MATH 20700 (Honors Analysis in $\mathbb{R}^n$ I) Notes

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Part I

Linear Algebra

Chapter 1

Basic Notions

1.1 Notes

9/27:
- **Vector space**: Basically, a set for which you have an addition and multiplication.

- $\mathbb{F}^d$ is used for $\mathbb{R}^d$ or $\mathbb{C}^d$ in Treil (2017).

- $\mathbb{P}_n$ is the vector space of polynomials up to degree n.

- $C([0,1])$ is the set of continuous functions defined on $[0,1]$, an infinite-dimensional vector space.

- **Generating set**: A subset of a vector space, all linear combinations of which generate the vector space. *Also known as* **spanning set**.

  - Any element of VS is a linear comb. of elements of the generating set.

- **Linearly independent** (list): A list of vectors $\mathbf{v}_1, \ldots, \mathbf{v}_k \in V$ such that $\sum_{i=1}^{k} \alpha_i \mathbf{v}_i = 0$ implies $\alpha_i = 0$ for all i.

- **Base**: A generating set consisting of linearly independent vectors.

- Any element of a VS can be written as a *unique* linear combination of the vectors in a base.

  - If $\mathbf{x} = \sum_{i=1}^{k} \alpha_i \mathbf{v}_i = \sum_{i=1}^{k} \beta_i \mathbf{v}_i$, then $\alpha_i = \beta_i$ for all i.

- **Linear transformation**: A function $T : X \to Y$, where X, Y are VSs, such that

$$T(\alpha \mathbf{x} + \beta \mathbf{y}) = \alpha T \mathbf{x} + \beta T \mathbf{y}$$

  for all $\mathbf{x} \in X$, $\mathbf{y} \in Y$.

- Examples of linear transformations:

  - Consider $\mathbb{P}_n$. Let $T p_n = p'_n$. This T is linear.
  - Rotation in $\mathbb{R}^d$.
    - Think graphically about two vectors $\mathbf{x}, \mathbf{y}$.
    - Rotating and summing them is the same as summing and rotating. Same for scaling.
    - Thus, rotation is actually linear!
  - Reflection as well.

- Consider $T : \mathbb{R} \to \mathbb{R}$.

  - Any linear map on the line is a line.
  - We must have $Tx = \alpha x$: $Tx = T(1x) = xT(1) = x\alpha$.

- Consider $T : \mathbb{R}^n \to \mathbb{R}^m$ linear.

  - Any linear map between $\mathbb{R}^n$ and $\mathbb{R}^m$ is linear.
  - Thus, $T(\mathbf{x}) = A\mathbf{x}$ for all $\mathbf{x} \in \mathbb{R}^n$, where A is an $m \times n$ matrix.

- To find A, do the same calculation as for $Tx = \alpha x$ but more carefully:

  - Let $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$ be a basis.
  - So $\mathbf{x} = \sum_{i=1}^n \alpha_i \mathbf{e}_i$.
  - Thus, $T\mathbf{x} = \sum_{i=1}^n \alpha_i T(\mathbf{e}_i)$.
  - Each $T(\mathbf{e}_i)$ is part of the matrix that we multiply by the column vector representing $\mathbf{x}$.

- Multiplication of matrices is equivalent to composition of linear maps.

- Consider $T_1 : \mathbb{R}^n \to \mathbb{R}^m$ and $T_2 : \mathbb{R}^m \to \mathbb{F}^r$.

  - $T_2 \circ T_1$ is equivalent to BA, if A represents T_1 and B represents T_2. In other words, $(T_2 \circ T_1)(\mathbf{x}) = BA\mathbf{x}$ for all $\mathbf{x}$.

- Recall that if $A = (\alpha_{ij})$ and $B = (\beta_{ij})$, then $(BA)_{ij} = \left(\sum \beta_{ik}\alpha_{kj}\right)$.

- Properties of multiplication:

$$(AB)C = A(BC)$$
$$A(B + C) = AB + AC$$
$$(A + B)C = AC + BC$$

  - However, it is not true in general that $AB = BA$.

- **Trace** (of an $n \times n$ matrix A): The sum of the diagonal entries of A. *Denoted by* $\mathbf{tr}\,(\mathbf{A})$. *Given by*

$$\mathrm{tr}(A) = \sum \alpha_{ii}$$

- It is true that $\mathrm{tr}(AB) = \mathrm{tr}(BA)$.

  - Indeed, on the diagonals, multiplication is commutative; it's the other terms that mess you up in general.

- Invertibility of matrices.

  - In general, matrices are not invertible: Not every system of equations is solveable; $Ax = b$ does not always have a solution $x = A^{-1}b$.

- C is the inverse from the left: $CA = I$. B is the inverse from the right: $AB = I$. A matrix can have a left and a right inverse and still not be invertible. A matrix is invertible iff $C = B$.

- Any time we write "inverse," we do so under the assumption that it exists.

- $(AB)^{-1} = B^{-1}A^{-1}$ — easy proof by multiplication.

- If $A = (a_{ij})$, $A^T = (a_{ji})$.

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

- Let X, Y VS.

  - $X \cong Y$[1] if there exists a linear $T : X \to Y$ that is one-to-one and onto.
  - Check: $A(\text{basis of } X) = \text{basis of } Y$. Prove by definition and expression of elements as linear combinations.

- **Subspace**: A subset of a vector space which happens to be a vector space, itself.

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[1] "X is isomorphic to Y."

1.2 Chapter 1: Basic Notions

From Treil (2017).

10/24:

- **Coordinates** (of $\mathbf{v} \in V$ wrt. a basis $\mathbf{v}_1, \ldots, \mathbf{v}_n$ of V): The unique scalars $\alpha_1, \ldots, \alpha_n \in \mathbb{F}$ such that $\mathbf{v} = \alpha_1 \mathbf{v}_1 + \cdots + \alpha_n \mathbf{v}_n$.

- **Spanning system**: A list of vectors that spans V. *Also known as* **generating system**, **complete system**.

- **Trivial** (linear combination): A linear combination $\alpha_1 \mathbf{v}_1 + \cdots + \alpha_n \mathbf{v}_n$ of vectors such that $\alpha_k = 0$ for each $k = 1, \ldots, n$.

- **Transformation**: A function $T : X \to Y$. *Also known as* **transform**, **mapping**, **map**, **operator**, and **function**.

- The matrix of a linear transformation T is often denoted by $[\boldsymbol{T}]$.

- To compute the reflection of vectors over an arbitrary line through the origin in $\mathbb{R}^2$, represent the overall transformation as a composition of rotating the line to be the x-axis, reflecting over the x-axis, and rotating back.

- Theorem 1.5.1: If A is an $m \times n$ matrix and B is an $n \times m$ matrix, then

$$\mathrm{tr}(AB) = \mathrm{tr}(BA)$$

- Theorem 1.6.1: If a linear transformation is invertible, then its left and right inverses are unique and coincide.

- The column $(1,1)^T$ is left-invertible, with one possible left inverse being $(1/2, 1/2)$.

    - Note that it is not right invertible since its left inverses are not unique (see Theorem 1.6.1).

- An invertible matrix must be square.

- **Isomorphic** (vector spaces): Two vectors spaces V, W such that there exists an isomorphism $A : V \to W$. *Denoted by* $\boldsymbol{V} \cong \boldsymbol{W}$.

- Theorem 1.6.8: $A : X \to Y$ is invertible if and only if for any right side $\mathbf{b} \in Y$, the equation

$$A\mathbf{x} = \mathbf{b}$$

has a unique solution $\mathbf{x} \in X$.

- Corollary 1.6.9: An $m \times n$ matrix is invertible if and only if its columns form a basis in $\mathbb{F}^m$.

- **Linear span** (of $\mathbf{v}_1, \ldots, \mathbf{v}_n \in V$): The set of all linear combinations of $\mathbf{v}_1, \ldots, \mathbf{v}_n$. *Denoted by* $\boldsymbol{\mathcal{L}}\{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$, $\mathbf{span}\,(\mathbf{v}_1, \ldots, \mathbf{v}_n)$.

Chapter 2

Systems of Linear Equations

2.1 Notes

- Row elimination:

  - Let
  $$A = \begin{pmatrix} 1 & 2 & 3 & 1 \\ 3 & 1 & 2 & 7 \\ 2 & 1 & 2 & 1 \end{pmatrix}$$

  - Then the **echelon form** matrix
  $$A_e = \begin{pmatrix} 1 & 2 & 3 & 1 \\ 0 & 1 & 2 & -1 \\ 0 & 0 & 2 & -4 \end{pmatrix}$$

  - Lastly, the **reduced echelon form** matrix
  $$A_{re} = \begin{pmatrix} 1 & 0 & 0 & 7 \\ 0 & 1 & 0 & 3 \\ 0 & 0 & 1 & -2 \end{pmatrix}$$

- **echelon form**:

  - All zero rows are below nonzero rows.
  - For any nonzero row, its leading element is strictly to the left of the nonzero entry of the next row.

- **Reduced echelon form**:

  - All pivots are 1.
  - Used to solve systems of the form $Ax = b$.

- **Inconsistent** (system of equations): A system with no solution.

  - If the last row is of the form $(0, \ldots, 0, b)$ where $b \neq 0$, then there is no solution.

- Unique solution if A_e has a pivot in every column.

- There exists a solution for every b if there is a pivot in every row?

- Let $A : \mathbb{R}^n \to \mathbb{R}^m$ be a matrix. Then $\ker A = \{x \in \mathbb{R}^n : Ax = 0\}$ (subspace of $\mathbb{R}^n$) and range $A = \{Ax : x \in \mathbb{R}^n\}$ (subspace of $\mathbb{R}^m$).

- Also consider $\ker(A^T)$ and range(A^T), the basis of the kernel and range, and dimension.

- Finite-dimensional vector spaces:

  - A basis is a generating set (so every element of V can be written uniquely as a linear combination of the basis) the length of which is equal to the dimension of V.
  - All bases of finite-dimensional vector spaces have the same number of elements.
    - Let v_1, v_2, v_3 and w_1, w_2 be two generating sets of V.
    - Then

$$v_1 = \lambda_{11} w_1 + \lambda_{12} w_2$$
$$v_2 = \lambda_{21} w_1 + \lambda_{22} w_2$$
$$v_3 = \lambda_{31} w_1 + \lambda_{32} w_2$$

    - Suppose the only solution to $\alpha_1 v_1 + \alpha_2 v_2 + \alpha_3 v_3 = 0$ is $\alpha_1 = \alpha_2 = \alpha_3 = 0$.
    - But this is not true, as we can find another one in terms of the λs.
  - If you have a list of linearly independent vectors, you can complete it into a basis.
    - If there exists a vector that can't be written as a linear combination of the list, add it to the list.
  - If you find any particular solution to a system $Ax = b$, and you add to it any element of $\ker A$, you will obtain another solution.
    - $Ax_1 = b$ and $Ax_h = 0$ implies that $A(x_1 + x_h) = b$.
    - $Ax_1 = b$ and $Ax_2 = b$ imply that $A(x_1 - x_2) = 0$, i.e., that $x_1 - x_2 \in \ker A$.
  - If $A : \mathbb{R}^n \to \mathbb{R}^m$ and $\dim \operatorname{range} A = m$, then $Ax = b$ is solveable for all $b \in \mathbb{R}^m$.
  - Let $\operatorname{rank} A = \dim \operatorname{range} A$.
  - Rank theorem:
    - $\operatorname{rank} A = \operatorname{rank} A^T$.
    - Let $A : \mathbb{R}^n \to \mathbb{R}^m$. We know that $\dim \ker A + \dim \operatorname{range} A = n$.
    - $\dim \ker A^T + \operatorname{rank} A^T = m$.
    - This theorem survives linear algebra and enters functional analysis under the name **Fredholm's alternative**.

- **Fredholm's alternative**: $Ax = b$ has a solution for all $b \in \mathbb{R}^n$ iff $\dim \ker A^T = 0$.

  - $\dim \ker A^T = 0$ implies $\operatorname{rank} A^T = m$ implies $\operatorname{rank} A = m$ implies $\dim \operatorname{range} A = m$, as desired.

- **Pivot column** (of A): A column of A where A_e has pivots.

- The **pivot columns** of A give a basis for $\operatorname{range} A$.

- The pivot rows of A_e give a basis for $\operatorname{range} A^T$.

- A basis for the kernel is enough to solve $Ax = 0$.

- If you take these three things as givens, you can prove the rank theorem.

2.2   Chapter 2: Systems of Linear Equations

From Treil (2017).

10/24:
- A system is inconsistent iff the echelon form of the augmented matrix has a row of the form $\begin{pmatrix} 0 & \cdots & 0 & b \end{pmatrix}$.

- A solution to $A\mathbf{x} = \mathbf{b}$ is unique iff there are no free variables, i.e., iff there is a pivot in every column.

- $A\mathbf{x} = \mathbf{b}$ is consistent iff the echelon form of the coefficient matrix has a pivot in every row.

- $A\mathbf{x} = \mathbf{b}$ has a unique solution for any $\mathbf{b}$ iff the echelon form of the coefficient matrix A has a pivot in every row and column.

- Proposition 2.3.1: Let $\mathbf{v}_1, \ldots, \mathbf{v}_m \in \mathbb{F}^n$, and let $A = \begin{bmatrix} \mathbf{v}_1 & \cdots & \mathbf{v}_m \end{bmatrix}$ be an $n \times m$ matrix with columns $\mathbf{v}_1, \ldots, \mathbf{v}_m$. Then

  1. The system $\mathbf{v}_1, \ldots, \mathbf{v}_m$ is linearly independent iff the echelon form of A has a pivot in every column.

  2. The system $\mathbf{v}_1, \ldots, \mathbf{v}_m$ is complete iff the echelon form of A has a pivot in every row.

  3. The system $\mathbf{v}_1, \ldots, \mathbf{v}_m$ is a basis of $\mathbb{F}^n$ iff the echelon form of A has a pivot in every column and in every row.

- Proposition 2.3.6: A matrix A is invertible if and only if its echelon form has a pivot in every column and every row.

- Corollary 2.3.7: An invertible matrix must be square $(n \times n)$.

- Proposition 2.3.8: If a square $(n \times n)$ matrix is left invertible or if it is right invertible, then it is invertible. In other words, to check the invertibility of a square matrix A, it is sufficient to check only one of the conditions $AA^{-1} = I$, $A^{-1}A = I$.

- Any invertible matrix is row-equivalent to (can be row-reduced to) to the identity matrix.

- **Homogeneous** (system of linear equations): A system of the form $A\mathbf{x} = \mathbf{0}$.

- Theorem 2.6.1: Let a vector $\mathbf{x}_1$ satisfy the equation $A\mathbf{x} = \mathbf{b}$. and let H be the set of all solutions of the associated homogeneous system $A\mathbf{x} = \mathbf{0}$. Then the set

$$\{\mathbf{x}_1 + \mathbf{x}_h : \mathbf{x}_h \in H\}$$

  is the set of all solutions to the equation $A\mathbf{x} = \mathbf{b}$.

- The pivot columns are a basis of range A. The pivot rows are a basis of range A^T. The solutions to the equation $A\mathbf{x} = \mathbf{0}$ are a basis of ker A.

- Theorem 2.7.3: Let A be an $m \times n$ matrix. Then the equation $A\mathbf{x} = \mathbf{b}$ has a solution for every $\mathbf{b} \in \mathbb{R}^m$ iff the dual equation $A^T\mathbf{x} = \mathbf{0}$ has a unique (only the trivial) solution.

  - Note that this is a corollary to the rank theorem.

- Change of coordinates formula:

  - Let $T : V \to W$ be a linear transformation, and let $\mathcal{V} = \{\mathbf{v}_1, \ldots, \mathbf{v}_n\}$ and $\mathcal{W} = \{\mathbf{w}_1, \ldots, \mathbf{w}_n\}$ be bases of V and W, respectively.

  - The $m \times n$ matrix of T with respect to these bases is $[T]_{\mathcal{W}\mathcal{V}}$, and relates the coordinates of $[T\mathbf{v}]_{\mathcal{W}}$ and $[\mathbf{v}]_{\mathcal{V}}$ via

    $$[T\mathbf{v}]_{\mathcal{W}} = [T]_{\mathcal{W}\mathcal{V}}[\mathbf{v}]_{\mathcal{V}}$$

  - Change of coordinates matrix: If $\mathcal{A}, \mathcal{B}$ are two bases of V, then we can convert the coordinates of a vector in $\mathcal{B}$ to its in $\mathcal{A}$ with the identity matrix (with respect to the appropriate bases). In particular,

    $$[\mathbf{v}]_{\mathcal{B}} = [I]_{\mathcal{B}\mathcal{A}}[\mathbf{v}]_{\mathcal{A}}$$

    - Note that the kth column of $[I]_{\mathcal{B}\mathcal{A}}$ is the coordinate representation in $\mathcal{B}$ of $\mathbf{a}_k$, i.e., $[\mathbf{a}_k]_{\mathcal{B}}$.

  - The change of coordinates matrix from a basis $\mathcal{B}$ to the standard basis $\mathcal{S}$ is easy to compute; by the above, it's just

    $$[I]_{\mathcal{S}\mathcal{B}} = \begin{bmatrix} \mathbf{b}_1 & \cdots & \mathbf{b}_n \end{bmatrix}$$

    - It follows that $[I]_{\mathcal{B}\mathcal{S}} = ([I]_{\mathcal{S}\mathcal{B}})^{-1}$.

■ This allows us to compute $[I]_{\mathcal{BA}}$ as $[I]_{\mathcal{BS}}[I]_{\mathcal{SA}}$

– If $T : V \to W$, $\mathcal{A}, \tilde{\mathcal{A}}$ are bases of V, and $\mathcal{B}, \tilde{\mathcal{B}}$ are bases of W, and we have $[T]_{\mathcal{BA}}$, then

$$[T]_{\tilde{\mathcal{B}}\tilde{\mathcal{A}}} = [I]_{\tilde{\mathcal{B}}\mathcal{B}}[T]_{\mathcal{BA}}[I]_{\mathcal{A}\tilde{\mathcal{A}}}$$

• Change of basis ends up at similarity; two operators are similar if we can change the basis of one into another.

Chapter 3

Determinants

3.1 Notes

• The determinant, geometrically, is the volume of the object (in $\mathbb{R}^3$) you get when you take linear combinations of the vectors.

• In 2D:

  – Let v_1, v_2 be two vectors. Put tail to tail and forming a parallelogram, the determinant of the matrix (v_1, v_2) is the area of said parallelogram.

  – Linearity 1: $D(av_1, v_2, \ldots, v_n) = aD(v_1, \ldots, v_n)$ is the same as saying that if you stretch one vector by a, you scale up the area by that much, too.

  – Linearity 2: $D(v_1, \ldots, v_{k+} + v_{k-}, \ldots, v_n) = D(-) + D(+)$.

  – Antisymmetry: $D(v_1, \ldots, v_k, \ldots, v_j, \ldots, v_n) = -D(v_1, \ldots, v_j, \ldots, v_k, \ldots, v_n)$. Interchanging columns flips the sign of the determinant.

  – Basis: $D(e_1, \ldots, e_n) = 1$.

• Determinant: Denoted by $D(v_1, \ldots, v_n)$, where $(v_1, \ldots, v_n)$ is an $n \times n$ matrix.

• Consider an $n \times n$ matrix A consisting of n columns containing vectors $\mathbf{v}_1, \ldots, \mathbf{v}_n \in \mathbb{R}^n$.

  – $D(A)$ is the volume of the solid $V = \sum_{i=1}^{n} \alpha_i v_i$.

  – $D(\mathbf{e}_1, \ldots, \mathbf{e}_n) = 1$.
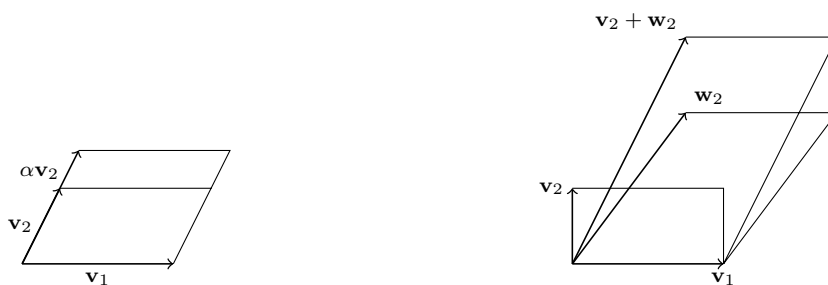
(a) $D(\mathbf{v}_1, \alpha\mathbf{v}_2) = \alpha D(\mathbf{v}_1, \mathbf{v}_2)$.   (b) $D(\mathbf{v}_1, \mathbf{v}_2 + \mathbf{w}_2) = D(\mathbf{v}_1, \mathbf{v}_2) + D(\mathbf{v}_1, \mathbf{w}_2)$.

Figure 3.1: Visualizing properties of determinants.

• Basic properties of the determinant.

  – If A has a zero column, then $\det A = 0$: Scalar property.

- If A has two equal columns, then $\det A = 0$: Multiply one by minus and add.
- If A has a column which is a multiple of another, then $\det A = 0$: Pull out the multiple and then you have the previous one.
- If columns are linearly dependent, then $\det A = 0$: Decompose it into sums, split, add back up with previous properties.
- The determinant is preserved under column reduction.
- $\det A^T = \det A$: Put everything in rref.
- If A is not invertible, then $\det A = 0$ (not invertible implies linearly dependent columns, implies $\det A = 0$).
- $\det(AB) = \det A \det B$.

- Determinant of...

  - A diagonal matrix: The product of the diagonal entries (pull out the terms, and then note that the remaining identity matrix has determinant 1).
  - An upper triangular matrix: The product of the diagonal entries (column reduction to make it into a diagonal matrix, and then the property above).

3.2 Chapter 3: Determinants

From Treil (2017).

10/24:
- Let $A_{j,k}$ denote the $(n-1) \times (n-1)$ matrix obtained from A by crossing out row j and column k and pushing it together.

- **Cofactors** (of A): The numbers $C_{j,k}$, one per entry, defined by

$$C_{j,k} = (-1)^{j+k} \det A_{j,k}$$

- **Cofactor matrix** (of A): The matrix

$$C = \{C_{j,k}\}_{j,k=1}^n$$

- Theorem 3.5.2: Let A be an invertible matrix and let C be its cofactor matrix. Then

$$A^{-1} = \frac{1}{\det A} C^T$$

- **Cramer's rule**: If A is invertible and $A\mathbf{x} = \mathbf{b}$, then

$$x_k = \frac{\det B_k}{\det A}$$

where B_k is obtained from A by replacing column k of A by the vector $\mathbf{b}$.

- **Minor** (of order k of A): The determinant of a $k \times k$ submatrix of A.

- Theorem 3.6.1: The rank of a nonzero matrix A is equal to the largest integer k such that there exists a nonzero minor of order k.

Chapter 4

Introduction to Spectral Theory

4.1 Notes

10/1:
- **Difference equation**: Like a differential equation, but instead of writing a differentials, you write differences.

  - Suppose we want to solve $x_{n+1} = Ax_n$ with x_0 given.

    - You will find that $x_n = A^n x_0$.
    - This gets hard to compute, so we want to find a way to simplify the computation.

  - Thus, we want to diagonalize the matrix, and this concept is inherently linked to eigenvalues and eigenvectors.

    - If you can decompose the x_0 into a linear combination of eigenvectors, then you can simplify the computation a lot:
    $$x_n = \sum \alpha_i A^n v_i = \sum \alpha_i \lambda_i^n v_i$$
    - An $n \times n$ matrix will have n eigenvalues. You want n linearly independent eigenvectors, creating an eigenbasis.

  - To find eigenvalues and eigenvectors, we need to solve $Ax = \lambda x$, i.e., $(A - \lambda I)x = 0$. Thus, $\ker(A - \lambda I) \neq \{0\}$, so $\det(A - \lambda I) = 0$.

  - The eigenvalues of A are independent of the choice of basis of the domain of A or the range.

10/4:
- We need to know everything in Treil (2017).

  - We don't need to know the applications sections, but you should be interested.

- **Spectral theory**: Decomposing a linear operator.

- Let $A : V \to V$ be a linear operator. $\lambda \in \mathbb{C}$ is an eigenvalue if there exists $x \in V$ nonzero such that $Ax = \lambda x$.

  - Let A be an $n \times n$ matrix over $\mathbb{C}$ or $\mathbb{R}$.
  - The eigenvalues are the roots of the polynomial $\det(A - \lambda I) = 0$ in λ.

- Things we want to do:

  - Given A, find the eigenvalues and eigenvectors (solve $(A - \lambda I)x = 0$).

- In order to simplify A, make it a diagonal matrix:

$$A = S \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix} S^{-1}$$

- Eigenvalues are independent of the choice of basis.

  - From the book, we have that
  $$[A]_{\mathcal{AA}} = [S]_{\mathcal{AB}}[B]_{\mathcal{BB}}[S]_{\mathcal{AB}}^{-1}$$

  - It follows that
  $$A - \lambda I = [S]_{\mathcal{AB}}(B - \lambda I)[S]_{\mathcal{AB}}^{-1}$$

  so

  $$\det(A - \lambda I) = \det\big([S]_{\mathcal{AB}}(B - \lambda I)[S]_{\mathcal{AB}}^{-1}\big) = \det\big([S]_{\mathcal{AB}}[S]_{\mathcal{AB}}^{-1}(B - \lambda I)\big) = \det(B - \lambda I)$$

- If $p(z) = (z - \lambda)^k q(z)$, then k is the **algebraic multiplicity** of λ. The **geometric multiplicity** of λ is $\dim \ker(A - \lambda I)$.

  - These terms are not always the same, but they are related.

- Diagonalization:

  - Given A that corresponds to $T : V \to V$, can we find a basis of V in which the operator is a diagonal matrix?
  - $A = SDS^{-1}$ iff there exists a basis of V consisting of the eigenvectors of A.
  - Proves $A^N = SD^N S^{-1}$ via $A^2 = SDS^{-1}SDS^{-1} = SDIDS^{-1} = SD^2 S^{-1}$.

- Let A be an $n \times n$ matrix over $\mathbb{F}$. If $\lambda_1, \ldots, \lambda_r$ are distinct eigenvalues, then their eigenvectors are linearly independent.

  - Prove with induction contradiction argument. Assume true for $\mathbf{v}_{r-1}$. Then
  $$0 = (A - \lambda_r I)[\mathbf{v}_1 + \cdots + \mathbf{v}_r] = (\lambda_1 - \lambda_r)\mathbf{v}_1 + \cdots + (\lambda_{r-1} - \lambda_r)\mathbf{v}_{r-1}$$

  - Implies $\lambda_r = \lambda_i$ for all $i \in [r - 1]$, a contradiction.
  - If A has n distinct eigenvalues, then A is diagonalizable.

- If $A : V \to V$ has n complex eigenvalues, then A is diagonalizable iff the algebraic multiplicity equals the geometric multiplicity for each eigenvalue.

- Goes through a sample diagonalization with $\left(\begin{smallmatrix} 1 & 2 \\ 8 & 1 \end{smallmatrix}\right)$.

  - We have
  $$A - \lambda I = \begin{pmatrix} 1 - \lambda & 2 \\ 8 & 1 - \lambda \end{pmatrix}$$

  so

  $$0 = \det(A - \lambda I) = (1 - \lambda)^2 - 16$$

  - It follows that $\lambda = 5, -3$.
  - This yields
  $$\begin{pmatrix} 1 & 2 \\ 8 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 2 & -2 \end{pmatrix} \begin{pmatrix} 5 & 0 \\ 0 & -3 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 2 & -2 \end{pmatrix}^{-1}$$

  by inspection.

- As another example, consider $\left(\begin{smallmatrix} 1 & 2 \\ -2 & 1 \end{smallmatrix}\right)$.

  - Here, we have $\lambda = 1 \pm 2i$.

4.2 Chapter 4: Introduction to Spectral Theory

From Treil (2017).

10/24:

- **Spectrum** (of A): The set of all eigenvalues of A. *Denoted by $\boldsymbol{\sigma(A)}$.*

- Proposition 4.1.1: The geometric multiplicity of an eigenvalue cannot exceed its algebraic multiplicity.

- Theorem 4.2.1: A matrix A (with values in $\mathbb{F}$) admits a representation $A = SDS^{-1}$ where D is a diagonal matrix and S is invertible if and only if there exists a basis of $\mathbb{F}^n$ of eigenvectors of A. Moreover, in this case diagonal entries of D are the eigenvalues of A and columns of S are the corresponding eigenvectors.

- Any operator on a complex vector space has n eigenvalues (counting multiplicities).

  - Think n necessary roots of the characteristic polynomial, or the necessary upper triangular representation.

- Theorem 4.2.8: Let an operator $A : V \to V$ have exactly $n = \dim V$ eigenvalues (counting multiplicities). Then A is diagonalizable if and only if for each eigenvalue λ, the dimension of the eigenspace $\ker(A - \lambda I)$ (i.e., the geometric multiplicity of λ) coincides with the algebraic multiplicity of λ.

- Theorem 4.2.9: A real $n \times n$ matrix A admits a real factorization (i.e., a real representation $A = SDS^{-1}$ where S and D are real matrices, D is diagonal, and S is invertible) if and only if it admits a complex factorization and all eigenvalues of A are real.

- Example of a nondiagonalizable matrix:
$$A = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix}$$

  - $p(\lambda) = (1 - \lambda)^2$, so $\lambda = 1$ with algebraic multiplicity 2.
  - However, $\dim \ker(A - I) = 1$ since $A - I$ has only one pivot, hence $2 - 1 = 1$ free variable.
  - Thus, apply Theorem 4.2.8.

Chapter 5

Inner Product Spaces

5.1 Notes

- We define

$$\ell^2(\mathbb{R}) = \left\{ \{a_n\}_{n \geq 1} \subset \mathbb{R} : \sum_1^\infty |a_n|^2 < \infty \right\}$$

- **Inner product**: A map $V \times V \to \mathbb{F}$ that takes $(\mathbf{x}, \mathbf{y}) \mapsto \mathbf{x} \cdot \mathbf{y}$. *Denoted by* $\cdot, (\cdot, \cdot), \langle \cdot, \cdot \rangle$.

- Properties of the inner product:

    - $(\mathbf{x}, \mathbf{y}) = \overline{(\mathbf{y}, \mathbf{x})}$ (symmetry).
    - $(\alpha \mathbf{x} + \beta \mathbf{y}, \mathbf{z}) = \alpha(\mathbf{x}, \mathbf{z}) + \beta(\mathbf{y}, \mathbf{z})$ (linearity).
    - $(\mathbf{x}, \mathbf{x}) \geq 0$.
    - $(\mathbf{x}, \mathbf{x}) = 0$ iff $\mathbf{x} = 0$.

- If $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, then

$$(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^n x_i y_i$$

- If $\mathbf{x}, \mathbf{y} \in \mathbb{C}^n$, then

$$(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^n x_i \bar{y}_i$$

- If $f, g \in \mathbb{P}_n(t)$, then

$$(f, g) = \int_{-1}^1 f \bar{g} \, \mathrm{d}t$$

    - The conjugate of a polynomial is the polynomial with the conjugate of the coefficients of the original polynomial. Symbolically, if $f = \sum_{i=0}^n \alpha_i t^i$ is a polynomial, then $\bar{f} = \sum_{i=0}^n \bar{\alpha}_i t^i$.

- It is a fact that

$$\left| \sum^\infty a_n \bar{b}_n \right| \leq \|(a_n)_{n \geq 1}\| \|(b_n)_{n \geq 1}\|$$

- Suppose we want to define the inner product between two matrices.

    - A common one is

$$(A, B) = \operatorname{tr}(B^* A)$$

    where $B^* = \bar{B}^T = \overline{B^T}$ is the conjugate transpose.

- We define the norm as a function $V \to [0, \infty)$ given by

$$\|\mathbf{x}\| = \sqrt{(\mathbf{x}, \mathbf{x})}$$

- Properties of the norm.

  - $\|\alpha \mathbf{x}\| = |\alpha| \|\mathbf{x}\|$.
  - $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$.
  - $\|\mathbf{x}\| = 0$ iff $\mathbf{x} = 0$.

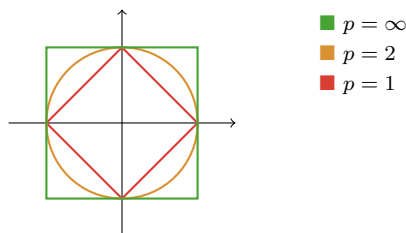- In $\mathbb{R}^n$,

Figure 5.1: The unit ball of norms corresponding to $p = 1, 2, \infty$.

  - The standard norm is

$$\|\mathbf{x}\| = \sqrt{\sum |x_i|^2}$$

  - We can also define

$$\|\mathbf{x}\|_p = \sqrt[p]{\sum |x_i|^p}$$

  - We can even define

$$\|\mathbf{x}\|_\infty = \max |x_i|$$

  - And we can prove that all of these are valid norms.
  - Only the norm corresponding to ℓ^2 is given by an inner product, but all the other quantities are still norms as defined by the properties (see Treil (2017)).
  - Figure 5.1 shows the unit ball of each norm, i.e., the set of all points which have norm 1.

- The parallelogram rule:
$$\|\mathbf{x} + \mathbf{y}\|^2 + \|\mathbf{x} - \mathbf{y}\|^2 = 2(\|\mathbf{x}\|^2 + \|\mathbf{y}\|^2)$$

- Orthogonality: Given $\mathbf{v}, \mathbf{w}$, if $\mathbf{v} \perp \mathbf{w}$, then $(\mathbf{v}, \mathbf{w}) = 0$.

- In particular, if $\mathbf{v} \perp \mathbf{w}$, then
$$\|\mathbf{v} + \mathbf{w}\|^2 = \|\mathbf{v}\|^2 + \|\mathbf{w}\|^2$$

- Let E be a subspace of V. If $\mathbf{v} \perp E$, then $\mathbf{v} \perp \mathbf{e}$ for all $\mathbf{e} \in E$, i.e., $\mathbf{v} \perp$ a set of vectors spanning E.

- Any set of orthogonal vectors is linearly independent. Thus, if V is n dimensional, then $\mathbf{v}_1, \ldots, \mathbf{v}_n$ orthogonal is a basis.

- Let E be a subspace of V. Take $\mathbf{v} \in V$. We want to define the projection $P_E \mathbf{v}$ of $\mathbf{v}$ onto E.

  - We have that $P_E \mathbf{v} \in E$ and $v - P_E \mathbf{v} \perp E$.
  - Additionally, we have that
$$\|\mathbf{v} - P_E \mathbf{v}\| \leq \|\mathbf{v} - \mathbf{e}\|$$

  for all $\mathbf{e} \in E$.

– Lastly, we have that $P_E\mathbf{v}$ is unique.

• If we receive a basis of a vector space, how do we create out of that a basis that is orthogonal? The process of doing this is called **Gram-Schmidt orthogonalization**.

– We keep $\mathbf{v}_1$, subtract $P_{\mathbf{v}_1}\mathbf{v}_2$ from $\mathbf{v}_2$, subtract $P_{\{\mathbf{v}_1,\mathbf{v}_2\}}\mathbf{v}_3$ from $\mathbf{v}_3$, and on and on.

• If we are given a set of orthogonal vectors, we can normalize them by dividing each by its norm. This creates an orthonormal list. The standard basis is orthonormal.

• Let
$$E^\perp = \{v \in V : v \perp E\}$$

– It follows that $V = E \oplus E^\perp$.

• How close can we come to solving $A\mathbf{x} = \mathbf{b}$ if we cannot solve it exactly (i.e., if the columns are not linearly independent)?

– Let A be an $m \times n$ matrix, and let $\mathbf{b} \in \mathbb{R}^m$.

– Then the best solution is given by minimizing $\|A\mathbf{x} - \mathbf{b}\|$. We minimize this with projections. A special case of this is least squares regression! More details in Treil (2017).

10/8: • Soug is gonna send us a hefty amount of reading for the weekend.

• Least square approximation:

– If we want to minimize $\|A\mathbf{x} - \mathbf{b}\|$, the best we can do is project $\mathbf{b}$ onto the range of A.

– Let $\mathbf{v}_1, \ldots, \mathbf{v}_k$ be an orthogonal basis of range A.

– Then
$$\text{Proj}|_{\text{range } A}\mathbf{b} = \sum^k \frac{(\mathbf{b}, \mathbf{v}_k)}{\|v_k\|^2}\mathbf{v}_k$$

– Matrix equation form:
$$\text{Projection}_{\text{range } A} = A(A^*A)^{-1}A^*$$

if A^*A is invertible, where $A^* = \bar{A}^T$.

▪ Soug never uses this though.

– The minimum is found when $\mathbf{b} - A\mathbf{x} \perp \text{range } A$. Implies that $\mathbf{b} - A\mathbf{x} \perp \mathbf{a}_k$ for all k. Implies $(\mathbf{b} - A\mathbf{x}, \mathbf{a}_k) = \bar{\mathbf{a}}_k^T(\mathbf{b} - A\mathbf{x}) = 0$.

– Note that we're letting $\bar{\mathbf{a}}_k^T$ be the row vector
$$\bar{\mathbf{a}}_k^T = \begin{pmatrix} \bar{a}_{1,k} & \cdots & \bar{a}_{n,k} \end{pmatrix}$$

– We also have $\bar{A}^T(\mathbf{b} - A\mathbf{x}) = 0$, from which it follows that $A^*A\mathbf{x} = A^*\mathbf{b}$, so $\mathbf{x} = (A^*A)^{-1}A^*\mathbf{b}$. Thus, $\text{Proj}|_{\text{range } A} = Ax$, so $\text{Proj}|_{\text{range } A} = A(A^*A)^{-1}A^*\mathbf{b}$.

• Adjoint of a linear map $T : V \to W$ is the A^* discussed above.

– First, we'll do this for matrices. And then we'll do it for any finite-dimensional vector space.

– Let A be an $m \times n$ matrix. We claim then that
$$(A\mathbf{x}, \mathbf{y}) = (\mathbf{x}, A^*\mathbf{y})$$

for all $\mathbf{x} \in \mathbb{C}^n$, $\mathbf{y} \in \mathbb{C}^m$. Proof:
$$\begin{aligned}(A\mathbf{x}, \mathbf{y}) &= \bar{\mathbf{y}}^T A\mathbf{x} \\ &= \mathbf{y}^* A\mathbf{x} \\ &= (A^*\mathbf{y})^*\mathbf{x} \\ &= (\mathbf{x}, A^*\mathbf{y})\end{aligned}$$

– Properties of the adjoint:

$$(AB)^T = B^T A^T$$
$$(AB)^* = B^* A^*$$
$$(A^*)^* = A$$

– A^* is the unique matrix B such that $(A\mathbf{x}, \mathbf{y}) = (\mathbf{x}, B\mathbf{y})$.
– Let $\mathbf{v}_1, \ldots, \mathbf{v}_n$ be a basis of V, and let $\mathbf{w}_1, \ldots, \mathbf{w}_m$ be a basis of W.
– Definition of A^*: If $(A\mathbf{x}, \mathbf{y}) = (y, A^*\mathbf{x})$ for all $\mathbf{x} \in V$ and $\mathbf{y} \in W$.
– But it's not enough to define something; we have to check that it exists.
– If $[A]_{\mathcal{AB}}$, then $[A^*]_{\mathcal{AB}}$.
– More properties (give criteria for solving systems of equations):

$$\ker A^* = (\operatorname{range} A)^\perp$$
$$\ker A = (\operatorname{range} A^*)^\perp$$
$$\operatorname{range} A = (\ker A^*)^\perp$$
$$\operatorname{range} A^* = (\ker A)^\perp$$

■ Soug proves these.

• Isometries and unitary operators.

– $U : X \to Y$ is an isometry if $\|\mathbf{x}\| = \|U\mathbf{x}\|$ for all $\mathbf{x} \in X$. It is an isometry because it preserves the distance between points.
– It immediately follows that $\|\mathbf{x}_1 - \mathbf{x}_2\| = \|U\mathbf{x}_1 - U\mathbf{x}_2\| = \|U(\mathbf{x}_1 - \mathbf{x}_2)\|$.
– This definition is equivalent to an inner product one: $(\mathbf{x}, \mathbf{y}) = (U\mathbf{x}, U\mathbf{y})$. This follows from the definition of the norm.
– We have

$$(\mathbf{a}, \mathbf{b}) = \frac{1}{4} \sum_{\alpha = \pm 1, \pm i} \alpha \|\mathbf{a} + \alpha \mathbf{b}\|^2$$

■ $(a + b)^2 - (a - b)^2 = 4ab$ for any $a, b \in \mathbb{R}$, so $ab = \frac{1}{4}[(a+b)^2 - (a-b)^2]$. Thus, in a real inner product space,

$$(\mathbf{a}, \mathbf{b}) = \frac{1}{4} \left(\|\mathbf{a} + \mathbf{b}\|^2 - \|\mathbf{a} - \mathbf{b}\|^2 \right)$$

■ It follows that isometries preserve inner products.

– U is an isometry if and only if $U^*U = I$. Proof:

$$(\mathbf{x}, \mathbf{x}) = (U\mathbf{x}, U\mathbf{y}) = (U^*U\mathbf{x}, \mathbf{x})$$
$$(\mathbf{x}, \mathbf{y}) = (U\mathbf{x}, U\mathbf{y}) = (U^*U\mathbf{x}, \mathbf{y})$$
$$(\mathbf{x}, \mathbf{y}) = (U\mathbf{x}, U\mathbf{y}) = (\mathbf{x}, \mathbf{y})$$

for all $\mathbf{y}$.

– An isometry is unitary if it is invertible.

■ Thus, $U : X \to Y$ an isometry is unitary iff $\dim X = \dim Y$.

– Note that it follows that $U^* = U^{-1}$ for U an isometry.
– U unitary implies $|\det U| = 1$, so λ an eigenvalue of U implies that $|\lambda| = 1$.
– A is diagonalizable iff it has an orthogonal basis of eigenvectors.

5.2   Chapter 5: Inner Product Spaces

From Treil (2017).

10/24:
- **Standard inner product** (on $\mathbb{C}^n$): The inner product $(\mathbf{z}, \mathbf{w})$ defined by

$$(\mathbf{z}, \mathbf{w}) = \mathbf{w}^* \mathbf{z}$$

- Corollary 5.1.5: Let $\mathbf{x}, \mathbf{y}$ be vectors in an inner product space V. The equality $\mathbf{x} = \mathbf{y}$ holds if and only if

$$(\mathbf{x}, \mathbf{z}) = (\mathbf{y}, \mathbf{z})$$

  for all $\mathbf{z} \in V$.

- Corollary 5.1.6: Suppose two operator $A, B : X \to Y$ satisfy

$$(A\mathbf{x}, \mathbf{y}) = (B\mathbf{x}, \mathbf{y})$$

  for all $\mathbf{x} \in x$ and $\mathbf{y} \in Y$. Then $A = B$.

- **Normed space**: A vector space V equipped with a norm that satisfies properties of homogeneity, the triangle inequality, non-negativity, and non-degeneracy.

- Any inner product space is naturally a normed space.

- If $1 \leq p < \infty$, we can define a corresponding norm on $\mathbb{R}^n$ or $\mathbb{C}^n$ by

$$\|\mathbf{x}\|_p = \left(\sum_{k=1}^{n} |x_k|^p \right)^{1/p}$$

- We can also define the norm for $p = \infty$ by

$$\|\mathbf{x}\|_\infty = \max\{|x_k| : k = 1, \ldots, n\}$$

  - Note that the norm of this form for $p = 2$ is the usual norm.
  - These norms are heavily associated with Figure 5.1.

- **Minkowski inequality**: One of the triangle inequalities for norms with $p \neq 2$.

- Theorem 5.1.11: A norm in a normed space is obtained from some inner product if and only if it satisfies the Parallelogram Identity

$$\|\mathbf{u} + \mathbf{v}\|^2 + \|\mathbf{u} - \mathbf{v}\|^2 = 2(\|\mathbf{u}\|^2 + \|\mathbf{v}\|^2)$$

  for all $\mathbf{u}, \mathbf{v} \in V$.

  - It follows that norms with $p \neq 2$ do not have associated inner products, since such norms fail to satisfy the parallelogram identity.

- Lemma 5.2.5 (Generalized Pythagorean Identity): Let $\mathbf{v}_1, \ldots, \mathbf{v}_n$ be an orthogonal system. Then

$$\left\| \sum_{k=1}^{n} \alpha_k \mathbf{v}_k \right\|^2 = \sum_{k=1}^{n} |\alpha_k|^2 \|\mathbf{v}_k\|^2$$

- Proposition 5.3.3: Let $\mathbf{v}_1, \ldots, \mathbf{v}_r$ be an orthogonal basis in E. Then the orthogonal projection $P_E \mathbf{v}$ of a vector $\mathbf{v}$ is given by the formula

$$P_E \mathbf{v} = \sum_{k=1}^{r} \frac{(\mathbf{v}, \mathbf{v}_k)}{\|\mathbf{v}_k\|^2} \mathbf{v}_k$$

- It follows that

$$P_E \mathbf{v} = \sum_{k=1}^{r} \frac{\mathbf{v}_k^* \mathbf{v}}{\|\mathbf{v}_k\|^2} \mathbf{v}_k$$

$$= \sum_{k=1}^{r} \frac{1}{\|\mathbf{v}_k\|^2} \mathbf{v}_k \mathbf{v}_k^* \mathbf{v}$$

$$= \left(\sum_{k=1}^{r} \frac{1}{\|\mathbf{v}_k\|^2} \mathbf{v}_k \mathbf{v}_k^* \right) \mathbf{v}$$

- Thus, we have that

$$P_E = \sum_{k=1}^{r} \frac{1}{\|\mathbf{v}_k\|^2} \mathbf{v}_k \mathbf{v}_k^*$$

- **Gram-Schmidt orthogonalization**: Let $\mathbf{x}_1, \dots, \mathbf{x}_n$ be a linearly independent system of vectors to orthogonalize. Then $\mathbf{v}_1 = \mathbf{x}_1$, $\mathbf{v}_2 = \mathbf{x}_2 - P_{\text{span}\{\mathbf{v}_1\}} \mathbf{x}_2$, $\mathbf{v}_3 = \mathbf{x}_3 - P_{\text{span}\{\mathbf{v}_1, \mathbf{v}_2\}} \mathbf{x}_3$, and on and on.

- To find the least squares solution to $A\mathbf{x} = \mathbf{b}$, solve $A\mathbf{x} = P_{\text{range } A} \mathbf{b}$.

  - We can do this by finding an orthogonal basis of range A and then applying the projection formula.
  - Alternatively, we can use the following formula to speed things up if $A^* A$ is invertible:

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

- Theorem 5.4.1: For an $m \times n$ matrix A,

$$\ker A = \ker(A^* A)$$

  - Thus, $A^* A$ is invertible iff A is invertible iff A is full rank. This gives us a condition on when we can use the projection formula.

- Theorem 5.6.1: An operator $U : X \to Y$ is an isometry if and only if it preserves the inner product, i.e., if and only if

$$(\mathbf{x}, \mathbf{y}) = (U\mathbf{x}, U\mathbf{y})$$

  for all $\mathbf{x}, \mathbf{y} \in X$.

- Lemma 5.6.2: An operator $U : X \to Y$ is an isometry if and only if $U^* U = I$.

- **Unitary** (operator): An invertible isometry.

- Proposition 5.6.3: An isometry $U : X \to Y$ is a unitary operator iff $\dim X = \dim Y$.

- **Orthogonal** (matrix): A unitary matrix with real entries.

- Unitary operator properties:

  1. $U^{-1} = U^*$.
  2. U unitary implies $U^* = U^{-1}$ unitary.
  3. If $\mathbf{v}_1, \dots, \mathbf{v}_n$ is orthonormal, $U\mathbf{v}_1, \dots, U\mathbf{v}_n$ is orthonormal.
  4. U, V unitary implies UV unitary.

- A matrix U is an isometry iff its columns form an orthonormal system.

- Proposition 5.6.4: Let U be a unitary matrix. Then

  1. $|\det U| = 1$. In particular, if U is orthogonal, then $\det U = \pm 1$.
  2. $|\lambda| = 1$ for every eigenvalue λ of U.

- Proposition 5.6.5: A matrix A is unitarily equivalent to a diagonal one iff it has an orthogonal (orthonormal) basis of eigenvectors.

Chapter 6

Structure of Operators on Inner Product Spaces

6.1 Notes

- Spectral decomposition of self-adjoint linear maps.

  - Can we write a map in term of the eigenvalues only?
  - Let $A : X \to X$ be linear and self-adjoint. Where $\dim X < \infty$.
  - Let A have eigenvalues $\lambda_1, \ldots, \lambda_n$ and eigenvectors $\mathbf{v}_1, \ldots, \mathbf{v}_n$. The there is an orthonormal basis of X consisting of eigenvectors of A. An operator is self-adjoint if $A = A^*$.
  - If A is self-adjoint, then A can be written as diagonal with the eigenvalues on the diagonal with respect to some orthonormal basis of eigenvectors.
  - Let $\mathbb{F} = \mathbb{C}$.

- If there exists an orthonormal basis $u_1, \ldots, u_n$ of X such that A is triangular, then $A = UTU^*$ where U is unitary and T is upper triangular.

  - Proved with induction on $\dim X$.
  - $\dim X = 1$ is clear.
  - Assume for $\dim X = n - 1$, WTS for $\dim X = n$.
  - The subspace has a basis $\mathbf{v}_1, \ldots, \mathbf{v}_{n-1}$ such that A has a diagonal form.
  - Let $u \in X$ be linearly independent of $\mathbf{v}_1, \ldots, \mathbf{v}_{n-1}$.
  - Let λ be the remaining eigenvalue and u the corresponding eigenvector. Let $E = \text{span}(u)$. Then make the matrix λ in the upper left corner, and block diagonal with "A_{n-1}" in the bottom right corner, zeroes everywhere else.

- **Self-adjoint** (matrix A): A linear map $A : X \to X$ where $\dim X < \infty$ such that $A = A^*$.

  - Similarly, $(Ax, y) = (x, Ay)$.
  - A self-adjoint implies all eigenvalues are real, eigenvectors corresponding to different eigenvalues are orthogonal.
    - Soug proves this.

- **Strictly positive** (operator A): A self-adjoint operator $A : X \to X$ such that $(Ax, x) > 0$ for all $x \neq 0$. *Also known as* **positive definite**.

  - Implies that all eigenvalues are strictly positive.

- **Nonnegative** (operator A): A self-adjoint operator $A : X \to X$ such that $(Ax, x) \geq 0$ for all $x \neq 0$. *Also known as* **definite**.

  – All eigenvalues are nonnegative.

- Suppose $A \geq 0$ is self-adjoint. Then there exists a unique self-adjoint $B \geq 0$ such that $B^2 = A$.

  – A self-adjoint is diagonal (wrt. some basis).

  – A positive means that all eigenvalues (diagonal entries) are positive.

  – Thus, take

$$B = \begin{pmatrix} \sqrt{\lambda_1} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sqrt{\lambda_n} \end{pmatrix}$$

  – Suppose $B^2 = A$, $C^2 = A$. Then we have an orthonormal basis corresponding to B and an orthonormal basis corresponding to C. It follows that $B^2 = C^2 = A$. Write $B^2 x$ and $C^2 x$ in terms of their bases; will necessitate that the bases are the same.

10/13:
- If we get yes/no questions, we don't have to justify.

- Cauchy-Schwarz inequality:
$$|(\mathbf{x}, \mathbf{y})| \leq \|\mathbf{x}\| \|\mathbf{y}\|$$

  – Real spaces, V vs. $(\cdot, \cdot)$ inner product.

  – Proof:

$$0 \leq \|\mathbf{x} + t\mathbf{y}\|^2$$
$$= t^2 \|\mathbf{y}^2\| + 2t(\mathbf{x}, \mathbf{y}) + \|\mathbf{x}\|^2$$

Thus, the discriminant must be less than zero (because the whole polynomial is positive, so the discriminant [the opposite of the x^0 term of the factored form of the polynomial] must be less than zero so the polynomial doesn't get dragged down to negative values):

$$(\mathbf{x}, \mathbf{y})^2 - \|\mathbf{x}\|^2 \|\mathbf{y}\|^2 \leq 0$$

Taking square roots of both sides proves the desired inequality.

- Recall that if $A^* = A$, then all eigenvalues are real and all eigenvectors of distinct eigenvalues are orthogonal to each other.

- **Normal** (matrix): A matrix N such that $N^* N = N N^*$.

  – Examples: Diagonal, self-adjoint, and unitary operators are all normal.

- Any normal operator in a complex vector spae has an orthonormal set of eigenvectors, e.g., $N = U D U^*$.

  – Proof: N is upper triangular wrt. some basis (because all matrices are). WTS any normal upper triangular matrix is diagonal. Done by induction on the dimension of N from $n = 2$.

  – Assume the claim for every $(n - 1) \times (n - 1)$ normal upper triangular matrix.

  – Let

$$N = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ 0 & & & \\ 0 & & & \\ \vdots & & N_1 & \\ 0 & & & \end{pmatrix}$$

(we know every normal matrix can be written in this upper triangular form)

- Then just compute NN^* and N^*N. Knowing they have to be equal, we have that $a_{12} = \cdots = a_{1n} = 0$.
  - We can also prove from the above (block diagonal multiplication) that N_1 is normal. Thus, it's diagonal, too. Therefore, the whole thing is diagonal.

- N is normal if and only if $\|N\mathbf{x}\| = \|N^*\mathbf{x}\|$.
  - Proof: $(N\mathbf{x}, N\mathbf{y}) = (N^*N\mathbf{x}, \mathbf{y}) = (NN^*\mathbf{x}, \mathbf{y}) = (N^*\mathbf{x}, N^*\mathbf{y})$. This is equivalent to the desired condition.

- If A is nonnegative and $(A\mathbf{e}_k, \mathbf{e}_k) = a_{kk}$, then

$$\sum_{i,j=1}^{n} a_{ij}\mathbf{x}_i\mathbf{x}_j$$

- **Positive definite** (matrix): An $n \times n$ self-adjoint matrix such that $(A\mathbf{x}, \mathbf{x}) > 0$ for all $\mathbf{x} \in X$.

- Let $A : X \to Y$, $\dim X = \dim Y$. Then AA^* is positive semidefinite. And there exists a unique square root $R = \sqrt{A^*A}$.
  - Proof: $(A^*A\mathbf{x}, \mathbf{x}) = (A\mathbf{x}, A\mathbf{x}) = \|A\mathbf{x}\|^2 \geq 0$.

- **Modulus** (of A): The matrix $|A| = \sqrt{A^*A}$.

- Check $\||A|\mathbf{x}\| = \|A\mathbf{x}\|$.

$$\||A|\mathbf{x}\|^2 = (|A|\mathbf{x}, |A|\mathbf{x}) = (|A|^*|A|\mathbf{x}, \mathbf{x}) = (A^*A\mathbf{x}, \mathbf{x}) = (A\mathbf{x}, A\mathbf{x}) = \|A\mathbf{x}\|^2$$

- Let $A : X \to X$ be a linear operator. Then $A = U|A|$ where U is unitary.

- Look at singular matrices.

10/15:
- Recall that if $A : X \to Y$, we have that A^*A is semidefinite, positive, and self adjoint.
  - Thus, there exists a unique matrix $R = \sqrt{A^*A} \geq 0$, which we define to be $|A| = \sqrt{A^*A}$.

- Polar form of a matrix:
$$A = U|A|$$

  - This may not be unique!
  - Proof: Suppose $A\mathbf{x} = U(|A|\mathbf{x})$. $A\mathbf{x} \in \operatorname{range} A$, and $|A|\mathbf{x} \in \operatorname{range}(|A|)$. $\mathbf{x} \in \operatorname{range}(|A|)$ implies that there exists $\mathbf{v} \in X$ such that $x = |A|\mathbf{v}$.
  - Define $U\mathbf{x} = A\mathbf{x}$. U is a well-defined linear map.
  - $\|U_0\mathbf{x}\| = \|A\mathbf{x}\| = \||A|\mathbf{v}\| = \|\mathbf{x}\|$.
  - U is an isometry.
  - $\operatorname{range}|A| \to X$.
  - Use $\ker A = \ker |A| = (\operatorname{range} A)^\perp$ to extend U_0 to U: $U = U_0 + U_1$.

- **Singular values** (of a matrix): The eigenvalues of $|A|$.
  - So if $\lambda_1, \ldots, \lambda_n$ are the eigenvalues of A^*A, the singular values of A are $\sqrt{\lambda_1}, \ldots, \sqrt{\lambda_n}$.

- Let $A : X \to Y$ be a linear map.
  - Let $\sigma_1, \ldots, \sigma_n$ be the signular values of A. Then $\sigma_1, \ldots, \sigma_n > 0$.
  - Additionally, if $\mathbf{v}_1, \ldots, \mathbf{v}_n$ is an orthonormal basis of eigenvectors of A^*A, then the list of n vectors $\mathbf{w}_1, \ldots, \mathbf{w}_n$ defined by $\mathbf{w}_k = 1/\sigma_k A\mathbf{v}_k$ for each $k = 1, \ldots, n$ is orthonormal.

■ Proof:

$$(\mathbf{w}_k, \mathbf{w}_j) = \frac{1}{\sigma_k \sigma_k}(A\mathbf{v}_k, A\mathbf{v}_j) = \frac{1}{\sigma_k \sigma_j} = \frac{1}{\sigma_k \sigma_j}(A^* A\mathbf{v}_k, \mathbf{v}_j) = \frac{\sigma_k^2}{\sigma_k \sigma_j}(\mathbf{v}_k, \mathbf{v}_j) = 0$$

and

$$\|\mathbf{w}_k\| = \frac{1}{\sigma_k}\|A\mathbf{v}_k\| = \frac{1}{\sigma_k}\|\,|A|\mathbf{v}_k\| = 1$$

  – Schmidt decomposition of A:

$$A\mathbf{x} = \sum^r \sigma_k(\mathbf{x}, \mathbf{v}_k)\mathbf{w}_k$$

■ This is because $\mathbf{x} = \sum(\mathbf{x}, \mathbf{v}_k)\mathbf{v}_k$, so by the above,

$$A\mathbf{x} = \sum^n (\mathbf{x}, \mathbf{v}_k)A\mathbf{v}_k = \sum^r \sigma_k(\mathbf{x}, \mathbf{v}_k)\mathbf{w}_k$$

- **Operator norm**: $\|A\| = \max\{\|A\mathbf{x}\| : \|\mathbf{x}\| \leq 1\}$.

- Properties of the operator norm:

  – $\|A\mathbf{x}\| \leq \|A\|\|\mathbf{x}\|$.
  – $\|\alpha A\| = |\alpha|\|A\|$.
  – $\|A + B\| \leq \|A\| + \|B\|$.
  – $\|A\| \geq 0$.
  – $\|A\| = 0$ iff $A = 0$.

- **Frobenius norm**: The norm $\|A\|_2^2 = \operatorname{tr}(A^* A)$.

- The operator norm is always less than or equal to the Frobenius norm.

- If $A : \mathbb{F}^n \to \mathbb{F}^n$, then $A = W\Sigma V^*$ where σ is a diagonal matrix of nonzero singular values.

- The operator norm of A is the largest of the singular values.

- An orthogonal matrix can be decomposed to a block-diagonal matrix of rotations.

10/18:　- Soug tests what he teaches and doesn't give super tricky questions.

- Structure of orthogonal matrices.

- **Orthogonal** (matrix): A unitary matrix U with all elements real and $|\det U| = 1$.

- Theorem: Let U be an orthogonal operator on $\mathbb{R}^n$ such that $\det U = 1$. Then there exists an orthonormal basis $\mathbf{v}_1, \ldots, \mathbf{v}_n$ such that with respect to this basis,

$$U = \begin{pmatrix} R_{\phi_1} & & & \mathbf{0} \\ & \ddots & & \\ & & \mathbb{R}_{\phi_k} & \\ \mathbf{0} & & & I_{n-2k} \end{pmatrix}$$

where each R_{ϕ_i} is a 2×2 rotation matrix.

  – If you are in $\mathbb{R}^7$ for example, you would be able to express U as a composition of at most 3 rotation maps and the identity map.

  – Each rotation map acts on two orthonormal vectors.

  – Proof: $P(\lambda)$ is the n-degree characteristic polynomial $\det(U - \lambda I) = 0$. The eigenvalues are the roots of it.

- $p(\lambda) = 0$ if and only if $p(\bar{\lambda}) = 0$.
  - ■ $\lambda \in \mathbb{C}$ is an eigenvalue with eigenvector $\mathbf{u} \neq 0$ iff $U\mathbf{u} = \lambda\mathbf{u}$ and $U\bar{\mathbf{u}} = \bar{\lambda}\bar{\mathbf{u}}$.
- Recall that U unitary implies $|\lambda| = 1$.
  - ■ Proof[1]: $\|U\mathbf{x}\| = \|\mathbf{x}\|$ and $U\mathbf{x} = \lambda\mathbf{x}$. Thus,

$$\|U\mathbf{x}\| = \|\lambda\mathbf{x}\| = |\lambda|\|\mathbf{x}\| = \|\mathbf{x}\|$$

  and since $\mathbf{x} \neq 0$, we can divide by $\|\mathbf{x}\|$, so $|\lambda| = 1$.
- Let $\mathbf{u} = \operatorname{Re}\mathbf{u} + \operatorname{Im}\mathbf{u}$.
- It follows that we may define

$$\mathbf{x} = \operatorname{Re}\mathbf{u} = \frac{\mathbf{u} + \bar{\mathbf{u}}}{2} \qquad\qquad \mathbf{y} = \operatorname{Im}\mathbf{u} = \frac{\mathbf{u} - \bar{\mathbf{u}}}{2}$$

- Thus, $\mathbf{u} = \mathbf{x} + i\mathbf{y}$ and $\bar{\mathbf{u}} = \mathbf{x} - i\mathbf{y}$.
- Since $U\mathbf{x} = \frac{U\mathbf{u} + U\bar{\mathbf{u}}}{2} = \frac{\lambda\mathbf{u} + \bar{\lambda}\bar{\mathbf{u}}}{2}$, $U\mathbf{y} = \operatorname{Im}(\lambda\mathbf{u}) = \operatorname{Re}(\lambda\mathbf{u})$.
- Since $|\lambda| = 1$, $\lambda = e^{i\alpha}$ and $\bar{\lambda} = e^{-i\alpha}$.
- It follows that $U\mathbf{x} = (\cos\alpha)\mathbf{x} - (\sin\alpha)\mathbf{y}$ and $U\mathbf{y} = (\cos\alpha)\mathbf{y} + (\sin\alpha)\mathbf{x}$.
- Thus, since $U\mathbf{x} = \operatorname{Re}\lambda\mathbf{u}$, we have that

$$\begin{aligned}\lambda\mathbf{u} &= (\cos\alpha + i\sin\alpha)(\mathbf{x} + i\mathbf{y})\\ &= (\cos\alpha)\mathbf{x} - (\sin\alpha)\mathbf{y} + i[(\cos\alpha)\mathbf{y} + (\sin\alpha)\mathbf{x}]\end{aligned}$$

- If E_λ is a 2 dimensional space spanned by $\mathbf{x}$ and $\mathbf{y}$ and invariant by U. Thus, any block of the desired matrix leaves its desired sub-block invariant.
- We also know that the eigenvectors of a unitary matrix corresponding to different eigenvalues are orthogonal.
- Thus, $\|\mathbf{x}\| = \|\mathbf{y}\| = \sqrt{2}/2\|\mathbf{u}\|$, $\mathbf{x} \perp \mathbf{y}$.
- Let $\mathbf{x}, \mathbf{y}$ complete the theorem to form a basis of $\mathbb{R}^n$.
- It will follow that

$$U = \begin{pmatrix} R_\alpha & \mathbf{0} \\ \mathbf{0} & U_1 \end{pmatrix}$$

  where U_1 is orthogonal, and we may repeat the process.

6.2 Chapter 6: Structure of Operators on Inner Product Spaces

From Treil (2017).

10/24:
- Theorem 6.1.1: Let $A : X \to X$ be an operator acting in a complex inner product space. Then there exists an orthonormal basis $\mathbf{u}_1, \ldots, \mathbf{u}_n$ of X such that the matrix of A in this basis is upper triangular. In other words, any $n \times n$ matrix A can be represented as $A = UTU^*$, where U is unitary and T is upper-triangular.

- Theorem 6.1.2: Let $A : X \to X$ be an operator acting on a real inner product space. Suppose that all eigenvalues of A are real. Then there exists an orthonormal basis $\mathbf{u}_1, \ldots, \mathbf{u}_n$ in X such that the matrix of A in this basis is upper triangular. In other words, any real $n \times n$ matrix A with all real eigenvalues can be represented as $T = UTU^* = UTU^T$, where U is orthogonal and T is a real upper-triangular matrix.

---

[1]This would be a good exam question.

- Theorem 6.2.1: Let $A = A^*$ be a self-adjoint operator in an inner product space X (the space can be complex or real). Then all eigenvalues of A are real and there exists an orthonormal basis of eigenvectors of A in X.

  Equivalently (see Theorem 6.2.2), A can be represented as $A = UDU^*$ where U is a unitary matrix and D is a diagonal matrix with real entries. Moreover, if A is real, U can be chosen to be real, i.e., orthogonal.

- Proposition 6.2.3: Let $A = A^*$ be a self-adjoint operator and let $\lambda, \mathbf{u}, \mu, \mathbf{v}$ be such that $A\mathbf{u} = \lambda\mathbf{u}$ and $A\mathbf{v} = \mu\mathbf{v}$. Then if $\lambda \neq \mu$, $\mathbf{u} \perp \mathbf{v}$.

- Since complex multiplication is commutative,

$$D^*D = DD^*$$

  for every diagonal matrix D.

  – It follows that $A^*A = AA^*$ if the matrix of A in some orthonormal basis is diagonal.

- Theorem 6.2.4: Any normal operator N in a complex vector space has an orthonormal basis of eigenvectors.

  Equivalently, any matrix N satisfying $N^*N = NN^*$ can be represented as $N = UDU^*$ where U is unitary and D is diagonal.

- Proposition 6.2.5: An operator $N : X \to X$ is normal iff

$$\|N\mathbf{x}\| = \|N^*\mathbf{x}\|$$

  for all $\mathbf{x} \in X$.

- **Hermitian square** (of A): The matrix A^*A.

- **Modulus** (of A): The unique positive semidefinite square root $\sqrt{A^*A}$.

- Proposition 6.3.3: For a linear operator $A : X \to Y$,

$$\||A|\mathbf{x}\| = \|A\mathbf{x}\|$$

- Corollary 6.3.4: $\ker A = \ker |A|$.

- Theorem 6.3.5: Let $A : X \to X$ be an operator (square matrix). Then A can be represented as

$$A = U|A|$$

  where U is a unitary operator.

- **Singular value** (of A): An eigenvalue of $|A|$.

  – A positive square root of an operator of A^*A.

- Proposition 6.3.6: Let $\sigma_1, \ldots, \sigma_n$ be the singular values of A, ordered such that $\sigma_1, \ldots, \sigma_r$ are the nonzero singular values, and let $\mathbf{v}_1, \ldots, \mathbf{v}_n$ be an orthonormal basis of eigenvectors of A^*A. Then the system

$$\mathbf{w}_k = \frac{1}{\sigma_k} A\mathbf{v}_k$$

  for $k = 1, \ldots, r$ is orthonormal.

- **Schmidt decomposition** (of A): The decompositions

$$A = \sum_{k=1}^{r} \sigma_k \mathbf{w}_k \mathbf{v}_k^*$$

and

$$A\mathbf{x} = \sum_{k=1}^{r} \sigma_k (\mathbf{x}, \mathbf{v}_k) \mathbf{w}_k$$

  - Note that these can be verified by plugging $\mathbf{x} = \mathbf{v}_j$ for each $j = 1, \ldots, n$ into the latter equation.

10/25:
- Lemma 6.3.7: A can be represented as the Schmidt decomposition

$$A = \sum_{k=1}^{r} \sigma_k \mathbf{w}_k \mathbf{v}_k^*$$

  where $\sigma_k > 0$ for any orthonormal systems $\mathbf{v}_1, \ldots, \mathbf{v}_r$ and $\mathbf{w}_1, \ldots, \mathbf{w}_r$.

- Corollary 6.3.8: Let $A = \sum_{k=1}^{r} \sigma_k \mathbf{w}_k \mathbf{v}_k^*$ be a Schmidt decomposition of A. Then

$$A^* = \sum_{k=1}^{r} \sigma_k \mathbf{v}_k \mathbf{w}_k^*$$

  is a Schmidt decomposition of A^*.

- **Reduced singular value decomposition** (of A): The decomposition

$$A = \tilde{W} \tilde{\Sigma} \tilde{V}^*$$

  where $A : \mathbb{F}^n \to \mathbb{F}^m$ has the Schmidt decomposition $A = \sum_{k=1}^{r} \sigma_k \mathbf{w}_k \mathbf{v}_k^*$, $\tilde{\Sigma} = \text{diag}\{\sigma_1, \ldots, \sigma_r\}$, and $\tilde{V}, \tilde{W}$ are matrices with columns $\mathbf{v}_1, \ldots, \mathbf{v}_r$ and $\mathbf{w}_1, \ldots, \mathbf{w}_r$, respectively. *Also known as* **compact singular value decomposition**.

  - Note that $\tilde{V}$ is an $n \times r$ matrix, $\tilde{\Sigma}$ is an $r \times r$ matrix, and $\tilde{W}$ is an $m \times r$ matrix.
  - Since $\mathbf{v}_1, \ldots, \mathbf{v}_r$ and $\mathbf{w}_1, \ldots, \mathbf{w}_r$ are orthonormal, $\tilde{V}, \tilde{W}$ are isometries.

- Note that $r = \text{rank}\, A$ (see Problem 6.3.1).

  - It follows that if A is invertible, then $m = n = r$, so $\tilde{V}, \tilde{W}$ are unitary and $\tilde{\Sigma}$ is an invertible diagonal matrix.

- However, A need not be invertible for us to get a representation similar to $A = \tilde{W} \tilde{\Sigma} \tilde{V}^*$.

  - Complete $\mathbf{v}_1, \ldots, \mathbf{v}_r$ and $\mathbf{w}_1, \ldots, \mathbf{w}_r$ to bases of $\mathbb{F}^n$ and $\mathbb{F}^m$, respectively.
  - Then we get the following.

- **Singular value decomposition** (of A): The decomposition

$$A = W \Sigma V^*$$

  where $V \in M_{n \times n}^{\mathbb{F}}$ and $W \in M_{m \times m}^{\mathbb{F}}$ are unitary matrices with columns $\mathbf{v}_1, \ldots, \mathbf{v}_n$ and $\mathbf{w}_1, \ldots, \mathbf{w}_n$, respectively, and $\Sigma \in M_{m \times n}^{\mathbb{R}^+}$ is a "diagonal" matrix such that

$$\Sigma_{j,k} = \begin{cases} \sigma_k & j = k \leq r \\ 0 & \text{otherwise} \end{cases}$$

- Notice that if $A = W\Sigma V^*$, then

$$A^*A = (W\Sigma V^*)^*(W\Sigma V^*) = V\Sigma^* W^* W\Sigma V^* = V\Sigma^2 V^*$$

  proving that the singular values of A, squared, are the eigenvalues of A^*A.

- If A is invertible, the reduced SVD is the matrix form of the Schmidt decomposition is the SVD.

- If $A = W\Sigma V^*$ is $n \times n$, then

$$A = (\underbrace{WV^*}_{U})(\underbrace{V\Sigma V^*}_{|A|})$$

  is a polar decomposition of A.

- Consider the unit ball $B = \{\mathbf{x} \in \mathbb{R}^n : \|\mathbf{x}\| \le 1\}$.

    - We want to describe $A(B)$, i.e., the image of the unit ball under A.
    - Let $\mathbf{x} = (x_1, \ldots, x_n)^T$ and let $\mathbf{y} = (y_1, \ldots, y_n)^T$. If $A = \mathrm{diag}\{\sigma_1, \ldots, \sigma_n\}$, we have $\mathbf{y} \in A(B)$ iff $\mathbf{y} = A\mathbf{x}$ where $\mathbf{x} \in B$ iff

$$\sum_{k=1}^n \frac{y_k^2}{\sigma_k^2} = \sum_{k=1}^n x_k^2 = \|\mathbf{x}\|^2 \le 1$$

    - Thus, $A(B)$ is an ellipsoid with half-axes $\sigma_1, \ldots, \sigma_n$.
    - In the more general case, if $A = W\Sigma V^*$, then since V^* is unitary, $V^*(B) = B$. $\Sigma V^*(B) = \Sigma(B)$ is thus by the above an ellipsoid in range Σ with half-axes $\sigma_1, \ldots, \sigma_r$. Thus, since isometries don't change geometry, $W(\Sigma(B))$ is also an ellipsoid with the same half-axes, but in range A.

- Conclusion: The image $A(B)$ of the closed unit ball B is an ellipsoid in range A with half-axes $\sigma_1, \ldots, \sigma_r$, where r is the number of nonzero singular values, i.e., the rank of A.

- Finding the maximum of $\|A\mathbf{x}\|$ for $\mathbf{x} \in B$.

    - For a diagonal matrix Σ with nonnegative entries, the maximum is clearly the maximal diagonal entry: In this case if s_1 is the maximal diagonal entry, then since

$$\Sigma\mathbf{x} = \sum_{k=1}^r s_k x_k \mathbf{e}_k$$

  we have that

$$\|A\mathbf{x}\|^2 = \sum_{k=1}^r s_k^2 |x_k|^2 \le s_1^2 \sum_{k=1}^r |x_k|^2 = s_1^2 \cdot \|\mathbf{x}\|^2$$

    - We get the following by a similar logic to before.

- Conclusion: The maximum of $\|A\mathbf{x}\|$ on the unit ball B is the maximal singular value of A.

- **Operator norm** (of A): The following quantity. *Denoted by* $\|\boldsymbol{A}\|$. *Given by*

$$\|A\| = \max\{\|A\mathbf{x}\| : \mathbf{x} \in X, \|\mathbf{x}\| \le 1\}$$

    - $\|A\|$ clearly satisfies the four properties of a norm.
    - Additionally,

$$\|A\mathbf{x}\| \le \|A\| \cdot \|\mathbf{x}\|$$

    - Alternate definition: The operator norm $\|A\|$ is the smallest number $C \ge 0$ such that $\|A\mathbf{x}\| \le C\|\mathbf{x}\|$.

- **Frobenius norm**: The following norm. *Also known as* **Hilbert-Schmidt norm**. *Denoted by* $\|A\|_2$. *Given by*

$$\|A\|_2^2 = \text{tr}(A^*A)$$

  - If we let $s_1, \ldots, s_n$ be the singular values of A and let s_1 be the largest value, then we have

$$\|A\|^2 = s_1^2 \leq \sum_{k=1}^{n} s_k^2 = \text{tr}(A^*A) = \|A\|_2^2$$

- Conclusion: The operator norm of a matrix cannot be more than its Frobenius norm.

- Suppose we want to solve $A\mathbf{x} = \mathbf{b}$ where A is invertible, but there is some (experimental) error $\Delta\mathbf{b}$ in $\mathbf{b}$. Then we are really solving for an approximate solution $\mathbf{x} + \Delta\mathbf{x}$ to the equation

$$A(\mathbf{x} + \Delta\mathbf{x}) = \mathbf{b} + \Delta\mathbf{b}$$

  - It follows since A is invertible that $\mathbf{x} = A^{-1}\mathbf{b}$ and $\Delta\mathbf{x} = A^{-1}\Delta\mathbf{b}$.
  - To estimate the relative error $\|\Delta\mathbf{x}\|/\|\mathbf{x}\|$ in the solution in comparison with the relative error $\|\Delta\mathbf{b}\|/\|\mathbf{b}\|$ in the data, use

$$\frac{\|\Delta\mathbf{x}\|}{\|\mathbf{x}\|} = \frac{\|A^{-1}\Delta\mathbf{b}\|}{\|\mathbf{b}\|}\frac{\|A\mathbf{x}\|}{\|\mathbf{x}\|} \leq \frac{\|A^{-1}\| \cdot \|\Delta\mathbf{b}\|}{\|\mathbf{b}\|}\frac{\|A\| \cdot \|\mathbf{x}\|}{\|\mathbf{x}\|} = \|A^{-1}\| \cdot \|A\| \cdot \frac{\|\Delta\mathbf{b}\|}{\|\mathbf{b}\|}$$

- **Condition number** (of A): The following quantity. *Given by*

$$\|A\| \cdot \|A^{-1}\|$$

  - If s_1 is the largest singular value of A and s_n is the smallest, then

$$\|A\| \cdot \|A^{-1}\| = s_1 \cdot \frac{1}{s_n} = \frac{s_1}{s_n}$$

- **Well-conditioned** (matrix): A matrix the condition number of which is not "too big."

- **Ill-conditioned** (matrix): A matrix that is not well-conditioned.

- Theorem 6.5.1: Let U be an orthogonal operator on $\mathbb{R}^n$ and let $\det U = 1$. Then there exists an orthonormal basis $\mathbf{v}_1, \ldots, \mathbf{v}_n$ such that the matrix of U in this basis has the block diagonal form

$$\begin{pmatrix} R_{\varphi_1} & & & & 0 \\ & \ddots & & & \\ & & R_{\varphi_k} & & \\ 0 & & & I_{n-2k} \end{pmatrix}$$

  where each R_{φ_j} is a two-dimensional rotation

$$R_{\varphi_j} = \begin{pmatrix} \cos \varphi_j & -\sin \varphi_j \\ \sin \varphi_j & \cos \varphi_j \end{pmatrix}$$

  and I_{n-2k} represents the $(n-2k) \times (n-2k)$ identity matrix.

  - Alternate interpretation: Any rotation in $\mathbb{R}^n$ can be represented as a composition of at most $n/2$ commuting planar rotations.

- Theorem 6.5.2: Let U be an orthogonal operator on $\mathbb{R}^n$ and let $\det U = -1$. Then there exists an orthonormal basis $\mathbf{v}_1, \ldots, \mathbf{v}_n$ such that the matrix of U in this basis has block diagonal form

$$
\begin{pmatrix}
R_{\varphi_1} & & & & 0 \\
& \ddots & & & \\
& & R_{\varphi_k} & & \\
& & & I_r & \\
0 & & & & -1
\end{pmatrix}
$$

where $r = n - 2k - 1$ and each R_{φ_j} is a two-dimensional rotation

$$
R_{\varphi_j} = \begin{pmatrix} \cos \varphi_j & -\sin \varphi_j \\ \sin \varphi_j & \cos \varphi_j \end{pmatrix}
$$

- Corollary: An orthogonal 2×2 matrix U with determinant -1 is always a reflection.

- Theorem 6.5.3: Any rotation U (i.e., any orthogonal transformation U with $\det U = 1$) can be represented as a product of at most $n(n-1)/2$ elementary rotations.

- Consider the following orthonormal bases of $\mathbb{R}^2$.

Figure 6.1: Orientation in $\mathbb{R}^2$.

  - Notice that a rotation will get you from the standard basis (a) to basis (b), but not from the standard basis (a) to basis (c).
  - This is the motivation for defining orientation.
  - More formally, we know that there is a unique linear transformation U such that $U\mathbf{e}_k = \mathbf{v}_k$ for each $k = 1, 2$. In particular, the matrix of U with respect to the standard basis is orthogonal with columns $\mathbf{v}_1, \mathbf{v}_2$.
  - By Theorems 6.5.1 and 6.5.2, if $\det U = 1$, then U is a rotation, and if $\det U = -1$, then U is not a rotation.

- **Similarly oriented** (bases $\mathcal{A}, \mathcal{B}$): Two bases $\mathcal{A}, \mathcal{B}$ of a real vector space such that the change of coordinates matrix $[I]_{\mathcal{B}\mathcal{A}}$ has a positive determinant.

- **Differently oriented** (bases $\mathcal{A}, \mathcal{B}$): Two bases $\mathcal{A}, \mathcal{B}$ of a real vector space that are not similarly oriented (i.e., $[I]_{\mathcal{B}\mathcal{A}}$ has a negative determinant).

- We usually let the standard basis of $\mathbb{R}^n$ have a **positive orientation**.

  - In an abstract vector space, we need only fix a basis and declare its orientation to be positive.

- **Continuously transformable** (bases $\mathcal{A}, \mathcal{B}$): Two bases $\mathcal{A}, \mathcal{B}$ such that $\mathcal{A} = \{\mathbf{a}_1, \ldots, \mathbf{a}_n\}$ can be continuously transformed to a basis $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$. In particular, there exists a **continuous family of bases** $\mathcal{V}(t) = \{\mathbf{v}_1(t), \ldots, \mathbf{v}_n(t)\}$, $t \in [a, b]$, such that

$$
\mathbf{v}_k(a) = \mathbf{a}_k \qquad\qquad\qquad \mathbf{v}_k(b) = \mathbf{b}_k
$$

for each $k = 1, \ldots, n$.

- **Continuous family of bases**: A family of bases $\mathcal{V}(t) = \{\mathbf{v}_1(t), \ldots, \mathbf{v}_n(t)\}$, $t \in [a, b]$, such that the vector-functions $\mathbf{v}_k(t)$ are continuous (their coordinates in some bases are continuous functions) and the system $\mathbf{v}_1(t), \ldots, \mathbf{v}_n(t)$ is a basis for all $t \in [a, b]$.

- Theorem 6.6.1: Two bases $\mathcal{A} = \{\mathbf{a}_1, \ldots, \mathbf{a}_n\}$ and $\mathcal{B} = \{\mathbf{b}_1, \ldots, \mathbf{b}_n\}$ have the same orientation if and only if one of the bases can be continuously transformed to the other.

Chapter 7

Bilinear and Quadratic Forms

7.1 Notes

- **Bilinear form**: A function $L : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ such that

$$L(\alpha \mathbf{x}_1 + \beta \mathbf{x}_2, \mathbf{y}) = \alpha L(\mathbf{x}_1, \mathbf{y}) + \beta L(\mathbf{x}_2, \mathbf{y}) \qquad L(\mathbf{x}, \alpha \mathbf{y}_1 + \beta \mathbf{y}_2) = \alpha L(\mathbf{x}, \mathbf{y}_1) + \beta L(\mathbf{x}, \mathbf{y}_2)$$

  - $L(\mathbf{x}, \mathbf{y}) = (A\mathbf{x}, \mathbf{y})$.

- **Quadratic form**: A bilinear form $L(\mathbf{x}, \mathbf{x})$.

  - $(\mathbf{x}, \mathbf{x})$ is a polynomial of degree 2 in $\mathbf{x}_1, \ldots, \mathbf{x}_n$:

$$L(\lambda \mathbf{x}, \lambda \mathbf{x}) = (\lambda \mathbf{x}, \lambda \mathbf{x}) = \lambda^2 (\mathbf{x}, \mathbf{x})$$

- We have that

$$(A\mathbf{x}, \mathbf{x}) = (A\lambda \mathbf{x}, \lambda \mathbf{x}) = \lambda^2 (A\mathbf{x}, \mathbf{x}) = \sum_{j,i=1}^{n} \alpha_{j,i} \mathbf{x}_i \mathbf{x}_j$$

- The general form of a quadratic form:

  - Can any quadratic form on $\mathbb{R}^n$ be written as $(A\mathbf{x}, \mathbf{x})$?

- Bilinear forms are linear in each argument when keeping the other fixed.

- Quadratic forms $Q(\mathbf{x}) = L(\mathbf{x}, \mathbf{x})$ are quadratic polynomials in the coordinates of x.

  - In particular, $Q(\lambda \mathbf{x}) = |\lambda|^2 Q(\mathbf{x})$.

- If Q quadratic is real, then $Q(\mathbf{x}) = (A\mathbf{x}, \mathbf{x})$ where A is some square matrix.

  - If $\mathbf{e}_1, \ldots, \mathbf{e}_n$ is an orthonormal basis of $\mathbb{R}^n$, then there exists a unique $A = A^*$ such that $(A)_{ij} = L(\mathbf{e}_i, \mathbf{e}_j)$.

  - Keeping $\mathbf{x} = \sum_{i=1}^{n} \mathbf{x}_i, \mathbf{e}_i$ foxed, we have

$$Q(\mathbf{x}) = L(\mathbf{x}, \mathbf{x})$$
$$= L\left(\sum^{n} \mathbf{x}_i \mathbf{e}_i, \sum^{n} \mathbf{x}_j \mathbf{e}_j\right)$$
$$= \sum_{i=1}^{n} \mathbf{x}_i L\left(\mathbf{e}_i, \sum^{n} \mathbf{x}_j \mathbf{e}_j\right)$$
$$= \sum_{i,j=1}^{n} \mathbf{x}_i \mathbf{x}_j \underbrace{L(\mathbf{e}_i, \mathbf{e}_j)}_{A_{ij}}$$

- We have that

$$
\begin{aligned}
(A\mathbf{x}, \mathbf{x}) &= (UDU^{-1}\mathbf{x}, \mathbf{x}) \\
&= (DU^{-1}\mathbf{x}, U^{-1}\mathbf{x}) \\
&= \sum_{i=1}^{n} \lambda_i \underbrace{(U^{-1}\mathbf{x})_i}_{\mathbf{y}_i} \underbrace{(U^{-1}\mathbf{x})_i}_{\mathbf{y}_i}
\end{aligned}
$$

- Can we characterize the set $\{\mathbf{x} : (A\mathbf{x}, \mathbf{x}) = 1\}$?

  – Note that this set is equivalent to $\{\mathbf{y} : (D\mathbf{y}, \mathbf{y}) = 1\}$ by teh above. This set is a rotation of the previous one. Ellipse?

- Positive quadratic form:

  – Q is positive definite if $Q(\mathbf{x}) > \mathbf{0}$ for all $\mathbf{x} \neq \mathbf{0}$ and Q is positive semidefinite if $Q(\mathbf{x}) \geq \mathbf{0}$ for all $\mathbf{x} \neq \mathbf{0}$.
  – Take a self-adjoint matrix $A = A^*$. It is positive definite if $Q(\mathbf{x}) = (A\mathbf{x}, \mathbf{x})$ is positive definite.

- Theorem: If $A = A^*$, then

  1. A is positive definite if and only if all eigenvalues of A are positive.
  2. A is positive semidefinite if and only if all eigenvalues of A are nonnegative.
  3. A is negative semidefinite if and only if all eigenvalues of A are nonpositive.
  4. A is negative definite if and only if all eigenvalues of A are negative.
  5. A is indefinite if and only if the eigenvalues of A have positive and negative values.

- Theorem: $A = A^*$ is positive definite iff $\det A_k > 0$ for all $k = 1, \ldots, n$ where A_k is the upper left $k \times k$ submatrix.

- Minimax representation of eigenvalues of a self-adjoint A.

  – Let E be a subspace of X where $\dim X < \infty$. We define $\operatorname{codim}(E) = \dim E^{\perp}$.
  – Thus, $\dim E + \operatorname{codim} E = \dim X$.
  – Theorem: Let $A = A^*$, $\lambda_1 \geq \cdots \geq \lambda_n$ eigenvalues of A. Then

  $$
  \lambda_k = \max_{\substack{E \text{ subspace} \\ \dim E = k}} \min_{\substack{\mathbf{x} \in E \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x}) = \min_{\substack{F \text{ subspace} \\ \operatorname{codim} F = k-1}} \max_{\substack{\mathbf{x} \in F \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x})
  $$

    ■ Proof: A diagonal equals $(\lambda_1, \ldots, \lambda_n)$.
    ■ An orthonormal basis of X such that $\dim E = k$, $\operatorname{codim} F = k - 1$, $\dim F = n - k + 1$.
    ■ There exists an $\mathbf{x}_0 \neq \mathbf{0}$ such that $\mathbf{x}_0 \in E \cap F$.
    ■ Note that if $B = B^*$, then the max and min of $(B\mathbf{x}, \mathbf{x})$ over the unit sphere is the maximal and minimal eigenvalue of B.
    ■ Thus,

  $$
  \min_{\substack{\mathbf{x} \in E \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x}) \leq (A\mathbf{x}_0, \mathbf{x}_0) \leq \max_{\substack{\mathbf{x} \in F \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x})
  $$

    ■ This is true for any E, F subspaces. $\dim E = k$, $\operatorname{codim} F = k - 1$, $E_0 = \operatorname{span}(\mathbf{e}_1, \ldots, \mathbf{e}_k)$ and $F_0 = \operatorname{span}(\mathbf{e}_k, \ldots, \mathbf{e}_n)$.
    ■ Thus,

  $$
  \min_{\substack{E_0 \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x}) = \lambda_k = \max_{\substack{F_0 \\ \|\mathbf{x}\| = 1}} (A\mathbf{x}, \mathbf{x})
  $$

■ Additionally,

$$\lambda_{k_1} \leq \max_{\dim E = k} \min_{\mathbf{x}} (A\mathbf{x}, \mathbf{x}) \leq \min_{\substack{F \\ \text{codim } F = k-1}} \max_{\mathbf{x}} (A\mathbf{x}, \mathbf{x}) \leq \lambda_k$$

- Corollary: Let $A = A^* = (a_{jk})_{1 \leq j,k \leq n}$ with eigenvalues $\lambda_1, \ldots, \lambda_n$ listed in decreasing order. Let $\tilde{A} = (a_{j,k})_{1 \leq j,k \leq n-1}$ with eigenvalues $\mu_1, \ldots, \mu_{n-1}$ listed in decreasing order. Then $\lambda_1 \geq \mu_1 \geq \lambda_2 \geq \mu_2 \geq \cdots \geq \mu_{n-1} \geq \lambda_n$.

    – Consider $(A\mathbf{x}, \mathbf{x})$ on $\{\mathbf{e}_1, \ldots, \mathbf{e}_n\}$, but then restrict yourself to $\mathbf{x} \in \mathbb{R}^{n-1}$ on $\{\mathbf{e}_1, \ldots, \mathbf{e}_{n-1}\}$.

7.2   Chapter 7: Bilinear and Quadratic Forms

From Treil (2017).

10/25:
- **Bilinear form** (on $\mathbb{R}^n$): A function $L(\mathbf{x}, \mathbf{y})$ of two arguments $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ that is linear in each argument.

    – Linearity in each argument:

$$L(\alpha \mathbf{x}_1 + \beta \mathbf{x}_2, \mathbf{y}) = \alpha L(\mathbf{x}_1, \mathbf{y}) + \beta L(\mathbf{x}_2, \mathbf{y}) \qquad L(\mathbf{x}, \alpha \mathbf{y}_1 + \beta \mathbf{y}_2) = \alpha L(\mathbf{x}, \mathbf{y}_1) + \beta L(\mathbf{x}, \mathbf{y}_2)$$

- If $\mathbf{x} = (x_1, \ldots, x_n)^T$ and $\mathbf{y} = (y_1, \ldots, y_n)^T$, then

$$\begin{aligned} L(\mathbf{x}, \mathbf{y}) &= \sum_{j,k=1}^{n} a_{j,k} x_k y_j \\ &= (A\mathbf{x}, \mathbf{y}) \\ &= \mathbf{y}^T A \mathbf{x} \end{aligned}$$

where

$$A = \begin{pmatrix} a_{1,1} & \cdots & a_{1,n} \\ \vdots & & \vdots \\ a_{n,1} & \cdots & a_{n,n} \end{pmatrix}$$

    – A is uniquely determined by L.

- **Quadratic form** (on $\mathbb{R}^n$): The diagonal of a bilinear form L, i.e., a bilinear form $Q[\mathbf{x}] = L(\mathbf{x}, \mathbf{x}) = (A\mathbf{x}, \mathbf{x})$.

    – Alternatively: A homogeneous polynomial of degree 2, i.e., a polynomial in $x_1, \ldots, x_n$ with only ax_k^2 and $cx_j x_k$ terms.

- There are infinitely many ways to write a quadratic form as $(A\mathbf{x}, \mathbf{x})$.

    – However, there is a unique representation $(A\mathbf{x}, \mathbf{x})$ where A is a (real) symmetric matrix.

- **Quadratic form** (on $\mathbb{C}^n$): A function of the form $Q[\mathbf{x}] = (A\mathbf{x}, \mathbf{x})$ where A is self-adjoint.

- Lemma 7.1.1: Let $(A\mathbf{x}, \mathbf{x})$ be real for all $\mathbf{x} \in \mathbb{C}^n$. Then $A = A^*$.

- To classify quadratic forms, consider the set of points $\mathbf{x} \in \mathbb{R}^n$ defined by $Q[\mathbf{x}] = 1$ for some quadratic form Q.

    – If the matrix of Q is diagonal, i.e., $Q[\mathbf{x}] = a_1 x_1^2 + \cdots + a_n x_n^2$, then the set of points can easily be visualized.

- The standard method of diagonalizing a quadratic form is change of variables.

- Orthogonal diagonalization.

- Let $Q[\mathbf{x}] = (A\mathbf{x}, \mathbf{x})$ in $\mathbb{F}^n$.
- Suppose $\mathbf{y} = S^{-1}\mathbf{x}$ where S is an invertible $n \times n$ matrix. Then

$$Q[\mathbf{x}] = Q[S\mathbf{y}] = (AS\mathbf{y}, S\mathbf{y}) = (S^*AS\mathbf{y}, \mathbf{y})$$

  so in the new variables $\mathbf{y}$, the quadratic form has matrix S^*AS.
- Thus, we can let $A = UDU^*$, choose $D = U^*AU$ as our new (diagonal) matrix, and let this matrix act on the variables $\mathbf{y} = U^*\mathbf{x}$.

- Non-orthogonal diagonalization:

  - Completing the square:
    - ■ Eliminate all x_ix_j terms by completing the square. Then substitute in a y_k for each squared term.
  - Row/column operations:
    - ■ Augment $(A|I)$. Row reduce A to D. Then $I \to S^*$.

10/28:
- **Silvester's Law of Inertia**: For a Hermitian matrix A (i.e., for a quadratic form $Q[\mathbf{x}] = (A\mathbf{x}, \mathbf{x})$) and any of its diagonalizations $D = S^*AS$, the number of positive, negative, and zero diagonal entries of D depends only on A, but not on a particular choice of diagonalization.

- **Positive** (subspace $E \subset \mathbb{F}^n$ corresponding to A): A subspace E such that $(A\mathbf{x}, \mathbf{x}) > 0$ for all nonzero $\mathbf{x} \in E$. *Also known as **A-positive***.

- **Negative** (subspace $E \subset \mathbb{F}^n$ corresponding to A): A subspace E such that $(A\mathbf{x}, \mathbf{x}) < 0$ for all nonzero $\mathbf{x} \in E$. *Also known as **A-negative***.

- **Neutral** (subspace $E \subset \mathbb{F}^n$ corresponding to A): A subspace E such that $(A\mathbf{x}, \mathbf{x}) = 0$ for all nonzero $\mathbf{x} \in E$. *Also known as **A-neutral***.

- Theorem 7.3.1: Let A be an $n \times n$ Hermitian matrix, and let $D = S^*AS$ be its diagonalization by an invertible matrix S. Then the number of positive (resp. negative) diagonal entries of D coincides with the maximal dimension of an A-positive (resp. A-negative) subspace.

- Lemma 7.3.2: Let $D = \text{diag}\{\lambda_1, \ldots, \lambda_n\}$. Then the number of positive (resp. negative) diagonal entries of D coincides with the maximal dimension of a D-positive (resp. D-negative) subspace.

- **Positive definite** (quadratic form Q): A quadratic form Q such that $Q[\mathbf{x}] > 0$ for all $\mathbf{x} \neq \mathbf{0}$.

- **Positive semidefinite** (quadratic form Q): A quadratic form Q such that $Q[\mathbf{x}] \geq 0$ for all $\mathbf{x}$.

- **Negative definite** (quadratic form Q): A quadratic form Q such that $Q[\mathbf{x}] < 0$ for all $\mathbf{x} \neq \mathbf{0}$.

- **Negative semidefinite** (quadratic form Q): A quadratic form Q such that $Q[\mathbf{x}] \leq 0$ for all $\mathbf{x}$.

- **Indefinite** (quadratic form Q): A quadratic form Q for which there exist $\mathbf{x}_1, \mathbf{x}_2$ such that $Q[\mathbf{x}_1] > 0$ and $Q[\mathbf{x}_2] < 0$.

- **Positive definite** (Hermitian matrix A): A matrix A for which the corresponding quadratic form $Q[\mathbf{x}] = (A\mathbf{x}, \mathbf{x})$ is positive definite.

  - Positive semidefinite, negative definite, negative semidefinite, and indefinite Hermitian matrices are defined similarly.

- Theorem 7.4.1: Let $A = A^*$. Then

  1. A is positive definite iff all eigenvalues of A are positive.
  2. A is positive semidefinite iff all eigenvalues of A are non-negative.

3. A is negative definite iff all eigenvalues of A are negative.

4. A is negative semidefinite iff all eigenvalues of A are non-positive.

5. A is indefinite iff it has both positive and negative eigenvalues.

- **Upper left submatrix** (of A): A $k \times k$ matrix A_k composed of all entries of A from row (column) 1 through k in the same arrangement.

- Theorem 7.4.2 (Silvester's Criterion of Positivity): A matrix $A = A^*$ is positive definite if and only if $\det A_k > 0$ for all $k = 1, \ldots, n$.

  - To check if a matrix A is negative definite, check that the matrix $-A$ is positive definite.

- Theorem 7.4.3 (Minimax characterization of eigenvalues): Let $A = A^*$ be an $n \times n$ matrix and let $\lambda_1 \geq \cdots \geq \lambda_n$ be its eigenvalues taken in decreasing order. Then

$$\lambda_k = \max_{E:\dim E=k} \min_{\mathbf{x} \in E: \|\mathbf{x}\|=1} (A\mathbf{x}, \mathbf{x}) = \min_{F:\operatorname{codim} F=k-1} \max_{\mathbf{x} \in F: \|\mathbf{x}\|=1} (A\mathbf{x}, \mathbf{x})$$

- Corollary 7.4.4 (Intertwining of eigenvalues): Let $A = A^* = \{a_{j,k}\}_{j,k=1}^{n}$ be a self-adjoint matrix and let $\tilde{A} = \{a_{j,k}\}_{j,k=1}^{n-1}$ be its submatrix of size $(n-1) \times (n-1)$. Let $\lambda_1, \ldots, \lambda_n$ and $\mu_1, \ldots, \mu_{n-1}$ be the eigenvalues of A and $\tilde{A}$ respectively, taken in decreasing order. Then

$$\lambda_1 \geq \mu_1 \geq \lambda_2 \geq \mu_2 \geq \cdots \geq \lambda_{n-1} \geq \mu_{n-1} \geq \lambda_n$$

Chapter 8

Dual Spaces and Tensors

8.1 Notes

- **Functional**: A linear bounded map $L : H \to F$, where H is finite dimensional (equivalent to $\mathbb{R}^n$).

- **Dual space**: The set of bounded linear functionals on H. *Denoted by* $\boldsymbol{H'}$, $\boldsymbol{H^*}$.

- If $l \leq p < \infty$, then
$$l^p = \left\{ (a_n)_{n \in \mathbb{N}} : \sum_{n=1}^{\infty} |a_n|^p < \infty \right\}$$

- Back to finite dimensions, $H' \approx \mathbb{R}^n$.

- Let $\mathbf{a}_1, \ldots, \mathbf{a}_n$ be a basis of H. Then $L\mathbf{x} = (L\mathbf{a}_1, \ldots, L\mathbf{a}_n) \approx \mathbb{R}^n$.

- Let $L((a_n)_{n \in \mathbb{N}}) = \sum_{n=1}^{\infty} a_n b_n$. Then $L((a_n)_{n \in \mathbb{N}})$ will be bounded if and only if $(b_n)_{n \in \mathbb{N}} \in l^q$ where $1 < p < q$ where $\frac{1}{q} + \frac{1}{p} = 1$.

- **Young's inequality**: The statement
$$ab \leq \frac{a^p}{p} + \frac{b^q}{q}$$

- We have $|\sum a_n b_n| \leq \|a_n\|_p \|b_n\|_p$.

- Conclusion:
$$\sum \frac{|a_n||b_n|}{\|a_n\|_p \|b_n\|_q} = 1$$

- We can define H'', too. This contains linear functionals on H'.

- We know that $L(x) = \langle x, L \rangle = x(L)$. $x \in H''$.

- Riesz representation theorem: Let H have an inner product. $L \in H'$ if and only if there exists a unique $y \in H$ such that $L(x) = (x, y)$.

  - Gives us a way to identify all bounded linear functionals on H.
  - In finite dimensions, $L(x)$, where $x = \sum_1^n \alpha_i a_i$ gives us $L(x) = \sum_1^n \alpha_i L(a_i)$.

8.2 Chapter 8: Dual Spaces and Tensors

10/28:
- Linear functionals are denoted by L.
    - L is given by a $1 \times n$ matrix denoted by $[L]$.
- The collection of all $[L]$ (the dual space) is isomorphic to $\mathbb{R}^n$ via $[L] \mapsto [L]^T$.
    - However, the objects are different: Let $[I]_{\mathcal{B}\mathcal{A}}$ be the change of coordinates matrix in $\mathbb{R}^n$. We thus have that
    $$[\mathbf{v}]_{\mathcal{B}} = [I]_{\mathcal{B}\mathcal{A}}[\mathbf{v}]_{\mathcal{A}}$$
    but we also have that
    $$[L]_{\mathcal{B}} = [L]_{\mathcal{A}}[I]_{\mathcal{A}\mathcal{B}}$$
    so that
    $$[L]_{\mathcal{B}}^T = ([L]_{\mathcal{A}}[I]_{\mathcal{A}\mathcal{B}})^T = [I]_{\mathcal{A}\mathcal{B}}^T[L]_{\mathcal{A}}^T$$
    - Essentially, "if S is the change of coordinate matrix in X... then the change of coordinate matrix in the dual space X' is $(S^{-1})^T$" (Treil, 2017, p. 219).
- Lemma 8.1.3: Let $\mathbf{v} \in V$. If $L(\mathbf{v}) = 0$ for all $L \in V'$, then $\mathbf{v} = \mathbf{0}$. As a corollary, if $L(\mathbf{v}_1) = L(\mathbf{v}_2)$ for all $L \in V'$, then $\mathbf{v}_1 = \mathbf{v}_2$.
- The second dual V'' is canonically (i.e., in a natural way) isomorphic to V.
- **Dual basis** (to $\mathbf{b}_1, \dots, \mathbf{b}_n \in V$): The system of vectors $\mathbf{b}_1', \dots, \mathbf{b}_n' \in V'$ uniquely defined by the following equation. *Also known as* **biorthogonal basis**.
    $$\mathbf{b}_k'(\mathbf{b}_j) = \delta_{kj}$$
    - The kth coordinate of a vector $\mathbf{v}$ in a basis $\mathbf{b}_1, \dots, \mathbf{b}_n$ is $\mathbf{b}_k'(\mathbf{v})$.
        - This is a baby version of the **abstract non-orthogonal Fourier decomposition** of $\mathbf{v}$.
- Theorem 8.2.1 (Riesz representation theorem): Let H be an inner product space. Given a linear functional L on H, there exists a unique vector $\mathbf{y} \in H$ such that
    $$L(\mathbf{v}) = (\mathbf{v}, \mathbf{y})$$
    for all $\mathbf{v} \in H$.
- If V is a real inner product space, we can define an isomorphism from V to V' by $\mathbf{y} \mapsto L_{\mathbf{y}} = (\mathbf{v}, \mathbf{y})$.
    - If V is complex, this function is not linear since if α is complex,
    $$L_{\alpha\mathbf{y}}(\mathbf{v}) = (\mathbf{v}, \alpha\mathbf{y}) = \bar{\alpha}(\mathbf{v}, \mathbf{y}) = \bar{\alpha}L_{\mathbf{y}}(\mathbf{v})$$
    - It follows by such a mapping that $\mathbf{b}_k' = \mathbf{b}_k$ for each k.
- **Conjugate linear** (transformation): A transformation T such that
    $$T(\alpha\mathbf{x} + \beta\mathbf{y}) = \bar{\alpha}T\mathbf{x} + \bar{\beta}T\mathbf{y}$$
- It is customary to write outputs of linear functionals $L(\mathbf{v})$ in the form $\langle \mathbf{v}, L \rangle$.
    - This expression is linear in both arguments, unlike the inner product.
- Defines the dual transformation as the unique transformation such that
    $$\langle A\mathbf{x}, \mathbf{y}' \rangle = \langle \mathbf{x}, A'\mathbf{y} \rangle$$
    for all $\mathbf{x} \in X$, $\mathbf{y}' \in Y'$.

   – It's matrix in the standard bases equals A^T.

- Annihilators are denoted by $E^\perp$ here.

- Proposition 8.3.6: The annihilator of the annihilator of E equals E.

- Let $A : X \to Y$ be an operator acting from one vector space to another. Then

  1. $\ker A' = (\operatorname{range} A)^\perp$.

  2. $\ker A = (\operatorname{range} A')^\perp$.

  3. $\operatorname{range} A = (\ker A')^\perp$.

  4. $\operatorname{range} A' = (\ker A)^\perp$.

Chapter 9

Advanced Spectral Theory

9.1   Notes

- Let $p(z) = \sum_{i=0}^{n} a_i z^i$ be a polynomial. Let A be an $n \times n$ matrix. We let $p(A) = \sum_{i=0}^{n} a_i A^i$.

- Theorem: If A is an $n \times n$ and $p(\lambda) = \det(A - \lambda I)$, then $p(A) = 0$.

  - We know that $p(\lambda) = a(z - \lambda_1) \cdots (z - \lambda_n)$ where $\lambda_1, \ldots, \lambda_n$ are the eigenvalues.
  - Thus $p(A) = a(A - \lambda_1 I) \cdots (A - \lambda_n I)$.
  - If you are in $\mathbb{R}^n$ and have this property, you can factorize your matrix.
  - Thus, $p(A)\mathbf{x} = \mathbf{0}$ since $\mathbf{x}$ can be decomposed into a linear combination of eigenvectors of A, which will be taken to 0 one by one by the terms of $p(A)$.

- $\sigma(B) = \{\text{eigenvalues of } B\}$ is known as the **spectrum** of B.

- If p is an arbitrary polynomial and A is $n \times n$, then μ is an eigenvalue of $p(A)$ if and only if $\mu = p(\lambda)$ where λ is an eigenvalue of A. In essence, $\sigma(p(A)) = p(\sigma(A))$.

- Chapter 9 will not be on the exam. We don't have to know the generalization to infinite dimensional spaces.

- If A is an $n \times n$ square matrix and $p(\lambda) = \det(A - \lambda I)$, then $p(A) = 0$.

  - Proof: WLOG, let A be an upper triangular matrix with diagonal entries equal to the eigenvalues.
  - Think of $p(z) = (-1)^n (z - \lambda_1) \cdots (z - \lambda_n)$.
  - Thus, $p(A) = (-1)^n (A - \lambda_1 I) \cdots (A - \lambda_n I)$.
  - WTS: $p(A)\mathbf{x} = 0$ for all $\mathbf{x} \in V$.
  - Let $E_k = \text{span}(e_1, \ldots, e_k)$ be the span of the first k eigenvectors of A, where $e_1, \ldots, e_n$ is a standard basis in $\mathbb{C}^n$.
  - A triangular implies $AE_k \subset E_k$. Thus, $(A - \lambda I)E_k \subset E_k$, so E_k is invariant under $A - \lambda I$ for all λ.
  - If we apply $A - \lambda_k I$ to a vector in E_k, we are left with a vector in E_{k-1}.
  - Thus, if we apply $\prod_{k=1}^{n}(A - \lambda_k I) = p(A)$ to any vector in $E_n = V$, we will kill it piece by piece down to zero.

- Let A be a square $n \times n$ matrix. Then p an arbitrary polynomial implies $\sigma(p(A)) = p(\sigma(A))$. (Any eigenvalue μ of $p(A)$ is $\mu = p(\lambda)$, where λ is an eigenvalue of A.)

  - Shows that polynomials of operators commute.

- Proof: Let λ be an eigenvalue of A. We want to show that $p(\lambda)$ is an eigenvalue of $p(A)$. This is obvious since $A\mathbf{x} = \lambda\mathbf{x}$ for some $\mathbf{x}$, so $A^k\mathbf{x} = \lambda^k\mathbf{x}$, so in particular, $p(A)\mathbf{x} = p(\lambda)\mathbf{x}$.

- On the other hand, if μ is an eigenvalue of $p(A)$, we want to show that there exists $\lambda \in \sigma(A)$ such that $\mu = p(\lambda)$.

- Consider $q(z) = p(z) - \mu$. Then $q(A) = p(A) - \mu I$. Since μ is an eigenvalue of $p(A)$, $q(A)$ is not invertible.

- Thus, $q(z) = (-1)^n(z - z_1) \cdots (z - z_n)$ and $q(A) = (-1)^k(A - z_1 I) \cdots (A - z_k I)$.

- But $q(A)$ is not invertible, so one of the $A - z_k I$ is not invertible. Take z_k such that $A - z_k I$ is not invertible. Then $z_k \in \sigma(A)$. It follows that $q(z_k) = p(z_k) - \mu = \sigma$.

- If A is $n \times n$, $\lambda_1, \ldots, \lambda_n$ are its eigenvalues, p is a polynomial, then $p(A)$ is invertible if and only if $p(\lambda_k) \neq 0$ for each $k = 1, \ldots, n$.

  - This is an immediate corollary to the previous result.

- We now build up to the **generalized eigenspace**, which is related to some "geometric" properties of the algebraic multiplicity of an eigenvalue.

- If $A : V \to V$ is a linear operator and $E \subset V$ is a subspace, E is A-invariant if $AE \subset E$.

- Facts:

  - If E is A-invariant, E is A^k-invariant.

  - Thus, E is $p(A)$-invariant.

- Consider the restriction map $A|_E$.

- A has a block-diagonalized matrix where each block corresponds to the generalized eigenvectors of a generalized eigenvalue of A.

  - Let $E_1, \ldots, E_r$ be a **basis of invariant subspaces**.

  - Let $A_k = A|_{E_k}$. Then the A_k's act independently of each other.

- **Generalized eigenvector** (of A): A vector $\mathbf{v}$ corresponding to an eigenvalue λ if there exists $k \geq 1$ such that $(A - \lambda I)^k\mathbf{v} = \mathbf{0}$.

- **Generalized eigenspace**: The set E_λ of all of the generalized eigenvectors of λ. *Given by*

$$E_k = \bigcup_{k \geq 1} \ker(A - \lambda I)^k$$

  - E_λ is a linear subspace of V.

- **Degree** (of λ): The smallest number k such that increasing k any more does not add further vectors to the generalized eigenspace. *Denoted by $\boldsymbol{d(\lambda)}$. Also known as* **depth**.

  - Symbolically, $d(\lambda)$ is the smallest number such that

$$E_\lambda = \bigcup_{k=1}^{d(\lambda)} \ker(A - \lambda I)^k$$

- Start working through the first 25 problems of Rudin (1976) (his metric spaces problems).

10/27:
- Jordan form.

- Reviews build up to generalized eigenvectors.

- Theorem: If $\sigma(A) = \{\lambda_1, \ldots, \lambda_n\}$ and $E_1, \ldots, E_n$ are the corresponding generalized eigenspaces, then $E_1, \ldots, E_n$ is a basis of subspaces of U, i.e., $V = \oplus_k E_k$.

- Corollary: $A : V \to V$ can be represented as $A = D + N$ where D is diagonalizable and N is nilpotent and $ND = DN$.

  - Proof: Consider the basis of generalized eigenspaces known to exist from the theorem. Then $A = \mathrm{diag}\{A_1, \ldots, A_r\}$.
  - Let
  $$N_k = A_k - \lambda_k I_{E_k}$$
  This is nilpotent.
  - Then let
  $$D = \mathrm{diag}\{\lambda_1 I_{E_1}, \ldots, \lambda_n I_{E_n}\}$$
  - These two matrices satisfy the necessary properties.

- Let $\dot{\mathbf{x}} = A\mathbf{x}$.

  - Let $\mathbf{x}(t) = e^{tA}$, where
  $$e^{tA} = \sum \frac{(tA)^k}{k!}$$

  - $\left\| e^{tA} \right\| \le \sum \frac{\|A^k\|}{k!} = \sum \frac{\|A\|^k}{k!}$.
  - Let p be a polynomial of degree k. Then
  $$p(a + x) = \sum_{k=0}^{d} \frac{p^{(k)}(a)}{k!} x^k$$

  - If $A = D + N$, then...

- Nilpotent operators:

  - Let $A = \mathrm{diag}\{A_1, \ldots, A_r\}$.
  - We know that $A_k = \lambda_k I_{E_k} + N_k$ for each k.
  - Every nilpotent N can be written in the form
  $$\begin{pmatrix} 0 & 1 & & 0 \\ & \ddots & \ddots & \\ & & \ddots & 1 \\ 0 & & & 0 \end{pmatrix}$$

10/28:

- The exam is long but not that hard. The only question is will you do good or very good.

- Revise the previous two homeworks, especially the last two.

- No justification for any of the true/false questions. Just circle T or F.

  - There are four problems. One is T/F (with multiple subparts); the other three are problem problems (with subparts, too).
  - Some of the questions will take you 2 seconds. Some you've already seen in the PSets.
  - The exam is supposed to be boring.

- Calculators?

  - No calculators needed. Calculators are for chem/physics exams.

- – Not a lot of computation.

- 50 minutes.

- Chloe will be proctoring.

- Remember the determinant of "special" matrices.

  - – $|\det U| = 1$ if U is unitary.
  - – $\det A = \pm 1$ if A is orthogonal.
  - – Make a list of matrix types that are automatically diagonalizable.
  - – Determinant is the product of the eigenvalues.
  - – Determinant of A is equal to the conjugate of the determinant of A^*.

- Most of the exercises use the inner product.

  - – Whenever you had something to prove about eigenvalues or eigenbasis, you went through diagonalization or SVD or the inner product or polar decomposition.
  - – Proving eigenvalues of self-adjoint matrices are real w/ the inner product.

- Eigenvalues/eigenvectors of a projection.

  - – It's implied that it's asking you the multiplicities!!!

- Know useful facts but have an idea how to prove them as well.

- Recommends against shorthanding in the exams.

- Not grading on clarity (since the exam is long).

- Max and min are for when you're sure something will be attained. Otherwise use sup and inf.

9.2   Chapter 9: Advanced Spectral Theory

10/28:
- Theorem 9.1.1 (Cayley-Hamilton): If p is the characteristic polynomial of A, $p(A) = 0$.

- Theorem 9.2.1 (Spectral Mapping Theorem): For a square matrix A and an arbitrary polynomial p, $\sigma(p(A)) = p(\sigma(A))$. In other words, μ is an eigenvalue of $p(A)$ if and only if $\mu = p(\lambda)$ for some eigenvalue λ of A.

- Corollary 9.2.2: Let A be a square matrix with eigenvalues $\lambda_1, \ldots, \lambda_n$ and let p be a polynomial. Then $p(A)$ is invertible iff $p(\lambda_k) \neq 0$ for all $k = 1, \ldots, n$.

- Algebraic multiplicity is the dimension of the corresponding generalized eigenspace.

Part II

Point Set Topology of Metric Spaces

Chapter 1

The Real and Complex Number Systems

1.1   Notes

11/1:
- Spent a lot of time trying to cheer us up regarding the midterm.

- There may be some true/false on linear algebra on the final.

- Facts:

    1. $\sqrt{2}$ is irrational.
    2. Archimedes principle: If $x > 0$ and $y \in \mathbb{R}$, then there exists n such that $nx > y$.
    3. If $x > y$, then there exists $q \in \mathbb{Q}$ such that $x > q > y$.

Chapter 2

Basic Topology

2.1 Notes

- Equivalence relationships are denoted $A \sim B$.

    - These are...

        - Reflexive ($A \sim A$).
        - Symmetric ($A \sim B \Longleftrightarrow B \sim A$).
        - Transitive ($A \sim B$ & $B \sim C \Longrightarrow A \sim C$).

    - Equivalence relations give rise to equivalence classes.

- **Countable** (set A): A set A such that $A \sim \mathbb{N}$, in the sense that there exists a one-to-one and onto map from $\mathbb{N} \to A$.

    - Alternatively, A can be written in the form $A = \{f(n) : n \in \mathbb{N}\}$.

- **Finite countable** vs. **infinite countable** (see Rudin (1976)).

- $\mathbb{N}$ denotes the natural numbers.

- $\mathbb{N}_0$ denotes the natural numbers including 0.

- $\mathbb{Z}$ denotes the integers.

- We know that $\mathbb{N} \sim \mathbb{Z}$: Let $f : \mathbb{N} \to \mathbb{Z}$ be defined by

$$f(n) = \begin{cases} \frac{n}{2} & n \text{ even} \\ \frac{n-1}{2} & n \text{ odd} \end{cases}$$

- More facts.

    1. Every subset of a countable set is countable.
    2. Unions of countable sets are countable.
        - If the sets E_n for some finite list of numbers are countable, then $\bigcup_n E_n$ is countable.
        - Soug goes over the diagonalization method of counting.
    3. n-fold Cartesian products of countable sets are countable (we induct on n).
        - If A is countable and B is countable, then $A \times B$ is countable.
        - If A is finite and to each $\alpha \in A$ we assign a countable set E_α, $\otimes_{\alpha \in A} E_\alpha$ is countable.

- **Metric space**: A space X along with a matrix $d : X \times X \to [0, \infty)$ such that

- $d(x,y) > 0$ iff $x \neq y$, and $d(x,x) = 0$ iff $x = 0$.
- $d(x,y) = d(y,x)$.
- $d(x,y) \leq d(x,z) + d(z,y)$.

- Example ($\mathbb{R}^n$):

  - We may define d by
  $$d(x,y) = \sqrt{\sum (x_i - y_i)^2}$$

  - We can also define the p-metrics (recall normed spaces) with p where 2 is.

- Example ($X_p = \{f : Y \to \mathbb{R} : 1 \leq p < \infty, \int_Y |f|^p \, dy < \infty\}$):

  - This is ℓ_p.
  - Define
  $$\|f - g\|_p = \left[\int_Y |f - g|^p \, dy \right]^{1/p}$$

- Convergence: $x_n \to x \iff d(x_n, x) \to 0$.

- **Neighborhood**: The set of all points a distance less than r away from p. *Denoted by $\boldsymbol{N_r(p)}$. Given by*
$$N_r(p) = \{q \in X : d(p,q) < r\}$$

- **Limit point** (of E): A point p such that every neighborhood of p intersects E at a point other than p. *Also known as* **accumulation point**.

  - Symbolically,
  $$N_r(p) \cap (E \setminus \{p\}) \neq \emptyset$$
  for all $r > 0$.

- **Isolated point** (of E): A point p such that $p \in E$ and p is not a limit point of E.

- **Closed** (set E): A set E that contains all of its limit points.

- **Interior** (point p): A point p such that there exists $N_r(p) \subset E$.

- **Open** (set E): A set E, all points of which are interior points.

- **Perfect** (set E): A set E that is closed and every point of E is a limit point of E.

- **Bounded** (set E): There exists a number M and a $y \in X$ such that $E \subset \{p : d(p,y) \leq M\}$.

- **Dense** (set E in X): A set E such that every point of X is a limit point of E or a point of E, itself.

11/3:
- Every neighborhood is an open set.

- If p is a limit point of E, every neighborhood of p contains infinitely many points of E.

  - Thus, a finite set cannot have a limit point.
  - Prove by contradiction: Suppose there is a neighborhood that contains only finitely many points of E. Then the neighborhood with radius smaller than the distance to the closest point does not contain any points of E, a contradiction.

- E is open iff $E^{C\,[1]}$ is closed.

  - Assume E^C closed. If $p \in E$, then p is not a limit point of E^C. It follows that there exists a neighborhood of p that is entirely contained within E, so p is interior, as desired.

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[1] The complement of E.

– Suppose E is open. Let p be any limit point of E^C. Then $p \in E^C$.

- F is closed iff F^C is open.

- If $(G_\alpha)_{\alpha \in A}$ is a family of open sets in X, then the union is open.

  – Let $p \in \bigcup_{\alpha \in A} G_\alpha$. Then $p \in G_\alpha$ for some $\alpha \in A$. It follows that p is an interior point of G_α, so thus an interior point of the union of G_α with everything else.

- Finite intersections of open sets are open.

  – In the infinite case $\bigcap_{n \in \mathbb{N}}(-1/n, 1/n) = \{0\}$, an intersection of infinitely many open sets is closed.

  – However, in the finite case, just consider the neighborhood with the smallest radius and take this one.

- The intersection of closed sets is closed.

- The union of finitely many closed sets is closed.

  – These follow from the previous two by De Morgan's rule.

- Let $\bar{E} = E \cup E'$ where E' is the set of limit points of E.

- Let X be a metric space and $E \subset X$. Then

  1. $\bar{E}$ is closed.
     – WTS: $\bar{E}^C$ is open. Let $p \in \bar{E}^C$. Then p is neither in E nor is it a limit point of E. Thus, there exists a neighborhood of $\bar{E}^C$ containing entirely points of $\bar{E}^C$. Therefore, $\bar{E}^C$ is open, so $\bar{E}$ is closed.
  2. $E = \bar{E}$ iff E is closed.
     – Think $p \in \bigcap G_\alpha$?
  3. $\bar{E} \subset F$ for any closed $F \supset E$.
     – If $E \subset F$, then any limit point of E will be a limit point of F. Thus, $E' \subset F'$. Then $\bar{E} = E \cup E' \subset F \cup F' = \bar{F} = F$ where the last equality holds because F is closed.

- Types of sets.

	Closed	Open	Perfect	Bounded
$\{z \in \mathbb{Q} : |z| < 1\}$	N	Y	N	Y
$\{z \in \mathbb{Q} : |z| \leq 1\}$	Y	N	Y	Y
Nonempty finite set	Y	N	N	Y
$\mathbb{Z}$	Y	N	N	N
$\{1/n : n \in \mathbb{N}\}$	N	N	N	Y
$\mathbb{R}^2$	Y	Y	Y	N
(a, b)	N	?	N	Y

Table 2.1: Types of sets.

- **Relatively open** (set E to Y): A set $E \subset Y \subset X$ such that if $p \in E$, then there exists a Y-neighborhood of E contained in E.

- Let $N_r^X(p) = \{y \in X : d(y, p) < r\}$ be a neighborhood of p in X, and let $N_r^Y(p) = \{y \in Y : d(y, p) < r\}$ be a neighborhood of p in Y. Then $N_r^Y(p) = N_r^X(p) \cap Y$.

- E is open relative to Y iff $E = G \cap Y$ where G is open relative to X.

- Introduces the supremum.

- If $E \subset \mathbb{R}$, $E \neq \emptyset$, and E is bounded above, $\sup E < \infty$.

- Let $y = \sup E$. Then $y \in \bar{E}$.

- There exists a sequence $a_n \in A$ such that $a_n \to x = \sup A$.

- A is compact iff any open cover of the set has a finite subcover.

- Study and *know* all of these proofs.

11/5:
- Compactness: Defines compactness in terms of open covers.

- Finite sets are compact.

- Compactness is "absolute" (i.e., it is not a relative property like openness).

  – If $K \subset Y \subset X$, then K is compact relative to X iff K is compact relative to Y.
  – V is open relative to Y iff $V = G \cap Y$ where G is open relative to X.

- Compact implies closed.

  – We will show K compact implies K^C open.
  – WTS: For all $p \in K^C$, there exists $N_r(p) \subset K^C$ suh that $N_r(p) \cap K = \emptyset$.

- A closed subset of a compact set is compact.

  – Let K be compact and let $F \subset K$ be closed.
  – Take any open cover of F. Extend it to an open cover of K. Take the finite subcover of K. Naturally, this finite subcover is also a finite cover of $F \subset K$.

- F closed, K compact implies $F \cap K$ compact.

- If $(K_\alpha)_{\alpha \in A}$ is compact in X with finite intersection property (every intersection of any finite number of these sets is nonempty), then $\bigcap_{\alpha \in A} K_\alpha \neq \emptyset$.

  – Argue by contradiction.
  – Let $G_\alpha = K_\alpha^C$.
  – Assume the intersection is empty. Assume WLOG that no point of K_1 is in any of the other K_α's.
  – Then $\{G_\alpha\}_{\alpha \in A}$ be an open cover of K_1.
  – K_1 compact implies there is a finite subcover $G_{\alpha_1}, \ldots, G_{\alpha_n}$. Then $K \subset G_{\alpha_1} \cup \cdots \cup G_{\alpha_n}$. This implies that $K_1 \cap K_{\alpha_1} \cap \cdots \cap K_{\alpha_n} = \emptyset$, a contradiction.

- Let E be an infinite subset of a compact K. Then E has a limit point in K.

  – Argue by contradiction.
  – Suppose for all $p \in K$, there exists $N_r(p)$ such that $N_r(p) \cap E = \{p\}$.
  – Consider the set $\{N_r(p) : p \in K\}$. This is an open cover of K. Thus, there exists a finite subcover of it. But since $E \subset K \subset N_{r_1}(p_1) \cup \cdots \cup N_{r_n}(p_n) = \{p_1\} \cup \cdots \cup \{p_n\}$, E is finite, a contradiction.

- **2-cell** (in $\mathbb{R}^2$): A set that is the Cartesian product of two closed intervals.

  – Generalizes to **k-cells**.

- Let $I_n = [a_n, b_n] \subset \mathbb{R}$ such that $I_{n+1} \subset I_n$. Then $\bigcap_{n=1}^{\infty} I_n \neq \emptyset$.
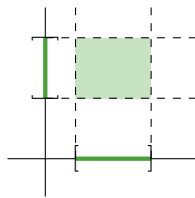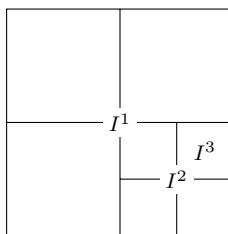
Figure 2.1: 2-cell.

– Let I_k be a k-cell in $\mathbb{R}^k$ such that $I_k \supset I_{k+1}$. Then $\bigcap_k I_k \neq \emptyset$.

– We know that $a_m \leq a_{m+n} \leq b_{m+n} \leq b_m$, so $\sup a_n \in \bigcap I_n$.

• Every k-cell is compact.

Figure 2.2: k-cells are compact.

– Argue by contradiction.

– Consider an open cover of the k-cell I^1. If it has a finite subcover, we're done. So suppose we have an open cover that doesn't have a finite subcover. Split the k-cell into 2^k chunks. At least one of the chunks I^2 must not have a finite subcover.

– Split that one into 2^k chunks. At least one of the chunks I^3 must not have a finite subcover.

– Continue.

– Thus, we have a decreasing family of k-cells, so by the previous result, their $\bigcap I^n \neq \emptyset$.

– Let $x \in \bigcap I^n$. Then the...

• Heine-Borel theorem: Let $E \subset \mathbb{R}^k$. Then TFAE[2]

1. E is closed and bounded.

2. E is compact.

3. Every infinite subset of E has a limit point in E.

– $(1 \Rightarrow 2)$ E closed and bounded implies E is a closed subset of some I_k, so it's compact.

– $(2 \Rightarrow 3)$ Already done.

– $(3 \Rightarrow 1)$

  ■ Suppose E not bounded. Then there is an infinite sequence of points in E that never converges. Contradiction.

  ■ Suppose E is not closed. Then there exists a sequence of points in E which "converges" to an $x_0 \notin E$.

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[2]The following are equivalent.

References

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