

Math 223: Linear Algebra
Lecture Notes

Lior Silberman

These are rough notes for the course in winter 2022. Problem sets solutions were posted on an internal website.

Contents

Introduction	4
0.1. Administrivia	4
0.2. Course plan (subject to revision)	4
0.3. Change-of-language	4
Chapter 1. Vector spaces and Linear maps	5
1.1. Vector spaces	5
1.2. Subspaces, examples	6
1.3. Linear dependence and independence	7
1.4. Geometric picture	8
Chapter 2. Linear Transformations	10
2.1. Linear Transformations	10
2.2. Matrices	11
2.3. Composing linear maps, multiplying matrices, space of endomorphisms	12
2.4. Linear equations	13
Chapter 3. Determinants	16
3.1. The determinant of a matrix	16
3.2. Determinants of linear maps	16
3.3. Properties of determinants	19
Chapter 4. Eigenvalues, eigenvectors, and diagonalization	20
4.1. Similarity and change of basis	20
4.2. Motivation	21
4.3. The characteristic polynomial, trace and determinant	22
4.4. Properties and diagonalization	23
4.5. Diversion: Graph eigenvalues and PageRank	24
Chapter 5. Inner product spaces	25
5.1. Inner product spaces	25
5.2. The Cauchy–Schwartz inequality	26
5.3. Orthogonality	27
5.4. Linear maps and : the adjoint	29
5.5. The spectral theorem	31

Introduction

Lior Silberman, lior@Math.UBC.CA, <https://www.math.ubc.ca/~lior>
Office: Math Annex 1112
Phone: 604-827-3031

0.1. Administrivia

Syllabus posted online. Key points:

- Problem sets will be posted on the course website. Solutions will be posted on a secure system.
 - The grader may only mark selected problems. Solutions will be complete.
- Absolutely essential to
 - ASK QUESTIONS IN CLASS
 - Read ahead according to the posted schedule. Lectures after the first will assume that you had done your reading.
 - Do homework.
- Office hours, Piazza.
- Course website has notes, problem sets, announcements, reading assignments etc.

0.2. Course plan (subject to revision)

Four aspects:

- Calculation (“matrix algebra”)
- Language (“linear algebra in the wild”)
- Linear Algebra
- Metamathematics

Topics

- Vector spaces
- Linear maps
- Linear Equations
- Determinants
- Eigenvectors and diagonalization
- Inner product spaces

0.3. Change-of-language

- Signal processing example: plug two guitars into amp. Ideally, output is sum of inputs, and rescaling inputs rescales output.
- Go from statements about functions to statements about sets of functions – see worksheet.

CHAPTER 1

Vector spaces and Linear maps

1.1. Vector spaces

DEFINITION 1. A (real) vector space is a triple $V = (V, +_V, \cdot_V)$ where:

- (0) V is a set; $+_V : V \times V \rightarrow V$ and $\cdot_V : \mathbb{R} \times V \rightarrow V$ are operations.
- (1) (addition of vectors) For every two elements (“vectors”) $\underline{u}, \underline{v} \in V$, there is a vector $\underline{u} +_V \underline{v} \in V$ and:
 - (a) (“Associativity”) For all $\underline{u}, \underline{v}, \underline{w} \in V$ we have $(\underline{u} +_V \underline{v}) +_V \underline{w} = \underline{u} +_V (\underline{v} +_V \underline{w})$.
 - (b) (“Commutativity”) For all $\underline{u}, \underline{v} \in V$ we have $\underline{u} +_V \underline{v} = \underline{v} +_V \underline{u}$.
 - (c) (“Zero”) There is a vector $\underline{0}_V \in V$ such that for all $\underline{u} \in V$, $\underline{u} +_V \underline{0}_V = \underline{u}$.
 - (d) (“Negatives”) For all $\underline{u} \in V$ there is a vector $\underline{u}' \in V$ such that $\underline{u} +_V \underline{u}' = \underline{u}' +_V \underline{u} = \underline{0}_V$.
- (2) (scalar multiplication) For every (“scalar”) $a \in \mathbb{R}$ and every vector $\underline{u} \in V$ there is a vector $a \cdot_V \underline{u} \in V$ and:
 - (a) (“Associativity”) For all $a, b \in \mathbb{R}$ and $\underline{u} \in V$ we have $a \cdot_V (b \cdot_V \underline{u}) = (a \cdot_V b) \cdot_V \underline{u}$.
 - (b) (“One”) For all $\underline{u} \in V$ we have $1 \cdot_V \underline{u} = \underline{u}$.
- (3) (distributive laws)
 - (a) For all $a \in \mathbb{R}$, $\underline{u}, \underline{v} \in V$ we have $a \cdot_V (\underline{u} +_V \underline{v}) = (a \cdot_V \underline{u}) +_V (a \cdot_V \underline{v})$.
 - (b) For all $a, b \in \mathbb{R}$, $\underline{u} \in V$ we have $(a + b) \cdot_V \underline{u} = (a \cdot_V \underline{u}) +_V (b \cdot_V \underline{u})$.

NOTATION 2. From now on we drop the subscript V and the dot from products.

EXAMPLE 3. $\{\underline{0}\}, \mathbb{R}, \mathbb{R}^n$.

PROBLEM 4. Decide whether any of the following is a vector space. If not, identify an axiom that fails.

- (1) $V = \mathbb{R}^n$, usual addition, $a\underline{v} = \underline{0}$ for all a, \underline{v} .
- (2) $V = \mathbb{R}^n$, usual scalar multiplication,
- (3) $V = \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \in \mathbb{R}^2 \mid x_1 + 2x_2 = 0 \right\}$, addition and multiplication as in \mathbb{R}^2
- (4) $V = \left\{ \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \in \mathbb{R}^2 \mid x_1 + 2x_2 = 1 \right\}$, addition and multiplication as in \mathbb{R}^2 .

LEMMA 5. For any nonzero $a \in \mathbb{R}^\times$ and any $\underline{b}, \underline{c} \in V$ the equation $a\underline{x} + \underline{b} = \underline{c}$ has the unique solution $\underline{x} = a^{-1}(\underline{c} + \underline{b}')$.

COROLLARY 6 (Zero).

- (1) If $\underline{u} + \underline{u} = \underline{u}$ then $\underline{u} = \underline{0}$.
- (2) There is a unique zero vector.
- (3) For all $a \in \mathbb{R}$, $a \cdot \underline{0} = \underline{0}$.
- (4) For all $\underline{u} \in V$, $0 \cdot \underline{u} = \underline{0}$.

COROLLARY 7 (Elementary properties).

- (1) Every vector has a unique negative, to be denoted $-\underline{u}$. We will use the shorthand $\underline{u} - \underline{v} \stackrel{\text{def}}{=} \underline{u} + (-\underline{v})$.

$$(2) (-1)\underline{u} = -\underline{u}$$

EXAMPLE 8. \mathbb{R}^X (in the book: $\mathcal{F}(X, \mathbb{R})$), hence \mathbb{R}^n , $M_{n \times m}(\mathbb{R}) \stackrel{\text{def}}{=} \mathbb{R}^{[n] \times [m]}$, $\mathbb{R}[x]$ (in the book $P(\mathbb{R})$), $\mathbb{R}[x]^{\leq n}$ (in the book $P_n(\mathbb{R})$).

1.2. Subspaces, examples

DEFINITION 9. Let $(V, +, \cdot)$ be a vector space. A subset $U \subset V$ is called a *subspace* of V if it is a vector space under the operations $+$, \cdot .

Note that every subspace must be non-empty, because it must contain a zero vector.

LEMMA 10. Let $U \subset V$ be a subspace. Then $\underline{0}_V \in U$.

PROOF. Let $\underline{u} \in U$ (exists since U is non-empty). Then $\underline{0}_V = 0 \cdot \underline{u} \in U$ by closure. \square

LEMMA 11. To check if U is a subspace of V it is necessary and sufficient to check that $\underline{0} \in U$ and that one of the following conditions:

- (1) For every $a \in \mathbb{R}$, $\underline{u}, \underline{v} \in U$ we have $a \cdot \underline{u}, \underline{u} + \underline{v} \in U$.
- (2) For every $a, b \in \mathbb{R}$, $\underline{u}, \underline{v} \in U$ we have $a\underline{u} + b\underline{v} \in U$.

PROOF. Problem Set 1 \square

EXAMPLE 12 (Subspaces). (0) Every vector space V has the “trivial” subspaces $\{\underline{0}_V\}$ and V itself (check!).

- (1) $\{\underline{v} \in \mathbb{R}^n \mid v_1 = 0\}$ is a subspace, but $\{\underline{v} \in \mathbb{R}^n \mid v_1 = 1\}$ is not.
- (2) $\{\underline{v} \in \mathbb{R}^n \mid \sum_{i=1}^n v_i = 0\}$ is a subspace, but $\{\underline{v} \in \mathbb{R}^n \mid \sum_{i=1}^n v_i = n\}$ is not.
- (3) $\{(x, y) \in \mathbb{R}^2 \mid y = e^x\}$ is not a subspace.
- (4) $\{f: [-1, 1] \rightarrow \mathbb{R} \mid f \text{ is continuous at } 0\} \subset \mathbb{R}^{[-1, 1]}$.
- (5) $C([a, b]) \subset \mathbb{R}^{[a, b]}$.
- (6) More generally, if $I \subset \mathbb{R}$ is an interval then $C^k(I) \subset \mathbb{R}^I$ is a subspace.
- (7) $\ell^\infty(X) \subset \mathbb{R}^X$ is a subspace. (PS 1)

LEMMA 13. Let $\{U_i\}_{i \in I}$ be a family of subspaces of a space V . Then $\bigcap_i U_i$ is a subspace as well.

PROOF. Let $W = \bigcap_i U_i$. By Lemma 11, $\underline{0} \in U_i$ for all i so $\underline{0} \in W$. Also, let $\underline{u}, \underline{v} \in W$, let $a, b \in \mathbb{R}$, and consider $a\underline{u} + b\underline{v}$. For all i , $\underline{u}, \underline{v} \in U_i$ since $W \subset U_i$. By the Lemma again it follows that $a\underline{u} + b\underline{v} \in U_i$. Since this is true for every i , $a\underline{u} + b\underline{v} \in W$ and we are done. \square

LEMMA 14. Let $U \subset V$ be a subspace, $n \geq 0$, $\{a_i\}_{i=1}^n \subset \mathbb{R}$, $\{\underline{u}_i\}_{i=1}^n \subset U$. Then $\sum_{i=1}^n a_i \underline{u}_i \in U$.

PROOF. PS1. \square

DEFINITION 15. A sum $\sum_{i=1}^n a_i \underline{u}_i$ is called a *linear combination*.

Let $S \subset V$ be a subset. The *span* $\text{Span}(S)$ is the set of linear combinations of elements of S .

REMARK 16. Note that $\underline{0} \in \text{Span}(S)$ for all S , as the value of the *empty sum*.

THEOREM 17. $\text{Span}(S)$ is a subspace of V . In fact,

$$\text{Span}(S) = \bigcap \{U \mid S \subset U \subset V \text{ and } U \text{ is a subspace}\}.$$

PROOF. By the Remark, $\text{Span}(S)$ contains zero. Closure under rescaling is automatic, under addition by concatenation of sequences. That $\text{Span}(S) \subset \bigcap \{U \mid S \subset U \subset V \text{ and } U \text{ is a subspace}\}$ is Lemma 14. For the reverse note that $\text{Span}(S)$ is a subspace containing S . \square

1.3. Linear dependence and independence

1.3.1. Linear dependence and independence. Fix a vector space V and a set $S \subset V$.

DEFINITION 18. Say that $\underline{v} \in V$ *depends linearly on* S if there are $\{\underline{v}_i\}_{i=1}^n \subset S$ and scalars $\{a_i\}_{i=1}^n$ such that $\sum_{i=1}^n a_i \underline{v}_i = \underline{v}$. Otherwise say that \underline{v} is *linearly independent* of S .

EXAMPLE 19 (Linear dependence). (0) The zero vector depends on every set S (via the empty combination)

(1) No non-zero vector depends on $\{\underline{0}\}$.

(2) \underline{v} depends on S iff $\underline{v} \in \text{Span}(S)$.

(3) (Useful to prove independence) If can find a subspace W such that $S \subset W$ and $\underline{v} \notin W$ then \underline{v} is independent of S .

DEFINITION 20. The set S is *linearly dependent* if some $\underline{v} \in S$ depends on $S \setminus \{\underline{v}\}$; linearly independent otherwise.

LEMMA 21. S is linearly independent iff whenever $\{\underline{v}_i\}_{i=1}^n \subset S$ are distinct and $\{a_i\}_{i=1}^n \subset \mathbb{R}$ are such that $\sum_{i=1}^n a_i \underline{v}_i = \underline{0}$ we have $a_i = 0$ for all i .

PROOF. Solve linear dependence for a vector with a non-zero coefficient. □

1.3.2. Bases.

LEMMA 22. S linearly independent and $v \notin \text{Span}(S)$ implies $S \cup \{v\}$ independent.

PROOF. Suppose $\sum_{i=1}^n a_i \underline{v}_i + a \underline{v} = \underline{0}$ where $\{\underline{v}_i\}_{i=1}^n \subset S$ are distinct. If $a \neq 0$ we'd have $\underline{v} = \sum_{i=1}^n (-a^{-1}a_i) \underline{v}_i \in \text{Span}(S)$, a contradiction. Thus $a = 0$. Then $\sum_{i=1}^n a_i \underline{v}_i = \underline{0}$ so all the other $a_i = 0$ by independence of S . □

COROLLARY 23. S maximal linearly independent then spanning.

PROOF. Contrapositive of Lemma: if not spanning, then there is a vector independent of S . □

DEFINITION 24. A spanning independent set is called a *basis*.

ALGORITHM 25. Find bases by adding vectors.

LEMMA 26. S spanning and minimal then independent.

PROOF. If there is a dependence then can remove a vector without affecting span. □

ALGORITHM 27. Find bases by subtraction.

COROLLARY 28. Every finitely generated vector space has a basis.

AXIOM 29. Every vector space has a basis.

1.3.3. Dimension. Standard basis of \mathbb{R}^n ; bases for space of polynomials. Bases for space of solutions of system of equations.

PROPOSITION 30 (Steinitz replacement lemma). Let $S \subset V$ be a generating set, and let $T \subset V$ be linearly independent. Suppose that $T \not\subset S$ and let $\underline{u} \in T \setminus S$. Then there is $\underline{v} \in S \setminus T$ so that $S \setminus \{\underline{v}\} \cup \{\underline{u}\}$ is also a generating set.

PROOF. Let $\underline{u} \in T \setminus S$. Then $\underline{u} \in \text{Span}(S)$ and therefore there are $\{\underline{v}_i\}_{i=1}^n \subset S$ and $\{a_i\}_{i=1}^n \subset \mathbb{R}$ such that $\underline{u} = \sum_{i=1}^n a_i \underline{v}_i$. Suppose that for every i , $a_i = 0$ or $\underline{v}_i \in T$. Then, omitting the zero contributions, we'd have that \underline{u} depends on $T \setminus \{\underline{u}\}$ ($\underline{v}_i \in S$ so they aren't equal to \underline{u}), contradicting the independence of T). It follows that there is j for which $a_j \neq 0$ and $\underline{v}_j \notin T$. We then have

$$\underline{v}_j = \sum_{\substack{i=1 \\ i \neq j}}^n (-a_j^{-1}a_i) \underline{v}_i + a_j^{-1} \underline{u}.$$

It follows that $\underline{v}_j \in \text{Span}(S \setminus \{\underline{v}_j\} \cup \{\underline{u}\})$, and hence that $V \supset \text{Span}(S \setminus \{\underline{v}_j\} \cup \{\underline{u}\}) \supset \text{Span}(S) = V$ so the span is as claimed. \square

THEOREM 31. *Let $S \subset V$ be a finite generating set, and let $T \subset V$ be linearly independent. Then $\#T \leq \#S$.*

PROOF. We repeatedly replace vectors of T into S until $T \subset S$.

Formally, let $A \subset S$ be minimal such that there is $A' \subset T$ such that $A \cup A'$ is a generating set of size at most $\#S$ (such A exist – take $A = S$). Then A is disjoint from T (otherwise we could reduce A and increase A' by moving the vectors over). If $A' = T$, $\#T \leq \#(A \cup A') \leq \#S$, so suppose that $A' \neq T$. Then there is $\underline{u} \in T \setminus A'$ so that $\underline{u} \notin A \cup A'$ and by the Proposition there is $\underline{v} \in (A \cup A') \setminus T = A$ so that $(A \setminus \{\underline{v}\}) \cup (A' \cup \{\underline{u}\})$ is also generating, of size at most $\#S$. This contradicts the minimality of A . \square

COROLLARY 32. *Let V be finitely generated. Then any two bases of V have the same size.*

DEFINITION 33. Let V be finitely generated. Then $\dim V$ is the size of any basis of V (these exist by Corollary 28).

1.4. Geometric picture

The Euclidean plane.

- (1) vectors, addition and the parallelogram law.
- (2) points and lines: subspaces and affine subspaces

Euclidean 3-space. points, lines, planes.

Rotations in the plane. Given two vectors $\underline{a} = \begin{pmatrix} x_1 \\ y_1 \end{pmatrix}$, $\underline{b} = \begin{pmatrix} x_2 \\ y_2 \end{pmatrix}$ in the plane, their *Euclidean distance* is defined by

$$\text{dist}(\underline{a}, \underline{b}) = ((x_2 - x_1)^2 + (y_2 - y_1)^2)^{1/2}.$$

Note that the distance only depends on the *displacement* $\underline{b} - \underline{a}$.

The *Euclidean plane* is \mathbb{E}^2 the plane \mathbb{R}^2 equipped with this distance function.

DEFINITION 34. A *Euclidean isometry* is a distance-preserving function $f: \mathbb{E}^2 \rightarrow \mathbb{E}^2$. The set of all such functions is called the *isometry group* or the *Euclidean group*.

This certainly includes the *translations*

$$T_{\underline{a}}(\underline{v}) = \underline{v} + \underline{a}.$$

Up to translation we can assume that an isometry preserves the origin, so let R be a Euclidean isometry such that $R\underline{0} = \underline{0}$.

- Goal: classify all such maps.

Let R be a Euclidean isometry such that $R\underline{0} = \underline{0}$.

We first note that $\text{dist}(\underline{e}_1, \underline{0}) = \text{dist}(\underline{e}_2, \underline{0}) = 1$ (they are “unit vectors”). Thus

$$\text{dist}(R\underline{e}_1, \underline{0}) = \text{dist}(R\underline{e}_1, R\underline{0}) = \text{dist}(\underline{e}_1, \underline{0}) = 1.$$

Thus $R\underline{e}_1 = \begin{pmatrix} x \\ y \end{pmatrix}$ where $x^2 + y^2 = 1$, and there is a unique angle θ so that $R\underline{e}_1 = \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$.

For the same reason we have $R\underline{e}_2 = \begin{pmatrix} \cos \phi \\ \sin \phi \end{pmatrix}$ for some angle ϕ . What is the distance between two unit vectors at these angles?

$$\begin{aligned}
\text{dist} \left(\begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}, \begin{pmatrix} \cos \phi \\ \sin \phi \end{pmatrix} \right) &= \sqrt{(\cos \phi - \cos \theta)^2 + (\sin \phi - \sin \theta)^2} \\
&= \sqrt{\cos^2 \phi + \cos^2 \theta - 2 \cos \phi \cos \theta + \sin^2 \phi + \sin^2 \theta - 2 \sin \phi \sin \theta} \\
&= \sqrt{2} \sqrt{1 - \cos(\theta - \phi)}
\end{aligned}$$

(this is called the “law of cosines”). But we must have

$$\text{dist}(R\underline{e}_1, R\underline{e}_2) = \text{dist}(\underline{e}_1, \underline{e}_2) = \sqrt{2}.$$

Since the distance between two unit vectors depends only on the angle between them, it follows that a distance -preserving function must preserve the angles. So in our case $\cos(\phi - \theta) = 0$ and hence $\phi - \theta = \pm \frac{\pi}{2}$. We consider the case $\phi = \theta + \frac{\pi}{2}$ first, where

$$R\underline{e}_2 = \begin{pmatrix} \cos(\theta + \frac{\pi}{2}) \\ \sin(\theta + \frac{\pi}{2}) \end{pmatrix} = \begin{pmatrix} -\sin \theta \\ \cos \theta \end{pmatrix}.$$

Now the formula above shows that the distance between two unit vectors only depends on the angle between them, so our map R must *preserve angles*. Thus if we take the vector $\begin{pmatrix} \cos \alpha \\ \sin \alpha \end{pmatrix}$ (which has angle α to \underline{e}_1 and $\frac{\pi}{2} - \alpha$ to \underline{e}_2) it must map to the unit vector at angle $\alpha + \theta$. We conclude that

$$\begin{aligned}
R \begin{pmatrix} \cos \alpha \\ \sin \alpha \end{pmatrix} &= \begin{pmatrix} \cos(\alpha + \theta) \\ \sin(\alpha + \theta) \end{pmatrix} \\
&= \begin{pmatrix} \cos \theta \cos \alpha - \sin \theta \sin \alpha \\ \sin \theta \cos \alpha + \cos \theta \sin \alpha \end{pmatrix}.
\end{aligned}$$

Now any vector can be recaled to be a unit vector, and R must respect this scaling (since that’s the distance to the origin). So for any vector x, y let $r = \sqrt{x^2 + y^2} = \text{dist} \left(\begin{pmatrix} x \\ y \end{pmatrix}, \underline{0} \right)$ and choose α so that $\frac{y}{x} = \tan \alpha$.

Then

$$\begin{aligned}
R \begin{pmatrix} x \\ y \end{pmatrix} &= rR \begin{pmatrix} \cos \alpha \\ \sin \alpha \end{pmatrix} = r \begin{pmatrix} \cos \theta \cos \alpha - \sin \theta \sin \alpha \\ \sin \theta \cos \alpha + \cos \theta \sin \alpha \end{pmatrix} \\
&= \begin{pmatrix} \cos \theta \cdot r \cos \alpha - \sin \theta \cdot r \sin \alpha \\ \sin \theta \cdot r \cos \alpha + \cos \theta \cdot r \sin \alpha \end{pmatrix} \\
&= \begin{pmatrix} \cos \theta \cdot x - \sin \theta \cdot y \\ \sin \theta \cdot x + \cos \theta \cdot y \end{pmatrix}
\end{aligned}$$

(check for $(x, y) = (1, 0)$ and $(x, y) = (0, 1)$!).

OBSERVATION 35. *Surprise: R is a linear function! the coordinates of $R\underline{v}$ are linear in the coordinates of \underline{v} . The investigation of such maps will be the next topic.*

CHAPTER 2

Linear Transformations

2.1. Linear Transformations

2.1.1. Definition; basic properties. *The* key definition for this course:

DEFINITION 36. Let U, V be vector spaces. A function $T: U \rightarrow V$ is a *linear transformation* (or *linear map* or *homomorphism of vector spaces*) if for all $\underline{u}, \underline{v} \in U$ and scalars a, b we have

$$T(a\underline{u} + b\underline{v}) = aT\underline{u} + bT\underline{v}.$$

REMARK 37. Note the notation for applying the function: no parentheses around the argument.

EXAMPLE 38 (Linear maps). (0) The zero map $f(\underline{u}) = \underline{0}_V$ for all \underline{u} is linear.

- (1) Recaling: for $a \in \mathbb{R}$ let $Z_a: U \rightarrow U$ be given by $Z_a\underline{u} = a\underline{u}$ (linearity follows from axioms of vector space).
- (2) Identity map: $\text{Id}\underline{u} = \underline{u}$ ($\text{Id} = Z_1$).
- (3) Calculus: $\frac{d}{dx}, f \mapsto (x \mapsto \int_a^x f(t) dt)$, say on $C^\infty(a, b)$.
- (4) The *shift* on $\mathbb{R}^{\mathbb{N}}$ and $\mathbb{R}^{\mathbb{Z}}$.
- (5) Linear functionals.
 - (a) Evaluation of functions: $\delta_x(f) \stackrel{\text{def}}{=} f(x)$ as a map $\delta_x: \mathbb{R}^X \rightarrow \mathbb{R}$.
 - (b) Limits of sequences: $\lim: c \rightarrow \mathbb{R}$.

LEMMA 39. Let T be a linear map. Then

- (1) $T\underline{0} = \underline{0}$.
- (2) $T(-\underline{u}) = -T\underline{u}$.

PROOF. Either multiplication by scalars (0, -1 respectively) or use that $T\underline{0} + T\underline{0} = T(\underline{0} + \underline{0}) = T\underline{0}$ and that $T\underline{u} + T(-\underline{u}) = T\underline{0} = \underline{0}$. □

LEMMA 40. $T(\sum_{i=1}^n a_i \underline{v}_i) = \sum_{i=1}^n a_i T\underline{v}_i$.

PROOF. Induction on n . □

COROLLARY 41. For any $S \subset U$, $T(\text{Span}(S)) = \text{Span}(T(S))$.

2.1.2. Range and kernel; rank-nullity.

PROPOSITION 42. Let $T: U \rightarrow V$ be linear.

- (1) Let $W \subset U$ be a subspace. Then the image $T(W) = \{T\underline{w} \mid \underline{w} \in W\}$ is a subspace of V .
- (2) Let $X \subset V$ be a subspace. Then the inverse image $T^{-1}X = \{\underline{u} \in U \mid T\underline{u} \in X\}$ is a subspace of U .

DEFINITION 43. $\text{Image}(T) = \text{Im}(T) \stackrel{\text{def}}{=} T(V)$ is called the *image* of T , $\text{Ker}(T) = \{\underline{u} \in U \mid T\underline{u} = \underline{0}\} = T^{-1}(\{\underline{0}\})$ is called the *kernel* of T .

COROLLARY 44. The Kernel of T is a subspace of U , the Image of T is a subspace of V .

THEOREM 45 (Rank-nullity). Let U be finite-dimensional and let $T: U \rightarrow V$ be linear. Then $\dim \text{Ker } T + \dim \text{Im } T = \dim U$.

EXAMPLE 46 (PS3). The case of a non-zero linear functional, where $\dim \text{Im } T = 1$.

PROOF. Let $n = \dim U$, $s = \dim \text{Ker } T$, $r = \dim \text{Im } T$. Let $\{\underline{u}_i\}_{i=1}^s \subset \text{Ker } T$ and $\{\underline{v}_j\}_{j=1}^r \subset \text{Im } T$ be bases for their respective spaces. For each \underline{v}_j choose $\underline{w}_j \in U$ such that $T\underline{w}_j = \underline{v}_j$. We claim that $\{\underline{u}_i\}_{i=1}^s \cup \{\underline{w}_j\}_{j=1}^r$ is a basis for U , so that $\dim U = s + r$ as claimed.

- (1) To see that they span U , let $\underline{u} \in U$. Then $T\underline{u} \in \text{Im } T$ so there are b_j for which $T\underline{u} = \sum_{j=1}^r b_j \underline{v}_j = \sum_{j=1}^r b_j T\underline{w}_j$. Then

$$T \left(\underline{u} - \sum_{j=1}^r b_j \underline{w}_j \right) = \underline{0},$$

that is $\underline{u} - \sum_{j=1}^r b_j \underline{w}_j \in \text{Ker } T$. It follows that there are a_i for which $\underline{u} - \sum_{j=1}^r b_j \underline{w}_j = \sum_{i=1}^s a_i \underline{u}_i$ and then

$$\underline{u} = \sum_{i=1}^s a_i \underline{u}_i + \sum_{j=1}^r b_j \underline{w}_j.$$

- (2) To see that the vectors are independent, let $\{a_i\}_{i=1}^s$ and $\{b_j\}_{j=1}^r$ be such that $\sum_{i=1}^s a_i \underline{u}_i + \sum_{j=1}^r b_j \underline{w}_j = \underline{0}$. Applying T to both sides, we have

$$\begin{aligned} \underline{0} &= \sum_{i=1}^s a_i T\underline{u}_i + \sum_{j=1}^r b_j T\underline{w}_j \\ &= \sum_{j=1}^r b_j \underline{v}_j. \end{aligned}$$

The independence of $\{\underline{v}_j\}_{j=1}^r$ now shows that $b_j = 0$ for all j . Accordingly we have $\sum_{i=1}^s a_i \underline{u}_i = \underline{0}$ and since the \underline{u}_i are also independent we see that the $a_i = 0$ as well. □

DEFINITION 47. $\dim \text{Ker } T$ is called the *nullity* of T , sometimes denoted $n(T)$. $\dim \text{Im}(T)$ is called the *rank* of T , will be denoted $r(T)$.

COROLLARY 48. $r(T) \leq \dim U$. Suppose $\dim V < \dim U$. Then $\dim \text{Ker } T > 0$.

EXAMPLE 49. Every system of homogenous linear equations with more unknowns than equations has a non-trivial solution.

2.2. Matrices

DEFINITION 50. $\text{Hom}(U, V)$ is the space of linear maps from U to V .

LEMMA 51. $\text{Hom}(U, V)$ is a vector space under pointwise addition and scalar multiplication.

LEMMA 52. Let $T \in \text{Hom}(\mathbb{R}^m, \mathbb{R}^n)$. Then there are numbers $a_{i,j}$ for $1 \leq i \leq n$, $1 \leq j \leq m$ such that $(T\underline{x})_i = \sum_{j=1}^m a_{ij} x_j$, that is such that

$$T\underline{x} = \begin{pmatrix} a_{1,1}x_1 + a_{1,2}x_2 + \cdots + a_{1,m}x_m \\ \vdots \\ a_{i,1}x_1 + \cdots + a_{i,m}x_m \\ \vdots \\ a_{n,1}x_1 + \cdots + a_{n,m}x_m \end{pmatrix}.$$

PROOF. For each j define $a_{i,j}$ by $T\underline{e}_j = \begin{pmatrix} a_{1,j} \\ \vdots \\ a_{i,j} \\ \vdots \\ a_{n,j} \end{pmatrix}$. Use linearity. □

DEFINITION 53. $M_{n,m}(\mathbb{R}) = \mathbb{R}^{[n] \times [m]}$. Given $A \in M_{n,m}(\mathbb{R})$ write A_{ij} or a_{ij} for the entries.

LEMMA 54. Given $A \in M_{n,m}(\mathbb{R})$, the map $L_{A\underline{x}} \stackrel{\text{def}}{=} \begin{pmatrix} a_{1,1}x_1 + a_{1,2}x_2 + \cdots + a_{1,m}x_m \\ \vdots \\ a_{i,1}x_1 + \cdots + a_{i,m}x_m \\ \vdots \\ a_{n,1}x_1 + \cdots + a_{n,m}x_m \end{pmatrix}$ is linear.

PROPOSITION 55. The map $A \mapsto L_A$ is an isomorphism $M_{n,m}(\mathbb{R}) \rightarrow \text{Hom}(\mathbb{R}^m, \mathbb{R}^n)$.

- Philosophy: describe linear maps and calculate using matrices.

Now let U, V be vector spaces, and ordered bases $\{\underline{u}_j\}_{j=1}^m$ of U , $\{\underline{v}_i\}_{i=1}^n$ of V (here $m = \dim U$, $n = \dim V$). Given $T \in \text{Hom}(U, V)$ define a matrix $A \in M_{n,m}(\mathbb{R})$ by setting $T\underline{u}_j = \sum_{i=1}^n a_{ij}\underline{v}_i$.

DEFINITION 56. Call this *the matrix of T with respect to the ordered bases $\{\underline{u}_j\}_{j=1}^m, \{\underline{v}_i\}_{i=1}^n$* .

LEMMA 57. This is a well-defined linear map $\text{Hom}(U, V) \rightarrow M_{n,m}(\mathbb{R})$.

To see that this is an isomorphism we construct the inverse map: given A we define T by $T(\sum_j x_j \underline{u}_j) = \sum_{i=1}^n (\sum_{j=1}^m a_{ij} x_j) \underline{v}_i$ (compare with above!)

REMARK 58. Existence of a_{ij} uses that \underline{v}_i are spanning, well-defined uses that they are independent. Where did we use info about \underline{u}_j ?

PROPOSITION 59. Let U be a vector space with basis B , V another vector space and $f: B \rightarrow V$. Then there is a unique linear map $T: U \rightarrow V$ extending f .

PROOF. Suppose T is such a map. For each $\underline{u} \in U$ we can write $\underline{u} = \sum_{i=1}^n x_i \underline{u}_i$ for some $\underline{u}_i \in B$ and $x_i \in \mathbb{R}$ since B is spanning. Then

$$T\underline{u} = T\left(\sum_{i=1}^n x_i \underline{u}_i\right) = \sum_{i=1}^n x_i T\underline{u}_i = \sum_{i=1}^n x_i f(\underline{u}_i)$$

so T , if it exists, is unique. Conversely, define T by the relation above. This is OK since every \underline{u} has a *unique* representation in the basis. Linearity easy to check. □

COROLLARY 60. We have an isomorphism $\text{Hom}(U, V) \simeq M_{n,m}(\mathbb{R})$.

COROLLARY 61. Since $M_{n,m}(\mathbb{R}) \simeq \mathbb{R}^{nm}$, $\dim \text{Hom}(U, V) = \dim M_{n,m}(\mathbb{R}) = nm = \dim U \cdot \dim V$.

2.3. Composing linear maps, multiplying matrices, space of endomorphisms

- Heisenberg discovers formula for matrix multiplication.
- Challenge: show associativity
- Go back: where did this come from?
- Compose linear maps

2.4. Linear equations

2.4.1. What is a linear equation?

DEFINITION 62. A *linear equation* is an equation $T\underline{x} = \underline{b}$ where $T \in \text{Hom}(U, V)$ and $\underline{b} \in V$. If $\underline{b} = \underline{0}$ we call the equation *homogenous*.

EXAMPLE 63 (Linear equations). (1)
$$\begin{cases} 2x + y = 1 \\ x + 2y = 3 \end{cases}$$

(2) $\frac{df}{dx} = e^{-x^2}$

(3) $-\frac{1}{2}\psi''(x) + \frac{1}{2}x^2\psi(x) = E\psi(x)$

(4) $F_{n+1} = F_n + F_{n-1}$

REMARK 64. **WARNING:** we use the term “linear equation” in two, distinct ways. Originally this described equations like the components of example (1) above, which are grouped together into a *system of linear equations*. But we just saw that we can think of the entire system as a *single* “linear equation” – where the unknown is now a single vector instead of several real numbers.

REMARK 65 (Linearity). • The set of solutions to a homogenous equation is the kernel of a linear map, so any linear combination of solution is again a solution. In physics this called the *principle of superposition*.

- Recognizing that an equation is linear is important.
- For diff eq the choice of function space in which to define the equation is technical.

LEMMA 66 (Particular and general solutions). *The equation has solutions iff $\underline{b} \in \text{Im}T$. If \underline{v}_0 is any solution then the set of solutions is $\underline{v}_0 + \text{Ker}T$.*

DEFINITION 67. If $E \in \text{Hom}(U, U)$ is invertible we call the equations $T\underline{x} = \underline{b}$ and $ET\underline{x} = E\underline{b}$ *equivalent*.

LEMMA 68. *This is an equivalence relation. Equivalent solutions have the same solutions. In particular hence rank=column rank.*

2.4.2. Gaussian Elimination. Now concentrate on the case $T = L_A \in \text{Hom}(\mathbb{R}^m, \mathbb{R}^n)$.

NOTATION 69. Augmented matrix

LEMMA 70. *Solution to diagonal equations*

Better:

LEMMA 71. *Solution to row echelon form.*

DEFINITION 72. An *elementary row operation* is rescaling a row, or adding a multiple of one row to another row.

DEFINITION 73. Pivot.

COROLLARY 74. *In row-reduced form, a variable without pivot is called free. General solution obtained by arbitrarily valuing the free variables (gives new proof of dimension formula = rank-nullity).*

ALGORITHM 75 (Gaussian elimination). *Find first column with a non-zero entry, exchange rows to make it in first row. Subtract multiples to make zeroes below. Find next column ...*

- Practice using the algorithm to solve systems of equations.

LEMMA 76. *The steps of the algorithm are equivalences.*

PROOF. Achieved by multiplication by $\text{diag}(1, \dots, d_i, \dots, 1)$ ($d_i \neq 0$) and by $I_n + cE^{ij}$, which are invertible. \square

REMARK 77. $\begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & -1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$. In other words we've also checked switching rows.

THEOREM 78. *Every equation $A\mathbf{x} = \mathbf{b}$ is equivalent to an equation $(MA)\mathbf{x} = M\mathbf{b}$ where M is a product of elementary matrices and MA is in row echelon form (or row-reduced form).*

2.4.3. Application of Gaussian elimination: row and column rank.

LEMMA 79. *Row operations preserve both row and column rank.*

LEMMA 80. *For a matrix in row echelon form both the row rank and the column rank equal the number of pivots.*

Together these gives

THEOREM 81. *For any matrix A the row rank and column rank are equal.*

2.4.4. Inverting matrices using Gaussian Elimination. Let $A \in M_n(\mathbb{R})$ be a square matrix, which we suppose invertible. Thinking of A^{-1} as a linear map, we can find its j th column by applying A^{-1} to the j th vector in the standard basis. But that means that the j th column solves $A\mathbf{x}_j = \mathbf{e}_j$, so finding the n columns of A^{-1} can be done by solving n systems of linear equations (one system per column). But note that the row operations of Gaussian elimination depend only on A – not on the RHS vector, so we can do them in parallel for several RHS by just using a single extended matrix with many right-hand-side columns.

Two notes:

- In order to get a formula for the columns, it is not enough to reach row echelon form (clearing *below* each pivot), because then we'd need back-substitution and can't read the answer off. Instead we should go for *reduced* row echelon form where we clear the whole column above and below the pivot.
- Either we find n pivots, so the “reduced row echelon form” is simply the identity matrix, or we don't – and the matrix isn't invertible.

EXAMPLE 82. We invert the matrix $\begin{pmatrix} 5 & 3 & -2 & 7 \\ 1 & 18 & 3 & 3 \\ 1 & 4 & 3 & 4 \\ 6 & 5 & 8 & 17 \end{pmatrix}$.

$$\begin{array}{l} \left[\begin{array}{cccc|cccc} 5 & 3 & -2 & 7 & 1 & 0 & 0 & 0 \\ 1 & 18 & 3 & 3 & 0 & 1 & 0 & 0 \\ 1 & 4 & 3 & 4 & 0 & 0 & 1 & 0 \\ 6 & 5 & 8 & 17 & 0 & 0 & 0 & 1 \end{array} \right] \xrightarrow{R_1 \leftrightarrow R_3} \\ \left[\begin{array}{cccc|cccc} \textcircled{1} & 4 & 3 & 4 & 0 & 0 & 1 & 0 \\ 1 & 18 & 3 & 3 & 0 & 1 & 0 & 0 \\ 5 & 3 & -2 & 7 & 1 & 0 & 0 & 0 \\ 6 & 5 & 8 & 17 & 0 & 0 & 0 & 1 \end{array} \right] \xrightarrow{\begin{array}{l} -R_1 \\ -5R_1 \\ -6R_1 \end{array}} \\ \left[\begin{array}{cccc|cccc} 1 & 4 & 3 & 4 & 0 & 0 & 1 & 0 \\ 0 & 14 & 0 & -1 & 0 & 1 & -1 & 0 \\ 0 & -17 & -17 & -13 & 1 & 0 & -5 & 0 \\ 0 & -19 & -10 & -7 & 0 & 0 & -6 & 1 \end{array} \right] \xrightarrow{R_2 \leftrightarrow -R_4} \end{array}$$

$$\begin{aligned}
& \left[\begin{array}{cccc|cccc} 1 & 4 & 3 & 4 & 0 & 0 & 1 & 0 \\ 0 & 19 & 10 & 7 & 0 & 0 & 6 & -1 \\ 0 & -17 & -17 & -13 & 1 & 0 & -5 & 0 \\ 0 & 14 & 0 & \textcircled{1} & 0 & 1 & -1 & 0 \end{array} \right] \begin{array}{l} +4R_4 \\ +7R_4 \\ -13R_4 \\ \end{array} \rightarrow \\
& \left[\begin{array}{cccc|cccc} 1 & 60 & 3 & 0 & 0 & 4 & -3 & 0 \\ 0 & 117 & 10 & 0 & 0 & 7 & -1 & -1 \\ 0 & -199 & -17 & 0 & 1 & -13 & 8 & 0 \\ 0 & 14 & 0 & -1 & 0 & 1 & -1 & 0 \end{array} \right] +2R_2 \rightarrow \\
& \left[\begin{array}{cccc|cccc} 1 & 60 & 3 & 0 & 0 & 4 & -3 & 0 \\ 0 & 117 & 10 & 0 & 0 & 7 & -1 & -1 \\ 0 & 35 & 3 & 0 & 1 & 1 & 6 & -2 \\ 0 & 14 & 0 & -1 & 0 & 1 & -1 & 0 \end{array} \right] -3R_3 \rightarrow \\
& \left[\begin{array}{cccc|cccc} 1 & 60 & 3 & 0 & 0 & 4 & -3 & 0 \\ 0 & 12 & \textcircled{1} & 0 & -3 & 4 & -19 & 5 \\ 0 & 35 & 3 & 0 & 1 & 1 & 6 & -2 \\ 0 & 14 & 0 & -1 & 0 & 1 & -1 & 0 \end{array} \right] \begin{array}{l} -3R_2 \\ -3R_2 \\ \end{array} \rightarrow \\
& \left[\begin{array}{cccc|cccc} 1 & 24 & 0 & 0 & 9 & -8 & 54 & -15 \\ 0 & 12 & 1 & 0 & -3 & 4 & -19 & 5 \\ 0 & -1 & 0 & 0 & 10 & -11 & 63 & -17 \\ 0 & 14 & 0 & -1 & 0 & 1 & -1 & 0 \end{array} \right] \begin{array}{l} +24R_3 \\ +12R_3 \\ +14R_3 \end{array} \rightarrow \\
& \left[\begin{array}{cccc|cccc} 1 & 0 & 0 & 0 & 249 & -272 & 1566 & -423 \\ 0 & 0 & 1 & 0 & 117 & -128 & 737 & 199 \\ 0 & -1 & 0 & 0 & 10 & -11 & 63 & -17 \\ 0 & 0 & 0 & -1 & 140 & -153 & 881 & -238 \end{array} \right] \begin{array}{l} \\ \\ \xrightarrow{R_2 \leftrightarrow -R_3} \\ -R_4 \end{array} \\
& \left[\begin{array}{cccc|cccc} 1 & 0 & 0 & 0 & 249 & -272 & 1566 & 75 \\ 0 & 1 & 0 & 0 & -10 & 11 & -63 & 17 \\ 0 & 0 & 1 & 0 & 117 & -128 & 737 & -199 \\ 0 & 0 & 0 & 1 & -140 & 153 & -881 & 238 \end{array} \right] \cdot
\end{aligned}$$

We therefore have
$$\begin{pmatrix} 5 & 3 & -2 & 7 \\ 1 & 18 & 3 & 3 \\ 1 & 4 & 3 & 4 \\ 6 & 5 & 8 & 17 \end{pmatrix}^{-1} = \begin{pmatrix} 249 & -272 & 1566 & 75 \\ -10 & 11 & -63 & 17 \\ 117 & -128 & 737 & -199 \\ -140 & 153 & -881 & 238 \end{pmatrix}.$$

OBSERVATION 83. Write the extended matrix of the n th step in the process above as $[A_n|B_n]$, starting with $A_0 = A, B_0 = I$. At each step we perform a step of Gaussian elimination, that is we multiply both sides by an elementary matrix E_n to get $A_{n+1} = E_{n+1}A_n, B_{n+1} = E_{n+1}B_n$.

Now the product $B_n^{-1}A_n$ is an invariant of the algorithm: we have $B_{n+1}^{-1}A_{n+1} = B_n^{-1}E_{n+1}^{-1}E_{n+1}A_n = B_n^{-1}A_n$. By induction it then follows that $B_n^{-1}A_n = B_0^{-1}A_0 = A$. Thus if we reach a stage where $A_n = I$ we have $B_n^{-1} = A$ and $B_n = A^{-1}$ as desired.

CHAPTER 3

Determinants

3.1. The determinant of a matrix

Notation: for a square matrix $A \in M_n(\mathbb{R})$ write a_{ij} for the entries, A_{ij} for the *minor*, the matrix $A_{ij} \in M_{n-1}(\mathbb{R})$ obtained by deleting the i th row and j th column.

DEFINITION 84. If $A \in M_1(\mathbb{R})$ set $\det A = a_{11}$. If $A \in M_n(\mathbb{R})$ for $n \geq 1$ set $\det A = \sum_{j=1}^n (-1)^{1+j} a_{1j} \det A_{1j}$.

EXAMPLE 85. $\det \begin{pmatrix} a & b \\ c & d \end{pmatrix} = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc$.

EXAMPLE 86. $\det(\text{diag}(a_1, \dots, a_n)) = a_1 \det(\text{diag}(a_2, \dots, a_n))$ so by induction $\det(\text{diag}(a_1, \dots, a_n)) = \prod_{i=1}^n a_i$.

DEFINITION 87. A matrix A is called *lower-triangular* if its entries above the main diagonal are zero: $a_{ij} = 0$ if $j > i$.

LEMMA 88. *Let A be lower-triangular. Then $\det A = \prod_{i=1}^n a_{ii}$.*

PROOF. Every $A \in M_1(\mathbb{R})$ is lower triangular and the formula holds by definition. Suppose this holds for $n \times n$ matrices and let $A \in M_{n+1}(\mathbb{R})$ be upper-triangular. Then every entry except a_{11} in the first row is zero, so $\det A = a_{11} \det A_{11}$. Now A_{11} is a lower-triangular matrix as well, and its diagonal consists of $a_{22}, \dots, a_{n+1, n+1}$. Thus $\det A = a_{11} \prod_{i=2}^{n+1} a_{ii} = \prod_{i=1}^{n+1} a_{ii}$. \square

3.2. Determinants of linear maps

3.2.1. Area of parallelograms in the plane.

3.2.2. Area forms in the plane. Let V be a two-dimensional vector space.

DEFINITION 89. A function $A: V^2 \rightarrow \mathbb{R}$ is an *area form* if

- (1) (“bilinearity”) A is linear in each argument separately.
- (2) (“alternativity”) For all $\underline{u} \in V$, $A(\underline{u}, \underline{u}) = 0$.

LEMMA 90. *The space of area forms is a subspace of \mathbb{R}^{V^2} .*

REMARK 91. Warning about multilinearity: this means $A(\underline{a} + \underline{b}, \underline{c} + \underline{d}) = A(\underline{a}, \underline{c}) + A(\underline{a}, \underline{d}) + A(\underline{b}, \underline{c}) + A(\underline{b}, \underline{d}) \neq A(\underline{a}, \underline{c}) + A(\underline{b}, \underline{d})$. Note that multiplication is multilinear.

LEMMA 92. *Let V be a vector space of any dimension. A bilinear form $A: V^2 \rightarrow \mathbb{R}$ is alternating iff its antisymmetric, in that $A(\underline{u}_1, \underline{u}_2) = -A(\underline{u}_2, \underline{u}_1)$ for all $\underline{u}_1, \underline{u}_2 \in V$.*

PROOF. Suppose A is alternating and consider $A(\underline{u}_1 + \underline{u}_2, \underline{u}_1 + \underline{u}_2)$. We have

$$\begin{aligned} 0 &= A(\underline{u}_1 + \underline{u}_2, \underline{u}_1 + \underline{u}_2) \\ &= A(\underline{u}_1, \underline{u}_1) + A(\underline{u}_1, \underline{u}_2) + A(\underline{u}_2, \underline{u}_1) + A(\underline{u}_2, \underline{u}_2) \\ &= A(\underline{u}_1, \underline{u}_2) + A(\underline{u}_2, \underline{u}_1). \end{aligned}$$

Conversely, suppose A is antisymmetric. Then exchanging the two arguments gives $A(\underline{u}, \underline{u}) = -A(\underline{u}, \underline{u})$ and hence $2A(\underline{u}, \underline{u}) = 0$ and $A(\underline{u}, \underline{u}) = 0$. \square

REMARK 93. The argument depended on $1 + 1 = 2$ being non-zero. There are situations where this isn't the case, which is why alternativity is the stronger hypothesis.

Now let $\{\underline{v}_1, \underline{v}_2\}$ be an ordered basis for V . Then given $(\underline{u}_1, \underline{u}_2) \in V^2$ there are a_{ij} such that $\underline{u}_1 = a_{11}\underline{v}_1 + a_{12}\underline{v}_2$ and $\underline{u}_2 = a_{21}\underline{v}_1 + a_{22}\underline{v}_2$ so that for any area form A , by the distributive remark above

$$\begin{aligned} A(\underline{u}_1, \underline{u}_2) &= a_{11}a_{21}A(\underline{v}_1, \underline{v}_1) + a_{11}a_{22}A(\underline{v}_1, \underline{v}_2) + a_{12}a_{21}A(\underline{v}_2, \underline{v}_1) + a_{12}a_{22}A(\underline{v}_2, \underline{v}_2) \\ &= a_{11}a_{22}A(\underline{v}_1, \underline{v}_2) - a_{12}a_{21}A(\underline{v}_1, \underline{v}_2) \\ &= [a_{11}a_{22} - a_{12}a_{21}]A(\underline{v}_1, \underline{v}_2). \end{aligned}$$

It follows that A is determined by the single number $A(\underline{v}_1, \underline{v}_2)$. Since evaluation is a linear map on functions, we have shown that the following linear map is injective:

$$\begin{aligned} \{\text{Area forms}\} &\rightarrow \mathbb{R} \\ A &\mapsto A(\underline{v}_1, \underline{v}_2). \end{aligned}$$

COROLLARY 94. *The space of area forms is at most 1-dimensional.*

LEMMA 95. *The map $\left(\begin{pmatrix} a \\ c \end{pmatrix}, \begin{pmatrix} b \\ d \end{pmatrix}\right) \mapsto ad - bc$ is a non-zero area form on \mathbb{R}^2 .*

COROLLARY 96. *The space of area form on a 2-dimensional space is exactly 1-dimensional.*

Now let $T \in \text{End}(V)$. Then for any area form A , $(\underline{u}_1, \underline{u}_2) \mapsto A(T\underline{u}_1, T\underline{u}_2)$ is also an area form (this is checked in PS8), and this map on area forms is linear. Since that space is 1d, there is c such that $A(T\underline{u}_1, T\underline{u}_2) = cA(\underline{u}_1, \underline{u}_2)$ for all area forms A and vectors $\underline{u}_1, \underline{u}_2$.

DEFINITION 97. The *determinant* $\det T$ is that number.

EXERCISE 98. Let T be represented by the matrix A . Then $\det T = \det A$.

3.2.3. Volume forms. Fix an n -dimensional vector space V .

DEFINITION 99. Let $f: V^n \rightarrow \mathbb{R}$ be a function.

- (1) Call f *multi-linear* if it's linear in every argument separately.
- (2) Call f *alternating* if exchanging any two arguments reverses the sign.

Call alternating multi-linear functions *volume forms*.

LEMMA 100. *Let $f: V^k \rightarrow V^k$ be multilinear. Then f is alternating iff f has the property that whenever some argument vanishes [or two are equal] f vanishes.*

PROOF. Given $i \neq j$ $g(\underline{u}_i, \underline{u}_j) \stackrel{\text{def}}{=} f(\underline{a}_1, \dots, \underline{a}_{i-1}, \underline{u}_i, \underline{a}_{i+1}, \dots, \underline{a}_{j-1}, \underline{u}_j, \underline{a}_{j+1}, \dots, \underline{a}_n)$ is a bilinear function. Now apply Lemma 92. \square

Now fix an ordered basis $\{\underline{v}_i\}_{i=1}^n \subset V$. Then given $(\underline{u}_1, \dots, \underline{u}_n) \in V^n$ let a_{ij} be such that $\underline{u}_i = \sum_{j=1}^n a_{ij}\underline{v}_j$. Then for any volume form f we have

$$\begin{aligned} f(\underline{u}_1, \dots, \underline{u}_n) &= f\left(\sum_{j_1=1}^n a_{1,j_1}\underline{v}_{j_1}, \dots, \sum_{j_n=1}^n a_{n,j_n}\underline{v}_{j_n}\right) \\ &= \sum_{(j_1, \dots, j_n) \in \{1, \dots, n\}^n} \left(\prod_{\ell=1}^n a_{\ell, j_\ell}\right) f(\underline{v}_{j_1}, \dots, \underline{v}_{j_n}) \\ &= \sum_{\sigma \text{ a rearrangement}} \left(\prod_{\ell=1}^n a_{\ell, \sigma(\ell)}\right) f(\underline{v}_{\sigma(1)}, \dots, \underline{v}_{\sigma(n)}) \\ &= \sum_{\sigma} (-1)^\sigma \left(\prod_{\ell=1}^n a_{\ell, \sigma(\ell)}\right) f(\underline{v}_1, \dots, \underline{v}_n) \end{aligned}$$

so again f is determined by $f(\underline{v}_1, \dots, \underline{v}_n)$.

COROLLARY 101. *The space of volume forms is a most 1-dimensional.*

THEOREM 102. *The map $f \mapsto f(\underline{v}_1, \dots, \underline{v}_n)$ is an isomorphism of vector spaces.*

PROOF. We show that the map $A \mapsto \det A$ of Definition 84 is a non-zero volume form on \mathbb{R}^n (thought of as a function of the columns), by induction on n .

The case $n = 1$ is easy, and $n = 2$ was done above. Now try $n + 1$. We first show that the function is multilinear: let $A \in M_{n+1}(\mathbb{R})$ and suppose that $a_{i,k} = \beta b_i + \gamma c_i$ for some particular k . Let B be the matrix where every column is the same as A except the k th column is (b_i) and similarly define C . Then for $j \neq k$, the minors A_{1j}, B_{1j}, C_{1j} have all columns the same except the one coming from the k th column – that column in A_{1j} is the *combination* of the respective columns in B_{1j}, C_{1j} . By induction $\det(A_{1j}) = \beta \det B_{1j} + \gamma \det C_{1j}$. For $j = k$ we see that A, B, C all have the same minor. It follows that

$$\begin{aligned} \det A &= \sum_{j=1}^{n+1} (-1)^{1+j} a_{1j} \det A_{1j} \\ &= \sum_{j \neq k} (-1)^{1+j} a_{1j} (\beta \det B_{1j} + \gamma \det C_{1j}) + (-1)^{1+k} (\beta b_1 + \gamma c_1) \det A_{1k} \\ &= \beta \left[\sum_{j \neq k} (-1)^{1+j} a_{1j} \det B_{1j} + (-1)^{1+k} b_1 \det B_{1k} \right] + \gamma \left[\sum_{j \neq k} (-1)^{1+j} a_{1j} \det C_{1j} + (-1)^{1+k} c_1 \det C_{1k} \right] \\ &= \beta \det B + \gamma \det C. \end{aligned}$$

Now suppose that the k th and ℓ th columns of A are equal. Then the same is true in every minor A_{1j} unless $j = k$ or $j = \ell$. It follows that

$$\det A = (-1)^{1+k} a_{1k} \det A_{1k} + (-1)^{1+\ell} a_{1\ell} \det A_{1\ell}.$$

Now $a_{1k} = a_{1\ell}$, and $A_{1\ell}$ is obtained from A_{1k} by repeatedly taking the ℓ th column and exchanging it with its left neighbour $\ell - k - 1$ times. It follows that

$$\det A = a_{1k} (-1)^{1+k} \left(\det A_{1k} + (-1)^{\ell-k} (-1)^{\ell-k-1} \det A_{1k} \right) = 0.$$

Finally it's easy to check by induction that $\det I_n = 1$. □

REMARK 103. The textbook shows by a very similar induction that this is also a volume form when considered as a function of the *rows*.

COROLLARY 104. *Let $T: V \rightarrow V$. Then $f \mapsto f(T \cdot, \dots, T \cdot)$ is a linear map on a 1d space, hence of the form $f \mapsto cf$.*

DEFINITION 105. Call this constant the *determinant* of T .

PROPOSITION 106. *Let A be a matrix of T wrt the basis $\{\underline{v}_i\}_{i=1}^n \subset V$. Then $\det A = \det T$. Here $\det A$ is given by Definition 84 while $\det T$ is given by Definition 105.*

PROOF. $f \in (V^n)^*$ be the volume form defined as follows: given $\{\underline{u}_i\}_{i=1}^n$ let a_{ij} be such that $\underline{u}_j = \sum_{i=1}^n a_{ij} \underline{v}_i$ and let $f(\underline{u}_1, \dots, \underline{u}_n) = \det \left((a_{ij})_{i,j=1}^n \right)$ (check that this is a volume form!), Then $f(\underline{v}_1, \dots, \underline{v}_n) = \det(I_n) = 1$. We thus have

$$\det T = (\det T) f(\underline{v}_1, \dots, \underline{v}_n) = f(T \underline{v}_1, \dots, T \underline{v}_n) = \det A$$

Since the matrix (a_{ij}) such that $T \underline{v}_j = \sum_i a_{ij} \underline{v}_i$ is exactly the matrix A of T in the given basis. □

3.3. Properties of determinants

Fix an n -dimensional space V .

PROPOSITION 107. For all $T, S \in \text{End}(V)$

- (1) $\det \text{Id}_V = 1$.
- (2) $\det(TS) = \det T \cdot \det S$.
- (3) $\det T \neq 0$ iff T is invertible

PROOF. (1) Any volume form is unchanged by composition with the identity transformation. For (2) let f be a volume form, and let f_T be the form $f_T(\underline{u}_1, \dots, \underline{u}_n) = f(T\underline{u}_1, \dots, T\underline{u}_n)$. Then

$$(\det(TD))f(\underline{u}_1, \dots, \underline{u}_n) = f(TS\underline{u}_1, \dots, TS\underline{u}_n) = f_T(S\underline{u}_1, \dots, S\underline{u}_n) = (\det S)f_T(\underline{u}_1, \dots, \underline{u}_n) = (\det S)(\det T)f(\underline{u}_1, \dots, \underline{u}_n)$$

Finally, if $TS = \text{Id}$ then $(\det T)(\det S) = 1$ no neither is zero. If T is not invertible let $\underline{v}_1 \in \text{Ker } T$ and extend this to a basis. Let f any volume form. Then $(\det T)f(\underline{v}_1, \dots, \underline{v}_n) = f(T\underline{v}_1, \dots, T\underline{v}_n) = f(\underline{0}, \dots) = 0$. Since a non-zero volume form is non-zero on a basis we see that $\det T = 0$. \square

THEOREM 108. Let A, B be two matrices related by a sequence of row or column combinations. Then $\det A = \det B$.

PROOF. If $B = E_r E_{r-1} \dots E_1 A E'_1 \dots E'_s$ then $\det A = \det B$ since $\det(I_n + cE^{ij}) = 1$ where $i \neq j$. \square

PROPOSITION 109. $\det A = \det A^t$.

PROOF. Exercise. \square

COROLLARY 110. Let A be upper-triangular, then $\det A = \prod_{i=1}^n a_{ii}$.

COROLLARY 111 (Minor expansion). $\det A = \sum_{j=1}^n (-1)^{i+j} a_{ij} \det(A_{ij}) = \sum_{i=1}^n (-1)^{i+j} a_{ij} \det(A_{ij})$.

PROOF. By Prop 109, \square

EXAMPLE 112.
$$\begin{vmatrix} 1 & 2 & 3 \\ 3 & 1 & 0 \\ 3 & 3 & -2 \end{vmatrix} \stackrel{R_3 - R_2}{=} \begin{vmatrix} 1 & 2 & 3 \\ 3 & 1 & 0 \\ 0 & 2 & -2 \end{vmatrix} = 2 \begin{vmatrix} 1 & 2 & 3 \\ 3 & 1 & 0 \\ 0 & 1 & -1 \end{vmatrix} \stackrel{R_1 + 3R_3}{=} 2 \begin{vmatrix} 1 & 5 & 0 \\ 3 & 1 & 0 \\ 0 & 1 & -1 \end{vmatrix} = -2 \begin{vmatrix} 1 & 5 \\ 3 & 1 \end{vmatrix} =$$

$$-2(1 - 15) = 28.$$

$$\begin{vmatrix} 1 & 2 & 3 \\ 3 & 1 & 0 \\ 3 & 3 & -2 \end{vmatrix} \stackrel{R_1 - 2R_2}{=} \begin{vmatrix} -5 & 0 & 3 \\ 3 & 1 & 0 \\ 3 & 3 & -2 \end{vmatrix} \stackrel{R_3 - 3R_2}{=} \begin{vmatrix} -5 & 0 & 3 \\ 3 & 1 & 0 \\ -6 & 0 & -2 \end{vmatrix} = -2 \begin{vmatrix} -5 & 0 & 3 \\ 3 & 1 & 0 \\ 3 & 0 & 1 \end{vmatrix} \stackrel{R_1 - 3R_3}{=} -2 \begin{vmatrix} -14 & 0 & 0 \\ 3 & 1 & 0 \\ 3 & 0 & 1 \end{vmatrix} = -2(-14 \cdot 1 \cdot 1) =$$

28.

Eigenvalues, eigenvectors, and diagonalization

4.1. Similarity and change of basis

Let V be a vector space with ordered basis $\mathcal{B} = \{\underline{v}_i\}_{i=1}^n$. To a linear map $T \in \text{End}(V)$ we associated a matrix A consisting of the coefficients of the $T\underline{v}_j$ in the basis:

$$T\underline{v}_j = \sum_{i=1}^n a_{ij}\underline{v}_i.$$

QUESTION 113. *What happens if we instead use a different basis?*

So let $\mathcal{C} = \{\underline{u}_k\}_{k=1}^n \subset V$ be another basis. We can expand each \underline{u}_k in the original basis, obtaining the *change of basis matrix* S , whose entries are defined by

$$\underline{u}_\ell = \sum_{j=1}^n s_{j\ell}\underline{v}_j.$$

Note that the columns of S are exactly the expansions of the elements of \mathcal{C} in the basis \mathcal{B} , and that S is the matrix with respect to \mathcal{B} of the linear map $R \in \text{End}(V)$ defined by $R\underline{v}_\ell = \underline{u}_\ell$.

Applying T to both sides we get:

$$\begin{aligned} T\underline{u}_\ell &= T\left(\sum_{j=1}^n s_{j\ell}\underline{v}_j\right) \\ &= \sum_{j=1}^n s_{j\ell}T\underline{v}_j \\ &= \sum_{j=1}^n s_{j\ell}\sum_{i=1}^n a_{ij}\underline{v}_i \\ &= \sum_{i=1}^n \left(\sum_{j=1}^n a_{ij}s_{j\ell}\right)\underline{v}_i. \end{aligned}$$

Note that the parentheses are exactly give the $i\ell$ th entry of the matrix AS . Next, expand \underline{v}_i in the basis \mathcal{C} . Suppose $\underline{v}_i = \sum_{k=1}^n t_{ki}\underline{u}_k$ (so the t_{ki} are the entries of the reverse change-of-basis matrix). We then have

$$\begin{aligned} \underline{v}_i &= \sum_{k=1}^n t_{ki}\underline{u}_k = \sum_{k=1}^n t_{ki}\sum_{j=1}^n s_{jk}\underline{v}_j \\ &= \sum_{j=1}^n \left(\sum_{k=1}^n s_{jk}t_{ki}\right)\underline{v}_j. \end{aligned}$$

But vectors have a unique representation in the basis, and we get

$$\sum_{k=1}^n s_{jk}t_{ki} = \begin{cases} 1 & j = i \\ 0 & j \neq i \end{cases} = \delta_{ij}$$

is the ij th entry of the identity matrix. In other words, the t_{ki} are the entries of the inverse matrix S^{-1} and the relation is

$$v_i = \sum_{\ell=1}^n (s^{-1})_{ki} u_\ell$$

and hence

$$\begin{aligned} T u_\ell &= \sum_{i=1}^n \left(\sum_{j=1}^n a_{ij} s_{j\ell} \right) v_i \\ &= \sum_{i=1}^n \left(\sum_{j=1}^n a_{ij} s_{j\ell} \right) \sum_{k=1}^n (s^{-1})_{ki} u_k \\ &= \sum_{k=1}^n \left(\sum_{i=1}^n \sum_{j=1}^n (s^{-1})_{ki} a_{ij} s_{j\ell} \right) u_k \\ &= \sum_{k=1}^n (S^{-1}AS)_{k\ell} u_k. \end{aligned}$$

But on the other hand by definition the coefficients here define the matrix of T in the basis \mathcal{C} , and we have proved

PROPOSITION 114. *Let $A, B \in M_n(\mathbb{R})$ be the matrices of $T \in \text{End}(V)$ wrt the bases $\{v_i\}_{i=1}^n, \{u_k\}_{k=1}^n \subset V$ respectively. Let $S \in M_n(\mathbb{R})$ be the change-of-basis matrix, defined by $u_\ell = \sum_{j=1}^n s_{j\ell} v_j$. Then*

$$B = S^{-1}AS.$$

DEFINITION 115. Two matrices $A, B \in M_n(\mathbb{R})$ are *similar* if there is a matrix $S \in M_n(\mathbb{R})$ such that $B = S^{-1}AS$. Two linear maps $S, T \in \text{End}(V)$ are *similar* if there is an invertible map $R \in \text{End}(V)$ such that $S = R^{-1}TR$.

OBSERVATION 116. *Two matrices are similar iff they represent the same linear map in different bases.*

EXERCISE 117. (PS6) Similarity is an equivalence relation.

4.2. Motivation

Fix a vector space V .

DEFINITION 118. Let $T \in \text{End}(V)$. Suppose we have a scalar λ and a non-zero $v \in V$ such that $Tv = \lambda v$. We then say that λ is an *eigenvalue* of T , and that v is an *eigenvector* corresponding to the eigenvalue λ .

REMARK 119. The equation is *non-linear*! [but linear in v for λ fixed]

Why care?

4.2.1. Diagonalization. Suppose we have a basis consisting of eigenvectors. Then the matrix is diagonal, hence simple (for example we can easily find the matrix of T^2 in that basis).

4.2.2. Solve differential equations. $1, \cos(2\pi kx), \sin(2\pi kx)$ are a basis for functions on the circle on which $\frac{d^2}{dx^2}$ acts by scalars. This is a good basis in which to study differential equations.

Note that eigenvalues are given by non-positive reals.

4.2.3. Solve difference equations. Let $L: \mathbb{R}^{\mathbb{N}} \rightarrow \mathbb{R}^{\mathbb{N}}$ be the left-shift operator. Then for any $r \in \mathbb{R}$, $(r^n)_{n \geq 0}$ is an eigenvector with eigenvalue r .

Now let F_n be the Fibonacci sequence satisfying $F_{n+2} = F_{n+1} + F_n$. From our earlier work on difference equations we know to write this as $(L^2 - L - 1)\underline{F} = \underline{0}$ and that the space of solutions is two-dimensional. Now let $r_{1,2} = \frac{1 \pm \sqrt{5}}{2}$ be the two roots of $r^2 - r - 1 = 0$. It follows that $\left\{ (r_1^n)_{n \geq 0}, (r_2^n)_{n \geq 0} \right\}$ both belong to $\text{Ker}(L^2 - L - 1)$. They are not proportional, hence a basis. We have proven:

THEOREM 120. Let F_n be the Fibonacci sequence with $F_0 = 0, F_1 = 1$. Then $F_n = \frac{1}{\sqrt{5}} \left(\left(\frac{1+\sqrt{5}}{2} \right)^n - \left(\frac{1-\sqrt{5}}{2} \right)^n \right)$.

PROOF. There are A, B such that $Ar_1^n + Br_2^n = F_n$ for all n . Specifically for $n = 0, 1$ we see:

$$\begin{aligned} A + B &= 0 \\ Ar_1 + Br_2 &= 1 \end{aligned}$$

and this has the solution $A = -B = \frac{1}{\sqrt{5}}$. □

COROLLARY 121. $F_n^{1/n} \rightarrow \frac{1+\sqrt{5}}{2}$ and $\frac{1}{\sqrt{5}} \left(\frac{1+\sqrt{5}}{2} \right)^n$ is exponentially close to being an integer.

4.2.4. Quantum Mechanics. Observables are linear operator

4.2.5. PCA = FA.

4.3. The characteristic polynomial, trace and determinant

4.3.1. Work by hand.

EXAMPLE 122. Let $A = \begin{pmatrix} 4 & 3 \\ 1 & 2 \end{pmatrix}$. Then we need to solve $\begin{pmatrix} 4 & 3 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda \begin{pmatrix} x \\ y \end{pmatrix}$, that is $\begin{cases} (4-\lambda)x + 3y = 0 \\ x + (2-\lambda)y = 0 \end{cases}$.

Suppose (x, y, λ) is a solution. Then $x = (\lambda - 2)y$ so

$$(4 - \lambda)(\lambda - 2)y + 3y = 0$$

that is

$$(\lambda^2 - 6\lambda + 5)y = 0.$$

Thus either $y = 0$ at which point $x = 0$ and λ can be arbitrary, or $y \neq 0$ at which point $\lambda \in \{1, 5\}$ and $x = (\lambda - 2)y$ for arbitrary y (check that these are solutions!)

CONCLUSION 123. The eigenvalues of A are 1, 5 and the corresponding eigenspaces are $\text{Span} \left\{ \begin{pmatrix} -1 \\ 1 \end{pmatrix} \right\}$, $\text{Span} \left\{ \begin{pmatrix} 3 \\ 1 \end{pmatrix} \right\}$.

4.3.2. The char poly. Recap:

- The eigenvalue problem is non-linear – we found λ as roots of a polynomial.
- Given λ , the problem is purely linear.

Fix $V, T \in \text{End}(V)$. Then λ is an eigenvalue iff there is non-zero \underline{v} such that $T\underline{v} = \lambda\underline{v}$ that is iff $\text{Ker}(\lambda \text{Id}_V - T) \neq \{0\}$. If V is finite-dimensional this is equivalent to $\lambda - T$ being non-invertible and hence to $\det(\lambda \text{Id}_V - T) = 0$.

DEFINITION 124. Let V be finite dimensional. The *characteristic polynomial* of $T \in \text{End}(V)$ is $p(x) = p_T(x) = \det(x\text{Id}_V - T)$.

REMARK 125. Best to think of the matrix of $x\text{Id}_V - T$ as a matrix in $M_n(\mathbb{R}[x])$, showing that the determinant is indeed a polynomial.

We have proved:

THEOREM 126. λ is an eigenvalue of T iff λ is a root of $p_T(x)$.

REMARK 127. In practice this is a terrible way of finding eigenvalues – can't find roots of polynomials.

EXERCISE 128. The characteristic polynomial is always monic of degree is $\dim V$. Any such polynomial is the char poly of a linear map.

EXAMPLE 129. The characteristic polynomial of $\begin{pmatrix} 4 & 3 \\ 1 & 2 \end{pmatrix}$ is $x^2 - 6x + 5$.

PROOF. Can do direct calculation, but also note that must be monic and divisible by $(x - 5)(x - 1)$ since those are eigenvalues. \square

REMARK 130. The polynomial doesn't have to have real roots (consider $\begin{pmatrix} & 1 \\ -1 & \end{pmatrix}$), but the F.T.Algebra says that always factor over complex numbers (exercise: the 2x2 case).

The following aside will help us identify "obvious" roots:

THEOREM 131 (Rational roots). Let $p(x) \in \mathbb{Z}[x]$ satisfy $p(x) = \sum_{i=0}^d a_i x^i$ with $a_0 a_d \neq 0$. Suppose that $p(\frac{r}{s}) = 0$ with $r, s \in \mathbb{Z}$ relatively prime, $s \neq 0$. Then $r|a_0, s|a_d$.

PROOF. Clear denominators to get $\sum_{i=0}^d a_i s^{d-i} r^i = 0$. Now $a_0 s^d = -r (\sum_{i=1}^d a_i s^{d-i} r^{i-1})$ and $a_d r^d = -s (\sum_{i=0}^{d-1} a_i s^{(d-1)-i} r^i)$. \square

4.4. Properties and diagonalization

Fix $V, T \in \text{End}(V)$.

DEFINITION 132. $V_\lambda = \text{Ker}(V - \lambda \text{Id}_V)$; $\text{Spec}(\lambda) = \{\lambda \in \mathbb{C} \mid V_\lambda \neq \{0\}\}$.

LEMMA 133. Let $\{v_i\}_{i=1}^r$ be eigenvectors of T with distinct eigenvalues λ_i . Then the $\{v_i\}$ are independent.

PROOF. Consider a minimal dependence and apply T . \square

COROLLARY 134. The sum $\sum_\lambda V_\lambda$ is direct. In particular, at most n distinct eigenvalues (also follows from char poly).

DEFINITION 135. Let λ be a scalar. The algebraic multiplicity of λ as an eigenvalue is the maximum r such that $(x - \lambda)^r$ divides $p_T(\lambda)$. The geometric multiplicity is $\dim V_\lambda$.

PROPOSITION 136. Algebraic \geq Geometric

PROOF. Let $\{v_i\}_{i=1}^r$ be a basis for V_λ . Complete this into a basis $\{v_i\}_{i=1}^n$ for V . Let A be the matrix for T in this basis. Then $p_A(x) = (x - \lambda)^r p_B(x)$ for the lower-right square B of A (repeatedly expand by columns).

Let $\{v_i\}_{i=1}^r$ span the λ -eigenspace; complete to a basis. Let A be matrix by this basis, and expand $\det(xI_n - A)$ by first r columns to see that $(x - \lambda)^r$ divides $p_A(x)$. \square

EXAMPLE 137. $\begin{pmatrix} 1 & \\ -2 & -1 \end{pmatrix}, \begin{pmatrix} 1 & 1 \\ & 1 \end{pmatrix}$.

DEFINITION 138. Call T diagonalable (or diagonalizable) if V has a basis consisting of eigenvectors.

This is equivalent to saying that in some basis the matrix of T is diagonal.

LEMMA 139. Let T be a linear map, $\{\underline{v}_i\}_{i=1}^n, \{\underline{u}_j\}_{j=1}^n$ two bases of V . Let A, A' be the matrices of T wrt the two bases. Let B be the matrix whose j th column is the decomposition of \underline{u}_j in \underline{v}_i . Then S is invertible and $A' = B^{-1}AB$.

PROOF. B is the matrix of the map S such that $S\underline{v}_i = \underline{u}_i$ wrt basis \underline{v}_i . Maps basis to basis so invertible. B^{-1} is matrix of $S^{-1}\underline{u}_i = \underline{v}_i$ in basis \underline{v}_i , so columns are decomposition of \underline{v}_j in terms of \underline{u}_i . Now

$$T\underline{u}_j = T\left(\sum_i b_{ij}\underline{v}_i\right) = \sum_i b_{ij}T\underline{v}_i = \sum_i b_{ij}\sum_k a_{ki}\underline{v}_k = \sum_{i,k,l} a_{ki}b_{ij}\sum_l (b^{-1})_{lk}\underline{u}_k = \sum_k (B^{-1}AB)_{kj}\underline{u}_k. \quad \square$$

THEOREM 140. Let $A \in M_n(\mathbb{R})$ and let $\{\underline{v}_i\}_{i=1}^n$ be linearly independent such that $A\underline{v}_i = \lambda_i\underline{v}_i$. Let S be the matrix with columns \underline{v}_i . Then S is invertible and $S^{-1}AS = \text{diag}(\lambda_1, \dots, \lambda_n)$. Equivalently, $A = SDS^{-1}$ where $D = \text{diag}(\lambda_1, \dots, \lambda_n)$.

EXAMPLE 141. $\begin{pmatrix} 4 & 3 \\ 2 & 1 \end{pmatrix}$ has eigenvectors $\begin{pmatrix} -1 \\ 1 \end{pmatrix}, \begin{pmatrix} 3 \\ 1 \end{pmatrix}$.

LEMMA 142. Let A, B be similar matrices. Then they are the matrices of the same linear map in different bases.

4.5. Diversion: Graph eigenvalues and PageRank

CHAPTER 5

Inner product spaces

In this chapter the field of scalars is either \mathbb{R} or \mathbb{C} .

5.1. Inner product spaces

5.1.1. Motivation and basic examples. In Euclidean space \mathbb{E}^n we have a notion of distance between points. Equivalently we have a notion of distance in \mathbb{R}^n .

5.1.2. Definition. For real vector spaces

DEFINITION 143. Let V be a vector space over the real field. An *inner product* on V is a map $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ such that:

- (1) (Bilinearity) The map is linear in the second coordinate: $\langle \underline{u}, \alpha \underline{v} + \beta \underline{w} \rangle = \alpha \langle \underline{u}, \underline{v} \rangle + \beta \langle \underline{u}, \underline{w} \rangle$.
- (2) (Symmetry) $\langle \underline{u}, \underline{v} \rangle = \langle \underline{v}, \underline{u} \rangle$.
- (3) (Positivity) $\langle \underline{u}, \underline{u} \rangle \geq 0$ with equality iff $\underline{u} = \underline{0}$.

An *inner product space* is a pair $(V, \langle \cdot, \cdot \rangle)$ where V is a real vector space and $\langle \cdot, \cdot \rangle$ is an inner product on V .

For complex scalars positivity requires a more complicated definition:

DEFINITION 144. Let V be a vector space over the complex field. A *hermitian product* on V is a map $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{C}$ such that:

- (1) (Conjugate linearity) The map is linear in the second coordinate: $\langle \underline{u}, \alpha \underline{v} + \beta \underline{w} \rangle = \alpha \langle \underline{u}, \underline{v} \rangle + \beta \langle \underline{u}, \underline{w} \rangle$.
- (2) (Conjugate symmetry) $\langle \underline{u}, \underline{v} \rangle = \overline{\langle \underline{v}, \underline{u} \rangle}$.
- (3) (Positivity) $\langle \underline{u}, \underline{u} \rangle \geq 0$ with equality iff $\underline{u} = \underline{0}$.

A *hermitian space* is a pair $(V, \langle \cdot, \cdot \rangle)$ where V is a complex vector space and $\langle \cdot, \cdot \rangle$ is a hermitian product on V .

When $\underline{u} = \underline{v}$, axiom (2) reads $\langle \underline{u}, \underline{u} \rangle = \overline{\langle \underline{u}, \underline{u} \rangle}$, ensuring that $\langle \underline{u}, \underline{u} \rangle \in \mathbb{R}$ so that axiom 3 makes sense.

REMARK 145. We often abuse terminology and use “inner product space” in both contexts.

EXAMPLE 146. The *standard inner product* on \mathbb{R}^n is the one from above. The analogues *standard inner product* on \mathbb{C}^n is

$$\langle \underline{z}, \underline{w} \rangle = \sum_{i=1}^n \bar{z}_i \cdot w_i.$$

EXAMPLE 147. Let $C(a, b)$ be the space of real- or complex-valued functions on the interval $[a, b]$. Setting

$$\langle f, g \rangle = \int_a^b \overline{f(x)} g(x) dx$$

defines an inner (respectively) hermitian product on $C(a, b)$.

PROOF. Linearity is immediate from properties of the Riemann integral and conjugate symmetry is clear. If $f = g$ we have

$$\langle f, f \rangle = \int_a^b |f(x)|^2 dx.$$

The is non-negative since the integrand is non-negative. Also, since f is continuous if f is non-zero then $|f|$ is positive on a subinterval, and the integral is strictly positive. \square

EXAMPLE 148. (PS12) On $M_n(\mathbb{C})$ set $\langle A, B \rangle = \text{Tr}(A^\dagger B)$ where $(A^\dagger)_{ij} = \overline{A_{ji}}$.

LEMMA 149. *Let V be an inner product space. Then the inner product is linear in the first variable (conjugate-linear if the scalars are complex).*

PROOF. We have

$$\begin{aligned} \langle \alpha \underline{u} + \beta \underline{v}, \underline{w} \rangle &= \overline{\langle \underline{w}, \alpha \underline{u} + \beta \underline{v} \rangle} \\ &= \overline{\alpha \langle \underline{w}, \underline{u} \rangle + \beta \langle \underline{w}, \underline{v} \rangle} \\ &= \overline{\alpha} \overline{\langle \underline{w}, \underline{u} \rangle} + \overline{\beta} \overline{\langle \underline{w}, \underline{v} \rangle} \\ &= \overline{\alpha} \langle \underline{u}, \underline{w} \rangle + \overline{\beta} \langle \underline{v}, \underline{w} \rangle. \end{aligned}$$

\square

LEMMA 150 (Restriction). *Let V be an inner product space and let W be a subspace. Then $(W, \langle \cdot, \cdot \rangle|_{W \times W})$ is an inner product space. If V is complex then $(V, \Re \langle \cdot, \cdot \rangle)$ is a real inner product space when we treat V as a real vector space.*

PROOF. All the axioms are universal. \square

5.2. The Cauchy–Schwartz inequality

Fix an inner product space V .

DEFINITION 151 (The norm). The *norm* of $\underline{u} \in V$ is the non-negative real number $\|\underline{u}\| = \sqrt{\langle \underline{u}, \underline{u} \rangle}$ (recall that this $\langle \underline{u}, \underline{u} \rangle$ is always a non-negative real number).

By the axioms for an inner product space we have $\|\underline{u}\| = 0$ iff $\underline{u} = \underline{0}$. We also observe that the norm is 1-homogenous:

$$\begin{aligned} \|\alpha \underline{u}\| &= \sqrt{\langle \alpha \underline{u}, \alpha \underline{u} \rangle} = \sqrt{\overline{\alpha} \alpha \langle \underline{u}, \underline{u} \rangle} \\ &= \sqrt{\overline{\alpha} \alpha} \sqrt{\langle \underline{u}, \underline{u} \rangle} \\ &= |\alpha| \|\underline{u}\|. \end{aligned}$$

LEMMA 152 (Cauchy–Schwartz). *Let $\underline{u}, \underline{v} \in V$. Then*

$$|\langle \underline{u}, \underline{v} \rangle| \leq \|\underline{u}\| \|\underline{v}\|,$$

with equality if and only if $\underline{u}, \underline{v}$ are multiples of each other.

PROOF. If $\langle \underline{u}, \underline{v} \rangle = 0$ there is nothing to prove. Otherwise there is a number α of modulus 1 such that $\alpha \langle \underline{u}, \underline{v} \rangle = |\langle \underline{u}, \underline{v} \rangle|$. Consider then the real-valued function

$$f(t) = \|t\underline{u} + \alpha \underline{v}\|^2 = \langle t\underline{u} + \alpha \underline{v}, t\underline{u} + \alpha \underline{v} \rangle.$$

Using the bilinearity we have

$$f(t) = t^2 \langle \underline{u}, \underline{u} \rangle + t \langle \underline{u}, \alpha \underline{v} \rangle + t \langle \alpha \underline{v}, \underline{u} \rangle + |\alpha|^2 \langle \underline{v}, \underline{v} \rangle.$$

Observe now that $\langle \underline{u}, \alpha \underline{v} \rangle = \alpha \langle \underline{u}, \underline{v} \rangle = |\langle \underline{u}, \underline{v} \rangle|$ is real, hence equal to its own complex conjugate, and we get that $\langle \alpha \underline{v}, \underline{u} \rangle = \langle \underline{u}, \alpha \underline{v} \rangle$. We also have $\langle \underline{u}, \underline{u} \rangle = \|\underline{u}\|^2$ and $\langle \underline{v}, \underline{v} \rangle = \|\underline{v}\|^2$ and $|\alpha| = 1$ so in the end

$$f(t) = t^2 \|\underline{u}\|^2 + 2t |\langle \underline{u}, \underline{v} \rangle| + \|\underline{v}\|^2.$$

Note that this is a quadratic function with positive real coefficients: if $\langle \underline{u}, \underline{u} \rangle$ or $\langle \underline{v}, \underline{v} \rangle$ vanishes then one of $\underline{u}, \underline{v}$ would vanish and then their inner product would vanish as well. Completing the square, we have

$$f(t) = \left(t \|\underline{u}\| + \frac{|\langle \underline{u}, \underline{v} \rangle|}{\|\underline{u}\|} \right)^2 + \|\underline{v}\|^2 - \frac{|\langle \underline{u}, \underline{v} \rangle|^2}{\|\underline{u}\|^2}.$$

Now as the norm of a vector we have $f(t) \geq 0$ for all t , so we must have

$$\|\underline{v}\|^2 - \frac{|\langle \underline{u}, \underline{v} \rangle|^2}{\|\underline{u}\|^2} \geq 0$$

Which can be rearranged to form the desired inequality. In addition equality holds iff there is t such that $f(t) = 0$, that is iff there is t such that $t\underline{u} + \alpha \underline{v} = \underline{0}$ or (assuming $\underline{u}, \underline{v} \neq \underline{0}$) that $\underline{u} = -t^{-1} \alpha \underline{v}$. \square

PROPOSITION 153 (Minkowsky's inequality; "triangle inequality"). *We have $\|\underline{u} + \underline{v}\| \leq \|\underline{u}\| + \|\underline{v}\|$ (and also $\|\alpha \underline{u}\| = |\alpha| \|\underline{u}\|$ and $\|\underline{u}\| = 0 \iff \underline{u} = \underline{0}$).*

PROOF. We apply CS:

$$\begin{aligned} \|\underline{u} + \underline{v}\|^2 &= \langle \underline{u} + \underline{v}, \underline{u} + \underline{v} \rangle \\ &= \langle \underline{u}, \underline{u} \rangle + \langle \underline{u}, \underline{v} \rangle + \langle \underline{v}, \underline{u} \rangle + \langle \underline{v}, \underline{v} \rangle \\ &\leq \|\underline{u}\|^2 + \|\underline{u}\| \|\underline{u}\| + \|\underline{v}\| \|\underline{u}\| + \|\underline{v}\|^2 \\ &= (\|\underline{u}\| + \|\underline{v}\|)^2. \end{aligned}$$

\square

COROLLARY 154. *The function $d(\underline{u}, \underline{v}) = \|\underline{v} - \underline{u}\|$ is a metric on V : $d: V \times V \rightarrow \mathbb{R}_{\geq 0}$ satisfies $d(\underline{u}, \underline{v}) = d(\underline{v}, \underline{u})$, $d(\underline{u}, \underline{v}) = 0 \iff \underline{u} = \underline{v}$ and $d(\underline{u}, \underline{w}) \leq d(\underline{u}, \underline{v}) + d(\underline{v}, \underline{w})$.*

In a real inner product space we observe that for any non-zero vectors $\underline{u}, \underline{v}$ we have

$$-1 \leq \frac{\langle \underline{u}, \underline{v} \rangle}{\|\underline{u}\| \|\underline{v}\|} \leq 1$$

and in particular there is a unique angle $\theta \in [0, \pi]$ such that

$$\langle \underline{u}, \underline{v} \rangle = \|\underline{u}\| \|\underline{v}\| \cos \theta.$$

DEFINITION 155. We call θ the *angle* between $\underline{u}, \underline{v}$.

5.3. Orthogonality

5.3.1. Intro. Fix an inner product space V . We identify particular configurations of vectors which are convenient for linear algebra. Three ideas:

- (1) Orthogonal and orthonormal systems
- (2) The Gram-Schmidt procedure
- (3) The orthogonal complement

DEFINITION 156. Two vectors $\underline{u}, \underline{v} \in V$ are *orthogonal* if $\langle \underline{u}, \underline{v} \rangle = 0$, (for non-zero vectors, if the angle between them is $\frac{\pi}{2}$). In that case we write $\underline{u} \perp \underline{v}$

5.3.2. Orthogonal and orthonormal systems.

DEFINITION 157. A set of vectors $B \subset V$ is an *orthogonal system* if the vectors are non-zero and mutually orthogonal.

LEMMA 158. *An orthogonal system is linearly independent.*

PROOF. Suppose we have a linear combination

$$\sum_{i=1}^n a_i \underline{v}_i = \underline{0}$$

where a_i are scalars and $\underline{v}_i \in B$ are distinct. Taking inner product with \underline{v}_j we have

$$\begin{aligned} 0 &= \langle \underline{v}_j, \underline{0} \rangle = \left\langle \underline{v}_j, \sum_{i=1}^n a_i \underline{v}_i \right\rangle \\ &= \sum_{i=1}^n a_i \langle \underline{v}_j, \underline{v}_i \rangle && \text{linearity} \\ &= a_j \langle \underline{v}_j, \underline{v}_j \rangle && i \neq j \Rightarrow \underline{v}_j \perp \underline{v}_i. \end{aligned}$$

Since $\langle \underline{v}_j, \underline{v}_j \rangle > 0$ we have $a_j = 0$. □

Orthogonality is powerful because determining the coefficients of a vector with respect to an orthogonal system does not require solving systems of linear equations:

LEMMA 159. *Let B be an orthogonal system, and let $\underline{v} \in \text{Span}(B)$ have the form $\underline{v} = \sum_{i=1}^n a_i \underline{v}_i$ where $\underline{v}_i \in B$ are distinct. Then*

$$a_j = \frac{\langle \underline{v}_j, \underline{v} \rangle}{\langle \underline{v}_j, \underline{v}_j \rangle}.$$

PROOF. Same calculation as above. □

OBSERVATION 160. *The coefficient a_j depends only on \underline{v}_j – not on the whole system. Note that this is completely false for general basis B .*

Clearly rescaling the vectors does not change orthogonality, and helps with calculation above. Accordingly we set

DEFINITION 161. An orthogonal system B is *orthonormal* if every $\underline{v} \in B$ has norm 1. It is *complete* if the only vector orthogonal to the entire system is the zero vector.

REMARK 162. Complete orthonormal systems are often called “orthonormal bases”; this is often abbreviated o.n.b.

LEMMA 163. *Suppose $\dim V = n < \infty$. Then every complete orthonormal system in V is a basis.*

PROOF. Let $B = \{\underline{v}_i\}_{i=1}^m \subset V$ be a complete orthonormal system and let $\underline{v} \in V$. For each $\underline{v}_i \in B$ let $a_i = \langle \underline{v}_i, \underline{v} \rangle$ as above, and consider the vector

$$\underline{v} - \sum_{i=1}^m a_i \underline{v}_i.$$

We will verify that this vector is orthogonal to B , and it will follow that it is the zero vector, in other words that $\underline{v} = \sum_{i=1}^m a_i \underline{v}_i$.

Indeed

$$\begin{aligned} \left\langle \underline{v}_j, \underline{v} - \sum_{i=1}^m a_i \underline{v}_i \right\rangle &= \langle \underline{v}_j, \underline{v} \rangle - \sum_{i=1}^m a_i \langle \underline{v}_j, \underline{v}_i \rangle \\ &= a_j - a_j = 0. \end{aligned}$$

□

EXAMPLE 164. The infinite-dimensional situation is more complicated, because the natural notions of span involve series of vectors. As an example, let $C(\mathbb{R}/\mathbb{Z})$ denote the space of continuous complex-valued functions on \mathbb{R} which are \mathbb{Z} -periodic, that is functions such that $f(x+1) = f(x)$ for all x , equipped with the inner product $\langle f, g \rangle = \int_0^1 \overline{f(x)}g(x) dx$. Then the functions $e_n(x) = e^{2\pi i n x}$ are an orthonormal system in $C(\mathbb{R}/\mathbb{Z})$: it's easy to check that they are orthogonal, but completeness is more involved (given $f \in C(\mathbb{R}/\mathbb{Z})$ which is non-zero and perpendicular to all these functions, one uses the Stone–Weierstrass Theorem to produce an element $g = \sum_{|n| \leq N} a_n e_n$ in the span which is close to f pointwise. Since $|(f-g)(x)| \leq \varepsilon$ for all x we have $\|f-g\|^2 \leq \varepsilon^2$ (plug into the integral). On the other hand $f \perp g$ gives

$$\begin{aligned} \langle f-g, f-g \rangle &= \langle f, f \rangle + \langle g, g \rangle - \langle f, g \rangle - \langle g, f \rangle \\ &= \langle f, f \rangle + \langle g, g \rangle \geq \langle f, f \rangle \end{aligned}$$

producing a contradiction as soon as $\varepsilon < \|f\|$.

(If you prefer the real-valued version of this, use the orthonormal system $\{1\} \cup \{\sqrt{2} \sin(2\pi n x), \sqrt{2} \cos(2\pi n x)\}_{n=1}^{\infty}$ instead).

5.3.3. Gram–Schmidt.

5.3.4. Orthogonality and the orthogonal complement.

DEFINITION 165. A vector \underline{u} is orthogonal to a subset $S \subset V$ if $\langle \underline{u}, \underline{v} \rangle = 0$ for all $\underline{v} \in S$. The *orthogonal complement* of a subset S is $S^\perp = \{\underline{u} \in V \mid \underline{u} \perp S\}$.

LEMMA 166. *The orthogonal complement of a subset is a subspace.*

PROOF. By definition $S^\perp = \bigcap \{\underline{v}^\perp\}_{\underline{v} \in S}$ so it's enough to show that the orthogonal complement of each vector is a subspace. But

$$\begin{aligned} \underline{v}^\perp &= \{\underline{u} \mid \langle \underline{u}, \underline{v} \rangle = 0\} \\ &= \{\underline{u} \mid \langle \underline{v}, \underline{u} \rangle = 0\} \\ &= \text{Ker}(\langle \underline{v}, \cdot \rangle). \end{aligned}$$

□

PROPOSITION 167 (Orthogonal decomposition). *Let $W \subset V$ be a subspace. Then $W \cap W^\perp = \{\underline{0}\}$ and $V = W \oplus W^\perp$.*

5.4. Linear maps and : the adjoint

As usual we fix an inner product space $(V, \langle \cdot, \cdot \rangle)$, which we assume finite-dimensional, with $n = \dim V$.

So far we've taken a *geometric* point of view: focusing on distances, angles, orthogonality, etc. We now take an *algebraic* point of view: how inner products interact with the rest of linear algebra. We begin with linear functional.

REMARK 168. The results of this section apply in the infinite-dimensional case under further *analytic* assumptions such as *completeness* of the space and *compactness* of the linear operators. Interested students should look up the theory of *Hilbert spaces*.

5.4.1. The Riesz Representation Theorem.

OBSERVATION 169. Let $\underline{u} \in V$. We then get scalar-valued function on V by setting $\varphi_{\underline{u}}(\underline{v}) = \langle \underline{u}, \underline{v} \rangle$. This is actually a linear functional (by the definition of inner product!). The inner product thus gives an linear functional for each \underline{u} . In fact we get all linear functionals this way.

LEMMA 170 (Riesz Representation Theorem, finite-dimensional case). For each $\varphi \in V^*$ there is a unique $\underline{u} \in V$ such that $\varphi = \varphi_{\underline{u}}$. Furthermore, this bijection respects addition but is anti-linear for scalar multiplication: $\varphi_{c\underline{u}} = \bar{c}\varphi_{\underline{u}}$.

PROOF. We prove the uniqueness first, Suppose $\varphi_{\underline{u}} = \varphi_{\underline{u}'}$, that is $\langle \underline{u}, \underline{v} \rangle = \langle \underline{u}', \underline{v} \rangle$ for all $\underline{v} \in V$. This statement is equivalent to

$$0 = \langle \underline{u}, \underline{v} \rangle - \langle \underline{u}', \underline{v} \rangle = \langle \underline{u} - \underline{u}', \underline{v} \rangle$$

and now choosing $\underline{v} = \underline{u} - \underline{u}'$ shows $\|\underline{u} - \underline{u}'\| = 0$ so $\underline{u} = \underline{u}'$.

For existence, let $\varphi \in V^*$. If φ is the zero functional then $\varphi = \varphi_{\underline{0}}$ and we are done, so suppose φ is non-zero. Then its image is 1-dimensional so by the rank-nullity theorem we have $\dim \text{Ker } \varphi = n - 1$. Since $V = (\text{Ker } \varphi) \oplus (\text{Ker } \varphi)^\perp$ we have $\dim (\text{Ker } \varphi)^\perp = 1$ so we can choose a non-zero vector $\underline{t} \in (\text{Ker } \varphi)^\perp$ and set $\underline{u} = \frac{\varphi(\underline{t})}{\langle \underline{t}, \underline{t} \rangle} \underline{t}$. We claim that $\varphi = \varphi_{\underline{u}}$. Indeed any $\underline{v} \in V$ can be uniquely written as a sum of two vectors, one each from $\text{Ker } \varphi$ and $(\text{Ker } \varphi)^\perp$. In other words we can write $\underline{v} = \underline{w} + c\underline{t}$ for some $\underline{w} \in \text{Ker } \varphi$ and scalar c (recall that $(\text{Ker } \varphi)^\perp$ is one-dimensional hence spanned by \underline{t}). Then

$$\varphi(\underline{v}) = \varphi(\underline{w} + c\underline{t}) = \varphi(\underline{w}) + c\varphi(\underline{t}) = c\varphi(\underline{t})$$

since $\underline{w} \in \text{Ker } \varphi$. On the other hand $\underline{t} \in (\text{Ker } \varphi)^\perp$ and $\underline{w} \in \text{Ker } \varphi$ means $\langle \underline{t}, \underline{w} \rangle = 0$ and hence

$$\begin{aligned} \varphi_{\underline{u}}(\underline{v}) &= \langle \underline{u}, \underline{v} \rangle \\ &= \left\langle \frac{\overline{\varphi(\underline{t})}}{\langle \underline{t}, \underline{t} \rangle} \underline{t}, \underline{w} + c\underline{t} \right\rangle \\ &= \frac{\overline{\varphi(\underline{t})}}{\langle \underline{t}, \underline{t} \rangle} [\langle \underline{t}, \underline{w} \rangle + c \langle \underline{t}, \underline{t} \rangle] \\ &= \frac{\varphi(\underline{t})}{\langle \underline{t}, \underline{t} \rangle} c \langle \underline{t}, \underline{t} \rangle = c\varphi(\underline{t}) \end{aligned}$$

and thus $\varphi(\underline{v}) = \varphi_{\underline{u}}(\underline{v})$. □

EXERCISE 171. (PS12) Use the uniqueness to prove the claims about the (anti) linearity of the map.

5.4.2. The adjoint. If we interpret column vectors as $n \times 1$ matrices, then the standard inner product on \mathbb{R}^n is given by $\langle \underline{u}, \underline{v} \rangle = \underline{u}^T \cdot \underline{v}$ where the dot denotes matrix multiplication. Then for any linear map A we can use the formula $(AB)^T = B^T A^T$ and the associativity of multiplication to get:

$$\begin{aligned} \langle \underline{u}, A\underline{v} \rangle &= \underline{u}^T \cdot (A \cdot \underline{v}) = (\underline{u}^T \cdot A) \cdot \underline{v} \\ &= \left(\underline{u}^T \cdot (A^T)^T \right) \cdot \underline{v} \\ &= (A^T \underline{u})^T \cdot \underline{v} \\ &= \langle A^T \underline{u}, \underline{v} \rangle. \end{aligned}$$

In other words, the transpose matrix A^T is the matrix such the following formula holds:

$$\langle \underline{u}, A\underline{v} \rangle = \langle A^T \underline{u}, \underline{v} \rangle$$

for all $\underline{u}, \underline{v} \in \mathbb{R}^n$.

DEFINITION 172. Let $T \in \text{End}(V)$. The *adjoint* of T is the map T^* such that

$$\langle T^* \underline{u}, \underline{v} \rangle = \langle \underline{u}, T\underline{v} \rangle$$

LEMMA 173. *The adjoint exists and is unique. We have $(cS + T)^* = c^*S^* + T^*$ where c^* is the complex conjugate.*

PROOF. Observe that for each \underline{u} , the map

$$\underline{v} \mapsto \langle \underline{u}, T\underline{v} \rangle$$

is a linear functional. By the Reisz representation theorem there is a unique vector $T^*\underline{u}$ such that this functional equals $\phi_{T^*\underline{u}}$, in other words such that we have

$$\langle \underline{u}, T\underline{v} \rangle = \langle T^* \underline{u}, \underline{v} \rangle$$

for all \underline{v} . We need to check that T^* is a linear map. For this we use the uniqueness. Given two vectors $\underline{u}, \underline{u}'$ we get two vectors $T^*\underline{u}, T^*\underline{u}'$ such that for all \underline{v} we have

$$\begin{aligned} \langle \underline{u}, T\underline{v} \rangle &= \langle T^* \underline{u}, \underline{v} \rangle \\ \langle \underline{u}', T\underline{v} \rangle &= \langle T^* \underline{u}', \underline{v} \rangle. \end{aligned}$$

We then get for all \underline{v} that:

$$\begin{aligned} \langle T^*(c\underline{u} + \underline{u}'), \underline{v} \rangle &= \langle c\underline{u} + \underline{u}', T\underline{v} \rangle && \text{def of } T^* \\ &= c^* \langle \underline{u}, T\underline{v} \rangle + \langle \underline{u}', T\underline{v} \rangle && \text{inner pdt} \\ &= c^* \langle T^* \underline{u}, \underline{v} \rangle + \langle T^* \underline{u}', \underline{v} \rangle && \text{def of } T^* \\ &= \langle cT^* \underline{u} + T^* \underline{u}', \underline{v} \rangle && \text{inner pdt} \end{aligned}$$

and it follows that $T^*(c\underline{u} + \underline{u}') = cT^* \underline{u} + T^* \underline{u}'$. □

EXAMPLE 174. When $V = \mathbb{R}^n$ equipped with the standard inner product the adjoint of a matrix is the transpose.

EXERCISE 175. (PS12) Show that when $V = \mathbb{C}^n$ equipped with its standard Hermitian product, the adjoint of a matrix is the *conjugate transpose* T^\dagger (“*T dagger*”, written T^\dagger in BTEX), given by

$$T_{ij}^\dagger = \overline{T_{ji}}.$$

EXERCISE 176. Let $C_c^\infty(\mathbb{R})$ be the space of functions $f: \mathbb{R} \rightarrow \mathbb{C}$ which are infinitely differentiable and *compactly supported* in that there is an M such that $f(x) = 0$ if $|x| > M$ (i.e. the non-zero part of the graph of f happens over a finite interval). Equip $C_c^\infty(\mathbb{R})$ with the inner product $\langle f, g \rangle = \int_{-\infty}^{+\infty} \bar{f}g dx$.

Interpret the formula for integration by parts to show that the operator $D = i \frac{d}{dx}$ acting on $C_c^\infty(\mathbb{R})$ is self-adjoint, in that $D^\dagger = D$ (note the factor of $i!$).

5.5. The spectral theorem

We can finally discuss the notion of “an operator respecting an inner product”.

DEFINITION 177. We call a linear map *self-adjoint* if $T^\dagger = T$.

EXAMPLE 178. A matrix $A \in M_n(\mathbb{R})$ is called *symmetric* if $A^T = A$; a matrix $A \in M_n(\mathbb{C})$ is called *Hermitian* if $A^\dagger = A$.

Fix an inner product space V and a self-adjoint linear map $T \in \text{End}(V)$.

5.5.1. Eigenvalues and eigenvectors of self-adjoint operators.

LEMMA 179. *Suppose $T\underline{v} = \lambda\underline{v}$ and that \underline{v} is non-zero. Then λ is a real number.*

PROOF. We evaluate the inner product $\langle \underline{v}, T\underline{v} \rangle$ in two different ways. On the one hand

$$\langle \underline{v}, T\underline{v} \rangle = \langle \underline{v}, \lambda\underline{v} \rangle = \lambda \langle \underline{v}, \underline{v} \rangle$$

and on the other hand

$$\begin{aligned} \langle \underline{v}, T\underline{v} \rangle &= \langle T^\dagger \underline{v}, \underline{v} \rangle && \text{def of adjoint} \\ &= \langle T\underline{v}, \underline{v} \rangle && \text{self-adjointness} \\ &= \langle \lambda\underline{v}, \underline{v} \rangle \\ &= \bar{\lambda} \langle \underline{v}, \underline{v} \rangle. \end{aligned}$$

Since $\langle \underline{v}, \underline{v} \rangle \neq 0$ we must have $\lambda = \bar{\lambda}$ so $\lambda \in \mathbb{R}$. □

LEMMA 180. *Suppose $T\underline{v} = \lambda\underline{v}$ and $T\underline{w} = \mu\underline{w}$ and that $\lambda \neq \mu$. Then $\underline{v} \perp \underline{w}$.*

PROOF. We evaluate $\langle \underline{v}, T\underline{w} \rangle$ in two ways: We have:

$$\langle \underline{v}, T\underline{w} \rangle = \langle \underline{v}, \mu\underline{w} \rangle = \mu \langle \underline{v}, \underline{w} \rangle$$

and also

$$\langle \underline{v}, T\underline{w} \rangle = \langle T\underline{v}, \underline{w} \rangle = \langle \lambda\underline{v}, \underline{w} \rangle = \lambda \langle \underline{v}, \underline{w} \rangle$$

since λ is real. Subtracting the two expressions we get:

$$(\mu - \lambda) \langle \underline{v}, \underline{w} \rangle = \mu \langle \underline{v}, \underline{w} \rangle - \lambda \langle \underline{v}, \underline{w} \rangle = 0$$

and since $\mu - \lambda \neq 0$ we must have $\langle \underline{v}, \underline{w} \rangle = 0$. □

5.5.2. The Spectral Theorem. Recall that we have fixed a finite-dimensional inner product space V and a self-adjoint map $T \in \text{End}(V)$.

LEMMA 181. *T has at least one eigenvalue.*

PROOF. We have seen that every linear map has a complex eigenvalue. □

PROOF. Consider the continuous function $f(\underline{v}) = \langle \underline{v}, T\underline{v} \rangle$ on the sphere $\{\underline{v} \mid \|\underline{v}\| = 1\}$. This is a differentiable function so from calculus it has a maximum. We have $\nabla f(\underline{v}) = (T + T^\dagger)\underline{v} = 2T\underline{v}$ and $\nabla \|\underline{v}\|^2 = 2\underline{v}$. By the theory of Lagrange multipliers there is $\lambda \in \mathbb{R}$ such that at the maximum point \underline{v} we have

$$\nabla f(\underline{v}) = \lambda \nabla (\|\underline{v}\|^2 - 1)$$

or in other words

$$2T\underline{v} = 2\lambda\underline{v}.$$

□

PROOF. Consider the continuous function $f(\underline{v}) = \langle \underline{v}, T\underline{v} \rangle$ on the sphere $\{\underline{v} \mid \|\underline{v}\| = 1\}$. It attains its maximum at some point \underline{v} . Now let $\underline{w} \in \underline{v}^\perp$ be a non-zero unit vector. Then for each real number c we have $\|\underline{v} + c\underline{w}\|^2 = 1 + |c|^2$ by Pythagoras. Thus $\frac{\underline{v} + c\underline{w}}{\sqrt{1 + |c|^2}}$ has norm 1, and we set

$$g(c) = f\left(\frac{\underline{v} + c\underline{w}}{\sqrt{1 + |c|^2}}\right),$$

which attains a local maximum at $c = 0$. We have

$$\begin{aligned} f\left(\frac{\underline{v} + c\underline{w}}{\sqrt{1 + |c|^2}}\right) &= \left\langle \frac{\underline{v} + c\underline{w}}{\sqrt{1 + |c|^2}}, T \frac{\underline{v} + c\underline{w}}{\sqrt{1 + |c|^2}} \right\rangle \\ &= \frac{1}{1 + |c|^2} [\langle \underline{v}, T\underline{v} \rangle + c \langle \underline{v}, T\underline{w} \rangle + c \langle \underline{w}, T\underline{v} \rangle + c^2 \langle \underline{w}, T\underline{w} \rangle]. \end{aligned}$$

Differentiating at $c = 0$ we get

$$\begin{aligned} \frac{dg}{dc}(0) &= \langle \underline{v}, T\underline{w} \rangle + \langle \underline{w}, T\underline{v} \rangle \\ &= \langle T\underline{v}, \underline{w} \rangle + \langle \underline{w}, T\underline{v} \rangle \\ &= 2\Re \langle \underline{w}, T\underline{v} \rangle. \end{aligned}$$

It thus follows that $\Re \langle \underline{w}, T\underline{v} \rangle = 0$. Replacing \underline{w} with $i\underline{w}$ (which still has $\langle i\underline{w}, \underline{v} \rangle = 0$) we conclude that $\Im \langle \underline{w}, T\underline{v} \rangle = 0$ so $\langle \underline{w}, T\underline{v} \rangle = 0$. Since $\underline{w} \in \underline{v}^\perp$ was arbitrary we conclude that $T\underline{v} \in (\underline{v}^\perp)^\perp = \text{Span}\{\underline{v}\}$ and hence that $T\underline{v} = \lambda\underline{v}$ for some $\lambda \in \mathbb{C}$. \square

LEMMA 182. *Let $W \subset V$ be a T -invariant subspace (in that $T(W) \subset W$). Then W^\perp is also T -invariant.*

PROOF. Let $\underline{v} \in W^\perp$. Then for all $\underline{w} \in W$ we have $\langle \underline{w}, T\underline{v} \rangle = \langle T\underline{w}, \underline{v} \rangle = 0$ since $T\underline{w} \in W$ and $\underline{v} \in W^\perp$. It follows that $T\underline{v} \in W^\perp$ as well. \square

THEOREM 183. *Let V be a finite-dimensional inner product space, and let $T \in \text{End}(V)$ be self-adjoint. Then T is diagonalizable with real eigenvalues. In fact, there is an orthonormal basis of V consisting of eigenvectors of T .*

PROOF. Let $B \subset V$ be an orthonormal system consisting of eigenvectors of T which is as large as possible (this exists since $\#B \leq \dim V = n$). And let $W = \text{Span} B$. Suppose B is not complete, so that $B^\perp = W^\perp$ is non-zero. By Lemma 182, $T|_{W^\perp} \in \text{End}(W^\perp)$. This is a self-adjoint map with respect to the restricted inner product, so by Lemma 181 it has at least one eigenvector \underline{v} , which we may take to have norm 1. But then $\underline{v} \in W^\perp = B^\perp$ is orthogonal to B , so $B \cup \{\underline{v}\}$ is a larger orthonormal system consisting of eigenvectors of T , a contradiction. \square

5.5.3. Orthogonal and unitary maps.