

Linear Algebra Class on 5 January

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1.4 Linear Combination, Linear Independence, Dimension

Definition. $\mathbf{Sym}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid A^t = A\}$ and $\mathbf{Alt}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid A^t = -A\}$

Note. $A \in \mathfrak{M}_n(\mathbb{R})$ $A = \frac{1}{2}(A + A^t) + \frac{1}{2}(A - A^t)$

A square matrix can be written the sum of symmetric and skew-symmetric matrix.

Definition. Let \mathbf{V} be a vector space and S a nonempty subset of \mathbf{V} . A vector $\mathbf{v} \in \mathbf{V}$ is called a **linear combination** of vectors S if there exist a finite number of vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in S$ and scalars $a_1, a_2, \dots, a_n \in \mathbf{F}$ such that $\mathbf{v} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \dots + a_n\mathbf{v}_n$.

Definition. Let S be a nonempty subset of a vector space \mathbf{V} . Then **span** of S , denoted $\text{span}S$, is the set consisting of all linear combinations of the vectors in S . For convenience, we define $\text{span}\emptyset := \{\mathbf{0}\}$.

Remark. $\text{span}S$ is a subspace of \mathbf{V} . In particular, if $\mathbf{V} = \text{span}S$, then we say that S generates (spans) \mathbf{V} or S is a generating subset of \mathbf{V} .

Proof. Suppose $a_1\mathbf{v}_1 + \dots + a_n\mathbf{v}_n, b_1\mathbf{v}_1 + \dots + b_n\mathbf{v}_n \in S$ be given. We want to show that $c(a_1\mathbf{v}_1 + \dots + a_n\mathbf{v}_n) + b_1\mathbf{v}_1 + \dots + b_n\mathbf{v}_n \in S$.

$$c(a_1\mathbf{v}_1 + \dots + a_n\mathbf{v}_n) + b_1\mathbf{v}_1 + \dots + b_n\mathbf{v}_n = (ca_1 + b_1)\mathbf{v}_1 + \dots + (ca_n + b_n)\mathbf{v}_n \in \text{span}S$$

□

Definition. S is linearly independent if $a_1\mathbf{v}_1 + \dots + a_n\mathbf{v}_n = \mathbf{0} \implies a_1 = \dots = a_n = 0$

Example 1. $\mathbf{V} := \mathbb{R}^2$, $S_1 = \{(1,0), (0,1), (1,1)\}$ is linearly dependent subset because $1(1,0) + 1(0,1) - 1(1,1) = (0,0)$. But $S_2 = \{(1,0), (0,1)\}$ is linearly independent subset because $a_1(1,0) + a_2(0,1) = (0,0) = (a_1, a_2)$. Note that $\mathbb{R}^2 = \text{span}S_1$, but $(3,2) = 3(1,0) + 2(0,1) + 0(1,1) = 1(1,0) + 0(0,1) + 2(1,1)$. The expression is not unique.

Definition. S is called a basis for \mathbf{V} if $\mathbf{V} = \text{span}S$ and S is linearly independent.

Note. Every vector space has a basis.

Definition. $\dim \mathbf{V} := |S|$ where S is a basis for \mathbf{V} and called "dimension of \mathbf{V} ".

Note. All bases for \mathbf{V} have the same cardinality.

Theorem. Let $\beta = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ subset of \mathbf{V} . Then β is a basis if and only if $\forall \mathbf{v} \in \mathbf{V}$ can be uniquely expressed as linear combinations of vectors of β .

Proof. \implies

Suppose that $\beta = \{bv_1, \dots, v_n\}$ be a basis for \mathbf{V} . Then $\mathbf{v} = a_1\mathbf{v}_1 + \dots + n\mathbf{v}_n = b_1\mathbf{v}_1 + \dots + b_n\mathbf{v}_n \forall \mathbf{v} \in \mathbf{V}$.
 $(a_1 - b_1)\mathbf{v}_1 + \dots + (a_n - b_n)\mathbf{v}_n = \mathbf{0}$. Since β is a linearly independent subset of \mathbf{V} , $(a_i - b_i) = 0$ for all i . I.e., $a_i = b_i$ for all i .

$\therefore \mathbf{v}$ can be uniquely expressed as linear combinations of vectors of β .

\Longleftarrow

Since every \mathbf{v} can be uniquely expressed as linear combinations of β , $\text{span}\beta = \mathbf{V}$. Suppose $a_1\mathbf{v}_1 + a_n\mathbf{v}_n = \mathbf{0}$ and let's assume that there is at least non-zero coefficient a_i . With out the loss of generality, suppose that $a_1 \neq 0$. Then $\mathbf{v}_1 = -a_1^{-1}(a_2\mathbf{v}_2 + \dots + a_n\mathbf{v}_n)$. But it contradicts to the assumption. Because \mathbf{v}_1 can be expressed as two different linear combinations. $\mathbf{v}_1 = 1 \cdot \mathbf{v}_1 = -a_1^{-1}(a_2\mathbf{v}_2 + \dots + a_n\mathbf{v}_n)$. Thus there cannot be non-zero coefficient a_i , i.e., $a_i = 0$ for $i = 1, \dots, n$.

$\therefore \beta$ is a basis for \mathbf{V} . □

Example 2.

1. A basis of \mathbb{R}^n is $\mathcal{E} := \{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ and is called standard basis for \mathbb{R}^n . $\dim \mathbb{R}^n = |\mathcal{E}| = n$
2. A basis of $\mathfrak{M}_{m \times n}(\mathbb{R})$ is E^{ij} where $(E^{ij})_{ij} = 1$ otherwise 0. Thus $A = \sum_{i=1}^m \sum_{j=1}^n a_{ij} E^{ij}$ and $\dim \mathfrak{M}_{m \times n}(\mathbb{R}) = mn$
3. $\mathbf{P}_n(\mathbb{R}) = \{f(x) \in \mathbf{P}(\mathbb{R}) \mid \deg f(x) \leq n\} = \{a_0 + a_1X + \dots + a_nX^n \mid a_i \in \mathbb{R}\} = \text{span}\{1, X, \dots, X^n\}$
 $\dim \mathbf{P}_n(\mathbb{R}) = n + 1$
4. A basis of $\mathbf{U}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid a_{ij} = 0 \forall i > j\}$ is $\{E^{ij} \mid 1 \leq i \leq j \leq n\}$ and dimension is $\frac{n(n+1)}{2}$.
5. A basis of $\mathbf{L}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid a_{ij} = 0 \forall i < j\}$ is $\{E^{ij} \mid 1 \leq j \leq i \leq n\}$ and dimension is $\frac{n(n+1)}{2}$.
6. A basis of $\mathbf{D}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid a_{ij} = 0 \forall i \neq j\}$ is $\{E^{ii} \mid i = 1, \dots, n\}$ and dimension is n .
7. A basis of $\mathbf{SL}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid \text{tr}A = 0\}$ is $\{E^{ij} \mid i \neq j\} \cup \{E^{ii} - E^{i+1, i+1} \mid 1 \leq i < n\}$ and dimension is $n^2 - 1$
8. A basis of $\mathbf{Alt}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid A^t = -A\}$ is $\{E^{ii} \mid i = 1, \dots, n\} \cup \{E^{ij} - E^{ji} \mid i < j\}$ and dimension is $\frac{n(n-1)}{2}$.
9. A basis of $\mathbf{Sym}_n(\mathbb{R}) := \{A \in \mathfrak{M}_n(\mathbb{R}) \mid A^t = A\}$ is $\{E^{ii} \mid i = 1, \dots, n\} \cup \{E^{ij} + E^{ji} \mid i < j\}$ and dimension is $\frac{n(n+1)}{2}$