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

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Part I Linear Algebra

Basic Notions

- 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 $\mathbf{v}_1, \dots, \mathbf{v}_k \in V$ 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 $Tp_n = p'_n$. This T is linear.
 - Rotation in \mathbb{R}^d .
 - \blacksquare 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 $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ 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 $(BA)_{ij} = (\sum \beta_{ik} \alpha_{kj})$.
- 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 trace (A). Given by

$$\operatorname{trace}(A) = \sum \alpha_{ii}$$

- It is true that trace(AB) = trace(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(basis of X) = 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.

 $^{^1}$ "X is isomorphic to Y."

Systems of Linear Equations

9/29: • Row elimination:

- Let

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

- Then the **eschelon form** matrix

$$A_e = \begin{pmatrix} 1 & 2 & 3 & 1 \\ 0 & 1 & 2 & -1 \\ 0 & 0 & 2 & -4 \end{pmatrix}$$

- Lastly, the **reduced eschelon form** matrix

$$A_{re} = \begin{pmatrix} 1 & 0 & 0 & 7 \\ 0 & 1 & 0 & 3 \\ 0 & 0 & 1 & -2 \end{pmatrix}$$

• Eschelon 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 eschelon 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 $(0, \dots, 0, b)$ 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 $\alpha_1v_1 + \alpha_2v_2 + \alpha_3v_3 = 0$ is $\alpha_1 = \alpha_2 = \alpha_3 = 0$.
- But this is not true, as we can find another one in terms of the λ s.
- 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 range A=m, then Ax=b is solveable for all $b \in \mathbb{R}^m$.
- Let rank $A = \dim \operatorname{range} A$.
- Rank theorem:
 - \blacksquare rank $A = \operatorname{rank} A^T$.
 - Let $A: \mathbb{R}^n \to \mathbb{R}^m$. We know that dim ker $A + \dim \operatorname{range} A = n$.

 - This theorem survives linear algebra and enters functional analysis under the name Fred-holm'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 rank $A^T = m$ implies rank A = m implies dim 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 range A.
- The pivot rows of A_e give a basis for 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.

Determinants

- 9/29: 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: $D(e_1, ..., e_n) = 1$.
 - Determinant: Denoted by $D(v_1, \ldots, v_n)$, where (v_1, \ldots, v_n) is an $n \times n$ matrix.
- 10/1: Consider an $n \times n$ matrix A consisting of n columns containing vectors $\mathbf{v}_1, \dots, \mathbf{v}_n \in \mathbb{R}^n$.
 - D(A) is the volume of the solid $V = \sum_{i=1}^{n} \alpha_i v_i$.
 - $-D(\mathbf{e}_1,\ldots,\mathbf{e}_n)=1.$

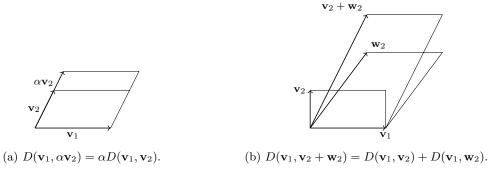


Figure 3.1: Visualizing properties of determinants.

- 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).

Introduction to Spectral Theory

- **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.

References

Treil, S. (2017). Linear algebra done wrong [http://www.math.brown.edu/streil/papers/LADW/LADW_2017-09-04.pdf].