

Linear, affine, conic and convex hulls

Let $X \subseteq \mathbb{R}^n$:

Farkas' Lemma:

$$\text{lin. hull}(X) = \{ \lambda_1 x_1 + \dots + \lambda_t x_t \mid t \in \mathbb{N}_0, \\ x_1, \dots, x_t \in X, \lambda_1, \dots, \lambda_t \in \mathbb{R} \}$$

$$Ax \leq b$$

$$\text{affine. hull}(X) = \{ \lambda_1 x_1 + \dots + \lambda_t x_t \mid t \in \mathbb{N}_+, \\ x_1, \dots, x_t \in X, \sum_{i=1}^t \lambda_i = 1, \lambda_1, \dots, \lambda_t \in \mathbb{R} \}$$

not feas. $\Rightarrow \lambda \in \mathbb{R}_{\geq 0}^m$
s.t. $\lambda^T A = 0$
 $\lambda^T b = -1$

$$\text{cone}(X) = \{ \lambda_1 x_1 + \dots + \lambda_t x_t \mid t \in \mathbb{N}_0, \\ x_1, \dots, x_t \in X, \lambda_1, \dots, \lambda_t \in \mathbb{R}_{\geq 0} \}$$

$$\text{conv}(X) = \{ \lambda_1 x_1 + \dots + \lambda_t x_t \mid t \in \mathbb{N}_+, \\ x_1, \dots, x_t \in X, \sum_{i=1}^t \lambda_i = 1, \lambda_1, \dots, \lambda_t \in \mathbb{R}_{\geq 0} \}$$

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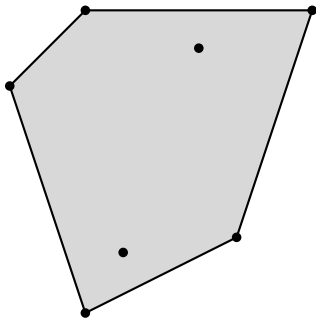


Figure: The convex hull of 7 points in \mathbb{R}^2 .

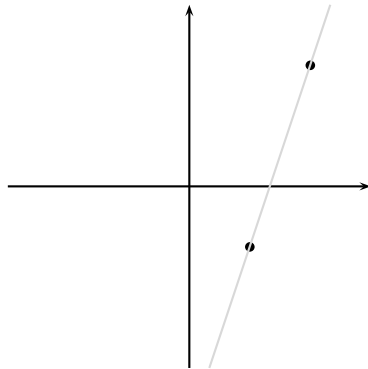
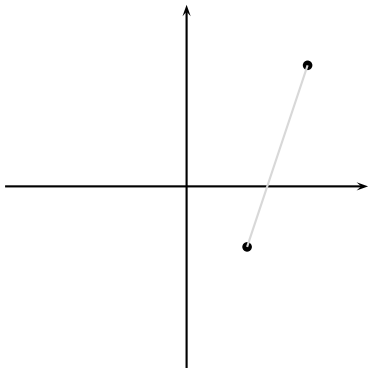


Figure: Two points with their convex hull on the left and their affine hull on the right.

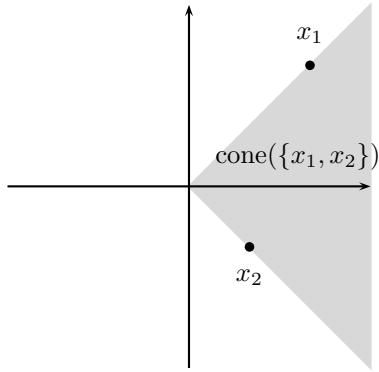


Figure: Two points with their conic hull

Linear and affine hulls

$$X - x_0 = \{x - x_0 : x \in X\}$$

Theorem

Let $X \subseteq \mathbb{R}^n$ and $x_0 \in X$. One has

$$\text{affine.hull}(X) = x_0 + \text{lin.hull}(X - x_0),$$

where for $u \in \mathbb{R}^n$ and $V \subseteq \mathbb{R}^n$, $u + V$ denotes the set $u + V = \{u + v \mid v \in V\}$.

" \subseteq " Let $y \in \text{affine.hull}(X)$. This means $\exists t \in \mathbb{N}_+$ ~~and~~ $x_1, \dots, x_t \in X$
and $\lambda_1, \dots, \lambda_t \in \mathbb{R}$ with $\sum \lambda_i = 1$ and $y = \sum_{i=1}^t \lambda_i x_i$

$$y = \sum_{i=1}^t \lambda_i X_i - x_0 + x_0 \quad \sum \lambda_i = 1$$

$$= \underbrace{\sum_{i=1}^t \lambda_i (X_i - x_0)}_{\in \text{lin. hull}(X - x_0)} + x_0$$

⇒ Let $y \in x_0 + \text{lin. hull}(X - x_0)$. This means there exists

$$t \in \mathbb{N}_0, X_1, \dots, X_t \in X \text{ s.t. } y = x_0 + \sum_{i=1}^t \lambda_i (X_i - x_0)$$

and $\lambda_1, \dots, \lambda_t \in \mathbb{R}$

$$= \sum_{i=1}^t \lambda_i X_i + x_0 - \sum_{i=1}^t \lambda_i \cdot x_0$$

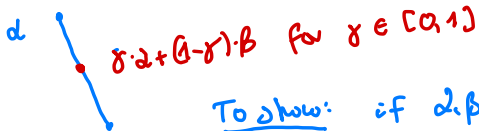
$$= \sum_{i=1}^t \lambda_i X_i + \left(1 - \sum_{i=1}^t \lambda_i\right) x_0 \quad \text{showing } \in \text{affine hull}(X)$$

Convex hull is convex

$$\text{conv}(X) = \left\{ \lambda_1 x_1 + \dots + \lambda_t x_t : t \in \mathbb{N}_+, \lambda_1, \dots, \lambda_t \geq 0, \sum_{i=1}^t \lambda_i = 1 \right\}$$

Theorem

Let $X \subseteq \mathbb{R}^n$ be a set of points. The convex hull, $\text{conv}(X)$, of X is convex.



To show: if $\alpha, \beta \in \text{conv}(X)$, then $\bullet \in \text{conv}(X)$

proof:

$$\alpha = \sum_{i=1}^t \lambda_i \cdot x_i$$

$$\beta = \sum_{i=1}^t \mu_i \cdot x_i$$

with
 $\mu_i, \lambda_i \in \mathbb{R}_{\geq 0}^t$

and $\sum \lambda_i = \sum \mu_i = 1$

Let $\gamma \in [0, 1]$ and consider

$$\begin{aligned} & \gamma \cdot \alpha + (1-\gamma) \cdot \beta \\ &= \sum_{i=1}^t (\gamma \cdot \lambda_i + (1-\gamma) \cdot \mu_i) x_i \end{aligned}$$

But

$$\begin{aligned} & \sum_{i=1}^t \underbrace{\gamma \cdot \lambda_i}_{\geq 0} + \underbrace{(1-\gamma) \mu_i}_{\geq 0} \\ &= \gamma \cdot \sum_{i=1}^t \lambda_i + (1-\gamma) \sum_{i=1}^t \mu_i \\ &= 1 \end{aligned}$$

finite set $\subseteq X$

$$\alpha \in \text{conv}(X_1)$$

finite set $\subseteq X$

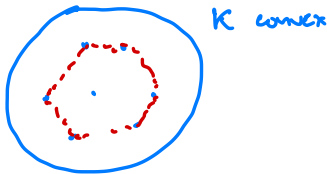
$$\beta \in \text{conv}(X_2)$$

$$\alpha, \beta \in \text{conv}(X_1 \cup X_2)$$

Convex hull is minimal

Theorem

Let $X \subseteq \mathbb{R}^n$ be a set of points. Each convex set K containing X also contains $\text{conv}(X)$.



proof: to show for $x_1, \dots, x_t \in X$ and $\lambda_1, \dots, \lambda_t \geq 0$ with

$$\sum \lambda_i = 1$$

$$\Rightarrow \sum_{i=1}^t \lambda_i x_i \in K$$

Induction: $t=1$ follows from $X \subseteq K$

$t \geq 1$

$$\sum_{i=1}^t \lambda_i x_i = \lambda_1 \cdot x_1 + \sum_{i=2}^t \lambda_i x_i = x = (1-\lambda_1) \cdot x$$

if $\lambda_1 = 0$, then by induction $x \in K$
or $\lambda_1 = 1$

$$= \frac{1}{(1-\lambda_1)} \cdot \left(\sum_{i=2}^t \lambda_i \right) \cdot x = 1 \cdot x = x$$

otherwise: $x = \lambda_1 \cdot x_1 + (1-\lambda_1) \cdot \left(\sum_{i=2}^t \frac{\lambda_i}{(1-\lambda_1)} \cdot x_i \right) \in K$ by induction.

then $x \in K$ by def. of convexity. \blacksquare

Corollary

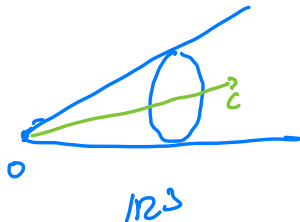
$$\operatorname{conv}(X) = \bigcap_{\substack{K \supseteq X \\ K \text{ convex}}} K.$$

Cones

OBSERVATION: if $C \subseteq \mathbb{R}^n$ is cone, $C \neq \emptyset$, then $0 \in C$.

Definition

A set $C \subseteq \mathbb{R}^n$ is a **cone**, if it is convex and for each $c \in C$ and each $\lambda \in \mathbb{R}_{\geq 0}$ one has $\lambda \cdot c \in C$.



Analogous theorems for cones

$$y \in \text{cone}(X) \quad y = \sum_{i=1}^t \beta_i \lambda_i \cdot x_i \quad \text{for } \lambda_i \in \mathbb{R}_{\geq 0} \quad x_1, \dots, x_t \in X$$

$\beta_i \in \mathbb{R}_{\geq 0}$

Theorem

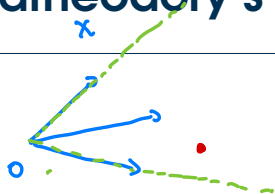
For any $X \subseteq \mathbb{R}^n$, the set $\text{cone}(X)$ is a cone.

Theorem

Let $X \subseteq \mathbb{R}^n$ be a set of points. Each cone containing X also contains $\text{cone}(X)$.

$$\text{cone}(X) = \bigcap_{\substack{C \supseteq X \\ C \text{ is a cone}}} C.$$

Carathéodory's Theorem



Theorem

Let $X \subseteq \mathbb{R}^n$, then for each $x \in \text{cone}(X)$ there exists a set $\tilde{X} \subseteq X$ of cardinality at most n such that $x \in \text{cone}(\tilde{X})$. The vectors in \tilde{X} are linearly independent.

Proof: Let $x \in \text{cone}(X)$. This means that there exists $t \in \mathbb{N}$, $x_1, \dots, x_t \in X$
 $\lambda_1, \dots, \lambda_t \in \mathbb{R}_{\geq 0}$ with $x = \sum_{i=1}^t \lambda_i \cdot x_i$. If $\lambda_i = 0$ for some $i \in \{1, \dots, t\}$ then $x \in \text{cone}(\tilde{X} - x_i)$
 $\underbrace{x_1, \dots, x_t}_{:= \tilde{X}}$

We assume therefore $\lambda_1, \dots, \lambda_t > 0$. We now show: if \tilde{X} lin dependent,
 $\Rightarrow \exists i \in \{1, \dots, t\}$ s.t. $x \in \text{cone}(\tilde{X} - x_i)$

if \vec{x} lin dependent, then $\exists \beta_1, \dots, \beta_t \in \mathbb{R}$ not all zero s.t.

$$\beta_1 x_1 + \dots + \beta_t x_t = 0, \Rightarrow \forall \varepsilon > 0: \varepsilon \cdot \beta_1 x_1 + \dots + \varepsilon \cdot \beta_t x_t = 0$$

w.l.o.g: $\exists i: \beta_i < 0$

$$x = (\lambda_1 + \varepsilon \beta_1) x_1 + \underbrace{(\lambda_2 + \varepsilon \beta_2)}_{\text{Goal } \geq 0} x_2 + \dots + \underbrace{(\lambda_i + \varepsilon \beta_i)}_{< 0} x_i \dots + (\lambda_t + \varepsilon \beta_t) x_t$$

$$\forall i: \lambda_i + \varepsilon \cdot \beta_i \geq 0 \Leftrightarrow \lambda_i \geq -\varepsilon \cdot \beta_i \quad \forall i \in \{1, \dots, t\}$$

$$\Leftrightarrow \lambda_i \geq -\varepsilon \cdot \beta_i \quad i \in \{1, \dots, t: \beta_i < 0\}$$

$$\Leftrightarrow \varepsilon \leq \frac{\lambda_i}{-\beta_i} \quad i \in \underbrace{\{1, \dots, t: \beta_i < 0\}}_{I^-}$$

Let: $j \in \{1, \dots, t: \beta_i < 0\}$ be index where $\min_{i \in I^-} \left\{ \frac{\lambda_i}{-\beta_i} \right\}$ is attained.

let ε^* be the corresponding value: $\frac{\lambda_j}{-\beta_j} = \varepsilon^*$.

\Rightarrow With ε^* :

$$X = \underbrace{(\lambda_1 + \varepsilon^* \cdot \beta_1)}_{\geq 0} x_1 + \dots + \underbrace{(\lambda_j + \varepsilon^* \cdot \beta_j)}_{= 0} x_j + \dots + \underbrace{(\lambda_t + \varepsilon^* \beta_t)}_{\geq 0} x_t.$$

is conc combination of the set $\{x_1, \dots, x_t\} \setminus \{x_j\}$.



Bounded continuous functions

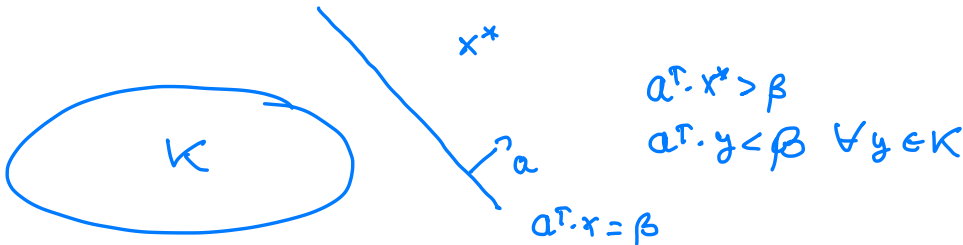
Theorem

Let $X \subseteq \mathbb{R}^n$ be compact and $f : X \rightarrow \mathbb{R}$ be continuous. Then f is bounded and there exist points $x_1, x_2 \in X$ with $f(x_1) = \sup\{f(x) : x \in X\}$ and $f(x_2) = \inf\{f(x) : x \in X\}$.

Separation theorem

Theorem

Let $K \subseteq \mathbb{R}^n$ be a closed convex set and $x^* \in \mathbb{R}^n \setminus K$, then there exists an inequality $a^T x \leq \beta$ such that $a^T y < \beta$ holds for all $y \in K$ and $a^T x^* > \beta$.

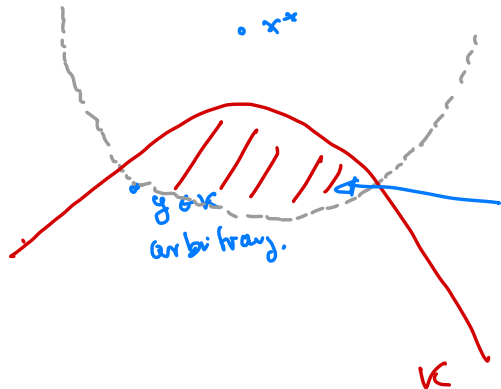


proof: $K \subseteq \mathbb{R}^n$ is convex and closed. $x^* \in K$.

$\min_{x \in K} \|x^* - x\|$ is attained.

$f: \mathbb{R}^n \rightarrow \mathbb{R}$

$x \mapsto \|x^* - x\|$ is continuous.

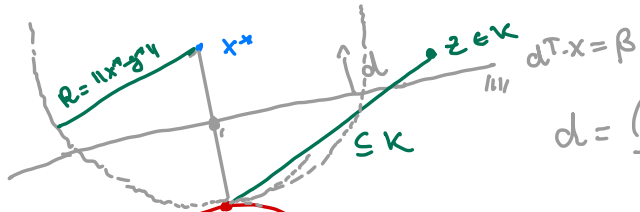


$B \subseteq \mathbb{R}^n$. $B = \{x \in \mathbb{R}^n : \|x - x^*\| \leq \|y - x^*\|\}$.

$K \cap B$

is convex and closed and bounded \Rightarrow compact.

\Rightarrow min is attained.



$$d = \frac{(x^* - y^*)^T d}{\|x^* - y^*\|}$$

$$\beta = \frac{d^T (x^* - y^*)}{2}$$

Suppose $d^T x = \beta$ is not separating.

then: $\exists z \in K$ s.t. $d^T z \geq \beta$

\Downarrow to $y^* \in K$ of min. distance to x^* .

Exercise: Formal proof of \Downarrow .

Farkas' Lemma – Version 1

Theorem (Farkas' lemma)

Let $A \in \mathbb{R}^{m \times n}$ be a matrix and $b \in \mathbb{R}^m$ be a vector. The system $Ax = b, x \geq 0$ has a solution if and only if for all $\lambda \in \mathbb{R}^m$ with $\lambda^T A \geq 0$ one has $\lambda^T b \geq 0$.

Proof: " \Rightarrow " Let $x^* \in \mathbb{R}_{\geq 0}^n$ be a solution. Then, with $\lambda \in \mathbb{R}^m$ and

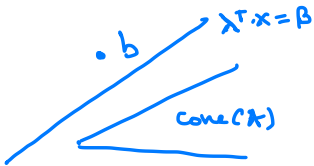
$$\lambda^T \cdot A \geq 0, \text{ one has } \lambda^T \cdot b = \lambda^T \cdot (A \cdot x^*)$$

$$= \underbrace{(\lambda^T \cdot A)}_{\geq 0} \underbrace{x^*}_{\geq 0} \geq 0$$

\Leftarrow if $Ax=b, x \geq 0$ has no solution. We show: $\exists \lambda \in \mathbb{R}^m$
 with $\lambda^T A \geq 0$ and $\lambda^T b < 0$

$\text{cone}(A) = \{Ax : x \in \mathbb{R}_{\geq 0}^n\}$ cone generated by columns of A .

Exercise: $\text{cone}(A)$ is closed. (and convex).



$$\lambda^T b > \beta \geq 0 \text{ since } 0 \in \text{cone}(A)$$

$$\forall \text{ column } a_i \in A (\in \text{cone}(A))$$

$$\text{we have } \lambda^T a_i \leq 0$$

$$\lambda^T b > 0$$

$$\text{and } \lambda^T A \leq 0$$



Since if $\lambda^T a_i > 0$, then for $\gamma > 0$ large
 enough: $\lambda^T (\underbrace{\gamma a_i}_{\in \text{cone}}) > \beta \quad \nabla$

Farkas' Lemma – Version 2

Theorem (Farkas' lemma)

Let $A \in \mathbb{R}^{m \times n}$ be a matrix and $b \in \mathbb{R}^m$ be a vector. The system $Ax \leq b$ has a solution if and only if for all $\lambda \in \mathbb{R}_{\geq 0}^m$ with $\lambda^T A = 0$ one has $\lambda^T b \geq 0$.

Exercise!

$$\begin{array}{ll} Ax \leq b & \text{sol.} \\ A(x^+ - x^-) \leq b & \\ x^+, x^- \geq 0 & \left. \vphantom{\begin{array}{l} A(x^+ - x^-) \leq b \\ x^+, x^- \geq 0 \end{array}} \right\} \text{sol.} \end{array} \qquad \begin{array}{l} A(x^+ - x^-) + s = b \\ x^+, x^-, s \geq 0 \\ \text{has solution.} \end{array}$$