LINEAR ALGEBRA

Organized Results complied by Sarthak¹

November 2022

To my stars, Giuseppe, and the Doctor...

¹vijaysarthak@iitgn.ac.in

Contents

Ι	Matrices 1				
	1	Row echelon			
	2	LU decomposition			
	3	Determinants			
Π	I Vector spaces				
	1	Spaces and subspaces			
	2	Sums of subspaces			
	3	Algebra to simplify the later work			
	4	Spans, independence, bases 8			
	5	Subspaces associated with a matrix			
III	III Linear maps 13				
	1	Basics			
	2	Making linear maps act on tuples of vectors			
	3	Studying matrices of linear maps 16			
IV Inner product spaces 19					
	1	Basics			
		1.1 The Euclidean inner product on $\mathbb{K}^{m \times n}$			
	2	Orthogonality			
	3	Orthogonal complements			
	4	Applying to the matrices over \mathbb{K}			
	5	Orthogonal matrices			
\mathbf{V}	Eige	envalues and eigenvectors 28			
	1	Basics			
	2	Diagonalizability of matrices			
		2.1 Orthogonal diagonalization			

CONTENTS

3	Reflect	tions	31
4	Cardin	al polynomials	31
	4.1	Modules and algebras	31
	4.2	Characteristic polynomial	34
	4.3	Division	36
	4.4	Annihilators	37

Chapter I

Matrices

1 Row echelon

August 27, 2022

Remark. We'll take the matrix entries from a field.

Lemma 1.1.

- (i) Deleting rightmost column or a non-pivot column preserves row reduced echelon form.
- (ii) A row reduced echelon matrix in which each column contains a pivot is of the form

 $\begin{bmatrix} I_n \\ 0 \end{bmatrix},$

i.e., *its diagonal entries are* 1 *and rest are* 0.

(iii) Deleting corresponding columns preserves row equivalence.

Theorem 1.2. The row reduced echelon form of a matrix is unique.

2 LU decomposition

Lemma 2.1 (Triangular matrices).

(i) Product of lower (respectively upper) triangular square matrices is lower (respectively upper) triangular.

- (ii) The inverse of a lower (respectively upper) triangular square is lower (respectively upper) triangular.
- (iii) The diagonal entries of the product of lower (respectively upper) triangular square matrices is the product of their diagonal entries.

Definition 2.2 (LU decomposition). Expressing a square matrix as a product of a lower and respectively an upper triangular matrix is called an LU decomposition of it.

Proposition 2.3 (Uniqueness of LU decomposition). Let A be an invertible matrix with an LU decomposition. Then its LU decomposition in which all diagonal the entries of the upper triangular matrix are 1, is unique.

Remark. An invertible matrix needn't have an LU decomposition: Consider $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$.

A non-invertible matrix can have more than one "standard" LU decompositions: Consider $\begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$.

3 Determinants

Give a general formalism for (commutative) rings and prove all the things! Define det: $\bigcup_{n \in \mathbb{N}} \mathbb{R}^{n \times n} \to \mathbb{R}$. Also define $\mathbb{R}^{n \times n}$.

Definition 3.1 (Inversions). Let $n \ge 2$ and $\sigma \in S_n$. Then (i, j), for $1 \le i, j \le n$ is called an inversion of σ iff

$$i < j$$
 and $\sigma(i) > \sigma(j)$.

Definition 3.2 (Odd or even permutations). A permutation is said to be odd (respectively even) if it has odd (respectively even) number of inversions.

Lemma 3.3. Let A be a finite set and $f: A \to A$ such that $f \circ f = \text{id}$ and $f(a) \neq a$ for all $a \in A$. Then |A| is even.

Theorem 3.4. A transposition changes the parity of permutation.

Definition 3.5 (Determinant). Let A be an $n \times n$ square matrix for $n \ge 1$. Then we define

$$\det A := \sum_{\sigma \in S_n} a_{1,\sigma(1)} \cdots a_{n,\sigma(n)}.$$

Corollary 3.6 (Immediate facts).

- (i) Determinant of of triangular matrices is the product of its diagonal entries.
- (ii) We have

$$\det(A^t) = \det A.$$

(iii) We have

$$\det(I) = 1.$$

(iv) If a row or a column of a matrix is zero, then its determinant is 0.

Theorem 3.7 (Determinant under elementary row operations). Let A be a square matrix. Then the following hold:

- (i) $i \rightarrow i + cj$ leaves determinant unchanged.
- (ii) $i \leftrightarrow j$ negates the determinant for $i \neq j$.
- (iii) $i \to ci$ scales the determinant by c.

Corollary 3.8 (Determinant of elementary matrices). The determinant of the elementary matrix corresponding to the row operations $i \to i + cj$, $i \leftrightarrow j$ (for $i \neq j$), $i \to ci$ are respectively 1, -1, c.

Corollary 3.9. For an elementary matrix E, we have

$$\det(EA) = (\det E)(\det A).$$

Lemma 3.10. The reduced row echelon form R of a square matrix A is either I or has the last row as zero. Further, A is invertible $\iff R = I$.

Theorem 3.11. We have

$$\det(AB) = (\det A)(\det B).$$

Theorem 3.12 (Characterizing invertibility). A square matrix A is invertible $\iff \det A \neq 0$.

Corollary 3.13. If A is invertible, then $det(A) \neq 0$, and

$$\det(A^{-1}) = (\det A)^{-1}.$$

Definition 3.14 (Determinant-like functions). A function δ that assigns to each square matrix a scalar is called a determinant-like function iff]tfh:

(i) We have

$$\delta(I) = 1.$$

- (ii) δ gets negated if two rows are interchanged.
- (iii) δ is "linear" in the first row, *i.e.*, for any $1 \times n$ row vectors r_1, \ldots, r_n, r'_1 and scalars k, l, we have

$$\delta \begin{bmatrix} kr_1 + lr'_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix} = k \, \delta \begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix} + l \, \delta \begin{bmatrix} r'_1 \\ r_2 \\ \vdots \\ r_n \end{bmatrix}.$$

Theorem 3.15 (Characterizing det). The determinant given by Definition 3.5 is the unique determinant-like function.

Remark. Having defined determinants, Now we are in a shape to analyze Atul's parity definition.

Theorem 3.16 (Equivalence of the parity definitions for permutations). Parity of the number of inversions in a permutation is the same as the parity of the number of the transpositions that it can be decomposed into.

Chapter II

Vector spaces

1 Spaces and subspaces

October 11, 2022

Definition 1.1 (Vector spaces). Let V be an additive abelian group and F be a field, along with a scalar multiplication operation $F \times V \to V$. Then V is called a vector space over F iff the following hold:

(i) 1v = v.

(ii)
$$(ab)v = a(bv)$$
.

(iii) (a+b)v = av + bv, and a(u+v) = au + av.

Remark. We have followed the usual convention that any "multiplicative" operation (here, the scalar multiplication) precedes over the "additive" operation (here, the vector addition).

We'll call the elements of V as vectors, and the group operation of V as vector addition.

We'll often omit specifying F, and just call the elements of xF as scalars.

Example 1.2 (Matrices). The set of $m \times n$ matrices with scalar entries, $F^{m \times n}$ for $m, n \ge 1$ forms a vector space over F with the usual operations.

Notation. We'll sometimes denote $F^{m \times 1}$ by simply F^m .

Proposition 1.3. Let V be a vector space, $v_1, \ldots, v_n \in V$ and a_1, \ldots, a_n be a scalars with $m, n \geq 0$. Then

$$\left(\sum_{i=1}^{m} a_i\right)\left(\sum_{j=1}^{n} v_j\right) = \sum_{i=1}^{m} \sum_{j=1}^{n} a_i v_j.$$

Definition 1.4 (Subspaces). Let V be a vector space over a field F. Then $W \subseteq V$ is called a subspace of V iff the operations of vector addition and scalar multiplication can be inherited to W such that W itself forms a vector space over F under these inherited operations.

Proposition 1.5 (Characterizing subspaces). Let V be a vector space and $W \subseteq V$. Then W is a subspace of $V \iff W \neq \emptyset$ and W is closed under vector addition and scalar multiplication.

Proposition 1.6.

- (i) Subspaces of a subspace are subspaces of the parent space.
- (ii) Nonempty intersections of subspaces are subspaces.
- (iii) If U, W are subspaces of a vector space V such that $W \subseteq U$, then W is a subspace of U.

2 Sums of subspaces

October 11, 2022

Definition 2.1 (Sums of subspaces). Let V be a vector space and W_i 's be subspaces of V for $i \in I$. Then we define

$$\sum_{i\in I} W_i := \bigg\{ \text{finite sums in } \bigcup_{i\in I} W_i \bigg\}.$$

Proposition 2.2.

- (i) Sums of subspaces are subspaces.
- (ii) $\sum_{i} W_i$ is the smallest subspace containing $\cup_i W_i$.

Definition 2.3 (Sum of two subspaces). Let U, W be subspaces of a vector space V. Then we define

$$U+W := \sum_{X \in \{U,W\}} X.$$

Proposition 2.4. For subspaces U, W, X of a vector space V, we have

$$U + W = W + U,$$

 $(U + W) + X = U + (W + X), and$
 $U + \{0\} = U.$

Proposition 2.5 (No notational collision). The inductive definition of finite sums of subspaces via the binary operation + gives the same subspace as the one given by Definition 2.1.

Proposition 2.6 (Finite sums of subspaces). Let $n \ge 0$ and W_1, \ldots, W_n be subspaces of a vector space V. Then

$$W_1 + \dots + W_n = \{w_1 + \dots + w_n : w_i \in W_i\}.$$

Definition 2.7 (Direct sums). Let V be a vector space and W_i 's be subspaces of V for $i \in I$. Then V is called the direct sum of W_i 's iff for each $v \in V$, there exists a unique $w \in \prod_{i \in I} W_i$ such that the set $J := \{i \in I : w_i \neq 0\}$ is finite, and

$$v = \sum_{i \in J} w_i$$

We call this w as the *decomposition* of w in the direct sum.

Remark. We'll denote this fact by

$$V = \bigoplus_{i \in I} W_i.$$

Proposition 2.8 (Characterizing direct sums). Let W_i 's be subspaces of a vector space V, for $i \in I$ such that $V = \sum_{i \in I} W_i$. Then the following are equivalent:

- (i) 0 vector admits a unique finite sum of nonzero vectors in $\bigcup_{i \in I} W_i$ (i.e., the empty sum).
- (*ii*) $V = \bigoplus_{i \in I} W_i$.

Proposition 2.9 (Finite direct sums). Let $n \ge 0$ and W_1, \ldots, W_n be subspaces of a vector space V such that $V = W_1 + \cdots + W_n$. Then the following are equivalent:

- (i) For each $v \in V$, there exists a unique $w \in \prod_{i=1}^{n} W_i$ such that $v = w_1 + \cdots + w_n$.
- (ii) The above holds for v = 0.

(*iii*) $V = W_1 \oplus \cdots \oplus W_n$

Proposition 2.10 (Characterizing direct sums of two subspaces). Let U and W be subspaces of a vector space V such that V = U + W. Then the following are equivalent:

- (i) $U \cap W = \{0\}.$
- (ii) $V = U \oplus W$.

3 Algebra to simplify the later work

October 15, 2022

Definition 3.1 (Simplifying notation for linear combinations). Let V be a vector space, $v \in V^m$ and a be an $m \times n$ matrix of scalars, for $m, n \ge 0$. Then we define $va \in V^n$ as

$$(va)_j := \sum_{i=1}^m a_{i,j} v_i.$$

Proposition 3.2 (Algebra of V^n over matrices). Let V be a vector space and $n \ge 1$. Then V^n forms an abelian group under slot-wise addition, and for $v \in V^n$ and matrices a, b of scalars of appropriate sizes, the following hold:

$$(va)b = v(ab)$$
$$(v+w)a = va + wa$$
$$v(a+b) = va + vb$$

4 Spans, independence, bases...

October 11, 2022

Definition 4.1 (Span). Let V be a vector space and $S \subseteq V$. Then we define

 $\operatorname{span} S := \operatorname{smallest} \operatorname{subspace} \operatorname{of} V \operatorname{containing} S.$

Corollary 4.2. For subspaces W_i 's of a vector space V, we have

$$\sum_{i} W_i = \operatorname{span}\left(\bigcup_{i} W_i\right).$$

9

Definition 4.3 (Linear combinations). Let V be a vector space and $S \subseteq V$. Then a linear combination of vectors in S is a vector of the form

$$a_1v_1 + \cdots + a_nv_n$$

where $v_1, \ldots, v_n \in S$ for an $n \ge 0$ and a_1, \ldots, a_n are scalars.

We'll denote this by

Proposition 4.4 (Characterizing spans). Let V be a vector space and $S \subseteq V$. Then

 $\operatorname{span} S = \{ \operatorname{linear \ combinations \ of \ vectors \ in \ } S \}.$

Proposition 4.5 (Characterizing spans of finite sets). Let V be a vector space and $v \in V^n$ for $n \ge 0$. Then

$$\operatorname{span}(\{v_1,\ldots,v_n\}) = \{va: a \in F^n\}.$$

Definition 4.6 (Independence). Let V be a vector space. Then a set $L \subseteq V$ is called independent iff for any $v \in L^n$ for $n \ge 0$ with distinct v_i 's, we have that

$$va = 0 \implies a = 0$$

for all $a \in F^n$.

Proposition 4.7 (Independence of finite sets). Let V be a vector space and $v \in V^n$ for $n \ge 0$ with distinct v_i 's. Then the following are equivalent:

- (i) $\{v_1, \ldots, v_n\}$ is independent.
- (ii) $va = 0 \implies a = 0$ for any $a \in F^n$.

Proposition 4.8.

- (i) Any subset of an independent set is independent as well.
- (ii) Independence in a subspace is the same as that in the parent space.

Definition 4.9 (Bases). A subset B of a vector space V is called a basis iff it is independent and span B = V.

Lemma 4.10. Let L be an independent set in a vector space V and $v \in V \setminus \text{span } L$. Then $L \cup \{v\}$ is independent too.

Theorem 4.11 (Extending independent sets to bases¹). Let V be a vector space and $L, S \subseteq V$ such that L is independent and span S = V with $|S| < \infty$. Then there exists a subset $T \subseteq S$ such that $L \cup T$ is a basis for V.

¹For $|S| = \infty$, the same result can be proven using Zorn's lemma.

Definition 4.12 (Finite-dimensional vector spaces). A vector space is called finitedimensional iff it can be spanned by some finite subset of it.

Corollary 4.13 (Existence of bases). Every finite-dimensional vector space has a basis.

Theorem 4.14 (Independence, span and cardinality). Let V be a vector space and $L, S \subseteq V$ such that L is independent and span S = V with $|S| < \infty$. Then

 $|L| \le |S|.$

Corollary 4.15 (Dimension of finite-dimensional vector spaces). Let V be a finitedimensional vector space. Then there exists a unique natural dim $V \ge 0$ such that any basis for V has dim V number of vectors.

Corollary 4.16. Let V be a finite-dimensional vector space and $L, S \subseteq V$ such that L is independent and span S = V. Then the following hold:

- (i) $|L| \leq \dim V \leq |S|$.
- (ii) $|L| = \dim V \implies L$ is a basis.
- (iii) $|S| = \dim V \implies S$ is a basis.

Proposition 4.17 (Dimension of subspaces). Let W be a subspace of a finitedimensional vector space V. Then the following hold:

- (i) W is finite-dimensional.
- (*ii*) dim $W \leq \dim V$.
- (*iii*) dim $W = \dim V \iff W = V$.

Proposition 4.18. Let W_1, \ldots, W_n be finite-dimensional subspaces of a vector space V for $n \ge 0$. Then $\sum_{i=1}^{n} W_i$ is finite-dimensional too.

Proposition 4.19 (Dimension of sum of two finite-dimensional subspaces). Let U, W be subspaces of a finite-dimensional vector space V such that V = U + W. Then

 $\dim V = \dim U + \dim W - \dim U \cap W.$

Proposition 4.20 (Dimension of finite sum of finite-dimensional subspaces). Let W_1, \ldots, W_n be subspaces of a finite-dimensional vector space V for $n \ge 0$ such that $V = W_1 + \cdots + W_n$. Then the following hold:

(i) $\dim V \leq \dim W_1 + \dots + \dim W_n$.

(*ii*) dim $V = \dim W_1 + \dots + \dim W_n \iff V = W_1 \oplus \dots \oplus W_n$.

Corollary 4.21. Let U, V be subspaces of a finite-dimensional vector space V such that $U \cap V = \{0\}$. Then dim $V = \dim U + \dim W \iff V = U \oplus W$.

5 Subspaces associated with a matrix

October 16, 2022

Remark. Here, the matrices are over *F*.

Definition 5.1 (Row, column and null spaces and their dimensions). Let A by an $m \times n$ matrix. Then we define the following spaces:

$$row(A) := span\{rows\} \subseteq F^{1 \times n}$$
$$col(A) := span\{columns\} \subseteq F^{m \times 1}$$
$$null(A) := \{X : AX = 0\} \subseteq F^{n \times 1}$$

We further define

row rank :=
$$\dim row(A)$$
,
column rank := $\dim col(A)$, and
nullity := $\dim null(A)$.

Proposition 5.2. For a square matrix A of size n, the following are equivalent:

- (i) Row rank is n
- (ii) A is invertible.
- (iii) Column rank is n.

Lemma 5.3. For matrices A = BC, we have that

$$\operatorname{row}(A) \subseteq \operatorname{row}(C), and$$

 $\operatorname{col}(A) \subseteq \operatorname{col}(B).$

Theorem 5.4. For any matrix, we have

row rank = column rank.

Remark. This allows to talk of the "rank" of matrices.

Also, prove the above in two ways: first by Gauss elimination, and second by using the above lemma.

Corollary 5.5 (Somme immediate consequences).

- (i) Rank of a matrix is bounded by the its number of rows and columns.
- (ii) Rank of AB is bounded by those of A and B.
- (iii) If $A_{m \times n} B_{n \times m} = I_m$, then $m \leq n$.

Proposition 5.6. Row operations on matrices preserve the span of rows and the independence of columns.

Proposition 5.7. Complex conjugation of a complex matrix preserves the independence of rows and columns.

Corollary 5.8 (Rank preserving operations). *The following operations on a matrix preserve its rank:*

- (i) Row operations.
- (ii) Transpositions.
- (iii) Complex conjugation for complex matrices.

Lemma 5.9. For the linear map $F^n \to F^m$ given by $X \mapsto AX$ for $A \in F^{m \times n}$, we have that

$$\ker = \operatorname{null}(A), and$$
$$\operatorname{im} = \operatorname{col}(A).$$

Theorem 5.10 (Rank-nullity). For any matrix, we have

rank + nullity = #(columns).

Chapter III

Linear maps

Remark. Again, we'll fix a field F, and call its elements, scalars.

1 Basics

October 15, 2022

Definition 1.1 (Linear maps and isomorphisms). Let V, W be vector spaces over a common field. Then a function $\phi: V \to W$ is called a linear maps iff

- (i) $\phi(u+v) = \phi(u) + \phi(v)$, and
- (ii) $\phi(au) = a \phi(u)$.

If ϕ is a bijection too, then we call it a *(linear) isomorphism*, and call V and W, *isomorphic*.

Notation. We'll write " $T: V \to W$ is linear" to mean "V, W are vector spaces over a common field and $T: V \to W$ is a linear map".

We'll also, for a linear map $T: V \to W$, write Tv for T(v).

Example 1.2 (Matrix operations). Let $m, n, k \ge 1$.

- (i) An $m \times n$ matrix A induces a linear map $F^{n \times k} \to F^{m \times k}$ given by $X \mapsto AX$. (Similarly, another map due to right-multiplication is also induced.)
- (ii) Matrix transposition $X \mapsto X^t$ gives another linear map $F^{m \times n} \to F^{n \times m}$.

Proposition 1.3 (Properties of linear maps).

- (i) Composition of linear maps (respectively isomorphisms) is a linear map (respectively an isomorphism).
- (ii) A linear map is injective \iff its kernel is $\{0\}$.
- (iii) The kernel of a linear map is a subspace of the domain space.
- (iv) Restriction of a linear map to a subspace of the domain space is linear.
- (v) Inclusion map from a subspace is linear.
- (vi) Inverse of an isomorphism is linear too.
- (vii) "Being isomorphic" is an equivalence relation.

Proposition 1.4 (Properties preserved by isomorphisms). Let $T: V \to W$ be an isomorphism and $S \subseteq V$. Then the following hold:

- (i) S is independent in $V \iff T(S)$ is independent in W.
- (*ii*) $\operatorname{span}(S) = V \iff \operatorname{span}(T(S)) = W.$
- (iii) S is a basis of $V \iff T(S)$ is a basis of W.
- (iv) V (or equivalently, W) is finite-dimensional \implies W (and equivalently V) is finite-dimensional and dim V = dim W.

Proposition 1.5 (Algebra of linear maps). Let V, W be vector spaces over a common field F. Then the set $\mathcal{L}(V, W)$ of linear maps $V \to W$, forms a vector space over F under the following operations:

$$(T+S)(v) := Tv + Sv$$
$$(aT)(v) := a(Tv)$$

Further, if V = W, then we can also define the products

$$TS := T \circ S$$

This makes $\mathcal{L}(V, V)$ into an associative F-algebra¹ with identity id_V and the corresponding homomorphism is given by

$$a \mapsto a \operatorname{id}_V.$$

Result 1.6 (Projections on component spaces in direct sums). Let V be a vector space and U, W be subspaces such that $V = U \oplus W$. For each $v \in V$, define $\mathcal{P}_U v \in U$ and $\mathcal{P}_W v \in W$ so that

$$\mathcal{P}_U v + \mathcal{P}_W v = v$$

Then the following hold:

 $^{1}See \ §4.1.$

- (i) $\mathcal{P}_U, \mathcal{P}_W: V \to V$ are linear.
- (ii) $\mathcal{P}_U^2 = \mathcal{P}_U$ and $\mathcal{P}_W^2 = \mathcal{P}_W$.
- (iii) $\mathcal{P}_U + \mathcal{P}_W = \mathrm{id}_V$.

Remark. Note that P_U depends not just on U, but the entire direct product decomposition of V, *i.e.*, on U as well as W.

Result 1.7 (Characterizing such projections). Let $T: V \to V$ be linear with $T^2 = T$. Then

- (i) $V = \operatorname{im} T \oplus \operatorname{ker} T$.
- (ii) T is precisely the projection on $\operatorname{im} T$ in the direct sum $V = \operatorname{im} T \oplus \ker T$.

Theorem 1.8 (A linear map is uniquely determined by its action of basis). Let V, W be vector spaces over a common field, B be a basis of V and $f: B \to W$ be any function. Then there exists a unique linear map $T: V \to W$ such that for all $u \in B$, we have

$$Tu = f(u).$$

Theorem 1.9 (Fundamental theorem of linear maps). For a linear map T from a finite-dimensional domain space V, we have that im T is finite-dimensional, and

 $\dim V = \dim(\ker T) + \dim(\operatorname{im} T).$

Corollary 1.10. Let $T: V \to W$ be linear with V, W being finite-dimensional. Then the following hold:

(i) T is surjective $\implies \dim V \ge \dim W$.

(ii) T is injective $\implies \dim V \le \dim W$.

(iii) If dim $V = \dim W$, then T is surjective \iff T is injective.

2 Making linear maps act on tuples of vectors

October 15, 2022

Remark. The elements of V^n should be viewed as *n*-tuples. For us, tuples and matrices are different things.

This collides with the earlier notation of F^n which contained column vectors. Thus clarification will be needed when not clear from context. **Definition 2.1** (*T* acting on V^n). Let $T: V \to W$ be a linear map and $v \in V^n$ for $n \ge 0$. Then we define $Tv \in W^n$ so that

$$(Tv)_i := Tv_i.$$

Proposition 2.2 (*T*'s action V^n is "linear"). Let $T: V \to W$ be a linear map, $v, w \in V^m$ and a be an $m \times n$ matrix of scalars for $m, n \ge 0$. Then

$$T(v+w) = Tv + Tw$$
$$T(va) = (Tv)a$$

3 Studying matrices of linear maps

October 15, 2022

Definition 3.1 (Ordered bases for finite-dimensional spaces). Let V be a finitedimensional vector space. Then an n-tuple of distinct vectors (u_1, \ldots, u_n) for $n \ge 0$ is called an ordered basis for V iff $\{u_1, \ldots, u_n\}$ is a basis for V.

Theorem 3.2 (Finite-dimensional spaces isomorphic to F^{n} 's). Let V be a finitedimensional vector space and B be an ordered basis. Then for each $v \in V$, there exists a unique column vector $[v]_B \in F^n$ so that

$$v = B[v]_B.$$

The map $V \to F^n$ given by $v \mapsto [v]_B$ is an isomorphism.

Corollary 3.3. Any finite-dimensional vector space V is isomorphic to $F^{\dim V \times 1}$.

Notation. Unless stated otherwise, the vectors e_i 's will be reserved for the standard basis of F^n (for the specified n's).

Theorem 3.4. Any linear map $T: F^n \to F^m$ for $m, n \ge 1$ is due to the leftmultiplication by a unique $m \times n$ matrix [T], which is given by

$$[T] := \left[\begin{array}{ccc} | & & | \\ Te_1 & \cdots & Te_n \\ | & & | \end{array} \right].$$

CHAPTER III. LINEAR MAPS

Remark. It'll turn out (in Theorem 3.5) that this [T] is precisely $[T]_{C \leftarrow B}$ where C and B are the standard ordered bases for F^m and F^n respectively.

Theorem 3.5 (Matrices of linear maps). Let $T: V \to W$ be a linear map with V, W finite-dimensional. Let B and C respectively be ordered bases for V and W. Then there exists a unique dim $W \times \dim V$ matrix $[T]_{C \leftarrow B}$ such that

$$[Tv]_C = [T]_{C \leftarrow B} [v]_B.$$

This is given by

$$[T]_{C \leftarrow B} = \begin{bmatrix} | & | \\ [Tu_1]_C \cdots & [Tu_n]_C \\ | & | \end{bmatrix},$$

where $(u_1, ..., u_n) = B$.

We have the following commutative diagrams:



Further, the map $\mathcal{L}(V, W) \to F^{\dim W \times \dim V}$ given by

$$T \mapsto [T]_{C \leftarrow B}$$

is an isomorphism.

Remark. Strictly speaking, we must require dim V, dim $W \ge 1$ since we normally don't have $0 \times n$ or $m \times 0$ matrices. We'll not care in the future to make this remark.

Notation. For composable linear maps S, T, we'll denote $T \circ S$ by TS.

Theorem 3.6 (Matrix of compositions). Let $S: U \to V$ and $T: V \to W$ be linear maps with U, V, W being finite-dimensional. Let B, C, D be their respective ordered bases. Then

$$[TS]_{D \leftarrow B} = [T]_{D \leftarrow C} [S]_{C \leftarrow B}.$$

We have the following commutative diagram:



Remark. This says that the map on $\mathcal{L}(V, V) \to F^{n \times n}$ given by $T \mapsto [T]_{B \leftarrow B}$ in Theorem 3.5 is an algebra isomorphism!²

Corollary 3.7 (Change of basis). Let V be a finite-dimensional vector space and B, C be ordered bases of V. Then $[id_V]_{C \leftarrow B}$ is such that

$$[v]_C = [\mathrm{id}_V]_{C \leftarrow B} [v]_B.$$

This is given by

$$[\mathrm{id}_V]_{C \leftarrow B} \begin{bmatrix} | & | \\ [u_1]_C \cdots & [u_n]_C \\ | & | \end{bmatrix}$$

where $(u_1, \ldots, u_n) = B$.

Further, we have that

$$\left[\mathrm{id}_V\right]_{B\leftarrow C} \left[\mathrm{id}_V\right]_{C\leftarrow B} = I$$

Corollary 3.8 (Change of bases in maps). Let $T: V \to W$ be a linear map and V, W be finite-dimensional vector spaces. Let B, B' be ordered bases of V and C, C' be those of W. Then

$$[T]_{C'\leftarrow B'} = [\mathrm{id}_W]_{C'\leftarrow C} [T]_{C\leftarrow B} [\mathrm{id}_V]_{B\leftarrow B'}.$$

²See ^{4.1}. Also see Proposition 4.36 that uses this.

Chapter IV

Inner product spaces

Remark. In this chapter, our field F would be either \mathbb{R} or \mathbb{C} . We'll denote this fact by changing our notation to \mathbb{K} .

Remark. When writing $A \in \mathbb{K}^{m \times n}$, we'll omit saying " $m, n \ge 1$ ".

1 Basics

October 15, 2022

Definition 1.1 (Inner product spaces). A vector space V over \mathbb{K} along with a function (called the inner product) $\langle \cdot, \cdot \rangle \colon V \times V \to \mathbb{K}$ is called an inner product space iff the following hold:

(i)
$$\langle v, v \rangle \ge 0$$
.

- (ii) $\langle v, v \rangle = 0 \iff v = 0.$
- (iii) $\langle w, v \rangle = \overline{\langle v, w \rangle}.$
- (iv) $\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle$.
- (v) $\langle av, w \rangle = a \langle v, w \rangle$.

We'll also define

$$||v|| := \sqrt{\langle v, v \rangle}.$$

Proposition 1.2 (Easy identities). Let V be an inner product space. Then the

following hold:

$$\begin{aligned} \langle u, v + w \rangle &= \langle u, v \rangle + \langle u, w \rangle \\ \langle u, av \rangle &= \overline{a} \langle u, v \rangle \\ \|av\| &= |a| \|v\| \\ \|x + y\|^2 + \|x - y\|^2 &= 2\left(\|x\|^2 + \|y\|^2\right) \\ \langle x, y \rangle &= \begin{cases} \frac{\|x + y\|^2 - \|x - y\|^2}{4} + i\frac{\|x + iy\|^2 - \|x - iy\|^2}{4}, & \mathbb{K} = \mathbb{C} \\ \frac{\|x + y\|^2 - \|x - y\|^2}{4}, & \mathbb{K} = \mathbb{R} \end{cases} \end{aligned}$$

Theorem 1.3 (Cauchy-Schwarz inequality). Let V be an inner product space and $u, v \in \mathbb{V}$. Then

$$|\langle u, v \rangle| \le \|u\| \, \|v\|.$$

with equality holding if and only if $\{u, v\}$ is dependent.

Proposition 1.4 (Triangle inequality). Let V be an inner product space and $u, v \in V$. Then

$$||u+v|| \le ||u|| + ||v||$$

with equality holding if and only if $\langle u, v \rangle = ||u|| ||v||$.

Proposition 1.5 (Matrix representation of inner product). Let V be a finite-dimensional inner product space with an ordered basis $B := (u_1, \ldots, u_n)$ for $n \ge 1$. Then we have

$$\langle v, w \rangle = [v]_B^t A \overline{[w]_B}$$

where $A \in \mathbb{K}^{n \times n}$ is given by

$$A := \begin{bmatrix} \langle u_1, u_1 \rangle & \cdots & \langle u_1, u_n \rangle \\ \vdots & & \vdots \\ \langle u_n, u_1 \rangle & \cdots & \langle u_n, u_n \rangle \end{bmatrix}.$$

Remark. If B is orthonormal (see Definition 2.1), then this reduces to $\langle u, v \rangle = [v]_B^t \overline{[w]_B}$.

1.1 The Euclidean inner product on $\mathbb{K}^{m \times n}$

October 17, 2022

Definition 1.6 (Complex conjugation of matrices). Let $A \in \mathbb{K}^{m \times n}$. Then we define $\overline{A} \in \mathbb{K}^{m \times n}$ as

$$(\overline{A})_{i,j} := \overline{A_{i,j}}.$$

Remark. Hence, we are also defining complex conjugation for real matrices, for which this will leave the matrix unchanged.

Proposition 1.7 (Properties of complex conjugation). Let A, B be matrices over \mathbb{K} and $\lambda \in \mathbb{K}$. Then whenever defined, the following hold:

$$\overline{A + B} = \overline{A} + \overline{B}$$

$$\overline{\lambda A} = \overline{\lambda} \overline{A}$$

$$\overline{AB} = \overline{A} \overline{B}$$

$$(\overline{A})^t = \overline{A^t}$$

$$(\overline{A})^{-1} = \overline{A^{-1}} \quad if A \text{ is invertible}$$

$$\det(\overline{A}) = \overline{\det A} \quad if A \text{ is square}$$

Notation. We denote $(\overline{A})^t$ by A^* .

Definition 1.8 (Trace). For a square matrix A over any field, we define

$$\operatorname{tr} A := \sum_{i} A_{i,i}.$$

Proposition 1.9. Let A, B be matrices over any field. Then whenever defined, the following hold:

$$tr(A + B) = tr A + tr B$$
$$tr(\lambda A) = \lambda(tr A)$$
$$tr(AB) = tr(BA)$$

Proposition 1.10 (An inner product on $\mathbb{K}^{m \times n}$). On $\mathbb{K}^{m \times n}$ over \mathbb{K} , we can define an inner product as

$$\langle A, B \rangle := \operatorname{tr}(A^T \overline{B}).$$

It follows that, whenever defined, the following equalities hold across the appropriate spaces:

$$\langle A^t, B^t \rangle = \langle A, B \rangle \\ \langle \overline{A}, \overline{B} \rangle = \overline{\langle A, B \rangle}$$

Example 1.11 (An inner product on C[0,1]). On C[0,1], the space of continuous \mathbb{K} -valued functions on interval [0,1],

$$\langle f,g\rangle := \int_0^1 g(t)\,\overline{f(t)}\;\mathrm{d}t$$

defines an inner product.

2 Orthogonality

October 17, 2022

Definition 2.1 (Orthogonal and orthonormal sets). Let V be an inner product space. Then an $L \subseteq V$ is called *orthogonal* iff for each $u, v \in L$, we have

$$\langle u, v \rangle = 0$$
 whenever $u \neq v$.

If we further have

||v|| = 1

for each $v \in L$, we call L orthonormal.

For $M, N \subseteq V$, we also say that M is orthogonal to N, written $M \perp N$, iff

 $u \in M$ and $v \in N \implies \langle u, v \rangle = 0$.

Corollary 2.2 (Preservation of orthonormality). The following preserve the orthonormality and orthogonality of a set in an inner product space:

(i) Taking subsets.

(ii) Scaling vectors by scalars of absolute value 1.

Proposition 2.3. Orthogonal set of nonzero vectors is independent.

Proposition 2.4 (Expansion in orthogonal bases). Let V be a finite-dimensional inner product space and B be an ordered orthogonal basis. Then for any $v \in V$, we have

$$[v]_B = \left(\frac{\langle v, u_1 \rangle}{\|u_1\|^2}, \dots, \frac{\langle v, u_n \rangle}{\|u_n\|^2}\right)$$

where $(u_1, ..., u_n) = B$.

Proposition 2.5 (Pythagoras). Let V be an inner product space and $v_1, \ldots, v_n \in V$ be distinct and orthogonal for $n \geq 0$. Then

$$||v_1 + \dots + v_n||^2 = ||v_1||^2 + \dots + ||v_n||^2.$$

Theorem 2.6 (Gram-Schmidt¹). Let V be an inner product space and v_1, \ldots, v_n be distinct independent vectors for $n \ge 1$. Define e_1, \ldots, e_n as

$$e_{1} := \frac{v_{1}}{\|v_{1}\|}, \text{ and}$$
$$e_{i+1} := \frac{v_{i+1} - \sum_{j=1}^{i} \langle v_{i+1}, e_{j} \rangle e_{j}}{\|v_{i+1} - \sum_{j=1}^{i} \langle v_{i+1}, e_{j} \rangle e_{j}\|} \quad \text{for } 1 \le i < n.$$

Then e_1, \ldots, e_n so obtained are orthonormal such that for each $1 \leq i \leq n$, we have

 $\operatorname{span}(\{e_1,\ldots,e_i\}) = \operatorname{span}(\{v_1,\ldots,v_i\}).$

Corollary 2.7. Every orthonormal set in a finite-dimensional inner product space can be extended to an orthonormal basis.²

3 Orthogonal complements

October 16, 2022

Proposition 3.1 (Orthogonal complements). Let V be an inner product space and W be a subspace. Then

$$W^{\perp} := \{ v \in V : \langle v, w \rangle = 0 \text{ for all } w \in W \}$$

is a subspace of W such that

¹Countable bases can be orthonormalized using this too.

²Complete infinite-dimensional inner product spaces have no orthonormal basis.

- (i) $W \cap W^{\perp} = \{0\}, and$
- (ii) W if finite-dimensional $\implies V = W \oplus W^{\perp}$.

Remark. This allows to talk of "orthogonal projections on a subspace W" whenever $V = W \oplus W^{\perp}$.

Proposition 3.2 $((W^{\perp})^{\perp}$ and W). Let U, W be subspaces of an inner product space V. Then the following hold:

- (i) $U \subseteq W \implies W^{\perp} \subseteq U^{\perp}.^{3}$
- (*ii*) $U \subset (U^{\perp})^{\perp}$.⁴
- (iii) $V = U \oplus U^{\perp} \implies U = (U^{\perp})^{\perp}.$
- (iv) V = U + W and $U \perp W \implies U^{\perp} = W$ and $W^{\perp} = U$.

Proposition 3.3. Let V be an inner product space and U, W be orthogonal subspaces.

Proposition 3.4 (Orthogonal projections). Let V be an inner product space and W be a subspace such that $V = W \oplus W^{\perp}$. Let $P_W \colon V \to V$ be the orthogonal projection onto W. Then

$$\langle P_W u, v \rangle = \langle u, P_W v \rangle.$$

Proposition 3.5 (Characterizing orthogonal projections). Let V be an inner product space and $T: V \to V$ be linear with such that $T^2 = T$ and $\langle Tu, v \rangle = \langle u, Tv \rangle$. Then in addition to the conclusion of Result 1.7, we also have

$$(\operatorname{im} T)^{\perp} = \ker T \text{ and } (\ker T)^{\perp} = \operatorname{im} T$$

so that T is the orthogonal projection onto $\operatorname{im} T$.

Proposition 3.6 (Orthogonal projections via orthogonal bases). Let V be an inner product space and W be a finite-dimensional subspace with an ordered orthogonal basis (u_1, \ldots, u_n) for $n \ge 0$. Then the orthogonal projection $P_W: V \to V$ onto W is given by

$$P_W v = \sum_{i=1}^n \frac{\langle v, u_i \rangle}{\|u_i\|^2} u_i.$$

³For a counterexample for converse, consider $V := \ell^2$ and $U := \{x \in \ell^2 :$ only finitely many x_i 's are nonzero $\}$.

⁴Same example to show proper inclusion.

⁵For a counterexample to the converse, see this.

Lemma 3.7. Let V be a vector space and U, W be subspaces such that $V = U \oplus W$. Let $\mathcal{P}_U \colon V \to V$ be the projection onto U in the direct sum. Let $u \in U$ and $v \in V$. Then

$$u = \mathcal{P}_U v \iff v - u \in W.$$

Theorem 3.8 (Orthogonal projections as approximations). Let V be an inner product space and W be a subspace such that $V = W \oplus W^{\perp}$. Let $v_0 \in V$ and $w \in W$ and $P_W: V \to V$ be the orthogonal projection onto W. Then

 $||w - v_0|| \ge ||P_W v_0 - v_0||$

with equality holding if and only if $w = P_W v_0$, or equivalently, $w - v_0 \in W^{\perp}$.

4 Applying to the matrices over \mathbb{K}

October 17, 2022

Lemma 4.1. Let $A \in \mathbb{K}^{m \times n}$. Then under the Euclidean inner product in $\mathbb{K}^{n \times 1}$, we have

 $\operatorname{col}(A^*) \perp \operatorname{null}(A).$

Remark. A^* is the usual complex conjugate of the complex matrix A.

Theorem 4.2. Let $A \in \mathbb{K}^{m \times n}$. Then in $\mathbb{K}^{n \times 1}$ with the Euclidean inner product, the following hold:

$$\mathbb{K}^{n \times 1} = \operatorname{col}(A^*) \oplus \operatorname{null} A$$
$$\operatorname{col}(A^*) = (\operatorname{null} A)^{\perp}$$

Remark. $col(A^*)$ is just (the transpose of) row(A).

Theorem 4.3 (Least squares in \mathbb{K}^n). Let $A \in \mathbb{K}^{m \times n}$, and $x \in \mathbb{K}^{n \times 1}$ and $b \in \mathbb{K}^{m \times 1}$. Let $P_{\operatorname{col}(A)} \colon \mathbb{K}^{m \times 1} \to \mathbb{K}^{m \times 1}$ be the orthogonal projection onto $\operatorname{col}(A)$. Then the following are equivalent:

- (i) $||Ax b|| = ||P_{col(A)}b b||.$
- (*ii*) $Ax = P_{\operatorname{col}(A)}b$.
- (iii) $A^*Ax = A^*b$.

Corollary 4.4 (On A^*A). For $A \in \mathbb{K}^{m \times n}$, the following hold:

(i) $A^*Ax = 0 \iff Ax = 0$.

(ii) A's columns are independent $\iff A^*A$ is invertible.

Corollary 4.5 (Orthogonal projections in \mathbb{K}^n). Let $A \in \mathbb{K}^{m \times n}$ with independent columns. Then the orthogonal projection $P_{\operatorname{col}(A)} \colon \mathbb{K}^{m \times 1} \to \mathbb{K}^{m \times 1}$ onto $\operatorname{col}(A)$ is given by

$$P_{\text{col}(A)} b = A(A^*A)^{-1}A^*b$$

5 Orthogonal matrices

October 17, 2022

Definition 5.1 (Orthogonal matrices). An square matrix A over \mathbb{K} is called orthogonal iff

 $A^t \overline{A} = I.$

Remark. We could have equivalently demanded $A^*A = I$.

Remark. "Unitary" vs "orthogonal": Unitary is stuck because $U^*U = I$ is like an extension of complex units.

Remark. (This remark is imprecise!) Given a linear map $T: V \to W$ where V, W are inner product spaces, it's possible to define an "adjoint operator" T^* so that $[T^*] = [T]^*$. This allows to define "orthogonal operators".

It's possible to generalize these even further so that we don't require V and W to be inner product spaces.

Proposition 5.2 (Properties of orthogonal matrices). Let $A \in \mathbb{K}^{n \times n}$ be orthogonal. Then

$$\left|\det A\right| = 1$$

rendering A invertible with

 $A^{-1} = A^*.$

Further, A^t , \overline{A} , A^* are orthogonal too. Also, product of orthogonals is orthogonal. **Proposition 5.3** (Characterizing orthogonal matrices). Let $A \in \mathbb{K}^{n \times n}$. Then the following are equivalent:

- (i) A is orthogonal.
- (ii) Rows of A are orthonormal.
- (iii) Columns of A are orthonormal.
- (iv) A preserves $\|\cdot\|$.
- (v) A preserves $\langle \cdot, \cdot \rangle$.

Remark. The eigenvalues of an orthogonal matrix have absolute value 1. (Result 2.7.)

Result 5.4. Let V be a finite-dimensional inner product space and E, F be ordered orthonormal bases. Then $[id_V]_{F \leftarrow E}$ is orthogonal.

Lemma 5.5. An upper-triangular matrix orthogonal matrix with positive diagonal entries is necessarily I.

Theorem 5.6 (QR decomposition). Let $A \in \mathbb{K}^{m \times n}$ with independent columns. Then there exist unique $Q \in \mathbb{K}^{m \times n}$ and $R \in \mathbb{K}^{n \times n}$ such that

- (i) A = QR,
- (ii) Q's columns are orthonormal, i.e., $Q^*Q = I_n$, and
- (iii) R is upper-triangular with positive diagonal entries.

Further, this R is invertible, and if $A = [a_1, \ldots, a_n]$ and $Q = [q_1, \ldots, q_n]$, then R is given by

$$R = \begin{bmatrix} \langle a_1, q_1 \rangle & \cdots & \langle a_n, q_1 \rangle \\ & \ddots & \vdots \\ & & \langle a_n, q_n \rangle \end{bmatrix}.$$

Chapter V

Eigenvalues and eigenvectors

1 Basics

October 25, 2022

Definition 1.1 (Linear operators). A linear operator is a linear map from one vector space to itself.

Definition 1.2 (Eigenvalues and eigenvectors). Let $T: V \to V$ be linear, λ be a scalar and $v \in V$ be nonzero. Then v is called an *eigenvector* of T, and v a corresponding *eigenvector*, iff

 $Tv = \lambda v.$

Similarly, we define eigenvalues and eigenvalues of square matrices (which are precisely the linear operators on F^n).

Remark. We had a choice here: We could've defined this so that 0 would be an eigenvector of each scalar. But then we'd have had to specify nonzero-ness of eigenvectors each time (like we now do for "nonzero zero divisors").

Proposition 1.3 (Eigenspaces are subspaces). Let $T: V \to V$ be linear with an eigenvalue λ . Then

$$\{v \in V : Tv = \lambda v\} = \ker(T - \lambda \operatorname{id}_V).$$

Theorem 1.4. Vectors corresponding to distinct eigenvalues of a linear operator are independent.

Definition 1.5 (Diagonalizability). A linear operator $T: V \to V$ is called diagonalizable iff there exists a basis of V, comprising only of eigenvectors of T.¹

In the same way, we define diagonalizability of square matrices.

Corollary 1.6. If $T: V \to V$ with V being finite-dimensional and T having dim V many distinct eigenvalues, then T is diagonalizable.

Proposition 1.7 (Matrices suffice for finite-dimensional spaces). Let $T: V \to V$ be linear with V being finite-dimensional. Let B be an ordered basis of V. Then the following hold:

- (i) For any vector v and any scalar λ , the following are equivalent:
 - (a) v is an eigenvector of T with eigenvalue λ .
 - (b) $[v]_B$ is an eigenvector of $[T]_{B\leftarrow B}$ with eigenvalue λ .
- (ii) T is diagonalizable $\iff [T]_{B \leftarrow B}$ is diagonalizable.

Remark. All of this above can be seen elegantly by formulating "morphisms between maps" and then we'll have that isomorphisms between maps preserve eigenvalues, eigenvectors and diagonalizability.

2 Diagonalizability of matrices

October 25, 2022

Definition 2.1 (Similar matrices). Two square matrices A and B (of same size) are called similar iff there exists an invertible P such that

$$A = P^{-1}BP.$$

Proposition 2.2. Similarity is an equivalence relation.

Proposition 2.3 (Similar matrices have same eigenvalues²). Let $A, P \in F^{n \times n}$ with P invertible. Then for any $\lambda \in F$ and any $v \in F^{n \times 1}$, the following are equivalent:

- (i) v is an eigenvector of A with eigenvalue λ .
- (ii) $P^{-1}v$ is an eigenvector of $P^{-1}AP$ with eigenvalue λ .

Corollary 2.4. Similarity preserves diagonalizability.

 $^{^1 \}mathrm{See}$ Corollary 2.6 for the motivation to call it "diagonalizability". $^2 \mathrm{Also}$ see Proposition 4.10.

Theorem 2.5 (Diagonalizing matrix contains eigenvectors). Let $A, P \in F^{n \times n}$ with $P =: [v_1, \ldots, v_n]$ invertible and let $\lambda_1, \ldots, \lambda_n \in F$. Then the following are equivalent: (i) $P^{-1}AP = \operatorname{diag}(\lambda_1, \ldots, \lambda_n)$.

(*ii*)
$$Av_i = \lambda_i v_i$$
 for $i = 1, \ldots, n$.

Corollary 2.6. An $n \times n$ matrix is diagonalizable iff it is similar to a diagonal matrix.

Result 2.7. Orthogonal matrices over \mathbb{K} have eigenvalues with absolute value 1.

Proposition 2.8. Eigenspaces corresponding to distinct eigenvalues are independent.

Theorem 2.9 (Characterizing diagonalizability³). Let $T: V \to V$ be linear with V finite-dimensional and $\lambda_1, \ldots, \lambda_k$ be distinct eigenvalues of T for $k \ge 0$. Let E_{λ_i} be the corresponding eigenspaces. Then the following are equivalent:

- (i) T is diagonalizable.
- (*ii*) $V = E_{\lambda_1} \oplus \cdots \oplus E_{\lambda_k}$.
- (*iii*) dim $V = \dim E_{\lambda_1} + \dots + \dim E_{\lambda_k}$.

2.1 Orthogonal diagonalization

October 25, 2022

Definition 2.10 (Orthogonal diagonalizability). Let V be an inner product space. Then a linear operator $T: V \to V$ is called orthogonally diagonalizable iff there exists an orthonormal basis of V comprising of eigenvectors of T.

Similarly, we define orthogonal diagonalizability for square matrices over \mathbb{K} (under the Euclidean inner product on \mathbb{K}^n).

Definition 2.11 (Hermitian matrices). An $n \times n A$ matrix over K is called Hermitian iff

 $A^* = A.$

Proposition 2.12. Eigenvalues of a Hermitian matrix are real and its eigenspaces are orthogonal.

Theorem 2.13 (Spectral theorem for matrices). A square matrix over \mathbb{K} is orthogonally diagonalizable with real eigenvalues \iff it is Hermitian.

 3 Also see

3 Reflections

October 25, 2022

Proposition 3.1 (Reflections and reflection matrices). Let V be an inner product space and $u \in V$ with ||u|| = 1. Then the function $V \to V$ given by

$$v \mapsto v - 2\langle v, u \rangle u$$

is linear and has eigenvalues ± 1 with

$$E_{-1} = \text{span}(\{u\}), and$$

 $E_1 = E_{-1}^{\perp}.$

If $V = \mathbb{K}^{n \times 1}$ with the Euclidean inner product, then this map is given by

 $v \mapsto (I - uu^*)v.$

The matrix $R := I - uu^*$ is Hermitian and orthogonal, and hence $R^2 = I$.

Remark. When there's no confusion, we'll denote eigenspaces by E_{λ} .

4 Cardinal polynomials

Remark. For this section, fix a general ring R. As usual, we'll assume V to be a vector space over some fixed general field F.

4.1 Modules and algebras

October 27, 2022

Definition 4.1 (*R*-modules). An *R*-module is an abelian additive group (M, +) along with a scalar multiplication $R \times M \to M$ (denoted by juxtaposition) such that the following hold:

- (i) (r+s)m = rm + sm.
- (ii) r(m+n) = rm + rn.
- (iii) (rs)m = r(sm).

(iv) If R has an identity, then $1_R m = m$.

Definition 4.2 (*R*-algebras). An *R*-module *A* along with a multiplication $\times : A \times A \to A$ is said to be an *R*-algebra iff \times is bilinear in both slots, *i.e.*,

(i)
$$a \times (b+c) = a \times b + a \times c$$
,

- (ii) $(a+b) \times c = a \times c + b \times c$, and
- (iii) $(ra) \times (sb) = (rs)(a \times b).$

We say that A is associative (respectively commutative; has an identity) iff \times is associative (respectively commutative; has an identity).

Definition 4.3 (Nice homomorphisms). A ring homomorphism $\phi: R \to S$ is called nice iff this holds: R has an identity $\implies \phi(1_R)$ is the identity in S.

Definition 4.4 (Algebras via homomorphisms). Let S be a ring. Then a nice ring homomorphism $\phi: R \to S$ is called an algebra iff $\phi(R)$ is central in S.

We say that ϕ is commutative (respectively, has an identity) iff S is commutative (respectively, has an identity).

Theorem 4.5 (Interplay of Definitions 4.2 and 4.4). Let R have identity and A be an associative R-algebra with identity. Define $\phi: R \to A$ as

$$\phi(r) := r \mathbf{1}_A$$

Then A is a ring and ϕ is an algebra with identity.

Conversely, let S be a ring and $\phi: R \to S$ be a nice ring homomorphism. Define scalar multiplication $R \times S \to S$ as

$$(r,s) \mapsto \phi(r)s.$$

Then S forms an R-module. If $\phi(R)$ is further central in S (i.e., ϕ is an algebra), then S is an associative R-algebra.

Lemma 4.6 ("Transitivity" of modules and algebras). Let $\phi: R \to S$ and $\psi: S \to T$ be ring homomorphisms. Then the following hold:

- (i) ϕ , ψ are nice $\implies \psi \circ \phi$ is nice.
- (ii) $\psi(S)$ is central $\implies (\psi \circ \phi)(R)$ is central.

Proposition 4.7. We have the following nice ring homomorphisms:



If R is commutative, then $a \mapsto a x^0$ is a commutative algebra as well.

Remark. To distinguish elements of R from the constant polynomials in R[x], we'll use x^0 .

Lemma 4.8 (When is $\phi: R[x] \to S$ a homomorphism?). For a ring S, a function $\phi: R[x] \to S$ is a ring homomorphism \iff the following hold:

- (i) $\phi(0_{R[x]}) = 0_S$.
- (*ii*) $\phi(p + ax^i) = \phi(p) + \phi(ax^i)$.
- (iii) $\phi(ax^i bx^j) = \phi(ax^i) \phi(bx^j).$

Proposition 4.9 (Substitution homomorphisms). Let $\phi \colon R \to S$ be an algebra and $s \in S$. Then the function $R[x] \to S$ given by

$$a_0x^0 + \dots + a_nx^n \mapsto \phi(a_0) + \phi(a_1)s^1 + \dots + \phi(a_n)s^n$$

is a nice homomorphism.

Remark. Strictly speaking, the well-defined-ness of this function needs to be shown.

Notation. For such homomorphisms, we'll use the notation $p \mapsto p(s)$, and also denote the image of R[x] as $\phi(R)[s]$.

Remark. If R is a subring of S, we'll take ϕ to be the inclusion $R \hookrightarrow S$ if not explicitly mentioned.

Proposition 4.10 (*T* and p(T) have the same eigenvectors). Let $T: V \to V$ be linear and $p \in F[x]$. Let $v \in V$ and $\lambda \in F$. Then

$$Tv = \lambda v \implies p(T)v = p(\lambda)v.$$

4.2 Characteristic polynomial

Proposition 4.11 (Matrices of polynomials and vice-versa). We have the following commutative diagram with the canonical nice homomorphisms:



Here, the homomorphism $R^{n \times n}[x] \to (R[x])^{n \times n}$ is given by

$$\left[a_{ij}^{(0)}\right]x^{0} + \dots + \left[a_{ij}^{(n)}\right]x^{n} \mapsto \left[a_{ij}^{(0)}x^{0} + \dots + a_{ij}^{(n)}x^{n}\right].$$

The solid arrows become algebras if R is commutative.

Definition 4.12 (Characteristic polynomial of matrices). Let R be commutative and $A \in \mathbb{R}^{n \times n}$. Then we define the characteristic polynomial to be the polynomial in $\mathbb{R}[x]$ given by

$$\det(f(-Ax^0 + Ix))$$

where $f: R^{n \times n}[x] \to (R[x])^{n \times n}$ is the homomorphism as given in Proposition 4.11.

Remark. We have the nice properties of determinants holding only when the matrix entries come from a commutative rings. Hence we care to define det only here.

Proposition 4.13. Let R be commutative and $A \in \mathbb{R}^{n \times n}$. Then the characteristic polynomial of A is monic and of degree n.

Proposition 4.14. The eigenvalues of a square matrix over a field are precisely the zeroes of its characteristic polynomial.

Proposition 4.15. Similar matrices have the same characteristic polynomial.

Corollary 4.16 (Characteristic polynomial of operators). Let $T: V \to V$ be linear with V finite-dimensional⁴ and B, C ordered bases of V. Then the characteristic polynomials of $[T]_{B\leftarrow B}$ and $[T]_{C\leftarrow C}$ are the same.

⁴Finite-dimensionality is needed to talk of any matrix of T.

Remark. This allows us to talk of "the characteristic polynomial of T".

Corollary 4.17. Let $T: V \to V$ be linear with V being finite-dimensional. Then the eigenvalues of T are precisely the zeroes of its characteristic polynomial.

Theorem 4.18 (Characterizing diagonalizability). Let $T: V \to V$ be linear with V finite-dimensional. Let $\lambda_1, \ldots, \lambda_k$ be eigenvalues of T and $E_{\lambda_1}, \ldots, E_{\lambda_k}$ be the corresponding eigenspaces. Then T is diagonalizable \iff the characteristic polynomial of T is given by

$$(x-\lambda_1)^{\dim E_{\lambda_1}}\cdots(x-\lambda_k)^{\dim E_{\lambda_k}}$$

Remark. In writing statements on vector spaces, we'll simply write x instead of $1_F x$, etc.

Proposition 4.19. Let R be commutative. Then for a square block matrix over R, we have

$$\det \begin{bmatrix} A & B \\ 0 & D \end{bmatrix} = \det A \, \det D,$$

where A and B are square of possibly different sizes.

Similarly, we have that the characteristic polynomial also factorizes as above.

Definition 4.20 (Invariant subspaces). Let $T: V \to V$ be linear. Then a subspace W of V is called T-invariant iff

$$T(W) \subseteq W.$$

Notation. We'll denote the restriction of T on $W \to W$ by T_W .

Corollary 4.21. Let $T: V \to V$ be linear with V being finite-dimensional. Let W be a T-invariant subspace. Then the characteristic polynomial of T_W divides that of T.

Result 4.22. Let $T: V \to V$ be linear. Then the following hold:

- (i) $\{0\}, V, \ker T, \operatorname{im} T$ as well as eigenspaces are all T-invariant.
- (ii) Let W be a subspace and $p \in F[x]$. Then W is T-invariant $\implies W$ is p(T)-invariant.

4.3 Division

Proposition 4.23 (Associates). Let R have an identity. Then the relation on R defined by

 $a \sim b$ iff a = ub for some invertible $u \in R$

is an equivalence relation.

Remark. Similarly, "a = bu" will define another equivalence relation. For commutative rings, both the relations coincide.

Theorem 4.24 (Division is a "partial order" in integral domains). Let R be an integral domain. Then the following hold:

(i) $a \mid a$. (ii) $a \mid b \text{ and } b \mid a \implies a, b \text{ are associates.}$ (iii) $a \mid b \text{ and } b \mid c \implies a \mid c$.

Remark. This allows to define gcd and lcm with these being "greatest" and "least" in some sense.

Definition 4.25 (gcd and lcm in integral domains). Let R be an integral domain and $a, b \in R$. Then an $x \in R$ is called

- (i) a gcd of a, b iff
 - (a) x is a common divisor of a, b, and
 - (b) if d is any common divisor of a, b, then $d \mid x$;
- (ii) an lcm of a, b iff
 - (a) x is a common multiple of a, b, and
 - (b) if m is any common multiple of a, b, then $x \mid m$.

Proposition 4.26. In an integral domain, gcd's (respectively lcm's) of a pair of elements are unique up to associativity.

Definition 4.27 (Coprimes). Let R be an integral domain. Then $a, b \in R$ are said to be coprime iff they have 1_R as a gcd.

Definition 4.28 (Primes). Let R be commutative. Then $p \in R \setminus \{0_R\}$ ($p \neq 1_R$ too if R has identity) is called prime iff

$$p \mid ab \implies p \mid a \text{ or } p \mid b.$$

Proposition 4.29 (Divisors of prime products). Let R be an integral domain p_1, \ldots, p_n be primes for $n \ge 0$. Let u be invertible and $d_1, \ldots, d_n \ge 0$. Then divisors of $up_1^{d_1} \cdots p_n^{d_n}$ are precisely of the form

$$vp_1^{e_1}\cdots p_n^{e_n}$$

where v is invertible and $0 \leq e_i \leq d_i$.

Lemma 4.30. Primes are irreducible in an integral domain.

Proposition 4.31. Let R be an integral domain and $\lambda, \mu \in R$ be distinct. Then $1_R x^1 - \lambda x^0$ and $1_R x^1 - \mu x^0$ are non-associate primes.

Proposition 4.32. R is an integral domain $\iff R[x]$ is an integral domain.

Theorem 4.33 (Division in R[x] and the factor theorem). Let R have identity and $f, g \in R[x]$ with g being monic.⁵ Then the following hold:

(i) There exist $q, r \in R[x]$ such that

f = qg + r with r = 0, or else, $\deg r < \deg q$.

(ii) For $\alpha \in R$, we have that

 $p(\alpha) = 0_R \iff (1_R x^1 - \alpha x^0)$ divides p from both sides.

(iii) If R further has no nonzero zero divisor, then these q, r are unique.

Remark. Exactly similar proposition will hold for the quotient q appearing on the right of q.

4.4 Annihilators

Definition 4.34 (Annihilating and minimal polynomials⁶). Let $\phi: R \to S$ be an R-algebra.⁷ Let I be an ideal of S and $s \in S$. Then a polynomial $p \in R[x]$ is called an I-annihilator of s iff

$$p(s) \in I.$$

If p is such a nonzero polynomial with least degree, it's called a minimal I-annihilator of s.

When $I = \{0_S\}$, we'll simply call these annihilators.

⁵We can weaken this by demanding the leading coefficient of q to be invertible.

⁶In this case, S fails in general to be an R[x]-algebra (we could define a product $(p, s) \mapsto p(s)$

on $R[x] \times S \to S$, hence the "annihilators of a module" will not suffice for us.

 $^{^{7}\}phi$ is required to be an *R*-algebra to talk of p(s).

CHAPTER V. EIGENVALUES AND EIGENVECTORS

Remark. I am allowing minimal annihilators to be non-monic.

In the case of a vector space V over F, we'll have R = F, $S = \mathcal{L}(V, V)$ or $F^{n \times n}$ (all of which have identities), and $I = \{0\}$ with $\phi: \alpha \mapsto \alpha \operatorname{id}_V$ or αI_n .

Proposition 4.35 (Monic minimals divide all the annihilators, and are unique). Let $\phi: R \to S$ be an algebra. Let I be an ideal of S and $s \in S$. Then the following hold:

(i) The set

$$\mathcal{A} := \{ I \text{-annihilators of } s \}$$

forms an ideal of R[x].

(ii) If R further has an identity⁸ and $m \in R[x]$ is any monic minimal I-annihilator for s, then

$$\mathcal{A} = m R[x] = R[x] m = (m).$$

(iii) In addition, R further has no nonzero zero divisors, then the monic minimal I-annihilator of s, if existent, is unique.

Proposition 4.36 (Polynomials over matrices suffice for finite-dimensional). Let $T: V \to V$ be linear with V being finite-dimensional. Let B be an ordered basis for V and $p \in F[x]$. Then

$$[p(T)]_{B \leftarrow B} = p([T]_{B \leftarrow B})$$

Hence, the (minimal) annihilators of T are precisely the (minimal) annihilators of $[T]_{B \leftarrow B}$.

Corollary 4.37. Each $T \in \mathcal{L}(V, V)$ for finite-dimensional V has a unique minimal annihilator.

Proposition 4.38 (Minimals also give eigenvalues). For any $A \in F^{n \times n}$, the characteristic and minimal polynomials have the same zeros.

Proposition 4.39. Similarity preserves (minimal) annihilators.

⁸This is required to talk of monic m which is in turn required for division. See Theorem 4.33.