

# Math, Problem Set #5, Convex Analysis

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*July 21, 2017*

## 7.1

Prove: If  $S$  is a nonempty subset of  $V$ , then  $\text{conv}(S)$  is convex.

$S$  is a nonempty subset of  $V$

$\text{conv}(S)$  is the set of all finite sums of the form

$$\lambda_1 \mathbf{x}_1 + \dots + \lambda_k \mathbf{x}_k, \mathbf{x}_i \in S, k \in \mathbb{N}$$

where  $\lambda_i \geq 0$  and  $\lambda_1 + \dots + \lambda_k = 1$

Consider the subset of all sums of 2-element combinations:

i.e.,  $\lambda_1 \mathbf{x}_1 + \dots + \lambda_k \mathbf{x}_k$  where  $\lambda_n = 0$  for all but 2 of the elements, " $x_i$ " and " $x_j$ "

$\Rightarrow$  Given  $\lambda_i$ , then  $\lambda_j = 1 - \lambda_i \Rightarrow \text{conv}(S)$  is convex

## 7.2

i

Take hyperplane  $P$  in  $V$ , where  $P = \{\mathbf{x} \in V | \langle \mathbf{a}, \mathbf{x} \rangle = b\}$

$\forall \mathbf{x}, \mathbf{y} \in V, \langle \mathbf{a}, \mathbf{x} \rangle = b$  and  $\langle \mathbf{a}, \mathbf{y} \rangle = b$

Show:  $\lambda \mathbf{x} + (1 - \lambda) \mathbf{y} \in V \forall 0 \leq \lambda \leq 1$

$$\langle \mathbf{a}, \lambda \mathbf{x} + (1 - \lambda) \mathbf{y} \rangle$$

$$= \langle \mathbf{a}, \lambda \mathbf{x} \rangle + \langle \mathbf{a}, \mathbf{y} \rangle + \langle \mathbf{a}, -\lambda \mathbf{y} \rangle$$

$$= \lambda \langle \mathbf{a}, \mathbf{x} \rangle + b - \lambda \langle \mathbf{a}, \mathbf{x} \rangle$$

$$= \lambda b + b - \lambda b = b$$

ii

The proof of convexity for a half space is analogous; just replace " $=$ " with " $\leq$ "

## 7.4

For nonempty, convex, closed  $C$ :

$\mathbf{p} \in C$  is  $\text{proj}_C \mathbf{x}$ , if  $\|\mathbf{x} - \mathbf{p}\| \leq \|\mathbf{x} - \mathbf{y}\| \forall \mathbf{y} \in C$

i

Rewritten as all inner products:

$$\text{Show: } \langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y} \rangle = \langle \mathbf{x} - \mathbf{p}, \mathbf{x} - \mathbf{p} \rangle + \langle \mathbf{p} - \mathbf{y}, \mathbf{p} - \mathbf{y} \rangle + 2\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle$$

$$\text{RHS} = \langle \mathbf{x}, \mathbf{x} \rangle - 2\langle \mathbf{x}, \mathbf{p} \rangle + 2\langle \mathbf{p}, \mathbf{p} \rangle - 2\langle \mathbf{p}, \mathbf{y} \rangle + \langle \mathbf{y}, \mathbf{y} \rangle + 2\langle \mathbf{x}, \mathbf{p} \rangle - 2\langle \mathbf{x}, \mathbf{y} \rangle - 2\langle \mathbf{p}, \mathbf{p} \rangle + 2\langle \mathbf{p}, \mathbf{y} \rangle$$

$$= \langle \mathbf{x}, \mathbf{x} \rangle - 2\langle \mathbf{x}, \mathbf{y} \rangle + \langle \mathbf{y}, \mathbf{y} \rangle = \langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y} \rangle$$

ii

If (7.14) holds, then all RHS terms of the below equation are  $\geq 0$ .

(All squared norms are  $\geq 0$ ).

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

$$\Rightarrow \|\mathbf{x} - \mathbf{y}\|^2 > \|\mathbf{x} - \mathbf{p}\|^2 \quad \forall \mathbf{y} \neq \mathbf{p}$$

Take square root:  $\|\mathbf{x} - \mathbf{y}\| > \|\mathbf{x} - \mathbf{p}\|$

iii

$$\text{Use (i) to write } \|\mathbf{x} - \mathbf{z}\|^2 = \|\mathbf{x} - \mathbf{p}\|^2 + \|\mathbf{p} - \lambda\mathbf{y} - \mathbf{p} + \lambda\mathbf{p}\|^2 + 2\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \lambda\mathbf{y} - \mathbf{p} + \lambda\mathbf{p} \rangle$$

$$= \|\mathbf{x} - \mathbf{p}\|^2 + \|\lambda(\mathbf{p} - \mathbf{y})\|^2 + 2\langle \mathbf{x} - \mathbf{p}, \lambda(\mathbf{p} - \mathbf{y}) \rangle$$

$$= \|\mathbf{x} - \mathbf{p}\|^2 + \lambda^2\|\mathbf{p} - \mathbf{y}\|^2 + 2\lambda\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle$$

iv

Have  $\|\mathbf{x} - \mathbf{z}\| \geq \|\mathbf{x} - \mathbf{p}\|$  from definition of projection

$$\text{Rewrite (7.15): } \|\mathbf{x} - \mathbf{z}\|^2 - \|\mathbf{x} - \mathbf{p}\|^2 = 2\lambda\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle + \lambda^2\|\mathbf{y} - \mathbf{p}\|^2$$

$$\|\mathbf{x} - \mathbf{z}\|^2 - \|\mathbf{x} - \mathbf{p}\|^2 \geq 0 \text{ because definition of projection}$$

$$\Rightarrow 2\lambda\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle + \lambda^2\|\mathbf{y} - \mathbf{p}\|^2 \geq 0$$

$$\text{Divide by } \lambda: 2\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle + \lambda\|\mathbf{y} - \mathbf{p}\|^2 \geq 0$$

## Overall proof

If  $\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle \geq 0$ , then  $\mathbf{p} \in C$  is  $\text{proj}_C \mathbf{x}$ :

(7.14) and (i)  $\Rightarrow$  (ii) (definition of projection)

If  $\mathbf{p} \in C$  is  $\text{proj}_C \mathbf{x}$ , then  $\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle \geq 0$ :

(7.15)  $\Rightarrow$  (iv)

Consider  $\lambda = 0$ ; Clear that  $\langle \mathbf{x} - \mathbf{p}, \mathbf{p} - \mathbf{y} \rangle \geq 0$  to maintain the inequality in (iv)

## 7.6

$f : R^n \rightarrow R$  is a convex function  $\Rightarrow \forall \mathbf{x}_1, \mathbf{x}_2 \in R^n$ :

$$f(\lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) \leq \lambda f(\mathbf{x}_1) + (1 - \lambda)f(\mathbf{x}_2)$$

Consider set  $J = \{\mathbf{x} \in R^n | f(\mathbf{x}) \leq c\} \subset R^n$

Have  $f(\mathbf{x}_1) \leq c, f(\mathbf{x}_2) \leq c \quad \forall \mathbf{x}_1, \mathbf{x}_2 \in J$

Substitute these bounds into the convex function inequality:

$$f(\lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) \leq \lambda c + (1 - \lambda)c = c$$

$$\Rightarrow \forall \mathbf{x}_1, \mathbf{x}_2 \in J, \lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2 \in J$$

$\Rightarrow J$  is a convex set

## 7.7

$f(\mathbf{x}) = \sum_{i=1}^k \lambda_i f_i(\mathbf{x})$  is convex under the stated conditions:

Because each  $f_i$  is convex,  $\forall \mathbf{x}_1, \mathbf{x}_2 \in C$  and for  $0 \leq \lambda \leq 1$ :

$$f(\lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2) = \sum_{i=1}^k \lambda_i f_i(\lambda\mathbf{x}_1 + (1 - \lambda)\mathbf{x}_2)$$

$$\leq \sum_{i=1}^k \lambda_i [\lambda f_i(\mathbf{x}_1) + (1 - \lambda)f_i(\mathbf{x}_2)] = \lambda [\sum_{i=1}^k \lambda_i f_i(\mathbf{x}_1)] + (1 - \lambda) [\sum_{i=1}^k \lambda_i f_i(\mathbf{x}_2)]$$

$\Rightarrow f$  is convex

## 7.13

If  $f : R^n \rightarrow R$  is convex and bounded above,  $f$  is constant:

Suppose that  $f$  is not constant

i.e.,  $\exists \mathbf{x}, \mathbf{y}$  s.t.  $f(\mathbf{x}) < f(\mathbf{y})$

Function  $g(t) = f(\mathbf{x} + t(\mathbf{y} - \mathbf{x}))$  is convex, with  $f(\mathbf{x}) = g(0) < f(\mathbf{y}) = g(1)$

Jensen's Inequality:  $g(1) \leq \frac{t-1}{t}g(0) + \frac{1}{t}g(t) \quad \forall t > 1$

$\Rightarrow g(t) \geq tg(1) - (t-1)g(0) = g(0) + t(g(1) - g(0))$

$\Rightarrow g$  increases unboundedly as  $t \rightarrow \infty$ ,

which contradicts boundedness of  $f$

$\Rightarrow f$  is constant

## 7.20

Convex  $\Rightarrow \forall \mathbf{x}_1, \mathbf{x}_2 \in R^n$  and  $0 \leq \lambda \leq 1$ ,

Have  $f(\lambda \mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) \leq \lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$

and  $-f(\lambda \mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) \leq -\lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$

$\Rightarrow f(\lambda \mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) \geq \lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$

$\Rightarrow f(\lambda \mathbf{x}_1 + (1-\lambda)\mathbf{x}_2) = \lambda f(\mathbf{x}_1) + (1-\lambda)f(\mathbf{x}_2)$

$\Rightarrow f$  is affine

## 7.21

If  $\mathbf{x}^*$  is a minimizer of  $f \Rightarrow \mathbf{x}^*$  is a minimizer of  $\phi \circ f(\mathbf{x}^*)$ :

$\mathbf{x}^*$  is a minimizer of  $f \Rightarrow Df(\mathbf{x}^*)(\mathbf{y} - \mathbf{x}^*) \geq 0, \forall \mathbf{y} \in \Omega$

$\phi$  is strictly increasing  $\Rightarrow D\phi(f(\mathbf{x}^*)) > 0$

So  $D\phi(f(\mathbf{x}^*))Df(\mathbf{x}^*)(\mathbf{y} - \mathbf{x}^*) \geq 0, \forall \mathbf{y} \in \Omega$

$\Rightarrow \mathbf{x}^*$  is a minimizer of  $\phi \circ f(\mathbf{x}^*)$

If  $\mathbf{x}^*$  is a minimizer of  $\phi \circ f(\mathbf{x}^*) \Rightarrow \mathbf{x}^*$  is a minimizer of  $f$ :

$\mathbf{x}^*$  is a minimizer of  $\phi \circ f(\mathbf{x}^*) \Rightarrow D\phi(f(\mathbf{x}^*))Df(\mathbf{x}^*)(\mathbf{y} - \mathbf{x}^*) \geq 0, \forall \mathbf{y} \in \Omega$

$\phi$  is strictly increasing  $\Rightarrow D\phi(f(\mathbf{x}^*)) > 0$

So  $Df(\mathbf{x}^*)(\mathbf{y} - \mathbf{x}^*) \geq 0, \forall \mathbf{y} \in \Omega$

$\Rightarrow \mathbf{x}^*$  is a minimizer of  $f$