

# 1. LINEAR COMBINATIONS AND SPANS

Let  $V$  be a vector space.

**Definition 1.**

- A sum of the form

$$x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_n\mathbf{v}_n,$$

where  $x_1, x_2, \dots, x_n$  are scalars and  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in V$ , is called a *linear combination* of the vectors  $v_1, v_2, \dots, v_n$ .

- The *span* of  $S$ , written  $\text{span } S$  is the set of vectors  $\mathbf{v} \in V$  expressible as a linear combination of elements of  $S$ :

$$\mathbf{v} \in \text{span } S \iff \begin{array}{l} \exists \text{ finitely many vectors } \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in S \\ \text{and scalars } x_1, x_2, \dots, x_n \text{ such that} \\ \mathbf{v} = x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_n\mathbf{v}_n. \end{array}$$

**Theorem 2.** Let  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in V$ . Then  $\text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$  is a subspace of  $V$ .

*Proof.* Let  $W = \text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$  and let  $\mathbf{x}, \mathbf{y} \in W$  and let  $x$  be a scalar. Then there are scalars  $x_1, x_2, \dots, x_n$  and  $y_1, y_2, \dots, y_n$  such that

$$\mathbf{x} = x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_n\mathbf{v}_n \quad \text{and} \quad \mathbf{y} = y_1\mathbf{v}_1 + y_2\mathbf{v}_2 + \cdots + y_n\mathbf{v}_n$$

and

$$\begin{aligned} \mathbf{x} + \mathbf{y} &= (x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_n\mathbf{v}_n) + (y_1\mathbf{v}_1 + y_2\mathbf{v}_2 + \cdots + y_n\mathbf{v}_n) \\ &= (x_1 + y_1)\mathbf{v}_1 + (x_2 + y_2)\mathbf{v}_2 + \cdots + (x_n + y_n)\mathbf{v}_n. \end{aligned}$$

Thus,  $\mathbf{x} + \mathbf{y}$  is a linear combination of the  $\mathbf{v}_i$  and  $\mathbf{x} + \mathbf{y} \in W$ . We have established that  $W$  is closed under addition. We have

$$x\mathbf{x} = x(x_1\mathbf{v}_1 + x_2\mathbf{v}_2 + \cdots + x_n\mathbf{v}_n) = (xx_1)\mathbf{v}_1 + (xx_2)\mathbf{v}_2 + \cdots + (xx_n)\mathbf{v}_n \in W,$$

so  $W$  is closed under scalar multiplication as well. □

**Example 3.** Consider the vectors following vectors in  $\mathbf{R}^3$ :

$$\mathbf{a}_1 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{a}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{a}_3 = \begin{pmatrix} 1 \\ 1 \\ 0 \end{pmatrix} \quad \text{and} \quad \mathbf{b} = \begin{pmatrix} 1 \\ 0 \\ 3 \end{pmatrix}$$

Then  $\mathbf{a} \in \text{span}\{\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3\}$  as

$$\mathbf{a} = \mathbf{v}_1 + 2\mathbf{v}_2 - \mathbf{v}_3.$$

**Example 4.** The zero vector  $\mathbf{0}$  belongs to the span of any set of vectors  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$  because

$$0\mathbf{v}_1 + \mathbf{v}_2 + \cdots + 0\mathbf{v}_n = \mathbf{0}.$$

**Example 5.** Let  $\mathbf{e}_i \in \mathbf{R}^n$  be the column vector whose only nonzero entry is a 1 in row  $i$ . If  $\mathbf{x} = (x_1 \ x_2 \ \cdots \ x_n)^T \in \mathbf{R}^n$ , then  $\mathbf{x} \in \text{span}\{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_n\}$  as

$$\mathbf{x} = x_1\mathbf{e}_1 + x_2\mathbf{e}_2 + \cdots + x_n\mathbf{e}_n.$$

**Theorem 6** (Linear combinations are matrix-vector products). *Let  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n \in \mathbf{R}^m$  and let  $A$  be the matrix with column vectors  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$ :*

$$A = (\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n).$$

*Then the linear combinations of the vectors  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$  are precisely the matrix-vector products  $A\mathbf{x}$  for  $\mathbf{x} \in \mathbf{R}^n$ .*

*Proof.* The identity

$$x_1\mathbf{a}_1 + x_2\mathbf{a}_2 + \cdots + x_n\mathbf{a}_n = A \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$$

holds. □

**Corollary 7.** *Let  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$  and  $A$  be as in Theorem 6. The following are equivalent for a vector  $\mathbf{b} \in \mathbf{R}^m$ .*

- (1)  $\mathbf{b}$  can be expressed as a linear combination of the vectors  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$ .
- (2)  $\mathbf{b} \in \text{span}\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n\}$ .
- (3)  $A\mathbf{x} = \mathbf{b}$  has a solution.
- (4)  $\mathbf{b}$  belongs to  $C(A)$ .

**Remark 8.** The column space is called the column space because it's the space spanned by the columns.

**Example 9.** Let  $\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3$  and  $\mathbf{b}$  be as in Example 3. Since the matrix

$$A = (\mathbf{a}_1 \quad \mathbf{a}_2 \quad \mathbf{a}_3) = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix}$$

is invertible, the solution  $\mathbf{x} = (1 \quad 2 \quad -1)^T$  of the equation  $A\mathbf{x} = \mathbf{b}$  is unique. Therefore,  $\mathbf{b}$  does not belong to any of  $\text{span}\{\mathbf{e}_1, \mathbf{e}_2\}$ ,  $\text{span}\{\mathbf{e}_1, \mathbf{e}_3\}$  or  $\text{span}\{\mathbf{e}_2, \mathbf{e}_3\}$ .

**Example 10.** Let  $P$  be the set of polynomials in the variable  $x$  with coefficients in  $\mathbf{R}$ . Then

$$\text{span}\{1, x, x^2, x^3, \dots\} = P$$

because every polynomial is a **finite** sum of monomials<sup>1</sup> and a finite sum of monomials is a linear combinations of elements of  $\{1, x, x^2, x^3, \dots\}$ .

### 1.1. The pivot columns span the column space.

**Theorem 11.** *Let  $A = (\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n)$  be an  $m \times n$  matrix in reduced row echelon form with leading 1s in positions  $(i, j_i)$ ,  $1 \leq i \leq r$ . Then*

$$C(A) = \text{span}\{\mathbf{a}_{j_1}, \mathbf{a}_{j_2}, \dots, \mathbf{a}_{j_r}\}.$$

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<sup>1</sup>A *monomial* is a polynomial of the form  $ax^n$ , where  $a \in \mathbf{R}$  and  $n \geq 0$ .

*Proof.* Since rows  $r + 1$  through  $m$  of  $A$  have no leading 1s and  $A$  is in row echelon form, they are zero rows. Therefore,  $a_{ij} = 0$  for  $r + 1 \leq i \leq m$  and  $1 \leq j \leq n$ . Since  $A$  is in reduced row echelon form, the 1 in row  $i$  of the column vector  $\mathbf{a}_{j_i}$  is the only nonzero entry in  $\mathbf{a}_{j_i}$ . Combining these facts, we see that

$$\mathbf{a}_j = a_{1j}\mathbf{a}_{j_1} + a_{2j}\mathbf{a}_{j_2} + \cdots + a_{rj}\mathbf{a}_{j_r} \in \text{span}\{\mathbf{a}_{j_1}, \mathbf{a}_{j_2}, \dots, \mathbf{a}_{j_r}\}$$

for  $1 \leq j \leq n$ , proving that all the columns of  $A$  belong to  $\text{span}\{\mathbf{a}_{j_1}, \mathbf{a}_{j_2}, \dots, \mathbf{a}_{j_r}\}$ .  $\square$

**Exercise 12.** Suppose  $1 \leq i < j \leq n$ . Let  $\mathbf{v}^{ij} \in \mathbf{R}^n$  be the vector with 1s in positions  $i$  and  $j$  and 0s in all other positions and let

$$S_n = \{\mathbf{v}^{ij} : 1 \leq i < j \leq n\}.$$

For  $n = 2, 3, 4$ , answer the following:

- (1) Is it true that  $\text{span } S_n = \mathbf{R}^n$ ?
- (2) Find all ways of writing the zero vector  $\mathbf{0} \in \mathbf{R}^n$  as a linear combination of elements of  $S_n$ .
- (3) Find all ways of writing the “ones vector”  $\mathbf{1} = (1 \ 1 \ \cdots \ 1) \in \mathbf{R}^n$  as a linear combination of elements of  $S_n$ .

**Exercise 13.** Let  $\mathbf{e}^{ij} \in M_2(\mathbf{R})$  be the matrix whose only nonzero entry is a 1 in position  $(i, j)$ . Let

$$R = \{\mathbf{e}^{11}, \mathbf{e}^{12}, \mathbf{e}^{21}, \mathbf{e}^{22}\}, \quad S = \{\mathbf{e}^{11}, \mathbf{e}^{12} + \mathbf{e}^{21}, \mathbf{e}^{22}\}, \quad \text{and} \quad T = \{\mathbf{e}^{12} - \mathbf{e}^{21}\}.$$

Show that:

- (1)  $\text{span } R = M_2(\mathbf{R})$ .
- (2)  $\text{span } S$  is the set of symmetric matrices in  $M_2(\mathbf{R})$ . (A matrix  $A$  is *symmetric* if  $A^T = A$ .)
- (3)  $\text{span } T$  is the set of skew-symmetric matrices in  $M_2(\mathbf{R})$ . (A matrix  $A$  is *skew-symmetric* if  $A^T = -A$ .)

**Exercise 14.** Let  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$  and  $\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n$  be list of vectors in  $\mathbf{R}^n$ . Prove that  $\text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m\} \subset \text{span}\{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n\}$  if and only if  $\mathbf{v}_i \in \text{span}\{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n\}$  for all  $i$ ,  $1 \leq i \leq m$ . (How might you apply the result of this exercise to prove equality of two spans rather than containment?)

**Exercise 15.** Let  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in V$  and let  $x$  and  $y$  be scalars with  $x \neq 0$ . Prove:

- (1)  $\text{span}\{x\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\} = \text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ .
- (2)  $\text{span}\{\mathbf{v}_1 + y\mathbf{v}_2, \mathbf{v}_2, \dots, \mathbf{v}_n\} = \text{span}\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$ .

## 1.2. A spanning subset of $\mathbf{R}^m$ can't be too small.

**Theorem 16.** Let  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$  be vectors in  $\mathbf{R}^m$  and suppose that  $n < m$ . Then the vectors  $\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n$  do not span  $\mathbf{R}^m$ .

*Proof.* Let  $A = (\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_n)$ . Let  $R$  be any row echelon form of  $A$  and let  $U$  be an invertible  $m \times m$  matrix such that  $R = UA$ . Since  $R$  has  $n$  columns,  $A$  has at most  $n$  pivot rows. Since  $m > n$ ,  $R$  must have at least one zero row. In particular, the  $m$ -th row of  $R$  is zero. Therefore,  $A\mathbf{x} = \mathbf{e}_m$  has no solution, where  $\mathbf{e}_m \in \mathbf{R}^m$  is the column vector whose only nonzero entry is a 1 in row  $m$ . Setting  $\mathbf{b} = U^{-1}\mathbf{e}_m$ , it follows that  $A\mathbf{x} = \mathbf{b}$  has no solution. Therefore, by Corollary 7,  $\mathbf{b} \notin \text{span}\{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_n\}$ .  $\square$

### 1.3. Uniqueness of reduced row echelon form. (Under construction; do not read!)

**Lemma 17.** Let  $A = (\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_n)$  be an  $m \times n$  matrix in reduced row echelon form with pivot columns  $j_1 < j_2 < \cdots < j_r$ . The following are equivalent:

- (1)  $\mathbf{a}_j$  is a pivot column of  $A$ .
- (2)  $\mathbf{a}_j \notin \text{span}\{\mathbf{a}_{j_i} : j_i < j\}$ .
- (3)  $\mathbf{a}_j \notin \text{span}\{\mathbf{a}_k : k < j\}$ .

*Proof.* Let  $A_j = (\mathbf{a}_1 \ \mathbf{a}_2 \ \cdots \ \mathbf{a}_j)$ . Then  $A_j$  is in reduced row echelon form as  $A$  is (reference an exercise?) and  $\{\mathbf{a}_{j_i} : j_i < j\}$  is a basis for  $C(A_j)$  by Theorem 11. In particular, if  $1 \leq p \leq r$  then  $\{\mathbf{a}_{j_i} : 1 \leq i \leq p\}$  is a basis of  $C(A_{j_p})$ . Since bases are linearly independent,

$$\mathbf{a}_{j_p} \notin \text{span}\{\mathbf{a}_{j_i} : 1 \leq i < p\},$$

proving that (1) implies (2).

Conversely, suppose  $\mathbf{a}_j$  is not a pivot column of  $A$ . Now the column space of  $A_j$  is spanned by its pivot columns, namely, the  $\mathbf{a}_{j_i}$  with  $j_i < j$ , so  $\mathbf{a}_j \in \text{span}\{\mathbf{a}_{j_i} : j_i < j\}$ . This proves that (2) implies (1).

To see that (2) and (3) are equivalent, observe that  $\text{span}\{\mathbf{a}_k : k < j\}$  is by definition, the column space of  $A_j$  while  $\text{span}\{\mathbf{a}_{j_i} : j_i < j\}$  is the span of the pivot columns of  $A_j$ . But these spans are equal by Theorem 11.  $\square$

**Exercise 18.** Let  $A$  be an  $m \times n$  matrix in row echelon form whose leading 1s lie in positions  $(i, j_i)$ ,  $1 \leq i \leq r$ . Suppose  $j_i < j < j_{i+1}$ . Prove that  $a_{pj} = 0$  for  $i < p \leq m$ .

**Theorem 19.** Let  $A$  and  $B$  be row equivalent matrices in reduced row echelon form. Then  $A = B$ .

*Proof.* Suppose not. Then there is a pair of  $m \times n$  matrices  $(A, B)$  witnessing the failure of the theorem such that  $n$  is minimal among all such witnesses. In other words:

- (i)  $A$  and  $B$  are distinct, row equivalent matrices in reduced row echelon form.
- (ii) If  $A'$  and  $B'$  is another such pair then  $A$  has fewer columns than  $A'$ .

Since  $A$  and  $B$  are row equivalent and in reduced row echelon form, so are  $A_{n-1}$  and  $B_{n-1}$ . (Why?) By the minimality of  $n$ , the theorem holds for  $A_{n-1}$  and  $B_{n-1}$ . Therefore,  $A_{n-1} = B_{n-1}$ . Thus, to prove the theorem, it suffices to show that  $\mathbf{a}_n = \mathbf{b}_n$ .

Suppose, first, that  $\mathbf{a}_n$  is a pivot column of  $A$ . Then  $\mathbf{a}_n \notin C(A_{n-1})$  by Lemma 17. Since  $A$  and  $B$  are row equivalent,  $\mathbf{a}_n \in C(A_{n-1})$  if and only if  $\mathbf{b}_n \in C(B_{n-1})$ . (Row equivalence preserves linear relations between columns.) Therefore,  $\mathbf{b}_n \notin C(B_{n-1})$  and, by Lemma 17 again,  $\mathbf{b}_n$  is a pivot column of  $B$ . Let  $r = \text{rank } A_{n-1} = \text{rank } B_{n-1}$ . Then  $\mathbf{a}_n$  and  $\mathbf{b}_n$  must both equal  $\mathbf{e}_{r+1}$  because  $A$  and  $B$  are in reduced row echelon form. Thus,  $\mathbf{a}_n = \mathbf{b}_n$ .

Now suppose that  $\mathbf{a}_n$  is not a pivot column of  $A$ . Then  $\mathbf{a}_n \in C(A_{n-1})$  by Lemma 17, so there is a vector  $\mathbf{x} \in \mathbf{R}^{n-1}$  such that  $\mathbf{a}_n = A_{n-1}\mathbf{x}$ . Since  $A$  and  $B$  are row equivalent,  $\mathbf{b}_n = B_{n-1}\mathbf{x}$ . But  $A_{n-1} = B_{n-1}$ , so it follows once again that  $\mathbf{a}_n = \mathbf{b}_n$ .  $\square$

**Exercise 20.** Let  $W$  and  $W'$  be subspaces of  $W$ . Let  $S$  and  $S'$  be spanning sets of  $W$  and  $W'$ , respectively. Show that  $S \cup S'$  is a spanning set of  $W \cup W'$ .

**Exercise 21.** Let  $A \in \mathbf{R}^{m \times n}$  and let  $\mathbf{v} \in R(A)$ . Show that if  $\mathbf{v}^T \in N(A)$  then  $\mathbf{v} = \mathbf{0}^{1 \times m}$ . (Hint: Since  $\mathbf{v} \in R(A)$ , there is a row vector  $\mathbf{x} \in \mathbf{R}^{1 \times m}$  such that  $\mathbf{v} = \mathbf{x}A$ . If  $A\mathbf{v}^T = \mathbf{0}^{m \times 1}$  then

$$\mathbf{v}\mathbf{v}^T = \mathbf{x}A\mathbf{v}^T = \mathbf{x}\mathbf{0}^{m \times 1} = \mathbf{0}^{m \times 1}.$$

Explain why  $\mathbf{v}\mathbf{v}^T = 0$  implies  $\mathbf{v} = \mathbf{0}^{1 \times m}$ .) Conclude that  $R(A^T) \cap N(A) = \{0\}$ .