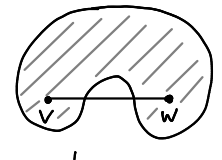


6. Convexity Fix \mathbb{R} -vector space V .

Def: $X \subseteq V$ is convex if $v, w \in X \Rightarrow$ line segment $\overline{vw} \subseteq X$.



convex



not convex

$$\begin{aligned} \overline{vw} &= \{ \alpha v + (1-\alpha)w \mid \alpha \in [0,1] \} = \{ \alpha v + \beta w \mid \alpha + \beta = 1, \alpha \geq 0, \beta \geq 0 \} = \text{all weighted averages of } v \text{ and } w \\ &= \{ w + \alpha(v-w) \mid \alpha \in [0,1] \} = \text{parametrized line segment from } w \text{ to } v \end{aligned}$$

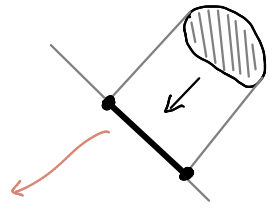
E.g. any interval $\subseteq \mathbb{R}$ $[a,b]$ (a,b) $a = -\infty$ or $b = \infty$ allowed



Pf: $a \leq v, w \leq b \Rightarrow [v,w] \subseteq [a,b]$ \square

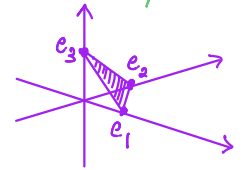
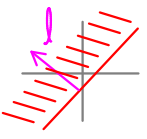
Properties

1. $\varphi: V \rightarrow W$ linear $\Rightarrow \varphi(\text{convex})$ is convex. Pf: $\varphi(\overline{vw}) = \overline{\varphi(v)\varphi(w)}$.
2. " $\Rightarrow \varphi^{-1}(\text{convex})$ is convex. Pf: same! $v, w \in \varphi^{-1}(Y) \Rightarrow \overline{\varphi(v)\varphi(w)} \subseteq Y \Rightarrow \overline{vw} \subseteq \varphi^{-1}(Y)$.
3. X convex $\Rightarrow a+X$ convex $\forall a \in V$. Pf: $a+v, a+w \in a+X \Leftrightarrow v, w \in X \Leftrightarrow \overline{vw} \subseteq X \Leftrightarrow \overline{a+v, a+w} \subseteq a+X$.
4. $\{X_i\}_{i \in I}$ all convex $\Rightarrow \bigcap_{i \in I} X_i$ convex. Pf: $\overline{vw} \subseteq X_i \forall i \Leftrightarrow \overline{vw} \subseteq \bigcap_{i \in I} X_i$.



Cor: 5. Every affine subspace is convex. Pf: 1+3.

6. Every open halfspace $\overline{H}^{\pm} = \{x \in V \mid l(x) \gtrless c\}$ for some $l \in V^*$ and $c \in \mathbb{R}$. Pf: $H^{\pm} = l^{-1}(\text{ray})$; use 2.
 sometimes \overline{H}^{\pm} to emphasize "open"



E.g. standard $(n-1)$ -simplex $\sigma = \{x \in \mathbb{R}^n \mid x_i \geq 0 \forall i \text{ and } x_1 + \dots + x_n = 1\}$ is convex.

Pf: $\mathbb{R}_+^n = \{x \in \mathbb{R}^n \mid x_i \geq 0 \forall i\} = \bigcap_{i=1}^n \{e_i^*(x) \geq 0\}$ convex by 6.+4.

$\{x \in \mathbb{R}^n \mid x_1 + \dots + x_n = 1\}$ convex by 5. or 2. Now apply 4. \square

Prop: $x_1, \dots, x_n \in V \Rightarrow 7. P = \{\alpha_1 x_1 + \dots + \alpha_n x_n \mid \alpha_i \geq 0 \forall i \text{ and } \alpha_1 + \dots + \alpha_n = 1\}$ is convex.

8. $X \supseteq \{x_1, \dots, x_n\}$ convex $\Rightarrow X \supseteq P$.

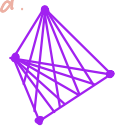
convex combinations of x_1, \dots, x_n

Def: $P =$ convex hull $= \text{conv}\{x_1, \dots, x_n\}$ is a polytope.

Pf: 7. $P = \varphi(\sigma)$ for $\varphi: \mathbb{R}^n \rightarrow V$. Use 1.
 $e_i \mapsto x_i$

8. Use induction on n . Trivial if $n=1$. And by definition if $n=2$, though that's not needed.

$n \geq 2$: need $\alpha_1 x_1 + \dots + \alpha_n x_n \in X$. Assume $\alpha_n \neq 1$. else trivial: $x_n \in X$



Then $\alpha_1 x_1 + \dots + \alpha_n x_n = \alpha (\underbrace{\beta_1 x_1 + \dots + \beta_{n-1} x_{n-1}}_{\substack{\text{by induction } \in X \\ \text{since } \sum_{i=1}^{n-1} \beta_i = 1}}) + (1-\alpha)x_n$ for $\alpha = 1-\alpha_n = \alpha_1 + \dots + \alpha_{n-1}$
 $\beta_i = \frac{\alpha_i}{\alpha}$ for $i=1, \dots, n-1$. \square

Further examples of convex sets:

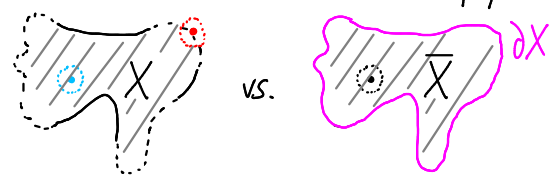
E.g. • $X = \{f \in \mathbb{R}[t] \mid f(\alpha) > 0 \forall \alpha \in (0,1)\}$

• $X = \{A \in \mathbb{R}^{n \times n} \mid A = A^* \text{ and } \lambda > 0 \forall \text{ eigenvalues } \lambda \text{ of } A\}$ see Lecture 9

Def: $v \in X \subseteq V$ is an interior point if $v \in U \subseteq X$ for some open $U \subseteq V$.

$v \in \partial X$ boundary point if $U \cap X$ and $U \cap (V \setminus X)$ both nonempty \forall open $v \in U \subseteq V$.

$\bar{X} = X \cup \partial X$ is the closure of X .



Prop: $\bar{X} = \{\lim x_k \mid \{x_k\} \subseteq X \text{ converges}\}$.

Pf: Prop, p. 11.

Q. Is \nearrow open?

A. In \mathbb{R}^1 : yes.

In \mathbb{R}^2 : no.

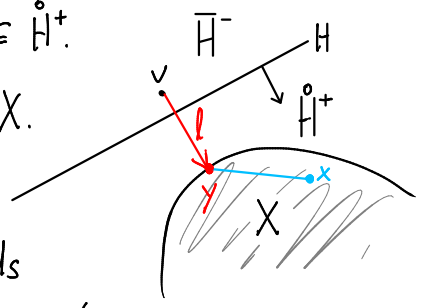
relative interior can fix this, but let's not get into it

Prop: $X \subseteq V$ convex $\Rightarrow \bar{X}$ convex.

Pf: $v_k \rightarrow v, w_k \rightarrow w \Rightarrow \alpha v_k + \beta w_k \rightarrow \alpha v + \beta w$. But $v_k \in X$ and $w_k \in X \forall k \xrightarrow{\alpha+\beta=1} \alpha v_k + \beta w_k \in X \forall k$ by convexity $\Rightarrow \alpha v + \beta w \in \bar{X}$ by Prop. \square

Def: A hyperplane $H \subseteq V$ separates v from X if $v \in \bar{H}^-$ and $X \subseteq \bar{H}^+$.

linear function $l \in V^*$ " " " " $l(v) < l(x) \forall x \in X$.



Thm: $X = \bar{X}$ convex and $v \notin X \Rightarrow \exists H$ separating v from X .

Pf: For any choice of inner product, the norm $\| \cdot \| = \langle \cdot, \cdot \rangle^{1/2}$ yields

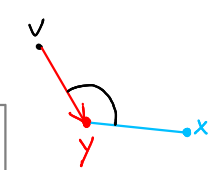
$f(x) = \|x - v\|: X \rightarrow \mathbb{R}$ continuous, bounded below (by 0), and proper (f^{-1} (bounded set) is bounded)

by topological equivalence: $f^{-1}([0, r]) = B_r^{\| \cdot \|}(v)$ is bounded. Since X is closed, f attains

a minimum on X , say at $y \in X$. Set $l = \langle y - v, \cdot \rangle$. Note $l \neq 0$ since $v \notin X$ (so $y \neq v$).

$\forall \alpha \in (0,1]$ and $x \in X, \|y - v\|^2 \leq \|y + \alpha(x - y) - v\|^2 = \|y - v + \alpha(x - y)\|^2$

$= \|y - v\|^2 + 2\alpha \langle y - v, x - y \rangle + \alpha^2 \|x - y\|^2$
 law of cosines $-2\alpha \langle v - y, x - y \rangle$

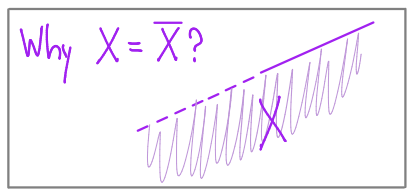


$\Rightarrow 0 \leq 2l(x - y) + \alpha \|x - y\|^2$

$\xrightarrow{\alpha \rightarrow 0} l(y) \leq l(x)$.

But $l(v) < l(y)$ because $l(y - v) = \|y - v\|^2 > 0$,

so $l(v) < l(x) \forall x \in X. \square$



Applications: optimization (linear programming), analysis (bounds away from 0), CS (support vector machines)