

## Convex Sets & Functionals

Given  $x, y \in L$  and  $\alpha, \beta \geq 0 \nexists \alpha + \beta = 1$

then  $\{ \alpha x + \beta y \mid \alpha, \beta \geq 0, \alpha + \beta = 1 \}$

is the line segment in  $L$  connecting  $x$  to  $y$ .

if  $\alpha \neq 0$  and  $\alpha \neq 1$  then it's an open segment

Given a set  $M \subset L$ , its interior  $I(M)$  is defined by:

$x \in I(M)$  if given  $y \in L \exists \varepsilon_y > 0$  so that  
 $x + \varepsilon y \in M \forall |\varepsilon| < \varepsilon_y$ .

This is the best we can do w/o a metric or anything like that. If  $L$  is finite dimensional then we can take one  $\varepsilon$  for all  $y$ .

defn:  $M \subset L$  is convex if for any  $x, y \in M$   
 the line segment connecting  $x$  and  $y$  is also in  $M$ .

defn: A convex set is also a convex body  
 if  $I(M) \neq \emptyset$

ex:  $[a, b]$  is a convex body in  $\mathbb{R}$   
 but not in  $\mathbb{R}^2$

Convex bodies are intuitive in  $\mathbb{R}^n$ . They're less intuitive in infinite dimensions. First of all, whether or not something's a convex body depends on the ambient space  $L$ .

For example. Let  $L = \ell^2(\mathbb{C}, \mathbb{Z})$ , fix  $\rho > 0, k > 0$  and define

$$\Sigma = \{x \in \ell^2(\mathbb{C}, \mathbb{Z}) \mid |x_n| \leq k e^{-\rho|n|}\}$$

then  $\Sigma$  is convex, but is not a convex body because you can take  $y \in \ell^2(\mathbb{C}, \mathbb{Z})$  so that  $|y_n| \downarrow$  more slowly than  $k e^{-\rho|n|}$ . (algebraically, for example.) Then no matter how small you take  $t$ , you won't have  $x + t y \in \Sigma$ .

thm: if  $M$  is convex then  $I(M)$  is convex

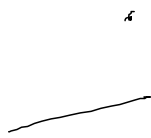
thm: if  $M_\alpha$  is convex for each  $\alpha$

then  $\bigcap_{\alpha} M_{\alpha}$  is convex.

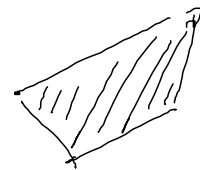
Given any set  $A \subset L$ , there is a smallest convex set that contains  $A$ . (i.e. the intersection of all convex sets that contain  $A$ ). This set is called the convex hull of  $A$ .

e.g

$A =$



the  
hull of  
 $A$



$p: L \rightarrow \mathbb{R} \cup \{+\infty\}$  convex if

( $L$  is a vector space over  $\mathbb{R}$ )

1)  $p(x) \geq 0 \quad \forall x \in L$

2)  $p(\alpha x) = \alpha p(x) \quad \forall x \in L, \forall \alpha \geq 0$

3)  $p(x+y) \leq p(x) + p(y) \quad \forall x, y$

ex: if  $L = L^2([a, b])$  (continuous real-valued functions w/  $L^2$  metric)

then  $p(f) = \sqrt{\int_a^b f(x)^2 dx}$

is a convex function.

Theorem: if  $p$  is a convex functional on a vector space  $L$  and  $k > 0$  then

$$E = \{x \mid p(x) \leq k\}$$

is convex. Further, if  $p$  is a finite convex functional then  $E$  is a convex body and  $I(E) = \{x \mid p(x) < k\}$ .

proof:  $x, y \in E$   $\alpha, \beta \geq 0$  so that  $\alpha + \beta = 1$

$$\begin{aligned} \text{then } p(\alpha x + \beta y) &\leq p(\alpha x) + p(\beta y) \\ &= \alpha p(x) + \beta p(y) \leq k \end{aligned}$$

$\Rightarrow \alpha x + \beta y \in E \Rightarrow E$  is convex. Now assume  $p$  is a finite functional.

Let  $x \in \{x \mid p(x) < k\}$ . Fix  $y \in L$ . I want to show  $\exists \varepsilon_y > 0$  so that  $|t| < \varepsilon_y \Rightarrow$

$$x + ty \in \{x \mid p(x) < k\}$$

This would show  $\{x \mid p(x) < k\} \subset I(E)$ .

Rather than allowing  $|t| < \varepsilon_y$ , we'll look at  $0 \leq t < \varepsilon_y$  and  $x \pm ty$ .

$$p(x \pm ty) \leq p(x) + t p(\pm y).$$

If  $p(y) = 0$  then take any  $t$ . If  $p(-y) = 0$  then take any  $t$ . If either  $p(y) < 0$  or  $p(-y) < 0$  then we

have to restrict the range of  $t$ .

$$\text{let } t < \frac{k - p(x)}{\max\{p(y), p(-y)\}} =: \epsilon_y$$

then if  $0 \leq t < \epsilon_y$  we'll have

$$p(x \pm ty) < k \Rightarrow x \pm ty \in \{x \mid p(x) < k\}$$

$$\Rightarrow \{x \mid p(x) < k\} \subset I(E).$$

Further, if  $x \in \{x \mid p(x) = k\}$  then  $x \notin I(E)$ .

Since we can't go in the direction  $x$ . Need

$$\epsilon_x > 0 \ni x + tx \in \{x \mid p(x) \leq k\} \forall |t| < \epsilon_x$$

but  $p(x + tx) = (1+t)p(x) \neq k$  if  $t > 0$ .

$$\Rightarrow I(E) = \{x \mid p(x) < k\}.$$

Now go in the opposite direction. Suppose  $E$  is a convex body whose interior contains  $\vec{0}$ . Use  $E$  to define a functional:

$$p_E(x) = \inf \left\{ r \mid \frac{x}{r} \in E, r > 0 \right\}$$

$p_E$  is the Minkowski functional of the convex body  $E$ .

Theorem: if  $E \subset L$  is a convex body such that  $\vec{0} \in I(E)$  then  $P_E$  is a finite, convex functional.

proof: Fix  $x \in L$ . Since  $\vec{0} \in I(E)$ ,  $\exists \epsilon_x > 0$  so that  $|t| < \epsilon_x \Rightarrow \vec{0} + t\vec{x} \in E$ .  
 $\Rightarrow$  for  $r$  sufficiently large,  $\frac{x}{r} \in E$ .  
 $\Rightarrow \inf \{ r \mid \frac{x}{r} \in E, r > 0 \}$  exists and is finite for each  $x \in L$ . This shows finiteness.

Now  $p(\vec{0}) = 0$  is immediate since  $\vec{0} \in E$ , and if  $\alpha > 0$  then

$$\begin{aligned} P_E(\alpha x) &= \inf \left\{ r \mid \frac{\alpha x}{r} \in E, r > 0 \right\} & r = \alpha r' \\ &= \inf \left\{ \alpha r' \mid \frac{\alpha x}{\alpha r'} \in E, r' > 0 \right\} \\ &= \inf \left\{ \alpha r' \mid \frac{x}{r'} \in E, r' > 0 \right\} \\ &= \alpha \inf \left\{ r' \mid \frac{x}{r'} \in E, r' > 0 \right\} \\ &= \alpha P_E(x) \quad \checkmark \end{aligned}$$

Now show  $P_E(x+y) \leq P_E(x) + P_E(y) \quad \forall x, y \in L$ .

Fix  $\varepsilon > 0$ . Choose  $r_1 > 0 \exists$

$$p_E(x) < r_1 < p_E(x) + \varepsilon$$

Choose  $r_2 > 0 \exists$

$$p_E(y) < r_2 < p_E(y) + \varepsilon.$$

$\Rightarrow \frac{x}{r_1}$  and  $\frac{y}{r_2} \in E$  by defn. Since

$E$  is convex, the segment connecting

$\frac{x}{r_1}$  to  $\frac{y}{r_2}$  is in  $E$ . Let  $r = r_1 + r_2$

$$\text{then } \frac{x+y}{r} = \frac{r_1 x}{r r_1} + \frac{r_2 y}{r r_2}$$

$$= \frac{r_1}{r} \left( \frac{x}{r_1} \right) + \frac{r_2}{r} \left( \frac{y}{r_2} \right) \quad \frac{r_1}{r} + \frac{r_2}{r} = 1$$

$\in E$ ,

$$\Rightarrow \frac{x+y}{r} \in E \Rightarrow p_E(x+y) \leq r = r_1 + r_2$$

$$< (p_E(x) + p_E(y)) + 2\varepsilon.$$

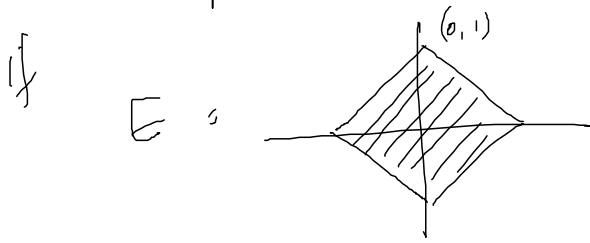
Since  $\varepsilon > 0$  was arbitrary, this

shows

$$p_E(x+y) \leq p_E(x) + p_E(y)$$

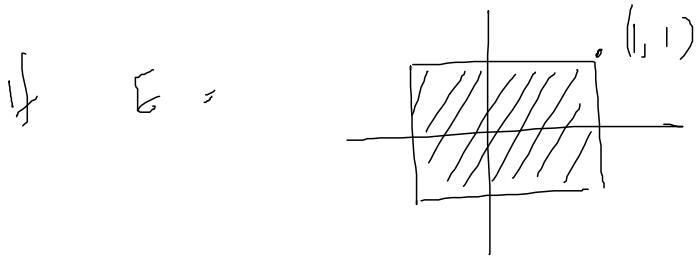
as desired. //

for example ... in  $\mathbb{R}^2$

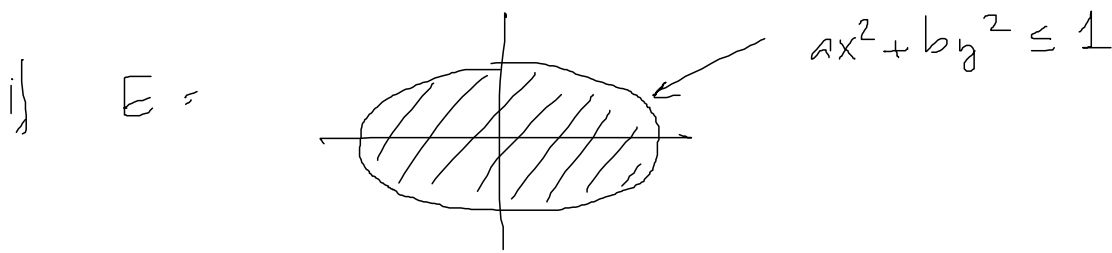


i.e.  $S_1((0,0), 1)$

then  $p_E((x,y)) = |x| + |y|$



then  $p_E((x,y)) = \max\{|x|, |y|\}$



then  $p_E((x,y)) = \sqrt{ax^2 + by^2}$