb{R}^n$ w/ the dot product, which is an inner product

$$(x, y) = x^T y = \text{dot product} \quad \leftarrow \text{dot product is symmetric}$$

By definition all inner products are bilinear forms.

That is expected b/c bilinear forms are a generalization of inner products.

Example:

Consider $V = \mathbb{R}^2$. Define bilinear form $d(x, y)$ on $x = \begin{bmatrix} a \\ c \end{bmatrix}$ & $y = \begin{bmatrix} b \\ d \end{bmatrix}$ as

$$d(x, y) = \begin{vmatrix} a & b \\ c & d \end{vmatrix} \quad \text{and } d \text{ is skew-symmetric}$$

Def:

We call a bilinear form f symmetric iff

$$f(v, w) = f(w, v) \quad \forall v, w \in V$$

We call it skew-symmetric iff

$$f(v, w) = -f(w, v)$$

Example:

Consider some arbitrary vector space V w/ $g, h \in V^*$.

We define a bilinear form

$$f(v, w) = g(v)h(w)$$

Essentially $f = g \otimes h \in V^* \otimes V^* \subseteq (V \otimes V)^*$.

Note that $V^* \otimes V^* = (V \otimes V)^*$ if V is finite dimensional.

Example:

Fix some matrix $A \in F^{n \times n}$ & let bilinear form $f(x, y)$ be defined

$$f(x, y) = x^T A y = (x, A y) \leftarrow \text{dot product } (x, y) = x^T y$$

where x & y are column matrices $x, y \in F^n$

We can actually use the above example to get a canonical form of every bilinear form.

Example: cont.

Continuing the previous example f is symmetric/skew-symmetric iff A is likewise symmetric/skew-symmetric.

Recall A is symmetric if $A = A^t$ & skew-symmetric iff $A = -A^t$
this likewise holds for degeneracy

Def:

The matrix in the above example is called the Gram matrix,
In particular where you identify your bilinear form w/ the matrix A .

We can construct A by

$A = (a_{ij})$ where $a_{ij} = f(e_i, e_j)$ where $\{e_1, \dots, e_n\}$ standard basis
for \mathbb{F}^n

We can generalize/apply this Gram matrix to any vector space V .

Let $B = \{v_1, \dots, v_n\}$ be a basis for vector space V . For any $v, w \in V$ we know
 $v = \sum_{i=1}^n x_i v_i \Leftrightarrow [v]_B = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} = X$ & $w = \sum_{j=1}^n y_j v_j \Leftrightarrow [w]_B = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = Y$

Using this we can thus define $f(v, w)$ as

$$f(v, w) = f\left(\sum x_i v_i, \sum y_j v_j\right) = \sum_i \sum_j x_i f(v_i, y_j) y_j = X^t A Y \text{ where } A = (a_{ij}).$$

Def:

Using the above work for some bilinear form f on vector space V wrt basis B , we can write the matrix of f wrt B as
 $[f]_B = A = (a_{ij})$ where $a_{ij} = f(v_i, v_j)$.

Thm:

For any bilinear f on vector space V we write for any $v, w \in V$
 $f(v, w) = [v]^t [f]_B [w]_B$ where $[f]_B = (a_{ij})$ & $a_{ij} = f(v_i, v_j)$.

Further the map $f \mapsto [f]_B$ is a vector space isomorphism from the space
of all linear forms $(V \otimes V)^*$ to $\mathbb{F}^{n \times n}$, where $n = \dim(V)$.

Remark:

The isomorphism $(V \otimes V)^* \cong \mathbb{F}^{n \times n}$ depends on the choice of basis B while
 $V^* \otimes V \cong \text{End}(V)$ doesn't

Let B & B' be bases for vector space V . Let P be the transition matrix
from B' to B , that is
 $[v]_B = P[v]_{B'} \quad \forall v \in V$

We claim then that for a bilinear form
 $[f]_{B'} = P^t [f]_B P$

Thm:

Given basis B & B' for V (W) transition matrix P from B' to B ,

For any bilinear form f
 $[f]_{B'} = P^t [f]_B P$

Pf:

Consider $v, w \in V$. We know
 $f(v, w) = [v]_B^t [f]_B [w]_B = [v]_B^t [f]_B' [w]_{B'}$

Since P is the transition matrix from B' to B , we know
 $[v]_B = P[v]_{B'} \quad \& \quad [w]_B = P[w]_{B'}$.

Thus

$$f(v, w) = (P[v]_{B'})^t [f]_B (P[w]_{B'}) = [v]_{B'}^t P^t [f]_B P [w]_{B'}$$

Using this & the earlier equation we get
 $[f]_{B'} = P^t [f]_B P$. \square

Rem:

For any bilinear form $f \in (V \otimes V)^*$, f is symmetric/skewsymmetric if & only if $[f]_B$ is symmetric/skewsymmetric for some basis B in V .

Indeed if $[f]_B$ is such for some basis B of V , then it is such for all basis.

Note:

$$(P^t A P)^t = P^t A^t P$$

Def:

The rank of a bilinear form f is the rank of any matrix representing it. That is
 $\text{rank}(f) = \text{rank}([f]_B)$.

This indeed is well-defined b/c it is independent of choice of basis. We know this b/c

$[f]_{B'} = P^t [f]_B P$ where P is the transition matrix $B' \rightarrow B$. Since P is the transition matrix, P & P^t are non-singular (i.e. invertible). Thus they do not affect the rank.

Rem:

A linear form is non-degenerate/non-singular if
 $\text{rank}(f) = \dim(V)$.

In other words $[f]_B$ is invertible.

Def:

If you fix an input vector on the bilinear form $f \in (V \otimes V)^*$, you get a linear functional, that is an element of V^* :

$$f(v) : V \rightarrow F \quad (L_f(v))(w) = f(v, w) \geq (L_f(v))(w) = f(v, w) = (R_f(w))(v)$$

$$R_f(w) : V \rightarrow F \quad (R_f(w))(v) = f(v, w)$$

Notice that $L_f : V \rightarrow V^*$ & $R_f : V \rightarrow V^*$

Recall:

For any linear transformation T , $\text{rank}(T) = \dim(\text{Im}(T)) = \text{rank}([T]_B)$ where B is any basis.

Thm:

Pick a basis $B = \{v_1, \dots, v_n\}$ for V & dual basis $B^* = \{g_1, \dots, g_n\}$ for V^* . Then

$$[f]_B = [L_f]_B^{B^*} = [R_f]_B^{B^*}$$

This can be proved by the construction of $[f]_B$ & $[L_f]_B^{B^*}$ & $[R_f]_B^{B^*}$.

Coro:

$$\text{rank}(f) = \text{rank}(L_f) = \text{rank}(R_f).$$

Thm:

A bilinear form $f : V \times V \rightarrow F$ (or $f \in (V \otimes V)^*$) is non-degenerate/non-singular iff
 iff $L_f : V \rightarrow V^*$ is an isomorphism
 iff $R_f : V \rightarrow V^*$ is an isomorphism

Equivalently $\forall v \in V \setminus \{0\} \exists w \in V \text{ st } f(v, w) \neq 0$ & $\forall w \in V \setminus \{0\} \exists v \in V \text{ st } f(v, w) \neq 0$. } From inner products, there is no vector orthogonal to all other vectors

Def:

The kernel/radical of a bilinear form f is defined by
 $\ker(f) = \{v \in V \mid f(v, w) = 0 \ \forall w \in V\} = \{w \in V \mid f(v, w) = 0 \ \forall v \in V\}$

Rem:

If f is symmetric, then $R_f = L_f$.

If f is skew-symmetric, then $R_f = -L_f$.

Symmetric Bilinear Forms

Recall:

A bilinear form $f \in (V \otimes V)^*$ is symmetric iff $f(v, w) = f(w, v)$.

Thm:

Let V be a vector space where $n = \dim(V) < \infty$ & $\text{char}(F) = 0$ (i.e. the characteristic of the field is 0, i.e. you can divide by any non-zero element).

Then for all symmetric bilinear forms f there exists a basis B for V st $[f]_B$ is diagonal.

PF:

This proof is done by induction on the dimension of V .

Trivially, if $\dim(V) = 1$, then $[f]_B$ is diagonal b/c any non-zero 1×1 matrix is diagonal. 27

Suppose now that this is true for some subspace W' w/ dimension k . We show it is true for a superspace W w/ dimension $k+1$. That is $W' \subset W$ & W' is a hyperspace/hyperplane of W . (We don't do exactly this.)

We pick some non-zero vector, $w \in W$ that is not orthogonal to itself, that is $f(w, w) \neq 0$.

Suppose that $f(v, v) = 0 \forall v \in V$. Then

$$\begin{aligned} f(v+w, v+w) &= f(v, v) + f(w, w) + 2f(v, w) \leftarrow \text{polarization identity} \\ &= 2f(v, w) \end{aligned}$$

But $f(v+w, v+w) = 0$. Thus $f(v, w) = 0$ for any $v, w \in V$. Thus $[f]_B = 0$.

Now pick some $v \in V$ st $f(v, v) \neq 0$. Consider $W = Fv = \text{span}\{v\}$ & $W^\perp = \{w \in V \mid f(v, w) = 0\}$. Then $V = W \oplus W^\perp$ since $\forall u \in V$

$$u = f(u, v)v + w.$$

Find $f(v, w)$.

$$f(v, w) = \underbrace{f(v, v)}_{f(v, v)} \underbrace{f(v, v)}_{f(v, v)} + f(v, w)$$

So $f(v, w) = 0 \Rightarrow w \in W^\perp$ & $W \cap W^\perp = \{0\}$. v not orthogonal to self.

Then by induction W^\perp has a basis $\{v_1, \dots, v_{n-1}\}$ st

$$f(v_i, v_j) = 0 \quad \forall i \neq j.$$

And by definition we know when we add $v_n = v$, we again have

$$f(v_i, v_j) = 0. \quad \forall i \neq j.$$

Thus we have basis $B = \{v_1, \dots, v_n\}$. \square

Coro:

If $\text{char}(F) = 0$, then for all $A \in F^{n \times n}$ where $A = A^T$ (i.e. for all symmetric matrices), there exists an invertible $P \in F^{n \times n}$ st $P^T A P$ is diagonalizable.

Coro:

For the complex numbers $F = \mathbb{C}$, there is always a basis st $[f]_B = \begin{bmatrix} 1 & & & \\ & \ddots & & 0 \\ & & \ddots & \\ 0 & & & 0 \end{bmatrix}$ where $\text{rank}(f) = r = \text{number of } 1's$.

d) For the real numbers $F = \mathbb{R}$, there is always a basis B st

$$[f]_B = \begin{bmatrix} 1 & r^+ \\ 0 & 0 \end{bmatrix}$$

where $\text{rank}(f) = r^+ + r^-$

k. $r^+ - r^-$ is called the signature of f .

If you take a vector space \mathbb{R}^n w/ an inner product $\langle \cdot, \cdot \rangle$ such a Gram matrix $[f]_B$, you get a space called \mathbb{R}^{r^+, r^-} .

In particular the Minkowski space is $\mathbb{R}^{3,1}$. The Minkowski space is useful in relativity.

Review

Example: Jordan Form

When asked about Jordan form, you find the characteristic polynomial to find the eigenspaces & their basis.

Let $A = \begin{bmatrix} 2 & 0 & 0 \\ 3 & 8 & -9 \\ 2 & 4 & -4 \end{bmatrix}$. We find char. polyn. $f(x)$

$$\begin{aligned} f(x) &= \det(xI - A) = \begin{vmatrix} x-2 & 0 & 0 \\ -3 & x-8 & 9 \\ -2 & -4 & x+4 \end{vmatrix} = (x-2)((x-8)(x+4) + 36) \\ &= (x-2)(x^2 - 4x + 4) \\ &= (x-2)^3 \end{aligned}$$

This gives us one eigenvalue 2. We find eigenvectors / a basis for this eigenspace

eigenvectors/basis vectors

To find such x , we solve $(A - 2I)x = 0$. Let $N = A - 2I$.

We do a brief diversion to find the minimal polynomial b/c we know $N^3 = (A - 2I)^3 = 0$ b/c $f(A) = (A - 2I)^3 = 0$ (Note: $f(x) = (x-2)^3$). We know $f(A) = 0$ by the Cayley-Hamilton theorem.

We know the min. polyn. $p(x)$ divides $f(x) = (x-2)^3$. Thus to find the min. polynomial, we just check if $N = 0$ or $N^2 = 0$.

$$N = \begin{bmatrix} 0 & 0 & 0 \\ 3 & 6 & -9 \\ 2 & 4 & -6 \end{bmatrix} \neq 0$$

$$N^2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = 0$$

Thus we know the minimal polynomial is $p(x) = (x-2)^2$.

We know A is thus not diagonalizable b/c its minimal polynomial is not a product of unique factors.

Now we actually solve $Nx = (A - 2I)x = 0$

$$\begin{bmatrix} 0 & 0 & 0 \\ 3 & 6 & -9 \\ 2 & 4 & -6 \end{bmatrix} \xrightarrow{R_3 - \frac{2}{3}R_2} \begin{bmatrix} 1 & 2 & -3 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow x = \begin{bmatrix} -2s+3t \\ s \\ t \end{bmatrix} \Rightarrow x \in \text{span}\left\{\begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 0 \\ 1 \end{bmatrix}\right\}$$

Thus the 2-eigenspace $\ker(A - 2I) = \ker(N)$ has a basis $B' = \left\{ \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 3 \\ 0 \\ 1 \end{bmatrix} \right\}$.

Now we find the Jordan form J of A . $\text{p}(x) = (x-2)^2$ we know we only have 2s along the diagonal & we have 2 Jordan blocks. Thus

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

To find a basis $\mathcal{B} = \{v_1, v_2, v_3\}$ such that $J = [A]_{\mathcal{B}}$, we need vectors v_1, v_2, v_3 st

$$Av_1 = 2v_1 + v_2 \quad Nv_1 = v_2$$

$$Av_2 = 2v_2 \quad \Rightarrow \quad Nv_2 = 0$$

$$Av_3 = 2v_3 \quad Nv_3 = 0$$

Under such a basis note that $[N]_{\mathcal{B}}$ is actually in rational form. Let's use the forms wrt N b/c they're simpler.

Here easily v_2 & v_3 are eigenvectors. Finding v_1 is more difficult tho. Let's start by picking v_1 in the image of N

Let's find $\text{Im}(N)$. In general the image of a matrix is the span of its column / columnspace.

$$\text{Im}(N) = \text{span} \left\{ \begin{bmatrix} 0 \\ 3 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 6 \\ 4 \end{bmatrix}, \begin{bmatrix} 0 \\ -9 \\ -6 \end{bmatrix} \right\} = \text{span} \left\{ \begin{bmatrix} 0 \\ 3 \\ 2 \end{bmatrix} \right\}$$

Note that $\text{nullity}(N) = 2$ (from earlier) & $\text{rank}(N) = 1$. This checks out by the rank-nullity theorem b/c $\text{rank}(N) + \text{nullity}(N) = 3$.

Take $v_2 = \begin{bmatrix} 0 \\ 3 \\ 2 \end{bmatrix} = Ne_1$. Thus $v_1 = e_1$. Now we just pick

v_3 st $\{v_2, v_3\}$ is a basis for $\ker(N)$, that is the eigenspace. Take $v_3 = \begin{bmatrix} -2 \\ 1 \\ 0 \end{bmatrix}$. (could have picked either one)

Let's find the rational form of A . Recall the cyclic decomposition theorem. By this theorem the cyclic decomposition of N is $\text{Z}(v_1; N) \oplus \text{Z}(v_3; N) = \text{span}\{v_1, v_2\} \oplus \text{span}\{v_3\}$.

However, to put A' in rational form we need basis $\{v_1, v_2\}$ for $Z(v_1; A)$.

Thus to put A in rational form we need basis $\{u_1, u_2, u_3\}$ such that

$$u_1 = v_1$$

$$u_2 = Av_1 = Au_1$$

$$u_3 = v_3$$

For the upper block of the rational form (for $Z(v_1; A)$), we need to write $A^2 u_1$ in terms of u_1 & u_2 . We can do this w/ the minimum polynomial $p(x) = (x-2)^2 = x^2 - 4x + 4 - x^2 + 4x - 4$. This gives us $A^2 = 4A - 4I$. We know this b/c $p(A) = 0$ by the Cayley-Hamilton theorem.

Thus $A^2 u_1 = 4Au_1 - 4Iu_1 = 4u_2 - 4u_1$, which gives us the following block for A

$$\begin{bmatrix} 0 & -4 \\ 1 & 4 \end{bmatrix} \leftarrow \text{companion matrix of } (x-2)^2 = x^2 - (4x - 4)$$

Recall $Au_3 = Av_3 = 2v_3 = 2u_3$ b/c v_3 is an eigenvector w/ eigenvalue 2. This gives us block

$\begin{bmatrix} 2 \end{bmatrix} \leftarrow \text{companion matrix of } x-2 = x-(2)$

Thus our rational form for A as

$$\begin{bmatrix} 0 & -4 & 0 \\ 1 & 4 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$

The companion matrix blocks make sense b/c A has invariant factors $(x-1), (x-2)^2$.

Example: Consider $A = \begin{bmatrix} 2 & 4 & -6 \\ 3 & 24 & -33 \\ 2 & 16 & -22 \end{bmatrix}$. Find the Jordan form of A . (Note: A not diagonalizable)

$$f(x) = \begin{vmatrix} x-2 & -4 & 6 \\ -3 & x-24 & 33 \\ -2 & -16 & x+22 \end{vmatrix} = (x-2)(x^2 - 2x) + 4(-3x - 18 + 26) + 6(12x + 2x - 18) = x(x-2)^2 - 2x + 12x = x(x-2)^2$$

Since the min. poly. divides $f(x)$, we know $p(x) = x(x-2)$ or $p(x) = x(x-2)^2$. If $A(A-2I) = 0$, then A is diagonalizable b/c the min. poly. would be a product of unique factors. We are given A isn't diagonalizable thus $f(x) = x(x-2)^2$.

Since $p(x) = x(x-2)^2$, we know the Jordan form J of A is

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

To find a basis for this we need a basis for $\text{Ker}(A-2I)^2$ & $\text{Ker}(A)$, that is the generalized eigenspaces. By the primary decomposition theorem we know $V = \text{Ker}(A-2I)^2 \oplus \text{Ker}(A)$.

Let $B = \{v_1, v_2, v_3\}$ be the basis st $J = [A]_B$. Then we know $Av_1 = 2v_1 + v_2 \Leftrightarrow N_1v_1 = (A-2I)v_1 = v_2$, $N_1v_2 = 0$ & $Av_3 = N_2v_3 = 0$.

We're running low on time & the rest of the example is purely computational, so let's move on.

Example: Bilinear Forms

Consider vector space V w/ $L_1, L_2 \in V^* = V \rightarrow F$.

We know by our theorem in class that

$$f(v, w) = L_1(v)L_2(w)$$

is a bilinear form on V .

Prove that such a bilinear form has rank 1, that is $\text{rank}(f)=1$, & conversely prove that every bilinear form of rank 1 can be written as such.

Recall from our isomorphism in class that

$f \leftrightarrow R_f: V \rightarrow V^*$ where $(R_f(w))(v) = f(v, w)$.

(Remember $(L_f(v))(w) = f(v, w)$.)

Further recall our theorem that

$$\text{rank}(f) = \text{rank}(L_f) = \text{rank}(R_f) = \dim(\text{Im}(f)).$$

IF $f(v, w) = L_1(v)L_2(w) = (L_2(w))(v)$. By definition of R_f

$$R_f(w) = L_2(w)L_1 \in V^* \quad (L_2(w) \in F).$$

Thus $\text{Im}(R_f) = \text{span}\{L_1\}$. Thus $\text{rank}(R_f) = 1$.

But since $\text{rank}(f) = \text{rank}(R_f)$, we know $\text{rank}(f) \leq 1$.

(Forwards)

Conversely suppose $\text{rank}(f)=1$. Then $\text{rank}(R_f)=1$. Thus $\dim(\text{Im}(R_f))=1$ & $\text{Im}(R_f) = \text{span}\{L_1\}$ for some $L_1 \neq 0$ in V^* .

Thus $R_f(w) = \alpha L_1$ where α is a scalar that depends on w . We write $\alpha = L_2(w)$ so $L_2: V \rightarrow F$. Thus

$$R_f(w) = L_2(w)L_1.$$

Since $R_f(w)$ is linear $L_2(w)$ must be linear. Thus $L_2 \in V^*$.

Thus we know $(R_f(w)) = L_2(w)L_1(v)$. But $(R_f(w)) = f(v, w)$ by definition. Thus $f(v, w)$ can be written as necessary. (backward)

We have thus shown both directions.

