

## Math, Problem Set #5, Convex Optimization

Instructor: Jorge Barro

Due Friday, July 21 at 8:00am

**Homework:** 1, 2, 4, 5, 7, 13, 20, and 21 at the end of Chapter 7 of Humpherys et al. (2017)

7.1 Show that the convex hull of any non-empty set  $S$  is convex with  $S \subset V$ . The hull  $H = \text{conv}(S)$  is given by the set of all finite sums of the form  $\lambda_1 x_1 + \dots + \lambda_n x_n$  for all  $x \in S$ ,  $n \in \mathbb{N}$  with  $\sum \lambda_i = 1$  and  $\lambda_i \geq 0$ .  $H$  is convex if  $\gamma y + (1 - \gamma)x \in H \forall x, y \in H$  and  $0 \leq \gamma \leq 1$ .  $\gamma y + (1 - \gamma)x = \gamma(\lambda_1 y_1 + \dots + \lambda_n y_n) + (1 - \gamma)(\lambda'_1 x_1 + \dots + \lambda'_k x_k) \in H$  iff  $\gamma \sum \lambda_i + (1 - \gamma) \sum \lambda'_j = 1$ . Since  $x, y \in H$  by definition of  $H$  it follows that  $\sum \lambda_i = \sum \lambda'_j = 1$ . Finally,  $\gamma 1 + (1 - \gamma)1 = 1$  is true.

7.2i Claim: A hyperplane is convex.

Let  $x_a$  and  $x_b$  be any two arbitrary points in  $P = \{x \in V \mid \langle a, x \rangle = b\}$ . Then,  $\lambda x_a + (1 - \lambda)x_b = \lambda a_1 x_{a1} + \dots + \lambda a_n x_{an} + \dots + (1 - \lambda)a_1 x_{b1} + \dots + (1 - \lambda)a_n x_{bn} = \lambda a_1 x_{a1} + a_1 x_{b1} - \lambda a_1 x_{b1} + \dots + \lambda a_n x_{an} + a_n x_{bn} - \lambda a_n x_{bn} = b + \lambda b - \lambda b = b$ . Since any convex combination of the two points is still in the hyperplane  $P$ , we know that the hyperplane is convex.

7.2ii Claim: Half-spaces are convex.

Let  $H = \{x \in V \mid \langle a, x \rangle \leq b\}$  be a half-space, where  $a \in V, a \neq 0$ , and  $b \in \mathbb{R}$ . Then, for any two arbitrary points  $x_a$  and  $x_b$  in the half-space, we know that  $\lambda(a_1 x_1 + \dots + a_n x_n) + (1 - \lambda)(a_1 x'_1 + \dots + a_n x'_n) = \lambda a_1 x_1 + a_1 x'_1 - \lambda a_1 x'_1 + \dots + \lambda a_n x_n + a_n x'_n - \lambda a_n x'_n \leq \lambda b + b - \lambda b = b$ . Since the convex combination of any two arbitrary points is in the half-space, we conclude that the half-space is convex.

7.4i Claim:  $\|x - y\|^2 = \|x - p\|^2 + \|p - y\|^2 + 2\langle x - p, p - y \rangle$ .

$$\|x - y\|^2 = \langle x - y, x - y \rangle = \langle x - p + p - y, x - p + p - y \rangle = \langle x - p, x - p \rangle + \langle x - p, p - y \rangle + \langle p - y, x - p \rangle + \langle p - y, p - y \rangle = \|x - p\|^2 + \|p - y\|^2 + 2\langle x - p, p - y \rangle.$$

7.4ii  $\|x - p\| \leq \|x - p\| + \|p - y\|$  because  $\|p - y\| \geq 0$ . Therefore squaring both sides, we preserve the inequality and obtain  $\|x - p\|^2 \leq \|x - p\|^2 + \|p - y\|^2 + 2\langle x - p, p - y \rangle = \|x - y\|^2$ . Taking the squareroot of both sides now, we obtain  $\|x - p\| \leq \|x - y\|$ .

7.4iii Given that  $z = \lambda y + (1 - \lambda)p$ , we can write  $\|x - z\|^2 = \|x - p\|^2 + \|p - z\|^2 + 2\langle x - p, p - z \rangle = \|x - p\|^2 + \|p - \lambda y - p + \lambda p\|^2 + 2\langle x - p, p - \lambda y - p + \lambda p \rangle = \|x - p\|^2 + \|\lambda p - \lambda y\|^2 + 2\langle x - p, \lambda p - \lambda y \rangle = \|x - p\|^2 + \lambda^2 \|p - y\|^2 + 2\lambda \langle x - p, p - y \rangle$ .

7.4iv Claim: If  $p$  is a projection of  $x$  onto the convex set  $C$ , then  $\langle x - p, p - y \rangle \geq 0 \forall y \in C$ .

Suppose  $p$  is the projection of  $x$  onto the convex set  $C$ . Then we know that  $\|x - z\|^2 = \|x - p\|^2 + 2\lambda\langle x - p, p - y \rangle + \lambda^2\|y - p\|^2$ . We know that the right hand side of the equation is greater than  $\|x - p\|^2$  since  $p$  is a projection onto  $C$  and  $z$  is a point in  $C$  ( $z$  is in  $C$  because  $C$  is convex and  $z$  is a convex linear combination of points in  $C$ ). Moreover, the right hand side can be rewritten as  $\|x - p\|^2 + \lambda(2\langle x - p, p - y \rangle + \lambda\|y - p\|^2)$  where  $\lambda\|y - p\|^2 \geq 0$ . Since the expression has to be greater than or equal to  $\|x - p\|^2$ , it follows that  $2\langle x - p, p - y \rangle + \lambda\|y - p\|^2 \geq 0$  for all  $y \in C$  and  $\lambda \in [0, 1]$ . Thus, we can let  $\lambda = 0$  and see that  $2\langle x - p, p - y \rangle \geq 0$ .

7.6 Claim: If  $f$  is a convex function, then the set  $\{x \in \mathbb{R}^n | f(x) \leq c\}$  is a convex set.

Suppose  $f$  is a convex function. Let  $x_a$  and  $x_b$  be arbitrary elements of  $S = \{x \in \mathbb{R}^n | f(x) \leq c\}$ . It remains to show that  $f(\lambda x_a + (1 - \lambda)x_b) \leq c$ .  $f(\lambda x_a + (1 - \lambda)x_b) \leq \lambda f(x_a) + (1 - \lambda)f(x_b) \leq \lambda c + (1 - \lambda)c = \lambda c - \lambda c + c = c$ , as desired.

7.7 To show that  $f(x)$  is convex, we need to show that for all  $x_1, x_2 \in C$ ,  $f(\mu x_1 + (1 - \mu)x_2) \leq \mu f(x_1) + (1 - \mu)f(x_2)$ .  $f(\mu x_1 + (1 - \mu)x_2) = \sum_{i=1}^k \lambda_i f_i(\mu x_1 + (1 - \mu)x_2) \leq \sum_{i=1}^k \lambda_i [\mu f_i(x_1) + (1 - \mu)f_i(x_2)] = \mu \sum_{i=1}^k \lambda_i f_i(x_1) + (1 - \mu) \sum_{i=1}^k \lambda_i f_i(x_2) = \mu f(x_1) + (1 - \mu)f(x_2)$ .

7.13 Claim: If  $f$  is convex and bounded above, then  $f$  is constant.

Suppose  $f$  is convex and bounded above, and suppose to the contrary that there exists  $x, y$  where  $f(x) > f(y)$ . Then for any  $x_1, x_2 \in C$  and  $0 \leq \lambda \leq 1$ , we have  $f(\lambda x_1 + (1 - \lambda)x_2) \leq \lambda f(x_1) + (1 - \lambda)f(x_2)$ . Thus, we know  $f(x) \leq \lambda f(\frac{x - (1 - \lambda)y}{\lambda}) + (1 - \lambda)f(y)$ , where  $x = \lambda x_1 + (1 - \lambda)x_2$  and  $y = x_2$ . Rearranging the inequality, we obtain  $\frac{f(x) - (1 - \lambda)f(y)}{\lambda} \leq f(\frac{x - (1 - \lambda)y}{\lambda}) \leq b$ , where  $b$  is a finite upper bound for  $f$ . As  $\lambda \rightarrow 0^+$ ,  $\frac{f(x) - (1 - \lambda)f(y)}{\lambda} \rightarrow \infty$ , which contradicts the assumption that  $f$  is bounded above. Therefore, it follows that  $f$  is constant, that is  $f(x) = f(y)$  for all  $x, y \in C$ .

7.20 Claim: If  $f$  is convex and  $-f$  is also convex, then  $f$  is affine.

Suppose  $f$  is convex. Then,  $f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y)$ . Suppose  $-f$  is convex. Then  $-f(\lambda x + (1 - \lambda)y) \leq -\lambda f(x) - (1 - \lambda)f(y)$ . Multiplying the last inequality by  $-1$  throughout and see that  $f(\lambda x + (1 - \lambda)y) \geq \lambda f(x) + (1 - \lambda)f(y)$ . The only way that both inequalities can be true is if  $f(\lambda x + (1 - \lambda)y) = \lambda f(x) + (1 - \lambda)f(y)$ . Therefore  $f$  is linear and thus affine.

7.21 Suppose  $f(x^*) \leq f(y) \forall y \in \mathbb{R}^n$ . Since  $\phi$  is strictly increasing, we know that

$f(x^*)$  minimizes  $\phi$  over the range of  $f$ , which means that  $x^*$  minimizes  $\phi \circ f$ . Suppose  $\phi \circ f(x^*) \leq \phi \circ f(y) \forall y \in \mathbb{R}^n$ . Then because  $\phi$  is strictly increasing,  $f(x^*) \leq f(y) \forall y \in C$ , which means that  $x^*$  minimizes  $f$ .