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Literally everything I know about

Linear Algebra

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A very reductionist summary of Linear Algebra and its Applications by Lay, Lay, and McDonald, as well as Linear Algebra Done Wrong by Treil.

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Chapter 1

Basic Notations

1.1 Vector Spaces

Definition 1.1.1. A **vector space** V is a collection of vectors, along with vector addition and scalar multiplication defined such that for vectors u, v, and w:

1. Commutative: v + w = w + v

2. Associative: (u + v) + w = u + (v + w)

3. Zero vector: v + 0 = v

4. Additive inverse: v + w = 0

5. Multiplicative identity: 1v = v

6. Multiplicative associative: $(\alpha \beta)v = \alpha(\beta v)$

7. Distribution of scalars: $\alpha(u+v) = \alpha u + \alpha v$

8. Distribution of vectors: $(\alpha + \beta)u = \alpha u + \beta u$

These properties are simply to ensure that vector spaces are **abelian groups**.

Definition 1.1.2. An $m \times n$ **matrix** is an array with m rows and n columns. Elements of a matrix are called *entries*. Given a matrix A, its **transpose** is defined as the matrix whose columns are A's rows, so A^T is an $n \times m$ matrix.

1.2 Linear Combinations

Definition 1.2.1. A linear combination of vectors $v_1, \dots, v_p \in V$ is a sum of the form

$$\alpha_1 v_1 + \dots + \alpha_p v_p = \sum_{k=1}^p \alpha_k v_k$$

Definition 1.2.2. A set of vectors v_1, \dots, v_n is said to be **linearly independent** if the equation

$$\alpha_1 v_1 + \cdots + \alpha_n v_n = 0$$

has only the trivial solution.

Definition 1.2.3. A **basis** is a set of vectors $v_1, \dots, v_n \in V$ such that any vector $u \in V$ has a *unique* representation as a linear combination

$$u = \alpha_1 v_1 + \dots + \alpha_n v_n$$

The coefficients $\alpha_1, \dots, \alpha_n$ are called *coordinates* of u.

Fundamentally, our definition of basis states that a basis must be spanning and unique. In order for a representation to be unique, we know the basis must be linearly independent.

Theorem 1.2.1. A set of vectors $v_1, \dots, v_p \in V$ is a basis if and only if it is linearly independent and complete (spanning).

Proof. We already know basis must be linearly independent and spanning, so we just need to prove the other direction.

Suppose the set v_1, \dots, v_p is linearly independent. Then we know for some vector $u \in V$:

$$u = \sum_{k=1}^{n} \alpha_k v_k$$

All that is remaining is to prove this representation is unique.

Suppose there is another representation, $u = \sum_{k=1}^{n} \beta_k v_k$. Then,

$$\sum_{k=1}^{n} (\alpha_k - \beta_k) v_k = v - v = 0$$

Since the set is linearly independent, we know $\alpha_k - \beta_k = 0$. Thus, the representation is unique.

1.3 Linear Transformations

Definition 1.3.1. A **transformation** T from set X to set Y assigns a value $y \in Y$ for every value $x \in X$: y = T(x). X is called the *domain* of T, Y is called the *codomain* of T, and the set of all T(x) is called the *range* of T.

Let V, W be vector spaces. A transformation $T: V \to W$ is **linear** if:

- 1. T(u + v) = T(u) + T(v)
- 2. $T(\alpha v) = \alpha T(v)$

A mapping $T : \mathbb{F}^n \to \mathbb{F}^m$ is *onto* \mathbb{F}^m if each b in \mathbb{F}^m is the image of at least one x in \mathbb{F}^n .

A mapping $T: \mathbb{F}^n \to \mathbb{F}^m$ is one-to-one if each b in \mathbb{F}^m is the image of at most one x in \mathbb{F}^n .

We can represent linear transformations with matrices. To represent a transformation $T: \mathbb{F}^n \to \mathbb{F}^m$, we need to only how our n basis vectors are transformed. To see this, note that any vector $u = \alpha_1 v_1 + \cdots + \alpha_n v_n$. So $T(x) = \alpha_1 T(v_1) + \cdots + \alpha_n T(v_n)$. If we join the vectors $T(v_1), \cdots, T(v_n)$ in a matrix $A = \begin{bmatrix} T(v_1) & \cdots & T(v_n) \end{bmatrix}$, we have captured all the information about T.

Definition 1.3.2. There are two ways to approach matrix-vector multiplication:

Column by coordinate rule: Multiply each column of the matrix by the corresponding coordinate of the vector and add.

$$\begin{bmatrix} 1 & 2 & 3 \\ 3 & 2 & 1 \end{bmatrix} \begin{vmatrix} 1 \\ 2 \\ 3 \end{vmatrix} = 1 \begin{bmatrix} 1 \\ 3 \end{bmatrix} + 2 \begin{bmatrix} 2 \\ 2 \end{bmatrix} + 3 \begin{bmatrix} 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 14 \\ 10 \end{bmatrix}$$

Row by column rule: To get entry *k* of the result, multiply row *k* of the matrix with the column.

$$\begin{bmatrix} 1 & 2 & 3 \\ 3 & 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 \cdot 1 + 2 \cdot 2 + 3 \cdot 3 \\ 3 \cdot 1 + 2 \cdot 2 + 1 \cdot 3 \end{bmatrix} = \begin{bmatrix} 14 \\ 10 \end{bmatrix}$$

Definition 1.3.3. The natural extension to **matrix multiplication** of two matrices AB is to multiply A by each column of B.

$$AB = A \begin{bmatrix} b_1 & \cdots & b_n \end{bmatrix} = \begin{bmatrix} Ab_1 & \cdots & Ab_n \end{bmatrix}$$

Using the *row by columns rule*, we can see that the $(AB)_{j,k} = (\text{row } j \text{ of } A) \cdot (\text{column } k \text{ of } B)$. This also means AB is only defined if A is $m \times n$ and B is $n \times r$.

Let A be an $m \times n$ matrix and let B and C have sizes for which the indicated sums and products are defined.

- 1. A(BC) = (AB)C
- 2. A(B+C) = AB + AC
- 3. (B + C)A = BA + CA
- 4. $\alpha(AB) = (\alpha A)B = A(\alpha B)$
- 5. $I_m A = A = A I_n$

Warnings:

- 1. In general, $AB \neq BA$
- 2. If AB = AC, then it is **not true** in general that B = C
- 3. If AB = 0, then it is **not true** always that A = 0 or B = 0

Definition 1.3.4. The **transpose** of A is the matrix whose columns are formed from the corresponding rows of A, denoted by A^T .

1.
$$(A^T)^T = A$$

2.
$$(A + B)^T = A^T + B^T$$

3.
$$(cA)^T = cA^T$$

4.
$$(AB)^T = B^T A^T$$

To understand the final property, let AB denote a $n \times m$ matrix so that

$$AB = \begin{bmatrix} A_{1*} \cdot B_1 & A_{1*} \cdot B_2 & \cdots & A_{1*} \cdot B_m \\ A_{2*} \cdot B_1 & A_{2*} \cdot B_2 & \cdots & A_{2*} \cdot B_m \\ \vdots & \vdots & \vdots & \vdots \\ A_{n*} \cdot B_1 & A_{n*} \cdot B_2 & \cdots & A_{n*} \cdot B_m \end{bmatrix}$$

$$(AB)^{T} = \begin{bmatrix} A_{1*} \cdot B_{1} & A_{2*} \cdot B_{1} & \cdots & A_{n*} \cdot B_{1} \\ A_{1*} \cdot B_{2} & A_{2*} \cdot B_{2} & \cdots & A_{n*} \cdot B_{2} \\ \vdots & \vdots & \vdots & \vdots \\ A_{1*} \cdot B_{m} & A_{2*} \cdot B_{m} & \cdots & A_{n*} \cdot B_{m} \end{bmatrix}$$

where $A_{\alpha*}$ denotes the α th row of a A. Note that $(AB)_{jk}^T = (\text{row } k \text{ of } A) \cdot (\text{column } j \text{ of } B) = (\text{row } j \text{ of } B^T) \cdot (\text{column } k \text{ of } A^T)$.

Definition 1.3.5. For a *square* matrix *A*, its **trace** is the sum of its diagonal entries.

$$trace(A) = \sum_{k=1}^{n} a_{k,k}$$

Theorem 1.3.1. Let A and B be size $m \times n$ and $n \times m$, respectively. Then

$$trace(AB) = trace(BA)$$

Proof. We need only show that the diagonal entries of AB are the same as the diagonal entries of BA. Using the *row by columns rule*, we know $(AB)_{j,k} = (\text{row } j \text{ of } A) \cdot (\text{column } k \text{ of } B)$, so when applying to diagonal entries we get $(AB)_{k,k} = (BA)_{k,k} = (\text{row } k \text{ of } A) \cdot (\text{column } k \text{ of } B)$

1.4 Invertible Transformations and Isomorphisms

Definition 1.4.1. An $n \times n$ matrix A is **invertible** if there is an $n \times n$ matrix A^{-1} such that $A^{-1}A = I$.

Theorem 1.4.1. If A and B are invertible (and such that AB is defined), then the product AB is invertible and

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

Proof. Direct computation:

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

and

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

Theorem 1.4.2. If A is invertible, then A^T is also invertible and

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

Proof. Using $(AB)^T = B^T A^T$,

$$(A^{-1})^T (A^T) = (AA^{-1})^T = I$$

and

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

Definition 1.4.2. An invertible linear transformation $A: V \to W$ is called an **isomorphism**. The two vector spaces V and W for which A is defined are called **isomorphic**, denoted $V \cong W$.

Isomorphic spaces can be considered different representations of the *same* space. The following theorem is an example.

Theorem 1.4.3. Let $A: V \to W$ be an isomorphism, and let v_1, \dots, v_n be a basis in V. Then Av_1, \dots, Av_n is a basis in W.

Proof. Because V and W are isomorphic, every $w \in W$ can be represented as some $v \in V$ by applying A^{-1} . For arbitrary $w \in W$

$$A^{-1}w = v = \sum_{k=1}^{n} \alpha_k v_k$$

Then we apply A to get

$$Av = w = \sum_{k=1}^{n} \alpha_k A v_k$$

1.5 Subspaces

Definition 1.5.1. A **subspace** of vector space V is a non-empty subset $V_0 \subset V$ which is also a vector space.

For any linear transformation $A: V \to W$, we can associate the following subspaces:

- 1. The *null space*, or *kernel*, of *A* which consists of all vectors $v \in V$ such that Av = 0.
- 2. The *range* of *A* which is the set of all vectors $w \in W$ which can be represented as w = Av for $v \in V$.

By the *column by coordinate rule*, we know that any vector in Range(A) can be represented as a weighted sum of the column vectors of A, which is why the term Column Space is sometimes used to refer to Range.

Chapter 2

Systems of Linear Equations