

1 Basic Definitions

Definition 1.1 Let $x^1, \dots, x^n \in \mathbf{R}^d$ and $\lambda_1, \dots, \lambda_n \in \mathbf{R}$. Then $x = \lambda_1 x^1 + \dots + \lambda_n x^n$ is

1. a *linear combination* of x^1, \dots, x^n ;
2. an *affine combination* of x^1, \dots, x^n if $\lambda_1 + \dots + \lambda_n = 1$;
3. a *nonnegative combination* of x^1, \dots, x^n if $\lambda_1, \dots, \lambda_n \geq 0$;
4. a *convex combination* of x^1, \dots, x^n if $\lambda_1 + \dots + \lambda_n = 1$ and $\lambda_1, \dots, \lambda_n \geq 0$.

Remark 1.2 For $x^1, \dots, x^n \in \mathbf{R}^d$, write

$$A = \begin{bmatrix} x^1 & \cdots & x^n \end{bmatrix}$$

and

$$A' = \begin{bmatrix} x^1 & \cdots & x^n \\ 1 & \cdots & 1 \end{bmatrix}.$$

Define also

$$\lambda = \begin{bmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{bmatrix}.$$

Then the four cases in the above definition can be expressed, respectively, as

1. $x = A\lambda$.
2. $\begin{bmatrix} x \\ 1 \end{bmatrix} = A'\lambda$.
3. $x = A\lambda, \lambda \geq 0$.
4. $\begin{bmatrix} x \\ 1 \end{bmatrix} = A'\lambda, \lambda \geq 0$.

Definition 1.3 Let $x^1, \dots, x^n \in \mathbf{R}^d$. Then $\{x^1, \dots, x^n\}$ is

1. *linearly dependent* if $\exists \lambda_1, \dots, \lambda_n \in \mathbf{R}$, not all zero, such that $\lambda_1 x^1 + \dots + \lambda_n x^n = 0$. Otherwise $\{x^1, \dots, x^n\}$ is *linearly independent*.

2. *affinely dependent* if $\exists \lambda_1, \dots, \lambda_n \in \mathbf{R}$, not all zero, such that $\lambda_1 x^1 + \dots + \lambda_n x^n = O$ and $\lambda_1 + \dots + \lambda_n = 0$. Otherwise $\{x^1, \dots, x^n\}$ is *affinely independent*.

Theorem 1.4

1. $\{x^1, \dots, x^n\} \subseteq \mathbf{R}^d$ is linearly dependent iff there exists one of the x^i that can be expressed as a linear combination of the others.
2. $\{x^1, \dots, x^n\} \subseteq \mathbf{R}^d$ is affinely dependent iff there exists one of the x^i that can be expressed as an affine combination of the others.

PROOF. Exercise. \square

Theorem 1.5 Let $S = \{x^1, \dots, x^n\} \subseteq \mathbf{R}^d$ and define A and A' as in Remark 1.2.

1. S is linearly independent iff $\text{rank } A = n$ iff $\dim\{\lambda \in \mathbf{R}^n : A\lambda = O\} = 0$. In particular, if $n > d$ then S is linearly dependent.
2. S is affinely independent iff $\text{rank } A' = n$ iff $\dim\{\lambda \in \mathbf{R}^n : A'\lambda = O\} = 0$. In particular, if $n > d + 1$ then S is affinely dependent.

PROOF. Exercise. \square

Exercise 1.6 $\{x^0, x^1, \dots, x^n\} \subseteq \mathbf{R}^d$ is affinely independent iff $\{x^1 - x^0, \dots, x^n - x^0\}$ is linearly independent.

Definition 1.7 Let $S \subseteq \mathbf{R}^d$.

1. S is a *linear set* or *subspace* if $S \neq \emptyset$ and $\forall x, y \in S, \forall \lambda, \mu \in \mathbf{R}, \lambda x + \mu y \in S$. I.e., S is nonempty (in particular S contains O) and closed under all linear combinations of two elements.
2. S is an *affine set*, *affine space*, or *flat* if $\forall x, y \in S, \forall \lambda, \mu \in \mathbf{R}$ such that $\lambda + \mu = 1, \lambda x + \mu y \in S$. I.e., S is closed under all affine combinations of two elements.
3. S is a (*convex*) *cone* if $S \neq \emptyset$ and $\forall x, y \in S, \forall$ nonnegative $\lambda, \mu \in \mathbf{R}, \lambda x + \mu y \in S$. I.e., S is nonempty (in particular S contains O) and is closed under all nonnegative combinations of two elements.
4. S is a *convex set* if $\forall x, y \in S, \forall$ nonnegative $\lambda, \mu \in \mathbf{R}$ such that $\lambda + \mu = 1, \lambda x + \mu y \in S$. I.e., S is closed under all convex combinations of two elements.

Remark 1.8 We often (but not always) refer to elements of linear subspaces and convex cones as *vectors* and elements of affine and convex sets as *points*.

Theorem 1.9 Let $\mathcal{L}, \mathcal{A}, \mathcal{K}, \mathcal{C}$ denote the collection of all linear subspaces, affine sets, cones, and convex sets, respectively, of \mathbf{R}^d . Then $\mathcal{A} \subseteq \mathcal{C}$ and $\mathcal{K} \subseteq \mathcal{C}$, and these inclusions are strict. Further, $\mathcal{A} \cap \mathcal{K} = \mathcal{L}$.

PROOF. Exercise. \square

Exercise 1.10 Classify the following sets.

1. $\{x \in \mathbf{R}^d : \|x\| \leq 1\}$.
2. $\{x \in \mathbf{R}^d : a^T x = \alpha\}$, where $0 \neq a \in \mathbf{R}^d$ and $\alpha \in \mathbf{R}$. (Such a set is called a *hyperplane*.)
3. $\{x \in \mathbf{R}^d : Mx = 0\}$ where M is an $n \times d$ matrix.
4. $\{x \in \mathbf{R}^d : Mx \leq 0\}$ where M is an $n \times d$ matrix.
5. $\{x \in \mathbf{R}^d : Mx = b\}$ where M is an $n \times d$ matrix and $b \in \mathbf{R}^n$.
6. $\{x \in \mathbf{R}^d : Mx \leq b\}$ where M is an $n \times d$ matrix and $b \in \mathbf{R}^n$.

Theorem 1.11 Let $S \subseteq \mathbf{R}^d$.

1. S is a linear subspace iff $S \neq \emptyset$ and S is closed under linear combinations of finite numbers of vectors in S .
2. S is an affine set iff S is closed under affine combinations of finite numbers of points in S .
3. S is a cone iff $S \neq \emptyset$ and S is closed under nonnegative combinations of finite numbers of vectors in S .
4. S is a convex set iff S is closed under convex combinations of finite numbers of points in S .

PROOF. Exercise. \square

Theorem 1.12 Let S be a nonempty subset of \mathbf{R}^d . Then S is an affine set iff there exists a linear subspace L of \mathbf{R}^d and a point y such that $S = L + y$; i.e., $S = \{x + y : x \in L\}$. In this case L is unique, and y can be chosen to be any particular point of S .

PROOF. Exercise. \square

Theorem 1.13 *Let $S \subseteq \mathbf{R}^d$.*

1. *S is a linear subspace iff S is a set of the form $\{x \in \mathbf{R}^d : Mx = O\}$ for some $n \times d$ matrix M .*
2. *S is an affine set iff S is a set of the form $\{x \in \mathbf{R}^d : Mx = b\}$ for some $n \times d$ matrix M and $b \in \mathbf{R}^n$. If S is nonempty, then in this case, $S = L + y$, where y is any particular point in S and $L = \{x \in \mathbf{R}^d : Mx = O\}$.*

PROOF. Exercise. \square

Remark 1.14 Not all cones are of the form $\{x \in \mathbf{R}^d : Mx \leq O\}$. Those that are are called (*convex*) *polyhedral cones*. Similarly, not all convex sets are of the form $\{x \in \mathbf{R}^d : Mx \leq b\}$. Those that are are called (*convex*) *polyhedra*.

PROOF. Exercise. \square

Theorem 1.15

1. *Every linear subspace is the intersection of a finite number of hyperplanes containing O .*
2. *Every affine set is the intersection of a finite number of hyperplanes.*

PROOF. Exercise. \square

Theorem 1.16 *The intersection of any collection of linear subspaces, affine sets, cones, convex sets is again a linear subspace, affine set, cone, convex set, respectively.*

PROOF. Exercise. \square

Definition 1.17 *Let $S \subseteq \mathbf{R}^d$.*

1. The *linear span* of S , $\text{span } S$, is the intersection of all linear subspaces containing S .
2. The *affine span* of S , $\text{aff } S$, is the intersection of all affine sets containing S .
3. The *cone* of S , $\text{pos } S$, is the intersection of all cones containing S .

4. The *convex hull* of S , $\text{conv } S$, is the intersection of all convex sets containing S .

Definition 1.18 Let $S, T \subseteq \mathbf{R}^d$.

1. If $S = \text{span } T$, then we say T (*linearly*) *spans* S .
2. If $S = \text{aff } T$, then we say T *affinely spans* S .

Theorem 1.19 Suppose S is a nonempty subset of \mathbf{R}^d . Then $\text{span } S$, $\text{aff } S$, $\text{pos } S$, $\text{conv } S$ is the set of all linear, affine, nonnegative, convex combinations, respectively, of finite numbers of elements in S .

PROOF. Exercise. \square

Definition 1.20 If $S \subseteq \mathbf{R}^d$ is a finite set, $\text{pos } S$ is called a *finite cone* and $\text{conv } S$ is called a (*convex*) *polytope*.

Theorem 1.21 Let $S \subseteq \mathbf{R}^d$.

1. If $S \neq \{O\}$ is a linear subspace, then $\exists x^1, \dots, x^n \in S$ such that every $x \in S$ can be expressed uniquely as a linear combination of x^1, \dots, x^n . In this case, n is the maximum size of a linearly independent subset of S and the minimum size of a subset of S that spans S linearly.
2. If $S \neq \emptyset$ is an affine set, then $\exists x^1, \dots, x^n \in S$ such that every $x \in S$ can be expressed uniquely as an affine combination of x^1, \dots, x^n . In this case, n is the maximum size of an affinely independent subset of S and the minimum size of a subset of S that spans S affinely.

PROOF. Exercise. \square

Definition 1.22 In the first case above, $\{x^1, \dots, x^n\}$ is called a *basis* of S and the *dimension* of S , $\dim S$, equals n . If $S = \{O\}$, then $\dim S = 0$. In the second case above, $\{x^1, \dots, x^n\}$ is called an *affine basis* of S and S is the translate $L + y$ of some linear $(n - 1)$ -dimensional subspace (verify this). We say that the *dimension* of S , $\dim S$, equals $n - 1$. An affine set is 0-dimensional iff it is a set consisting of a single point. Affine sets of dimension 1 and 2 are called *lines* and *planes*, respectively.

Exercise 1.23 Let S be an affine subset of \mathbf{R}^d . Show that S is a hyperplane iff $\dim S = d - 1$.

Exercise 1.24 Let $S \subseteq \mathbf{R}^d$.

1. Show that a linear basis for $\text{span } S$ can be chosen from S itself.
2. Show that an affine basis for $\text{aff } S$ can be chosen from S itself.

Exercise 1.25 Suppose M is an $n \times d$ matrix and $b \in \mathbf{R}^n$.

1. If $S = \{x \in \mathbf{R}^d : Mx = 0\}$, then $\dim S = d - \text{rank } M$.
2. If $\emptyset \neq S = \{x \in \mathbf{R}^d : Mx = b\}$, then $\dim S = d - \text{rank } M$.

Definition 1.26 Suppose S is a nonempty subset of \mathbf{R}^d . The *dimension* of S , $\dim S$, is defined to be $\dim(\text{aff } S)$. (Note that the definitions of dimension agree if S is an affine set.) The dimension of the empty set is defined to be -1 .