| Günter Ewald |
| :--- |
| $\quad$ Combinatorial Convexity and Algebraic Geometry |
| Jacob Aguirre <br> Last updated: November 7, 2023 <br> Email: aguirre@gatech.edu |

## 1 Introduction and Preliminaries

## Convex Bodies

## Convex sets

For most of my notes, the sets we'll be considering are subsets of Euclidean $n$-space. Many definitions and theorems could be stated in an affinely invariant manner. I won't, however, stress this point. If we're using the symbol $\mathbb{R}^{n}$, it should be clear from the context whether we mean real vector space, real affine space, or Euclidean space. In the latter case, we assume the ordinary scalar product

$$
\langle x, y\rangle=\xi_{1} \eta_{1}+\ldots+\xi_{n} \eta_{n} \quad \text { for } x=\left(\xi_{1}, \ldots, \xi_{n}\right), y=\left(\eta_{1}, \ldots, \eta_{n}\right)
$$

so that the square of Euclidean distance between points $x$ and $y$ equals

$$
\|x-y\|^{2}=\langle x-y, x-y\rangle
$$

Recall that an open ball with center $x$ and radius $r$ is the set $\{y \mid\|x-y\|<r\}$. By $\langle K, y\rangle \geq 0$, we mean $\langle x, y\rangle \geq 0$ for every $x \in K$. We assume the reader to be somewhat familiar with $n$-dimensional affine and Euclidean geometry.
1.1 Definition. A set $C \subset \mathbb{R}^{n}$ is called convex if, for all $x, y \in C, x \neq y$, the line segment

$$
[x, y]:=\{\lambda x+(1-\lambda) y \mid 0 \leq \lambda \leq 1\}
$$

is contained in $C$ (Figure 1).
Examples of convex sets are a point, a line, a circular disc in $\mathbb{R}^{2}$, the platonic solids (see Figure 10 in section 6) in $\mathbb{R}^{3}$. Also $\emptyset$ and $\mathbb{R}^{n}$ are convex.

If $B$ is an open circular disc in $\mathbb{R}^{2}$ and $M$ is any subset of the boundary circle $\partial B$ of $B$, then $B \cup M$ is also convex. So, a convex set need be neither open nor closed. In general we shall restrict ourselves to closed convex sets.

There is a simple way to construct new convex sets from given ones:
1.2 Lemma. The intersection of an arbitrary collection of convex sets is convex.

Proof: If a line segment is contained in every set of the collection, it is also contained in their intersection.
1.3 Definition. We say $x$ is a convex combination of $x_{1}, \ldots, x_{r} \in \mathbb{R}^{n}$ if there exist $\lambda_{1}, \ldots, \lambda_{r} \in \mathbb{R}$ such that

$$
\begin{gather*}
x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}  \tag{1}\\
\lambda_{1}+\ldots+\lambda_{r}=1  \tag{2}\\
\lambda_{1} \geq 0, \ldots, \lambda_{r} \geq 0 \tag{3}
\end{gather*}
$$

If condition (3) is dropped, we have an affine combination of $x_{1}, \ldots, x_{r}$, and $x, x_{1}, \ldots, x_{r}$ are called affinely dependent. If $x, x_{1}, \ldots, x_{r}$ are not affinely dependent, we say they are affinely independent.

So, convex combinations are special affine combinations (Figure 2).
If $x_{1}, \ldots, x_{r}$ are affinely independent, the numbers $\lambda_{1}, \ldots, \lambda_{r}$ are sometimes called barycentric coordinates of $x$ (with respect to the affine basis $x_{1}, \ldots, x_{r}$ ).
1.4 Definition. The set of all convex combinations of a set $M \subset \mathbb{R}^{n}$ is called the convex hull
conv M
of $M$; in particular, conv $\emptyset=\emptyset$. Analogously, the set of all affine combinations of elements of $M$ is called the affine hull
aff M
of $M$. We will denote by lin $M$ (linear hull) the linear space generated by $M$. It is the "smallest" linear space containing $M$.

If $M=\left\{x_{1}, \ldots, x_{r}\right\}$ is a finite set, we say $P:=$ conv $M$ is a convex polytope, or simply a polytope.

If $x_{1}, \ldots, x_{r}$ are affinely independent, we say

$$
T_{r-1}:=\operatorname{conv}\left\{x_{1}, \ldots, x_{r}\right\}
$$

is an $(r-1)$-simplex or, briefly, a simplex. aff $T_{r-1}$ and $T_{r-1}$ are said to have dimension $r-1$.

## Remarks.

1. Clearly, $M \subset \operatorname{conv} M \subset$ aff $M$.
2. Every polytope is compact (that is, bounded and closed).

### 1.5 Theorem.

1. (a) $A$ set $M \subset \mathbb{R}^{n}$ is convex if and only if it contains all its convex combinations, that is, if and only if

$$
M=\operatorname{conv} M
$$

2. The convex hull of $M \subset \mathbb{R}^{n}$ is the smallest convex set that contains $M$; this means $M \subset M^{\prime}$ and $M^{\prime}$ convex imply conv $M \subset M^{\prime}$

Proof. First, we will show that conv $M$ is convex.
If $x, y \in \operatorname{conv} M$, there exist $x_{1}, \ldots, x_{r}, y_{1}, \ldots, y_{s} \in M$ and real numbers $\lambda_{1}, \ldots, \lambda_{r}, \mu_{1}, \ldots, \mu_{s}$ such that

$$
x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}, \quad \lambda_{1}+\ldots+\lambda_{r}=1 \quad \lambda_{1} \geq 0, \ldots, \lambda_{r} \geq 0
$$

and

$$
y=\lambda_{1} y_{1}+\ldots+\lambda_{s} y_{s}, \quad \lambda_{1}+\ldots+\lambda_{s}=1 \quad \lambda_{1} \geq 0, \ldots, \lambda_{s} \geq 0
$$

Employing 0 coefficients, if necessary, we may assume $r=s$ and $y_{j}=x_{j}, j=1, \ldots, r$. For arbitrary $0 \leq \lambda \leq 1$,

$$
\begin{aligned}
& \lambda x+(1-\lambda) y=\lambda\left(\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}\right)+(1-\lambda)\left(\mu_{1} x_{1}+\ldots+\mu_{r} x_{r}\right) \\
& =\left[\lambda \lambda_{1}+(1-\lambda) \mu_{1}\right] x_{1}+\ldots+\left[\lambda \lambda_{r}+(1-\lambda) \mu_{r}\right] x_{r} .
\end{aligned}
$$

Since all coefficients are nonnegative, and since

$$
\lambda \lambda_{1}+(1-\lambda) \mu_{1}+\ldots+\lambda \lambda_{r}+(1-\lambda) \mu_{r}=\lambda+1-\lambda=1
$$

$\lambda x+(1-\lambda) y$ is a convex combination of $x_{1}, \ldots, x_{r}$. So, conv $M$ is convex and, in view of Remark 1, we obtain (a).

Now, to see (b), suppose $M^{\prime}$ is a convex set, $M^{\prime} \supset M$, and that $x \in$ conv $M$. Then there exist $x_{1}, \ldots, x_{r} \in M$ such that $x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}, \lambda_{1}+\ldots+\lambda_{r}=1$, and $\lambda_{1}, \ldots, \lambda_{r}>0$. Since $x_{1}, \ldots, x_{r} \in M^{\prime}$ as well, we find successively

$$
\begin{aligned}
& y_{1}:=\lambda_{1}\left(\lambda_{1}+\lambda_{2}\right)^{-1} x_{1}+\lambda_{2}\left(\lambda_{1}+\lambda_{2}\right)^{-1} x_{2} \\
& y_{2}:=\left(\lambda_{1}+\lambda_{2}\right)\left(\lambda_{1}+\lambda_{2}+\lambda_{3}\right)^{-1} y_{1}+\lambda_{3}\left(\lambda_{1}+\lambda_{2}+\lambda_{3}\right)^{-1} x_{3} \\
& \vdots x=\left(\lambda_{1}+\ldots+\lambda_{r-1}\right)\left(\lambda_{1}+\ldots+\lambda_{r}\right)^{-1} y_{r-2}+\lambda_{r}\left(\lambda_{1}+\ldots+\lambda_{r}\right)^{-1} x_{r}
\end{aligned}
$$

which are all in $M^{\prime}$, hence, conv $M \subset M^{\prime}$.
1.6 Definition. If $C$ is a convex set, we call

$$
\operatorname{dim} C:=\operatorname{dim}(\operatorname{aff} C)
$$

the dimension of $C$ By convention, $\operatorname{dim} \emptyset=-1$.
1.7 Definition. A compact convex set $C$ is called a convex body.

For example, note that points and line segments are convex bodies in $\mathbb{R}^{n}, n \geq 1$, so that a convex body in $\mathbb{R}^{n}$ need not have dimension $n$.
1.8 Definition. We say $x \in M \subset \mathbb{R}^{n}$ is in the relative interior of $M, x \in \operatorname{rint} M$, if $x$ is in the interior of $M$ relative to aff $M$ (that is, there exists an open ball $B$ in aff $M$ such that $x \in B \subset M$ ). If aff $M=\mathbb{R}^{n}$, then rint $M:=\operatorname{int} M$ (note that rint $\mathbb{R}^{0}=\operatorname{int} \mathbb{R}^{0}=\{0\}$ ).

Our main emphasis will be on convex polytopes and an unbounded counterpart of polytopes, called polyhedral cones:
1.9 Definition. If $M \subset \mathbb{R}^{n}$, the set of all nonnegative linear combinations

$$
x=\lambda_{1} y_{1}+\ldots+\lambda_{k} y_{k}, \quad y_{1}, \ldots, y_{k} \in M, \quad \lambda_{1} \geq 0, \ldots, \lambda_{k} \geq 0
$$

of elements of $M$ is called the positive hull

$$
\sigma:=\operatorname{pos} M
$$

of $M$ or the cone determined by $M$. By convention, pos $\emptyset:=\{0\}$.
For fixed $u \in \mathbb{R}^{n}, u \neq 0$, and $\alpha \in \mathbb{R}$, the set $H:=\{x \mid\langle x, u\rangle=\alpha\}$ is a hyperplane. $H^{+}:=\{x \mid\langle x, u\rangle \geq \alpha\}$ and $H^{-}:=\{x \mid\langle x, u\rangle \leq \alpha\}$ are called the half-spaces bounded by $H$. If $\sigma \subset H^{+}$and $\alpha=0$, we say $\sigma$ has an apex, namely 0 . (we use the symbol 0 for the number 0 , the zero vector, and the origin).

If $M=\left\{x_{1}, \ldots, x_{r}\right\}$ is finite, we call

$$
\sigma=\operatorname{pos}\left\{x_{1}, \ldots, x_{r}\right\}
$$

a polyhedral cone. Unless otherwise stated, by a cone we always mean a polyhedral cone. Sometimes we write

$$
\sigma=\mathbb{R}_{\geq 0} x_{1}+\ldots+\mathbb{R}_{\geq 0} x_{r}
$$

$\mathbb{R}_{\geq 0}$ denoting the set of nonnegative real numbers. From now on, we will use the notation $\mathbb{R}_{+}$denoting this set of nonnegative real numbers and $\mathbb{R}_{++}$denoting the set of strictly positive real numbers.

Example. A quadrant in $\mathbb{R}^{2}$ and an octant in $\mathbb{R}^{3}$ are cones with an apex, whereas a closed half-space or the intersection of two closed half-spaces $H_{1}^{+}, H_{2}^{+}$with $0 \in H_{1}, 0 \in H_{2}$ in $\mathbb{R}^{3}$, are cones without apex.

Since convex combinations are, by definition, nonnegative linear combinations, we have
1.10 Lemma. The positive hull of any set $M$ is convex.

Figure 3 illustrates a polyhedral cone of dimension three which is the positive hull of two-dimensional polytope $K$. Through pos $M$ might generally be called a cone, we reserve this term for polyhedral cones.

## Section Exercises

1. The convex hull of any compact (closed and bounded) set is again compact.
2. Find an example of a closed set $M$ such that conv $M$ is not closed.
3. Determine all convex subsets $C$ of $\mathbb{R}^{3}$, for which $\mathbb{R}^{3} \backslash C$ is also convex. (Except $\emptyset, \mathbb{R}^{\nVdash}$ there are, up to three such sets of affine transformations, that is, translations combined with linear maps.
4. Call a set $M \epsilon$-convex if, for a given $\epsilon>0$, each ball with radius $\epsilon$ and center in $M$ intersects $M$ in a convex set. Furthermore, call a set $M$ connected if any two if its points can be joined by a rectifiable arc (as is defined in calculus) contained in $M$. Prove: (a) Any $\epsilon$-convex closed connected set $M$ in $\mathbb{R}^{2}$ is convex. (b) Statement (a) is false without the assumption of $M$ being connected.

## Theorems of Radon and Caratheodory

The following theorem is helpful when handling convex combinations.
2.1 Theorem (Radon's Theorem). Let $M=\left\{x_{1}, \ldots, x_{r}\right\} \subset \mathbb{R}^{n}$ be an arbitrary finite set, and let $M_{1}, M_{2}$ be a partition of $M$, that is, $M=M_{1} \cup M_{2}, M_{1} \cap M_{2}=\emptyset, M_{1} \neq \emptyset, M_{2} \neq \emptyset$.

1. (a) If $r \geq n+2$ then the partition can be chosen such that

$$
\operatorname{conv} M_{1} \cap \operatorname{conv} M_{2} \neq \emptyset
$$

2. (b) If $r \geq n+1$ and 0 is an apex of pos $M$, yet $0 \notin M$ or $r \geq n+2$, then the partition can be chosen such that

$$
\operatorname{pos} M_{1} \cap \operatorname{pos} M_{2} \neq\{0\} .
$$

3. (c) The partition is unique if and only if, in case (a), $r=n+2$ and any $n+1$ points of $M$ are affinely independent, in case (b), $r=n+1$ and any $n$ points of $M$ are linearly independent.
2.2 Definition. We call $M_{1}, M_{2}$ in Theorem 2.1 a Radon partition of $M$. Proof of Theorem 2.1
(a) From $r \geq n+2$, it follows that $x_{1}, \ldots, x_{r}$ are affinely dependent. Hence,

$$
\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}=0 \text { can hold with } \lambda_{1}+\ldots+\lambda_{r}=0, \text { not all } \lambda_{i}=0 .
$$

We may assume that, for a particular $j, 0<j<r$,

$$
\lambda_{1}>0, \ldots, \lambda_{j}>0 ; \quad \lambda_{j+1} \leq 0, \ldots, \lambda_{r} \leq 0
$$

We set

$$
\begin{aligned}
& \lambda:=\lambda_{1}+\ldots+\lambda_{j}=-\lambda_{j+1}-\ldots-\lambda_{r}>0 \quad \text { and } \\
& x:=\lambda^{-1}\left(\lambda_{1} x_{1}+\ldots+\lambda_{j} x_{j}\right)=-\lambda^{-1}\left(\lambda_{j+1} x_{j+1}+\ldots+\lambda_{r} x_{r}\right) .
\end{aligned}
$$

Then, $x \in \operatorname{conv} M_{1} \cap \operatorname{conv} M_{2}$ for

$$
M_{1}:=\left\{x_{1}, \ldots, x_{j}\right\}, \quad M_{2}:=\left\{x_{j+1}, \ldots, x_{r}\right\} .
$$

(b) We prove the uniqueness only in case (a); case (b) is proved similarly. First, assume $r=n+2$ and no $n+1$ points are affinely dependent. Suppose that

$$
\tilde{M}_{1}=\left\{x_{1}, \ldots, x_{i_{k}}\right\}, \quad \tilde{M}_{2}=\left\{x_{i_{k+1}}, \ldots, x_{i_{n+2}}\right\}
$$

is a second Radon partition of $M$ and

$$
y \in \operatorname{conv} \tilde{M}_{1} \cap \operatorname{conv} \tilde{M}_{2}
$$

Then,

$$
y=\mu^{-1}\left(\mu_{1} x_{i_{1}}+\ldots+\mu_{k} x_{i_{k}}=-\mu^{-1}\left(\mu_{k+1} x_{i_{k+1}}+\ldots+\mu_{n+2} x_{i_{n+2}}\right)\right.
$$

where $\mu_{1}>0, \ldots, \mu_{k}>0 ; \mu_{k+1} \leq 0, \ldots, \mu_{n+2} \leq 0 ; k \geq 1$, and $\mu=\mu_{1}+\ldots+\mu_{k}=$ $-\mu_{k+1}-\ldots-\mu_{n+2}$. We may assume

$$
x_{i_{1}}=x_{j+1} \quad\left(\in M_{2}\right)
$$

We choose $0<\alpha<1$ such that

$$
\alpha \lambda^{-1} \lambda_{j+1}+(1-\alpha) \mu^{-1} \mu_{1}=0
$$

Then,

$$
\begin{aligned}
& \alpha \lambda^{-1}\left(\lambda_{1} x_{1}+\ldots+\lambda_{n+2} x_{n+2}\right) \\
& +(1-\alpha) \mu^{-1}\left(\mu_{1} x_{1}+\ldots+\mu_{n+2} x_{i_{n+2}}\right)=0+0=0
\end{aligned}
$$

and

$$
\alpha \lambda^{-1}\left(\lambda_{1}+\ldots+\lambda_{n+2}\right)+(1-\alpha) \mu^{-1}\left(\mu_{1}+\ldots+\mu_{n+2}\right)=0 .
$$

expresses an affine relation between $n+1$ of the points of $M\left(x_{i_{1}}\right.$ and $x_{j+1}$ cancel out $)$, unless all coefficients vanish. Therefore, $\lambda_{\varphi}=-\alpha^{-1}(1-\alpha) \lambda \mu^{-1} \mu_{i_{\varphi}}, \varphi=1, \ldots, n+2$, and there is a map $\varphi \mapsto \varphi^{\prime}, \varphi \in\{1, \ldots, j, j+2, \ldots, n+2\}, \varphi^{\prime} \in\left\{i_{2}, \ldots, n+2\right\}$ such that $\lambda_{\varphi}=-\alpha^{-1}(1-\alpha) \lambda \mu_{\varphi^{\prime}}$. Since $\alpha^{-1}>0,1-\alpha>0$, and $\lambda>0$, the set of those $\varphi^{\prime}$ for which $\mu_{\varphi^{\prime}}<0$ is the same as the set of those $\varphi$ for which $\lambda_{\varphi}>0$. Therefore $M_{1}=\left\{x_{1}, \ldots, x_{j}\right\}=$ $\left\{x_{i_{k+1}}, \ldots, x_{i_{n+2}}\right\}=\tilde{M}_{2}$ and consequently $M_{2}=\tilde{M}_{1}$, too.

To prove the converse, we distinguish these two cases.
(I) $r=n+2$, and $x_{1}, \ldots, x_{n+1}$ are affinely dependent, $\stackrel{\circ}{M}:=\left\{x_{1}, \ldots, x_{n+1}\right\}$.
(II) $r>n+2$.

In case I, $\stackrel{\circ}{M}$ is contained in a hyperplane so that, by (a), we find a partition of $\stackrel{\circ}{M}$ into $\stackrel{\circ}{M}_{1}, \stackrel{\circ}{M}_{2}$ with conv $\stackrel{\circ}{M}_{1} \cap$ conv $\stackrel{\circ}{M}_{2} \neq \emptyset$. Then, $\stackrel{\circ}{M}_{1} \cup\left\{x_{n+2}\right\}, \stackrel{\circ}{M}_{2}$ and $\stackrel{\circ}{M}_{1}, \stackrel{\circ}{M}_{2} \cup\left\{x_{n+2}\right\}$ are two different Radon partitions of $M$.

In case II, consider a proper subset $\tilde{M}$ of $M$ which has at least $n+2$ points. Let $\tilde{M}_{1}, \tilde{M}_{2}$ be a Radon partition of $\tilde{M}$. Then, $\tilde{M}_{1} \cup(M \backslash \tilde{M}), \tilde{M}_{2}$ and $\tilde{M}_{1}, \tilde{M}_{2} \cup(M \backslash \tilde{M})$ are different Radon partitions of $M$.
2.3 Theorem (Caratheodory's theorem).
(a) The convex hull conv $M$ of a set $M \subset \mathbb{R}^{n}$ is the union of all convex hulls of subsets of $M$ containing at most $n+1$ elements.
(b) The positive hull pos $M$ of a set $M \subset \mathbb{R}^{n}$ is the union of all positive hulls of subsets of $M$ containing at most $n$ elements of $M$.

Proof:
(a) Let

$$
x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r} \in \operatorname{conv} \mathrm{M},
$$

and let $r$ be the smallest number of elements of $M$ of which $x$ is a convex combination. Contrary to the claim, $r \geq n+2$ implies there exists an affine relation

$$
\mu_{1} x_{1}+\ldots+\mu_{r} x_{r}=0, \text { with } \mu_{1}+\ldots+\mu_{r}=0, \quad \text { but not all } \mu_{j}=0 .
$$

For $\mu_{j} \neq 0$, we obtain from (1) and (2)

$$
x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}=\left(\lambda_{1}-\frac{\lambda_{j}}{\mu_{j}} \mu_{1}\right) x_{1}+\ldots+\left(\lambda_{r}-\frac{\lambda_{j}}{\mu_{j}} \mu_{r}\right) x_{r} .
$$

We may assume $\mu_{j}>0$, and, for all $\mu_{k}>0, k=1, \ldots, r$,

$$
\frac{\lambda_{j}}{\mu_{j}} \leq \frac{\lambda_{k}}{\mu_{k}} .
$$

Then,

$$
\lambda_{i}-\frac{\lambda_{j}}{\mu_{j}} \mu_{i} \geq 0 \quad \text { for } i=1, \ldots, r \text {. }
$$

Since $\lambda_{j}-\frac{\lambda_{j}}{\mu_{j}} \mu_{j}=0$, equation (3) expresses $x$ as a convex combination of less than $r$ elements of $M$, a contradiction of the initial assumption.
(b) Replace in the proof of (a) "convex combination" by "positive linear combination" and "affine dependence of $n+1$ elements" by "linear dependence of $n$ elements" to obtain a proof of (b).

## Exercises

1. In analogy to the above examples in Figure 4, find all types of Radon partitions of $n+2$ points in $\mathbb{R}^{n}$ whose affine hull is $\mathbb{R}^{n}$.
2. If aff $M=\mathbb{R}^{n}$, then, conv $M$ is the union of $n$-simplices with vertices in $M$.
3. Every $n$-dimensional convex polytope is the union of finitely many simplices, no two of which have an interior point in common.
4. Helly's Theorem. Suppose every $n+1$ of the convex sets $K_{1}, \ldots, K_{m}$ in $\mathbb{R}^{n}$ has a nonempty intersection, $m \geq n+1$. Then $\bigcap_{i=1}^{m} K_{i} \neq \emptyset$. (Hint: For $m=n+1$ there is nothing to prove. Apply induction on $m$ and use Radon's Theorem).

## Nearest point map and supporting hyperplanes

Quite a few properties of a closed convex set $K$ can be studied by using the map that assigns to each point in $\mathbb{R}^{n}$ its nearest point on $K$. First, we show that this map is well defined.
3.1 Lemma. Let $K$ be a closed convex set in $\mathbb{R}^{n}$. To each $x \in \mathbb{R}^{n}$ there exists a unique $x^{\prime} \in K$ such that

$$
\begin{equation*}
\left\|x-x^{\prime}\right\|=\inf _{y \in K}\|x-y\| \tag{*}
\end{equation*}
$$

Proof: The existence of an $x^{\prime}$ satisfying (*) follows from $K$ being closed. Suppose that, for $x^{\prime \prime} \in K, x^{\prime \prime} \neq x^{\prime}$,

$$
\left\|x-x^{\prime \prime}\right\|=\inf _{y \in K}\|x-y\|
$$

Consider the isosceles triangle with vertices $x, x^{\prime}, x^{\prime \prime}$. The midpoint $m=\frac{1}{2}\left(x^{\prime}+x^{\prime \prime}\right)$ of the line segment between $x^{\prime}$ and $x^{\prime \prime}$ is, by convexity, also in $K$, but satisfies

$$
\|x-m\|<\inf _{y \in K}\|x-y\|,
$$

a contradiction.
3.2 Definition. The map

$$
\begin{aligned}
& p_{K}: \mathbb{R}^{n} \rightarrow K \\
& x \mapsto p_{K}(x)=x^{\prime}
\end{aligned}
$$

of lemma 3.1 is called the nearest point map relative to $K$.
Clearly,

### 3.3 Lemma.

1. (a) $p_{K}(x)=x$ if and only if $x \in K$;
2. (b) $p_{K}$ is surjective.

Generalizing the concept of a tangent hyperplane is the following.
3.4 Definition. A hyperplane $H$ is called a supporting hyperplane of a closed convex set $K \subset \mathbb{R}^{n}$ if $K \cap H \neq \emptyset$ and $K \subset H^{-}$or $K \subset H^{+}$.

We call $H^{-}$(or $H^{+}$, respectively) a supporting half-space of $K$ (possibly $K \subset H$ ).
If $u$ is a normal vector of $H$ pointing into $H^{+}$(or $H^{-}$, respectively), we say that $u$ is an outer normal of $K$ (Figure 5), and $-u$ an inner normal of $K$.
3.5 Lemma. Let $\emptyset \neq K \subset \mathbb{R}^{n}$ be closed and convex. For every $x \in \mathbb{R}^{n} \backslash K$ the hyperplane $H$ containing $x^{\prime}:=p_{K}(x)$ and perpendicular to the line joining $x$ and $x^{\prime}$ is a supporting hyperplane of $K$ described by $H=\{y \mid\langle y, u\rangle=1\}$, for $u=\frac{x-x^{\prime}}{\left\langle x^{\prime}, x-x^{\prime}\right\rangle}$, unless $H$ contains 0 . Proof: The hyperplane $H:=\{y \mid\langle y, u\rangle=1\}$ ( $u$ as before) is perpendicular to $x-x^{\prime}$ and satisfies $x^{\prime} \in H$. Moreover, $\left\langle x-x^{\prime}, x-x^{\prime}\right\rangle>0$ implies $\left\langle x, x-x^{\prime}\right\rangle>\left\langle x^{\prime}, x-x^{\prime}\right\rangle$ and, thus, $x \in H^{+}$. Suppose $H$ is not a supporting hyperplane of $K$. Then there exists some $y \in K \cap\left(H^{+} \backslash H\right), y \neq x$. By elementary geometry applied to the plane $E$ spanned by $x, x^{\prime}$, and $y$, the line segment $\left[y, x^{\prime}\right]$ contains a point $z$ interior to the circle in $E$ about $x$ with radius $\left\|x-x^{\prime}\right\|$. Then, $\|x-z\|<\left\|x-x^{\prime}\right\|$, a contradiction.
3.6 Lemma. Let $K \subset \mathbb{R}^{n}$ be closed and convex, and let $x \in \mathbb{R}^{n} \backslash K$. Suppose $y$ lies on the ray emanating from $x^{\prime}$ and containing $x$. Then $x^{\prime}=y^{\prime}$.
Proof: First, assume $y \in\left[x, x^{\prime}\right]$. Then in the case $x^{\prime} \neq y^{\prime}$,

$$
\left\|x-x^{\prime}\right\|=\left\|y-x^{\prime}\right\|+\|x-y\|>\left\|y-y^{\prime}\right\|+\|x-y\| \geq\left\|x-y^{\prime}\right\|,
$$

a contradiction.
If $x \in\left[y, x^{\prime}\right], x^{\prime} \neq y^{\prime}$, then, the line parallel to $\left[y, x^{\prime}\right]$ through $x$ meets $\left[x^{\prime}, y^{\prime}\right]$ in a point $x_{0} \neq x^{\prime}$. From $\left\|x-x_{0}\right\|=\left\|x-x^{\prime}\right\|\left\|y-y^{\prime}\right\|$ (similar triangles) and $\left\|y-y^{\prime}\right\|<\left\|y-x^{\prime}\right\|$ (Lemma 3.1), we obtain $\left\|x-x_{0}\right\|<\left\|x-x^{\prime}\right\|$, a contradiction.
3.7 Lemma (Busemann and Feller's lemma). $p_{K}$ does not increase distances, and, hence, is Lipschitz with Lipschitz constant 1. In particular, $p_{K}$ is uniformly continuous.

Proof: Let $x, y \in \mathbb{R}^{n} \backslash K$. For $p_{K}(x)=p_{K}(y)$, the lemma is trivial; so, suppose $p_{K}(x) \neq$ $p_{K}(y)$, and let $g$ be the line through $x^{\prime}:=p_{K}(x)$ and $y^{\prime}:=p_{K}(y)$. We denote by $H_{1}, H_{2}$ the hyperplanes perpendicular to $g$ in $x^{\prime}, y^{\prime}$, respectively.

Neither of $x$ and $y$ lies in the open stripe $S$ bounded by $H_{1}$ and $H_{2}$, for if, say, $x$ does, the foot $x_{0}$ (orthogonal projection) of $x$ on $g$ lies in $K$, and then

$$
\left\|x-x_{0}\right\|<\left\|x-x^{\prime}\right\|
$$

a contradiction. Also, the points $x, y$ cannot lie on the same side of $H_{1}$ or $H_{2}$ opposite to $S$ since $\left[x, x^{\prime}\right] \cap(S \backslash K) \neq \emptyset$ or $\left[y, y^{\prime}\right] \cap(S \backslash K) \neq \emptyset$ would contradict what we have just shown and Lemma 3.6.
3.8 Theorem. A closed convex proper subset of $\mathbb{R}^{n}$ is the intersection of its supporting half-spaces.

Proof: By Lemma 3.5, there exists a supporting half-space of $K$. Let $K^{\prime}:=\bigcap H^{+}$for all supporting half-spaces $H^{+}$of $K$. Clearly, $K \subset K^{\prime}$.

Suppose $x \in K^{\prime} \backslash K$. Then $p_{K}(x) \neq x$ and, hence, by Lemma 3.5, the hyperplane perpendicular in $p_{K}(x)$ to the line joining $x$ and $p_{K}(x)$ separates $x$ and $K$, so that $x \notin K^{\prime}$, a contradiction.

Remark. In general, not all supporting half-spaces of $K$ are needed to represent $K$ as their intersection. A triangle in $\mathbb{R}^{2}$, for example, has infinitely many supporting half-places, but three half-planes already suffice to represent the triangle as their intersection.
3.9 Theorem. Any closed convex set $K$ possesses a supporting hyperplane at each of its boundary points.

Proof: Suppose $x_{0} \in \partial K$ is a boundary point of $K$, that is, any open disc $U_{\delta}$ with center $x_{0}$ and radius $\delta>0$ contains points from $\mathbb{R}^{n} \backslash K$. Then, $x_{0}$ is the limit point of a sequence $\left\{x_{j}\right\} \rightarrow x_{0}$ with $x_{j} \in \partial K$, such that there exist supporting hyperplanes $H_{i}$ of $K$ at $x_{i}$ according to Lemma 3.5. Let $s_{i}$ be the ray of outer normals of $H_{i}$ in $i=1,2, \ldots$, and let $S$ be a sphere with center $x_{0}$.

For sufficiently large $i, s_{i} \cap S$ is a point $y_{i}$, and $x_{i}=p_{K}\left(y_{i}\right)$ by Lemma 3.6. $\left\{y_{i}\right\}$ has a cluster point $y_{0} \neq x_{0}$. Since $p_{K}$ is a continuous (Lemma 3.7), $p_{K}\left(y_{0}\right)=x_{0}$ and $y_{0} \notin K$ otherwise $p_{K}\left(y_{0}\right)=y_{0}=x_{0}$ would follow. Therefore, Lemma 3.5 applies, and the theorem follows.

## Exercises

1. Let $K \subset \mathbb{R}^{n}$ be closed and convex. Then, $\operatorname{dim} K=k$ if and only if, for any $x \in \operatorname{rint} K$, the set $p_{K}^{-1}(x)$ is an $(n-k)$-dimensional affine space, $0 \leq k \leq n$.
2. Every closed convex set is the intersection of countably many of its supporting halfspaces.
3. Let $M \subset \mathbb{R}^{n}$ be compact. pos $M$ has an apex if $0 \notin \operatorname{conv} M$.
4. A closed set $K \subset \mathbb{R}^{n}$ that possesses a well-defined nearest point map is convex. (Hint: Reduce the problem to $n=2$. Use increasing sequences $B_{1} \subset B_{2} \subset \ldots$ of circular discs $B_{j} \subset \mathbb{R}^{2} \backslash K, j=1,2, \ldots$.

## Faces and normal cones

Although faces and normal cones will mainly be used in the special case of polytopes, we introduce them for closed convex sets. This lets us see properties specific to polytopes.
4.1 Definition. If $H$ is a supporting hyperplane of the closed convex set $K$, we call $F:=K \cap H$ a face of $K$. By convention, $\emptyset$ and $K$ are called improper faces of $K$.

If we speak about faces, it should be clear from the context whether we include $\emptyset$ or $K$ or not.

By Lemma 1.2,
4.2 Lemma Every face of a closed convex set $K$ is again a closed convex set.

So we can speak about the dimension of a face. Recall the convention $\operatorname{dim} \emptyset=-1$.
4.3 Definition. By a $k$-face $F$ of $K$, we mean a face of dimension $k$. We call $F$

- (a) a vertex of $K$, if $k=0$
- (b) an edge of $K$, if $k=1$,
- (c) a facet of $K$, if $k=\operatorname{dim} K-1$.

We denote the set of vertices of $K$ by vert $K$.
4.4 Lemma. Let $F_{0}$ and $F_{1}$ be faces of a closed convex set $K$ such that $F_{0} \subset F_{1}$. Then, $F_{0}$ is a (possibly improper) face of $F_{1}$.

Proof: Let $F_{0}=K \cap H_{0}$, where $H_{0}$ is a supporting hyperplane of $K$ and, hence, also of $F_{1}$. Then,

$$
F_{1} \cap H_{0} \subset K \cap H_{0}=F_{0} \subset F_{1} \cap H_{0},
$$

hence, $F_{0}=F_{1} \cap H_{0}$ which proves the lemma.

Remark. The converse of Lemma 4.4 is false. As Figure 6 illustrates, $F_{0}$ can be a face of $F_{1}, F_{1}$ a fake of $K$, but $F_{0}$ cannot be a face of $K$. For a polytope, however, the converse of Lemma 4.4 is true (see Chapter $I I$, Theorem 1.7).

Now, we will generalize Lemma 4.4.
4.5 Lemma. If $F_{1}, \ldots, F_{r}$ are faces of a closed convex set $K$, then, $F:=F_{1} \cap \ldots \cap F_{r}$ is also a (possibly improper) face of $K$.

Proof: Since being a face is not affected by doing so, we may assume $0 \in F$ (unless $F=\emptyset$ in which case there is nothing to prove).

Let $H_{i}=\left\{x \mid\left\langle x, u_{i}\right\rangle=0\right\}$ be a supporting hyperplane of $K$ such that $F_{i}=K \cap H_{i}, i=$ $1, \ldots, r$. By possibly changing signs of some of the $u_{i}$, we can arrange

$$
K \subset H_{i}^{-}=\left\{x \mid\left\langle x, u_{i}\right\rangle \leq 0\right\}, \quad i=1, \ldots, r .
$$

We set $u:=u_{1}+\ldots+u_{r}$. If necessary, we can replace $u_{1}$ by $2 u_{1}$ so that $u \neq 0$ can always be assumed. We find

$$
\langle x, u\rangle=\left\langle x, u_{1}\right\rangle+\ldots+\left\langle x, u_{r}\right\rangle \leq 0 \quad \text { for all } x \in K
$$

Therefore, $H:=\{x \mid\langle x, u\rangle=0\}$ is a supporting hyperplane of $K$. Moreover, $\langle x, u\rangle=0$ is true if and only if $\left\langle x, u_{1}\right\rangle=\ldots=\left\langle x, u_{r}\right\rangle=0$. Hence,

$$
x \in K \cap H \text { if and only if } x \in\left(K \cap H_{1}\right) \cap \ldots \cap\left(K \cap H_{r}\right)=F .
$$

### 4.6 Lemma.

1. Suppose $F$ is a face of the closed convex set $K$ and $x, \tilde{x} \in$ rint $F$. Then, any supporting hyperplane of $K$ at $x$ also contains $\tilde{x}$.
2. If $F, F^{\prime}$ are faces of $K$ and $($ rint $F) \cap\left(\right.$ rint $\left.F^{\prime}\right) \neq \emptyset$, then, $F=F^{\prime}$.

Proof:

1. (a) The line segment $\left[x, x^{\prime}\right]$ is properly contained in a line segment $\left[y, y^{\prime}\right] \subset \operatorname{rint} F$. Should a supporting hyperplane at $x$ not contain $\tilde{x}$ two of the points $\tilde{x}$ and $y, \tilde{y}$, would be separated, a contradiction.
2. (b) is obvious.
4.7 Definition. Let $x$ be a point of the closed convex set $K$. We call

$$
N(x):=-x+p_{K}^{-1}(x)
$$

the normal cone of $K$ at $x$.
4.8 Lemma. $N(x)$ is a closed convex cone; it consists of 0 and all outer normals of $K$ in $x$. If $x \in$ int $K$, then, $N(x)=\{0\}$.

Proof: First, note that $N(x)$ is, indeed, a cone. From Lemmas 3.5 and 3.6, we deduce the second part of the lemma. $p_{K}^{-1}(x)$ and, hence, $-x+p_{K}^{-1}(x)$ is closed since $p_{K}$ is continuous (Lemma 3.7). To show that $N(x)$ is convex, we arrange for $x=0$ with a translation. Then, for $u, v \in N(0)$, we may assume $\langle K, u\rangle \leq 0$ and $\langle K, v\rangle \leq 0$, so that

$$
\langle K, \lambda u+(1-\lambda) v\rangle \leq 0 \quad \text { for } 0 \leq \lambda \leq 1 ;
$$

hence, $\lambda u+(1-\lambda) v \in N(0)$.
4.9 Definition. Let $\sigma$ be a cone. Then,

$$
\check{\sigma}:=\{y \mid\langle\sigma, y\rangle \geq 0\}
$$

is called the dual cone of $\sigma$ (Figure 7).
Lemma 4.8 implies Lemmas 4.10 and 4.11.
4.10 Lemma. If $\sigma$ is a cone with apex 0 , then $N(0)=-\check{\sigma}(\check{\sigma}$ reflected in 0$)$.
4.11 Lemma. Let $F$ be a face of the closed convex set $K$. For $x, \tilde{x} \in \operatorname{rint} F$, $N(x)=N(\tilde{x})$.

Proof: This follows readily from Lemma 4.6.
4.12 Definition. If $F$ is a face of a closed convex set $K$ and $x \in \operatorname{rint} F$, then $N(x)$ is denoted by $N(F)$ and is called the cone of normals of $K$ in $F$.
4.13 Theorem. Let $K$ be a convex body in $\mathbb{R}^{n}$ and $x(F)$ one of the relative interior points of a face $F \neq \emptyset$ of $K$. Then, $\{$ rint $N(x(F)) \mid F$ a face of $K\}=\{\operatorname{rint} N(F) \mid F$ a face of $K\}$ is a partition (disjoint covering) of $\mathbb{R}^{n}$.

Proof: Let $0 \neq u \in \mathbb{R}^{n}$. Since $K$ is bounded, there exists a hyperplane $H(\alpha, u)=\{z \mid\langle z, u\rangle=$ $\alpha\}$ such that $K \subset H^{-}(\alpha, u)$. Put $H^{-}=\bigcap_{\alpha} H^{-}(\alpha, u)$, the intersection taken for all $\alpha$, such that $K \subset H^{-}(\alpha, u)$. Clearly, $H^{-}$is again a closed half-space and $F:=H \cap K \neq \emptyset$. For $x(F) \in \operatorname{rint} F, u \in \operatorname{rint} N(x(F)) ;$ this is elementary in every plane passing through $x(F)$ and containing $u$; hence, it carries over the general situation. So, every $u \neq 0$ occurs in some cont rint $N(x(F))$. Also, the point 0 occurs in rint $N(x(K))$ since, for $x \in$ rint $K$, the cone $N(x)$ is a linear space $(=\{0\}$ if $\operatorname{dim} K=n)$.

Suppose $y \in \operatorname{rint} N\left(x\left(F_{1}\right)\right) \cap$ rint $N\left(x\left(F_{2}\right)\right)$. Then, $p_{K}\left(y+x\left(F_{1}\right)\right)=x\left(F_{1}\right)$ and $p_{K}(y+$ $\left.x\left(F_{2}\right)\right)=x\left(F_{2}\right)$ so that, by Lemma 3.5, the supporting hyperplanes in $x\left(F_{1}\right)$ and $x\left(F_{2}\right)$ coincide. This implies $F_{1}=F_{2}$.
4.14 Definition. $\Sigma(K)$ denotes the set of all cones $N(F)$ and is called the fan of $K$ (see Figure 8).

## Exercises

1. Let $K$ be convex and closed, int $K \neq \emptyset$, and let $L$ be an affine subspace such that $L \cap$ int $K=\emptyset, L \cap K \neq \emptyset$. Show that there exists a supporting hyperplane of $K$ which contains $L$.
2. Characterize convex polytopes which have the same fan.

## Support function and distance function

Now we will generalize the linear function $h_{\{a\}}:=\langle a, \cdot\rangle$ for arbitrary compact subsets $K$ of $\mathbb{R}^{n}$ :
5.1 Definition. Let $K \subset \mathbb{R}^{n}$ be a nonempty convex body. The map

$$
h_{K}: \mathbb{R}^{n} \rightarrow \mathbb{R} \text { defined by } u \mapsto \sup _{x \in K}\langle x, u\rangle
$$

is called the support function of $K$. The next statement is an obvious consequence of the definition.
5.2 Lemma. If $K+a$ is a translate of the convex body $K$, then,

$$
h_{K+a}(u)=h_{K}(u)+\langle a, u\rangle \quad \text { for all } u \in \mathbb{R}^{n} .
$$

Example 1. For $n=1$, set $K=[c, d]$. Then

$$
h_{[c, d]}(u)= \begin{cases}\langle d, u\rangle & \text { for } u \geq 0 \\ \langle c, u\rangle & \text { for } u \leq 0\end{cases}
$$

### 5.3. Lemma.

1. For every fixed nonzero $u \in \mathbb{R}^{n}$, the hyperplane

$$
\begin{equation*}
H_{K}(u):=\left\{x \mid\langle x, u\rangle=h_{K}(u)\right\}, \tag{*}
\end{equation*}
$$

is a supporting hyperplane of $K$.
2. Every supporting hyperplane of $K$ has a representation of the form (*).

Proof:

1. (1) Since $K$ is compact and $\langle\cdot, u\rangle$ is continuous, for some $x_{0} \in K$,

$$
\left\langle x_{0}, u\right\rangle=h_{K}(u)=\sup _{x \in K}\langle x, u\rangle .
$$

For an arbitrary $y \in K$, it follows that $\langle y, u\rangle \leq\left\langle x_{0}, u\right\rangle$; hence $K \subset H_{K}^{-}(u)$. This proves (1).
2. (2) Let $H=\left\{x \mid\langle x, u\rangle=\left\langle x_{0}, u\right\rangle\right\}$ be a supporting hyperplane of $K$ at $x_{0}$. We choose $u \neq 0$ such that $K \subset H^{-}$. Then, $\left\langle x_{0}, u\right\rangle=\sup _{x \in K}\langle x, u\rangle=h_{K}(u)$ which implies (2).
5.4 Definition. A function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is said to be convex if, for all $0 \leq \lambda \leq 1$ and $x, y \in \mathbb{R}^{n}$,

$$
f(\lambda x+(1-\lambda) y \leq \lambda f(x)+(1-\lambda) f(y)
$$

Note that if $f$ is convex and $L$ is an affine subspace of $\mathbb{R}^{n}$, then, $\left.f\right|_{L}$ is also convex.
Example 2. For $n=1$ and $x, y \in \mathbb{R}$, the graph $\Gamma(f)$ of a convex function $f$ lies "below" the line-segment $[(x, f(x)),(y, f(y))]$ in $\mathbb{R}^{2}$. Hence for convex $f$, if $a \leq-1<b<0, f(b)=1$, and $f(0)=0$, then, $(a, f(a))$ and $(-b,-f(-b))$ are "above" the line through $(b, 1)$ and $(0,0)$, so that $f(a) \geq-\frac{1}{b}$ and $f(b) \geq-f(-b)$.
5.5 Definition. A function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is called positive homogeneous if, for any $\lambda \geq 0$ and $x \in \mathbb{R}^{n}$,

$$
f(\lambda x)=\lambda f(x)
$$

5.6 Lemma. A positive homogeneous function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is convex if and only if

$$
\begin{equation*}
f(x+y) \leq f(x)+f(y) \quad \text { for all } x, y \in \mathbb{R}^{n} \tag{1}
\end{equation*}
$$

Proof: Let the positive homogeneous function $f$ be convex. Then (1) follows from

$$
\frac{1}{2} f(x+y)=f\left(\frac{1}{2} x+\frac{1}{2} y\right) \leq \frac{1}{2} f(x)+\frac{1}{2} f(y) .
$$

Conversely, if (1) holds for $f$, then, for $0 \leq \lambda \leq 1$,

$$
f(\lambda x+(1-\lambda) y) \leq f(\lambda x)+f((1-\lambda) y)=\lambda f(x)+(1-\lambda) f(y)
$$

so $f$ is convex.

### 5.7 Lemma.

1. A function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is convex if and only if, for every convex combination $x=$ $\lambda_{0} x_{0}+\ldots+\lambda_{n} x_{n}, \lambda_{0} \geq 0, \ldots, \lambda_{n} \geq 0, \lambda_{0}+\ldots+\lambda_{n}=1$ of points $x_{0}, \ldots, x_{n}$

$$
\begin{equation*}
f(x) \leq \lambda_{0} f\left(x_{0}\right)+\ldots+\lambda_{n} f\left(x_{n}\right) . \tag{1}
\end{equation*}
$$

2. Every convex function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is continuous.
3. $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is convex if and only if $\Gamma^{+}(f):=\left\{(x, \xi) \mid x \in \mathbb{R}^{n}, \xi \in \mathbb{R}, f(x) \leq \xi\right\}$ is a closed and convex subset of $\mathbb{R}^{n+1}$.
4. A positive homogeneous function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is convex if and only if $\Gamma^{+}(f)$ is a closed convex cone.

Proof:

1. (1) If eq. (1) is true, we obtain, for $x_{1}=\ldots=x_{n}$ (using $1-\lambda_{0}=\lambda_{1}+\ldots+\lambda_{n}$ ),

$$
f\left(\lambda_{0} x_{0}+\left(1-\lambda_{0}\right) x_{1}\right) \leq \lambda_{0} f\left(x_{0}\right)+\left(1-\lambda_{0}\right) f\left(x_{1}\right)
$$

so that $f$ is convex.
If conversely, $f$ is convex, we proceed by induction and assume $f$ satisfies (1) (with $n$ replaced by $n-1$ ) on each $(n-1)$-dimensional affine subspace of $\mathbb{R}^{n}$. Then, for $\lambda_{0}<1$ and $y:=\left(1-\lambda_{)}^{-1}\left(\lambda_{1} x_{1}+\ldots+\lambda_{n} x_{n}\right)=\left(\lambda_{1}+\ldots+\lambda_{n}\right)^{-1}\left(\lambda_{1} x_{1}+\ldots+\lambda_{n} x_{n}\right)\right.$, we find

$$
\begin{aligned}
& f\left(\lambda_{0} x_{0}+\ldots+\lambda_{n} x_{n}\right)=f\left(\lambda_{0} x_{0}+\left(1-\lambda_{0}\right) y\right) \\
& \leq \lambda_{0} f\left(x_{0}\right)+\left(1-\lambda_{0}\right) f(y) \\
& \leq \lambda_{0} f\left(x_{0}\right)+\left(\lambda_{1}+\ldots+\lambda_{n}\right)\left(\sum_{i=1}^{n}\left(\lambda_{1}+\ldots+\lambda_{n}\right)^{-1} \lambda_{i} f\left(x_{i}\right)\right) \\
& =\lambda_{0} f\left(x_{0}\right)+\lambda_{1} f\left(x_{1}\right)+\ldots+\lambda_{n} f\left(x_{n}\right)
\end{aligned}
$$

so that (1) follows.
2. (2) Given a point $x_{0}$ in $\mathbb{R}^{n}$, we consider a regular $n$-simplex $T:=\operatorname{conv}\left\{x_{1}, \ldots, x_{n+1}\right\}$ which possesses $x_{0}$ as center of gravity and for which $\left\|x_{1}-x_{0}\right\|=\ldots=\left\|x_{n+1}-x_{0}\right\|=1$. We set $d:=\max \left\{\left|f\left(x_{1}\right)-f\left(x_{0}\right)\right|, \ldots,\left|f\left(x_{n 1}\right)-f\left(x_{0}\right)\right|\right\}$. Let $x$ lie in a $\delta_{0}$-neighborhood $U_{\delta_{0}}\left(x_{0}\right)$ of $x_{0}$ such that $U_{\delta_{0}}\left(x_{0}\right) \subset T$. Since $T$ is covered by $n$-simplices $T_{i}:=\mathrm{conv}$ $\left\{x_{0}, \ldots, x_{i-1}, x_{i+1}, \ldots, x_{n+1}\right\}, i=1, \ldots, n+1$, we may assume $x$ to line in one of the $T_{i}$, say in $T_{n+1}, x=\lambda_{0} x_{0}+\ldots+\lambda_{n} x_{n}, \lambda_{0} \geq 0, \ldots, \lambda_{n} \geq 0, \lambda_{0}+\ldots+\lambda_{n}=1$. Clearly, $\lambda_{i}<\delta_{0} \leq 1, i=1, \ldots, n$. We may assume $f(x) \geq 0$ in $T$ (up to adding a constant). Given $\epsilon>0$, we may choose $\delta:=\frac{\epsilon}{n(d+1)}$ and obtain (using (1) and assuming $\delta \leq \delta_{0}$ )

$$
\begin{aligned}
\left|f(x)-f\left(x_{0}\right)\right| & \leq\left|\lambda_{0} f\left(x_{0}\right)+\ldots+\lambda_{n} f(n)-f\left(x_{0}\right)\right| \\
=\mid \lambda_{1}\left(f\left(x_{1}\right)\right. & \left.-f\left(x_{0}\right)\right)+\ldots+\lambda_{n}\left(f\left(x_{n}\right)-f\left(x_{0}\right)\right) \mid \\
& \leq\left(\lambda_{1}+\ldots+\lambda_{n}\right) d<n \delta(d+1)=\epsilon .
\end{aligned}
$$

Therefore, $f$ is continuous.
3. (3) let $f$ be convex. Given $(x, \xi),(y, \eta) \in \Gamma^{+}(f), 0 \leq \alpha \leq 1$,

$$
f(\alpha x+(1-\alpha) y) \leq \alpha f(x)+(1-\alpha) f(y) \leq \alpha \xi+(1-\alpha) \eta
$$

hence,

$$
\alpha(x, \xi)+(1-\alpha)(y, \eta)=(\alpha x+(1-\alpha) y, \alpha \xi+(1-\alpha) \eta) \in \Gamma^{+}(f)
$$

Therefore, $\Gamma^{+}(f)$ is convex. From (2), it readily follows that $\Gamma^{+}(f)$ is also closed. The arguments may, obviously, be reversed.
4. (4) Consider if $f$ is homogeneous and convex, the closed set $\Gamma^{+}(f)$ is a cone. If, conversely, $\Gamma^{+}(f)$ is a closed and convex cone, $f$ is homogeneous, and by (3), convex.

## Remarks.

1. By Caratheodory 's theorem, in (a) we may choose $x$ to be a convex combination of an arbitrary number of points.
2. If, in the definition of a convex function, $\mathbb{R}^{n}$ is replaced by a closed convex subset of $\mathbb{R}^{n},(2)$ and (3) need no longer be true. Example: Let the subset be the closed unit ball $B$ of $\mathbb{R}^{n}$, and let $f(x)=0$ for $x \in \operatorname{int} B, f(x)=1$ for $x \in \partial B$.
5.8 Lemma. The support function $h_{K}$ of a convex body $K$ is positive homogeneous and convex.

Proof: Let $\lambda \geq 0$. It's easy to see

$$
h_{K}(\lambda u)=\sup _{x \in K}\langle x, \lambda u\rangle=\lambda \sup _{x \in K}\langle x, u\rangle=\lambda h_{K}(u) .
$$

Hence, $h_{K}$ is positive homogeneous.
From $\langle x, u\rangle \leq h_{K}(u),\langle x, v\rangle \leq h_{K}(v) \forall x \in K$, we obtain

$$
\langle x, u+v\rangle \leq h_{K}(u)+h_{K}(v) \quad \text { for all } x \in K
$$

Hence,

$$
h_{K}(u+v)=\sup _{x \in K}\langle x, u+v\rangle \leq h_{K}(u)+h_{K}(v) .
$$

Therefore, by Lemma 5.6, $h_{K}$ is convex.
5.9 Lemma. $h_{K}$ is linear on each cone of the fan $\Sigma(K)$ of $K$.

Proof: All points $u$ in a fixed cone $\sigma$ of $\Sigma(K)$ have the same nearest point $x_{0}:=p_{K}(u)$. As in the proof of Lemma 5.3(b) we obtain

$$
\left.h_{K}\right|_{\sigma}=\left.\left\langle x_{0}, \cdot\right\rangle\right|_{\sigma}
$$

5.10 Definition. Let $K$ be an $n$-dimensional convex body in $\mathbb{R}^{n}$, and let $0 \in \operatorname{int} K$. Then we can denote the map as

$$
d_{K}: \mathbb{R}^{n} \rightarrow \mathbb{R}
$$

defined by

$$
d_{K}(\lambda \tilde{x}):=\lambda, \quad \text { for } \bar{x} \in \partial K \text { and } \lambda \geq 0
$$

is called the distance function of $K$.
We can show that $d_{K}$ is well defined (part (b) of the following lemma).
5.11 Lemma. Let $K$ be an $n$-dimensional convex body in $\mathbb{R}^{n}$.

1. If a line $g$ intersects $\partial K$ in three different points, then, $g$ is contained in a supporting hyperplane of $K$, so, in particular, $g \cap$ int $K=\emptyset$.
2. Any ray emanating from a point in int $K$ intersects a $K$ in one and only one point.

Proof:

1. Let $A, B, C \in g \cap \partial K$, and let $B$ lie between $A$ and $C$. We consider a supporting hyperplane $H=\{x \mid\langle x, u\rangle=c\}$ of $K$ in $B$. If $H$ did not contain both $A$ and $C$, it would separate these points properly, which contradicts the definition of a supporting hyperplane.
2. Let $y \in \operatorname{int} K, \sigma$ be a ray emanating from $y$, and $h$ be the line that contains $\sigma$. The intersection $h \cap K$ is a convex body, hence, a line segment $\left[y_{0}, y_{1}\right]$. Either $y_{0}$ or $y_{1}$ equals $\sigma \cap \partial K$.
5.12 Lemma. The distance function $d_{K}$ is positive homogeneous and convex.

Proof: By definition, $d_{K}$ is positive homogeneous.
To prove convexity, let $d_{K}(x)=\lambda, d_{K}(y)=\mu$. If $\lambda=0$ or $\mu=0$, then $x=0$ or $y=0$, and there is nothing to prove. So, let us consider $\lambda, \mu \neq 0$. Take $\delta:=\frac{\mu}{\lambda+\mu}$, we obtain $(1-\delta) \bar{x}+\delta \bar{y} \in K$, for $\lambda \bar{x}=x, \mu \bar{y}=y$, hence,

$$
\begin{aligned}
1 \geq d_{K}((1-\delta) \bar{x}+\delta \bar{y}) & =d_{K}\left(\frac{\lambda}{\lambda+\mu} \bar{x}+\frac{\mu}{\lambda+\mu} \bar{y}\right)=d_{K}\left(\frac{1}{\lambda+\mu}(x+y)\right) \\
& =\frac{1}{\lambda+\mu} d_{K}(x+y),
\end{aligned}
$$

hence, $d_{K}(x+y) \leq \lambda+\mu=d_{K}(x)+d_{K}(y)$. So $d_{K}$ is convex by Lemma 5.6.
5.13 Definition. A convex body $K$ is called centrally symmetric if it is mapped onto itself by a reflection in a point $c$ (which assigns to each $x=c+(x-c)$ the point $c-(x-c)=2 c-x$. We call $c$ the center of $K$.

From the above lemmas, we can derive Theorem 5.14.
5.14 Theorem. Let $K$ be a centrally symmetric convex body with $0 \in$ int $K$ as its enter. Then, $d_{K}$ defines a norm on the vector space $\mathbb{R}^{n}$, that is, a map

$$
d_{K}=\|\cdot\|: \mathbb{R}^{n} \rightarrow \mathbb{R}
$$

satisfying, for all $x, y \in \mathbb{R}^{n}$ and $\lambda \in \mathbb{R}$.

- $\|x\|=0$ if and only if $x=0$,
- $\|\lambda x\|=|\lambda| \cdot\|x\|$,
- $\|x+y\| \leq\|x\|+\|y\|$.

Example 3. The "maximum norm" in $\mathbb{R}^{2}$ is of the form

$$
d_{K}(x):=\max \left\{\left|x_{1}\right|,\left|x_{2}\right|\right\}
$$

where $x=\left(x_{1}, x_{2}\right)$ and $K$ is the square with vertices $(1,1),(1,-1),(-1,1),(-1,-1)$.
Example 4. Consider the "Manhattan norm" $d_{K^{\prime}}(x):=\left|x_{1}\right|+\left|x_{2}\right|$ where $K^{\prime}$ is the square with vertices $(1,0),(0,1),(-1,0),(0,-1)$.

In the following section, I will provide explanation into how these norms in the above examples are interconnected.
Exercises

## Polar bodies

Let us consider the polarity $\pi$ in $\mathbb{R}^{n}$ with respect to the unit sphere $S:=\{x \mid\langle x, x\rangle=1\}$. It assigns to every affine subspace $W$ of $\mathbb{R}^{n}$ with $0 \notin W$ a subspace $\pi(W)$ of of $\mathbb{R}^{n}$ of dimension $n-1-\operatorname{dim} W:$ If $0 \neq u$ is a point in $\mathbb{R}^{n}$, then,

$$
\pi(u)=H_{u}:=\{x \mid\langle x, u\rangle=1\} .
$$

If the affine subspaces $U$ and $V$ which generate $W$ are not parallel and if $W$ does not contain 0 , then, $\pi(W)=\pi(U) \cap \pi(V)$. Note that $\pi \circ \pi$ is the identity.

The exceptional role of the point 0 can be avoided by going over to the projective extension of $\mathbb{R}^{N}$ by adding a "hyperplane at infinity", $H_{\infty}$. Then, $\pi(0)=H_{\infty}$. That will be needed, for example, in Lemma 3.
6.1 Definition. Let $0 \in \operatorname{int} K$, where $K$ is a convex body. Then, for $u \neq 0$, the half-spaces $H_{u}^{-}$which contain 0 and, for $H_{0}^{-}:=\mathbb{R}^{n}$,

$$
K^{*}:=\bigcap_{u \in K} H_{u}^{-}
$$

is called the polar body of $K$. Clearly then, we see that $0 \in \operatorname{int} K^{*}$ and $K^{*}=\bigcap_{u \in \partial K} H_{u}^{-}$, since $0 \in \operatorname{int} K$.
6.2 Definition. We will represent the points of $\mathbb{R}^{n} \cup H_{\infty}$ by the one-dimensional subspaces of $\mathbb{R}^{n+1}$ such that the points of $H_{\infty}$ are spanned by vectors $(0, \ldots, 0, \xi), \xi \neq 0$. Then, a linear transformation of $\mathbb{R}^{n+1}$ up to multiplication by a nonzero factor is called a projective transformation of $\mathbb{R}^{n} \cup H_{\infty}$. It is called permissible with respect to the convex body $K \subset \mathbb{R}^{n}$ $\cup H_{\infty}$, if $H_{\infty}$ is mapped onto a hyperplane disjoint from $K$.
6.3 Lemma. If the convex body $K$ is so translated to $\tau(K)$ that 0 remains in the interior, then, $(\tau(K))^{*}$ is obtained from $K^{*}$ by a permissible projective transformation.

Proof: This follows from general facts on projective transformations.
6.4 Theorem. Let $K$ be a convex body with $0 \in$ int $K$. Then,

1. $K^{* *}=K$;
2. The distance function of $K$ equals the support function of $K^{*}$, and, conversely

$$
d_{K}=h_{K^{*}} \quad d_{K}^{*}=h_{K} .
$$

Proof.

- By definition of $H_{u}$, for every $u \neq 0$ of $K$,

$$
H_{u}^{-}=\{x \mid\langle u, x\rangle \leq 1\}
$$

Therefore, using the obvious notation of $\langle K, x\rangle \leq 1$, we can write $K^{*}$ as

$$
K^{*}=\{x \mid\langle K, x\rangle \leq 1\} \quad \text { and } \quad K^{* *}=\left\{y \mid\left\langle K^{*}, y\right\rangle \leq 1\right\} .
$$

If $y \in K$, then, the definition of $K^{*}$ yields $\left\langle y, K^{*}\right\rangle \leq 1$ and, thus, $K \subset K^{* *}$. Suppose $K \neq K^{* *}$. Then, let $x \in K^{* *} \backslash K$. For

$$
x^{\prime}:=p_{K}(x) \quad \text { and } \quad u:=\frac{x-x^{\prime}}{\left\langle x^{\prime}, x-x^{\prime}\right\rangle},
$$

Invoking Lemma 3.5 yields

$$
x \in H_{u}^{+} \backslash H_{u}, \quad \text { but also } K \subset H_{u}^{-},
$$

whence $u \in K^{*}$. Since $x \in K^{* *}$, it follows that $\langle u, x\rangle \leq 1$,i.e., $x \in H_{u}^{-}$, a contradiction. Thus we've proved part (a), but need two supporting lemmas to prove (b) first.
6.5 Lemma. Let $K_{1}, K_{2}$ be convex bodies such that $0 \in$ int $K_{1}$ and $K_{1} \subset K_{2}$. Then, $K_{2}^{*} \subset K_{1}^{*}$.

Proof: If $y \in K_{2}^{*}$, then, $\left\langle K_{2}, y\right\rangle \leq 1$, hence, in particular, $\left\langle K_{1}, y\right\rangle \leq 1$. This implies $y \in K_{1}^{*}$.
6.6 Lemma. If $x \in \partial K, 0 \in$ int $K$, then, $H_{x}$ is a supporting hyperplane of $K^{*}$.

Proof: We know that $K^{*}=\bigcap_{x \in \partial K} H_{x}^{-}$. For every $x \in \partial K$, there exists a $\beta_{x} \in \mathbb{R}_{\geq 1}$ such that $H_{\beta, x}$ is a supporting hyperplane of $K^{*}$. Thus, $\tilde{K}:=\operatorname{conv}\left(\left\{\beta_{x} x \mid x \in \partial K\right\}\right)$ includes $K$, obtaining

$$
\tilde{K}^{*}=\bigcap_{y \in \partial \tilde{K}} H_{y}^{-}=\bigcap_{x \in \partial K} H_{\beta, x}^{-} \supset K^{*}=\bigcap_{x \in \partial K} H_{x}^{-} .
$$

Since, obviously, $H_{\beta_{x}, x}^{-} \subset H_{x}^{-}$, we find that $\beta_{x}=1$ for every $x \in \partial K$.

Proof of (b) in Theorem 6.4. Let $u \in \mathbb{R}^{n} \backslash\{0\}$. We may assume $u \in \partial K$, hence, $d_{K}(u)=1$. By Lemma 6.6, $H_{u}$ is a supporting hyperplane of $K^{*}$, and we obtain $h_{K^{*}}(u)=1$ from Lemma 5.3.
6.7 Theorem. Let $K$ be a convex body in $\mathbb{R}^{n}$ with $0 \in$ int $K$. Set $K_{+}:=\Gamma^{+}\left(d_{K}\right) \subset \mathbb{R}^{n+1}$ (see Lemma 5.7) and $H:=\left\{(x, 1) \mid x \in \mathbb{R}^{n}\right\}$. Then,

1. $\partial K_{+}$is the graph of $d_{K}$ in $\mathbb{R}^{n+1}$.
2. $K_{+} \cap H$ is a translate of $K$.
3. $K_{+}^{*} \cap H$ is a translate of $K^{*}$.
4. $K_{+}, K_{+}^{*}$ are cones with apex 0 in $\mathbb{R}^{n+1}$.
6.8 Theorem. Every positive homogeneous and convex function $h: \mathbb{R}^{n} \rightarrow \mathbb{R}$ is the support function $h=h_{K}$ of a unique body $K$ (whose dimension is possibly less than $n$ ).

Proof. Let us write $\mathbb{R}^{n}=U \bigoplus U^{\perp}$, where $U$ is the maximal linear subspace of $\mathbb{R}^{n}$ on which $h$ is linear. Then, there exists $a \in U$ such that, for $\left(x, x^{\prime}\right) \in U \bigoplus U^{\perp}$,

$$
\begin{equation*}
h\left(x, x^{\prime}\right)=\langle x, a\rangle+\left.h\right|_{U^{\perp}}\left(x^{\prime}\right) . \tag{*}
\end{equation*}
$$

Moreover, $\Gamma^{+}\left(\left.h\right|_{U^{\perp}}\right)$ is a cone with apex 0 in $U^{\perp} \bigoplus \mathbb{R}$ (see Lemma 5.7). Thus, there exists some $b \in U^{\perp}$ such that the hyperplane $H:=\left\{(y,\langle y, b\rangle) \mid y \in U^{\perp}\right\}$ in $U^{\perp} \bigoplus \mathbb{R}$ intersects $\Gamma^{+}\left(\left.h\right|_{U^{\perp}}\right)$ only in the apex. Now the set

$$
K_{0}+(0,1):=\left(U^{\perp} \times\{1\}\right) \cap \Gamma^{+}\left(\left.h\right|_{U^{\perp}}-\langle\cdot, b\rangle\right)
$$

is a convex body and, by Lemma $5.2,\left.h\right|_{U^{\perp}}-\langle\cdot, b\rangle$, the support function of $K_{0}-b$. Finally, $(*)$ and Lemma 5.2 yield that $h$ is the support function of $K:=K_{0}-b+a$.

## Exercise

1. Let $K$ be an unbounded closed convex set, $\operatorname{dim} K=n$, and let $0 \in$ int $K$. We set $K^{*}:=\bigcap_{u \in K} H_{u}^{-}$where $H_{0}^{-}:=\mathbb{R}^{n}$.

- Show that $K^{*}$ is a convex body,
- Must $K^{* *}=K$ ?


## 2 Combinatorial theory of polytopes and polyhedral sets

### 2.1 The boundary complex of a polyhedral set

We will now turn to the specific properties of convex polytopes, or, briefly, polytopes. In 1.1 we introduced these as convex hulls of finite point sets in $\mathbb{R}^{n}$. Our first aim is to show that, equivalently, convex polytopes can be defined as bounded intersections of finitely many half-spaces.
1.1 Theorem. Each polytope possesses only finitely many faces; they, too, are polytopes.

Proof: Let $P=\operatorname{conv}\left\{x_{1}, \ldots, x_{r}\right\}$, and let $F:=P \cap H$ be a face where $H=\{x \mid\langle x, a\rangle=\alpha\}$ is a supporting hyperplane of $P$ such that $P \subset H^{-}$. We may assume the following

$$
x_{1}, \ldots, x_{s} \in H ; \quad x_{s+1}, \ldots, x_{r} \in \operatorname{int} H^{-}
$$

and find

$$
\begin{aligned}
& \left\langle x_{i}, a\right\rangle=\alpha \quad \text { for } i=1, \ldots, s \\
& \left\langle x_{i}, a\right\rangle=\alpha-\beta_{i}, \beta_{i}>0 \quad \text { for } i=s+1, \ldots, r .
\end{aligned}
$$

Then, for

$$
\begin{gathered}
x=\lambda_{1} x_{1}+\ldots+\lambda_{r} x_{r}, \quad \lambda_{1}+\ldots+\lambda_{r}=1, \quad \lambda_{j} \geq 0, \quad j=1, \ldots, r, \\
\langle x, a\rangle=\sum_{i=1}^{r} \lambda_{i}\left\langle x_{i}, a\right\rangle=\sum_{i=1}^{r} \lambda_{i} \alpha-\sum_{i=s+1}^{r} \lambda_{i} \beta_{i}=\alpha-\sum_{i=s+1}^{r} \lambda_{i} \beta_{i} .
\end{gathered}
$$

Therefore, $x \in H$ if and only if $\sum_{i=s+1}^{r} \lambda_{i} \beta_{i}=0$, which, in turn, is equivalent to $\lambda_{s+1}=$ $\ldots=\lambda_{r}=0$. So, $x$ is a convex combination of $x_{1}, \ldots, x_{s}$. Hence $H \cap P=\operatorname{conv}\left\{x_{1}, \ldots, x_{s}\right\}$ is a polytope.

Since only finitely many convex hulls of elements of $\left\{x_{1}, \ldots, x_{r}\right\}$ exist, the theorem follows.
1.2 Krein-Milman Theorem. Each polytope $P$ is the convex hull of its vertices, that is,

$$
P=\operatorname{conv}(\operatorname{vert} P)
$$

Proof: Obviously, we can see that $\operatorname{conv}($ vert $P) \subset P$. For the opposite inclusion, we may assume that $P=\operatorname{conv}\left\{x_{1}, \ldots, x_{r}\right\}$ and $x_{i} \notin \operatorname{conv}\left\{x_{1}, \ldots, x_{i-1}, x_{i+1}, \ldots, x_{r}\right\}=: P_{i}$ for $1 \leq$ $i \leq r$. Denote by $q_{i}:=p_{P_{i}}\left(x_{i}\right)$ to be the image of $x_{i}$ under the nearest point map $p_{P_{i}}$ with respect to $P_{i}$. By $I$, Lemma 5.3, the hyperplane $H_{i}$ through $q_{i}$ with normal $x_{i}-q_{i}$ is a supporting hyperplane of $P_{i}$. We translate $H_{i}$ by adding $x_{i}-q_{i}$ and so obtain a supporting hyperplane $H_{i}^{\prime}$ of $P$ for which

$$
\left\{x_{i}\right\}=H_{i}^{\prime} \cap P
$$

Therefore $x_{i}$ is a vertex of $P$. This implies $P \subset \operatorname{conv}($ vert $P)$. Hence, the theorem obviously follows.
1.3 Definition. The intersection of finitely many closed half-spaces in $\mathbb{R}^{n}$ is called a polyhedral set.
1.4 Theorem. Every polytope $P$ is a bounded polyhedral set.

Proof: We may assume that aff $P=\mathbb{R}^{n}$. Now let $F_{i}:=P \cap H_{i}$ to be the facets of $P((n-$ 1)-dimensional faces), and let $P \subset H_{i}^{-}, i=1, \ldots, s$.

Obviously, $P$ is contained in

$$
\bigcap_{i=1}^{s} H_{i}^{-}=: P^{\prime}
$$

Suppose then that $x_{0} \in P^{\prime} \backslash P$. Consider the union $\mathcal{A}$ of all affine subspaces of $\mathbb{R}^{n}$ spanned by $x_{0}$ and at most $n-1$ vertices of $P$. Since $\mathcal{A}$ has no interior points, there exists

$$
x \in(\text { int } \mathrm{P}) \backslash \mathcal{A} .
$$

The line segment $\left[x, x_{0}\right]$ is not contained in $\mathcal{A}$ and intersects $\partial P$ in a point $y$. Since $\partial P$ is the union of all (proper) faces of $P$ (I, Theorem 3.9), $y$ is contained in a face $F$. From dim $F<n-1$ would follow $x \in \mathcal{A}$, a contradiction. Therefore $F$ is a facet, say $F_{0}^{\prime}$ and $y \in$ rint $F$. But, then, aff $F_{0}$ would be one of the hyperplanes $H_{i}, i \in\{1, \ldots, s\}$, and so, $x_{0} \notin P^{\prime}$, a contradiction to the initial assumption.
1.5 Theorem. Every bounded polyhedral set is a polytope.

Proof: We will proceed by induction on $\operatorname{dim} P, P:=H_{1}^{-} \cap \ldots \cap H_{i}^{-}$. Let us assume that each of the (proper) faces $F_{j}:=H_{j} \cap P$ is a polytope. Replacing $\mathbb{R}^{n}$ by aff $P$ we may assume that $P$ is of maximal dimension. Obviously,

$$
\operatorname{conv}\left(\bigcup_{j=1}^{s} F_{j}\right) \subset P
$$

it suffices, thus, to show the opposite inclusion for int $P$. For $x \in$ int $P$, fix a ray $\sigma$ emanating from $x$ not parallel to any $H_{j}$ for $j=1, \ldots, s$. Then, by I, Lemma 5.11, $\sigma \cap \partial P$ consists of one point $x_{\sigma}$. Since $\partial P \subset \cup_{j=1}^{s} F_{j}$, the point $x_{\sigma}$ is contained in a face, say $F_{j_{\sigma}}$. The analogous statement holds for the ray opposite to $\sigma$. Since $x \in\left[x_{\sigma}, x_{\tau}\right]$, we find $x \in$ $\operatorname{conv}\left(F_{j_{\sigma}} \cup F_{\left.j_{\tau}\right]}\right)$, and, then,

$$
\operatorname{int} P \subset \operatorname{conv}\left(\bigcup_{j=1}^{s} F_{j}\right)
$$

We may then summarize Theorems 1.4 and 1.5 as follows:

$$
\text { polytopes }=\text { bounded polyhedral sets }
$$

1.6 Corollary. Any affine subspace $L$ of $\mathbb{R}^{n}$ intersects a given polyhedral set (polytope) $P$ in a polyhedral set (polytope).

We are now ready to prove the converse of $I$, Lemma 4.4, in the case of polytopes.
1.7 Theorem. Let $P$ be a polyhedral set. If $F_{1}$ is a face of $P$ and $F_{0}$ is a face of $F_{1}$, then, $F_{0}$ is a face of $P$.

Proof: First, let us assume $P$ to be bounded, that is, a polytope $P$ and vertices $P=$ : $\left\{x_{1}, \ldots, x_{m}\right\}$. We may assume that $x_{1}=0 \in F_{0} \neq F_{1}$. There are linearly independent $u_{0}$, $u_{1}$ such that, for $H_{i}:=\left\{x \mid\left\langle x, u_{i}\right\rangle=0\right\}, i=0,1$,

$$
\begin{aligned}
& F_{0}=H_{0} \cap F_{1}, \quad F_{1} \subset H_{0}^{-} \\
& F_{1}=H_{1} \cap P, \quad P \subset H_{1}^{-} .
\end{aligned}
$$

We denote by $x_{2}, \ldots, x_{s}$ the vertices of $P \backslash F_{1}$, by $x_{s+1}, \ldots, x_{t}$ those of $F_{1} \backslash F_{0}$. For $i=$ $2, \ldots, s$, there exist points $u_{i}$ such that

$$
H_{i}:=\operatorname{lin}\left(\left\{x_{i}\right\} \cup\left(H_{0} \cap H_{1}\right)\right)=\left\{x \mid\left\langle x, u_{i}\right\rangle=0\right\} .
$$

All $u_{i}$ lie in the plane $\left(H_{0} \cap H_{1}\right)^{\perp}$; hence, we may assume that $F_{1} \subset \bigcap_{i=2}^{s} H_{i}^{-}$and that all $u_{i}$, considered as points, lie on the line $g$ through $u_{0}$ and $u_{1}$,

$$
u_{i}=u_{0}+\alpha_{i}\left(u_{1}-u_{0}\right), \quad i=2, \ldots, s .
$$

The $u_{i}$ 's even lie on the ray of $g$ emanating from $u_{1}$ and including $u_{0}$, since $\alpha_{i} \in \mathbb{R}_{<1}$. From $x_{j} \in H_{i}^{-}$, for $j \in\{s+1, \ldots, t\}$, we see that

$$
0>\left\langle x_{j}, u_{i}\right\rangle=\left(1-\alpha_{i}\right)\left\langle x_{j}, u_{0}\right\rangle .
$$

Since $F_{1} \subset H_{0}^{-}$implies $\left\langle x_{j}, u_{0}\right\rangle<0,\left(1-\alpha_{i}\right)>0$. Hence, there exists a point $u \in g$ separating $u_{1}$ from $\left\{u_{2}, \ldots, u_{s}\right\}$ properly, that is,

$$
u=\lambda_{i} u_{1}+\left(1-\lambda_{i}\right) u_{i}, \quad \text { for some } 0<\lambda_{i}<1, \quad i=2, \ldots, s .
$$

The hyperplane $H:=\{x \mid\langle x, u\rangle=0\}$ is a supporting hyperplane of $P$ with $H \cap P=F_{0}$. For $x_{j} \in F_{1}$, we obtain

$$
\left\langle x_{j}, u\right\rangle=\lambda_{i}\left\langle x_{j}, u_{1}\right\rangle+\left(1-\lambda_{i}\right)\left\langle x_{j}, u_{i}\right\rangle=\left(1-\lambda_{i}\right)\left\langle x_{j}, u_{i}\right\rangle \leq 0,
$$

since $F_{1} \subset H_{i}^{-}$. Thus, $\left\langle x_{j}, u\right\rangle=0$ if and only if $x_{j} \in F_{0} \subset H_{0} \cap H_{1}$. For $x_{i} \in$ vertices $P \backslash F_{1},\left\langle x_{i}, u_{1}\right\rangle<0$ and, thus

$$
\left\langle x_{i}, u\right\rangle=\lambda_{i}\left\langle x_{i}, u-1\right\rangle+\left(1-\lambda_{i}\right)\left\langle x_{i}, u_{i}\right\rangle=\lambda_{i}\left\langle x_{i}, u_{1}\right\rangle<0,
$$

which implies $P \subset H^{-}$and $P \cap H=F_{0}$.
If $P$ is not a polytope, we choose a sufficiently large $n$-simplex $S$ so that int $S$ intersects each face of $P$. Then, all bounded faces of $P$ are contained in int $S$. If $F$ is an unbounded face of $P$, we find that $F=P \cap H, H$ is a supporting hyperplane of $P$, if and only if $F \cap S=P \cap S \cap H$. Each face $F$ of $P$ intersects $P \cap S$ in a face $F^{\prime}:=P \cap S \cap F$ of $P \cap S$ such that $\operatorname{dim} F=\operatorname{dim} F^{\prime}$. So, the theorem readily follows from its validity for $P \cap S$.

