## EE364a Homework 1 solutions

2.7 Voronoi description of halfspace. Let a and b be distinct points in  $\mathbf{R}^n$ . Show that the set of all points that are closer (in Euclidean norm) to a than b, i.e.,  $\{x \mid ||x-a||_2 \le ||x-b||_2\}$ , is a halfspace. Describe it explicitly as an inequality of the form  $c^T x \le d$ . Draw a picture.

**Solution.** Since a norm is always nonnegative, we have  $||x - a||_2 \le ||x - b||_2$  if and only if  $||x - a||_2^2 \le ||x - b||_2^2$ , so

$$||x - a||_2^2 \le ||x - b||_2^2 \iff (x - a)^T (x - a) \le (x - b)^T (x - b) \iff x^T x - 2a^T x + a^T a \le x^T x - 2b^T x + b^T b \iff 2(b - a)^T x \le b^T b - a^T a.$$

Therefore, the set is indeed a halfspace. We can take c = 2(b - a) and  $d = b^T b - a^T a$ . This makes good geometric sense: the points that are equidistant to a and b are given by a hyperplane whose normal is in the direction b - a.

2.10 Solution set of a quadratic inequality. Let  $C \subseteq \mathbf{R}^n$  be the solution set of a quadratic inequality,

$$C = \{ x \in \mathbf{R}^n \mid x^T A x + b^T x + c \le 0 \},$$

with  $A \in \mathbf{S}^n$ ,  $b \in \mathbf{R}^n$ , and  $c \in \mathbf{R}$ .

- (a) Show that C is convex if  $A \succeq 0$ .
- (b) Show that the intersection of C and the hyperplane defined by  $g^T x + h = 0$  (where  $g \neq 0$ ) is convex if  $A + \lambda g g^T \succeq 0$  for some  $\lambda \in \mathbf{R}$ .

Are the converses of these statements true?

**Solution.** A set is convex if and only if its intersection with an arbitrary line  $\{\hat{x} + tv \mid t \in \mathbf{R}\}$  is convex.

(a) We have

$$(\hat{x} + tv)^T A(\hat{x} + tv) + b^T (\hat{x} + tv) + c = \alpha t^2 + \beta t + \gamma$$

where

$$\alpha = v^T A v, \qquad \beta = b^T v + 2\hat{x}^T A v, \qquad \gamma = c + b^T \hat{x} + \hat{x}^T A \hat{x}.$$

The intersection of C with the line defined by  $\hat{x}$  and v is the set

$$\{\hat{x} + tv \mid \alpha t^2 + \beta t + \gamma \le 0\},\$$

which is convex if  $\alpha \geq 0$ . This is true for any v, if  $v^T A v \geq 0$  for all v, *i.e.*,  $A \succeq 0$ . The converse does not hold; for example, take A = -1, b = 0, c = -1. Then  $A \not\succeq 0$ , but  $C = \mathbf{R}$  is convex.

(b) Let  $H = \{x \mid g^T x + h = 0\}$ . We define  $\alpha$ ,  $\beta$ , and  $\gamma$  as in the solution of part (a), and, in addition,

$$\delta = q^T v, \qquad \epsilon = q^T \hat{x} + h.$$

Without loss of generality we can assume that  $\hat{x} \in H$ , *i.e.*,  $\epsilon = 0$ . The intersection of  $C \cap H$  with the line defined by  $\hat{x}$  and v is

$$\{\hat{x} + tv \mid \alpha t^2 + \beta t + \gamma \le 0, \ \delta t = 0\}.$$

If  $\delta = g^T v \neq 0$ , the intersection is the singleton  $\{\hat{x}\}\$ , if  $\gamma \leq 0$ , or it is empty. In either case it is a convex set. If  $\delta = g^T v = 0$ , the set reduces to

$$\{\hat{x} + tv \mid \alpha t^2 + \beta t + \gamma \le 0\},\$$

which is convex if  $\alpha \geq 0$ . Therefore  $C \cap H$  is convex if

$$g^T v = 0 \Longrightarrow v^T A v \ge 0.$$

This is true if there exists  $\lambda$  such that  $A + \lambda gg^T \succeq 0$ ; then the above condition holds, because then

$$v^T A v = v^T (A + \lambda g g^T) v \ge 0$$

for all v satisfying  $g^T v = 0$ .

Again, the converse is not true.

- 2.12 Which of the following sets are convex?
  - (a) A slab, i.e., a set of the form  $\{x \in \mathbf{R}^n \mid \alpha \leq a^T x \leq \beta\}$ .
  - (b) A rectangle, i.e., a set of the form  $\{x \in \mathbf{R}^n \mid \alpha_i \leq x_i \leq \beta_i, i = 1, \dots, n\}$ . A rectangle is sometimes called a hyperrectangle when n > 2.
  - (c) A wedge, i.e.,  $\{x \in \mathbf{R}^n \mid a_1^T x \le b_1, \ a_2^T x \le b_2\}.$
  - (d) The set of points closer to a given point than a given set, i.e.,

$$\{x \mid ||x - x_0||_2 \le ||x - y||_2 \text{ for all } y \in S\}$$

where  $S \subseteq \mathbf{R}^n$ .

(e) The set of points closer to one set than another, i.e.,

$$\{x \mid \mathbf{dist}(x, S) \le \mathbf{dist}(x, T)\},\$$

where  $S, T \subseteq \mathbf{R}^n$ , and

$$dist(x, S) = \inf\{||x - z||_2 \mid z \in S\}.$$

(f) The set  $\{x \mid x + S_2 \subseteq S_1\}$ , where  $S_1, S_2 \subseteq \mathbf{R}^n$  with  $S_1$  convex.

(g) The set of points whose distance to a does not exceed a fixed fraction  $\theta$  of the distance to b, *i.e.*, the set  $\{x \mid \|x-a\|_2 \leq \theta \|x-b\|_2\}$ . You can assume  $a \neq b$  and  $0 \leq \theta \leq 1$ .

## Solution.

- (a) A slab is an intersection of two halfspaces, hence it is a convex set (and a polyhedron).
- (b) As in part (a), a rectangle is a convex set and a polyhedron because it is a finite intersection of halfspaces.
- (c) A wedge is an intersection of two halfspaces, so it is convex set. It is also a polyhedron. It is a cone if  $b_1 = 0$  and  $b_2 = 0$ .
- (d) This set is convex because it can be expressed as

$$\bigcap_{y \in S} \{ x \mid ||x - x_0||_2 \le ||x - y||_2 \},$$

i.e., an intersection of halfspaces. (For fixed y, the set

$${x \mid \|x - x_0\|_2 < \|x - y\|_2}$$

is a halfspace; see exercise 2.9).

(e) In general this set is not convex, as the following example in **R** shows. With  $S = \{-1, 1\}$  and  $T = \{0\}$ , we have

$$\{x \mid \mathbf{dist}(x, S) \le \mathbf{dist}(x, T)\} = \{x \in \mathbf{R} \mid x \le -1/2 \text{ or } x \ge 1/2\}$$

which clearly is not convex.

(f) This set is convex.  $x + S_2 \subseteq S_1$  if  $x + y \in S_1$  for all  $y \in S_2$ . Therefore

$${x \mid x + S_2 \subseteq S_1} = \bigcap_{y \in S_2} {x \mid x + y \in S_1} = \bigcap_{y \in S_2} (S_1 - y),$$

the intersection of convex sets  $S_1 - y$ .

(g) The set is convex, in fact a ball.

$$\{x \mid ||x - a||_2 \le \theta ||x - b||_2 \}$$

$$= \{x \mid ||x - a||_2^2 \le \theta^2 ||x - b||_2^2 \}$$

$$= \{x \mid (1 - \theta^2) x^T x - 2(a - \theta^2 b)^T x + (a^T a - \theta^2 b^T b) \le 0 \}$$

If  $\theta = 1$ , this is a halfspace. If  $\theta < 1$ , it is a ball

$${x \mid (x - x_0)^T (x - x_0) \le R^2},$$

with center  $x_0$  and radius R given by

$$x_0 = \frac{a - \theta^2 b}{1 - \theta^2}, \qquad R = \left(\frac{\theta^2 \|b\|_2^2 - \|a\|_2^2}{1 - \theta^2} + \|x_0\|_2^2\right)^{1/2}.$$

- 2.15 Some sets of probability distributions. Let x be a real-valued random variable with  $\mathbf{prob}(x=a_i)=p_i,\ i=1,\ldots,n$ , where  $a_1 < a_2 < \cdots < a_n$ . Of course  $p \in \mathbf{R}^n$  lies in the standard probability simplex  $P=\{p\mid \mathbf{1}^Tp=1,\ p\succeq 0\}$ . Which of the following conditions are convex in p? (That is, for which of the following conditions is the set of  $p\in P$  that satisfy the condition convex?)
  - (a)  $\alpha \leq \mathbf{E} f(x) \leq \beta$ , where  $\mathbf{E} f(x)$  is the expected value of f(x), *i.e.*,  $\mathbf{E} f(x) = \sum_{i=1}^{n} p_i f(a_i)$ . (The function  $f: \mathbf{R} \to \mathbf{R}$  is given.)
  - (b)  $\operatorname{prob}(x > \alpha) \leq \beta$ .
  - (c)  $\mathbf{E}|x^3| \le \alpha \mathbf{E}|x|$ .
  - (d)  $\mathbf{E} x^2 \leq \alpha$ .
  - (e)  $\mathbf{E} x^2 > \alpha$ .
  - (f)  $\operatorname{var}(x) \leq \alpha$ , where  $\operatorname{var}(x) = \mathbf{E}(x \mathbf{E} x)^2$  is the variance of x.
  - (g)  $\operatorname{var}(x) \ge \alpha$ .
  - (h)  $\mathbf{quartile}(x) \ge \alpha$ , where  $\mathbf{quartile}(x) = \inf\{\beta \mid \mathbf{prob}(x \le \beta) \ge 0.25\}$ .
  - (i) quartile(x)  $\leq \alpha$ .

**Solution.** We first note that the constraints  $p_i \geq 0$ , i = 1, ..., n, define halfspaces, and  $\sum_{i=1}^{n} p_i = 1$  defines a hyperplane, so P is a polyhedron.

The first five constraints are, in fact, linear inequalities in the probabilities  $p_i$ .

(a)  $\mathbf{E} f(x) = \sum_{i=1}^{n} p_i f(a_i)$ , so the constraint is equivalent to two linear inequalities

$$\alpha \le \sum_{i=1}^{n} p_i f(a_i) \le \beta.$$

(b)  $\operatorname{\mathbf{prob}}(x \geq \alpha) = \sum_{i: a_i \geq \alpha} p_i$ , so the constraint is equivalent to a linear inequality

$$\sum_{i: a_i \ge \alpha} p_i \le \beta.$$

(c) The constraint is equivalent to a linear inequality

$$\sum_{i=1}^{n} p_i(|a_i^3| - \alpha |a_i|) \le 0.$$

(d) The constraint is equivalent to a linear inequality

$$\sum_{i=1}^{n} p_i a_i^2 \le \alpha.$$

(e) The constraint is equivalent to a linear inequality

$$\sum_{i=1}^{n} p_i a_i^2 \ge \alpha.$$

The first five constraints therefore define convex sets.

(f) The constraint

$$\mathbf{var}(x) = \mathbf{E} x^2 - (\mathbf{E} x)^2 = \sum_{i=1}^n p_i a_i^2 - (\sum_{i=1}^n p_i a_i)^2 \le \alpha$$

is not convex in general. As a counterexample, we can take n=2,  $a_1=0$ ,  $a_2=1$ , and  $\alpha=1/5$ . p=(1,0) and p=(0,1) are two points that satisfy  $\mathbf{var}(x) \leq \alpha$ , but the convex combination p=(1/2,1/2) does not.

(g) This constraint is equivalent to

$$\sum_{i=1}^{n} p_i a_i^2 - (\sum_{i=1}^{n} p_i a_i)^2 = b^T p - p^T A p \ge \alpha,$$

where  $b_i = a_i^2$  and  $A = aa^T$ . We write this as

$$p^T A p - b^T p + \alpha \le 0.$$

This defines a convex set, since the matrix  $aa^T$  is positive semidefinite. To show this set is convex for  $A \in \mathbf{S}_+$ , we first make the observation that

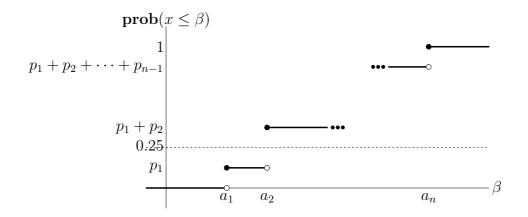
$$x^T A y \le \frac{x^T A x + y^T A y}{2}$$

which follows from  $(x - y)^T A(x - y) \ge 0$ . Now choose  $x, y \in \mathcal{C}$  and show  $z = \theta x + (1 - \theta)y \in \mathcal{C}$ :

$$\begin{split} z^T A z + b^T z + \alpha \\ &= \theta^2 x^T A x + (1 - \theta)^2 y^T A y + 2\theta (1 - \theta) x^T A y + b^T (\theta x + (1 - \theta) y) + \alpha \\ &\leq \theta^2 x^T A x + (1 - \theta)^2 y^T A y + \theta (1 - \theta) (x^T A x + y^T A y) + b^T (\theta x + (1 - \theta) y) + \alpha \\ &= \theta x^T A x + \theta b^T x + (1 - \theta) y^T A y + (1 - \theta) b^T y + \theta \alpha + (1 - \theta) \alpha \\ &= \theta (x^T A x + b^T x + \alpha) + (1 - \theta) (y^T A y + b^T y + \alpha) \\ &\leq 0 \end{split}$$

Therefore  $z \in \mathcal{C}$  and the set is convex.

Let us denote  $\mathbf{quartile}(x) = f(p)$  to emphasize it is a function of p. The figure illustrates the definition. It shows the cumulative distribution for a distribution p with  $f(p) = a_2$ .



(h) The constraint  $f(p) \ge \alpha$  is equivalent to

$$\operatorname{\mathbf{prob}}(x \leq \beta) < 0.25 \text{ for all } \beta < \alpha.$$

If  $\alpha \leq a_1$ , this is always true. Otherwise, define  $k = \max\{i \mid a_i < \alpha\}$ . This is a fixed integer, independent of p. The constraint  $f(p) \geq \alpha$  holds if and only if

$$\operatorname{prob}(x \le a_k) = \sum_{i=1}^k p_i < 0.25.$$

This is a strict linear inequality in p, which defines an open halfspace.

(i) The constraint  $f(p) \leq \alpha$  is equivalent to

$$\operatorname{prob}(x \leq \beta) \geq 0.25 \text{ for all } \beta \geq \alpha.$$

Here, let us define  $k = \max\{i \mid a_i \leq \alpha\}$ . Again, this is a fixed integer, independent of p. The constraint  $f(p) \leq \alpha$  holds if and only if

$$\operatorname{prob}(x \le a_k) = \sum_{i=1}^k p_i \ge 0.25.$$

If  $\alpha < a_1$ , then no p satisfies  $f(p) \leq \alpha$ , which means that the set is empty. Thus, the constraint  $f(p) \leq \alpha$  is a linear inequality on p.