

# DSA3102: Solutions to Homework 1

Assigned: 24/08/23, Due: 07/09/2023

Instructions:

- Please do all the four problems below. A (non-empty) subset of them will be graded.
- Write (legibly) on pieces of paper or Latex your answers. Convert your submission to PDF format.
- Submit to the Assignment 1 folder under Assignments in Canvas before 23:59 on 07/09/2023.

1. Consider the set defined by the following inequalities

$$S = \{x \in \mathbb{R}^2 : x_1 \geq x_2 - 1, x_2 \geq 0\} \cup \{x \in \mathbb{R}^2 : x_1 \leq x_2 - 1, x_2 \leq 0\}$$

(a) Draw the set  $S$ . Is it convex?

**Solutions:** See Fig. 1. Clearly the set  $S$  is not convex.

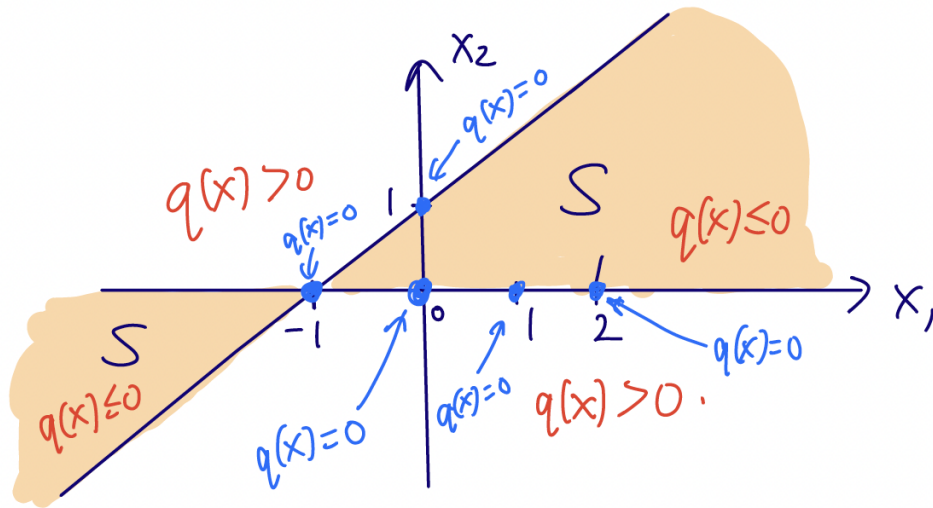


Figure 1: The set  $S$  in Question 1

(b) Show that the set  $S$  can be described as a single quadratic inequality of the form

$$q(x) = x^T A x + 2b^T x + c \leq 0$$

for a matrix  $A \in \mathbf{S}^2$  (2 by 2 symmetric matrix),  $b \in \mathbb{R}^2$  and  $c \in \mathbb{R}$  which you should determine.

*Hint: Note that  $q$  is continuous,  $q \leq 0$  on  $S$  and  $q > 0$  on  $S^c$ , hence  $q$  must be 0 on the boundary of  $S$ .*

(c) What is the convex hull of the set  $S$ ?

**Solutions:** We may write

$$q(x) = x^T A x + 2b^T x + c = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{12} & a_{22} \end{bmatrix} + 2 \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + c$$

We see from the figure that the points  $(0,0)^T, (1,0)^T, (-1,0)^T, (0,1)^T, (1,2)^T$  are on the boundary of  $S$ . On these points  $q(x) = 0$ . We will use these points to solve for  $a_{11}, a_{12}, a_{22}, b_1, b_2, c$ .

First using  $x = (0,0)^T$ , we see that  $x^T A x + 2b^T x = 0$  and hence,  $c = 0$ .

Next using  $x = (1,0)^T$ , we see that  $q(x) = a_{11} + 2b_1 = 0$ .

Next using  $x = (-1,0)^T$ , we see that  $q(x) = a_{11} - 2b_1 = 0$ .

The last two observations imply that  $a_{11} = b_1 = 0$ .

Next using  $x = (0,1)^T$ , we see that  $q(x) = a_{22} - 2b_2 = 0$ , which means that  $a_{22} = 2b_2$ .

Finally, using  $x = (1,2)$ , we see that  $q(x) = 4a_{21} + 4a_{22} + 4b_2 = 4a_{21} + 6a_{22} = 0$ . This means that  $a_{21} = -\frac{3}{2}a_{22}$ .

We may pick  $b_2 = t \in \mathbb{R}$ . Then  $a_{22} = 2t$  and  $a_{21} = -3t$  and  $c = 0$ . This means that

$$A = t \begin{bmatrix} 0 & -3 \\ -3 & 2 \end{bmatrix} \quad b = t \begin{bmatrix} 0 \\ 1 \end{bmatrix}.$$

Thus,

$$q(x) = t [-6x_1x_2 + 2x_2^2 + 2x_2].$$

**Solutions:** The convex hull of  $S$  is  $\mathbb{R}^2$ .

2. The following is a very important result in linear programming duality. Let  $A \in \mathbb{R}^{m \times n}$  and  $y \in \mathbb{R}^m$ . Show that one and only one of the following two conditions is satisfied.

- the system of linear equations  $Ax = y$  admits a non-negative solution  $x \geq 0$ ;
- there exists  $z \in \mathbb{R}^m$  such that  $z^T A \geq 0$  and  $z^T y < 0$ .

You should use the *strict separating hyperplane* theorem.

**Solutions:** It is easy to see that both Statements 1 and 2 cannot hold simultaneously. From Statement 2, we see that there exists  $z$  such that  $z^T A \geq 0$  and  $z^T y < 0$ . Let the nonnegative solution of  $Ax = y$  be  $x$ . Then  $z^T Ax \geq 0$  since both  $z^T A$  and  $x$  are nonnegative. But  $Ax = y$ . Thus,  $z^T y \geq 0$  contradicting  $z^T y < 0$ .

Now suppose Statement 1 does not hold. Then we claim that Statement 2 must hold. Suppose there is no  $x \geq 0$  such that  $Ax = y$ . Thus  $y \notin \text{conic}(A)$ , where  $\text{conic}(A)$  is the set of conic combinations of the columns of  $A$ . Since  $\{y\}$  is convex, closed and bounded and  $\text{conic}(A)$  is convex and closed, by the strict separating hyperplane theorem, there exists a hyperplane  $\{x : z^T x = q\}$  that strictly separates  $\{y\}$  and  $\text{conic}(A)$ , i.e.,

$$z^T y < q \quad \text{and} \quad z^T A v > q \quad \forall v \geq 0.$$

Note that  $q$  is necessarily negative from the second condition above. (Suppose  $q \geq 0$ . Then take  $v = 0$ , which yields  $z^T A v = 0$ , which contradicts  $z^T A v > q$ .) This implies that  $z^T y < 0$ .

Now, we prove that  $z^T A v > q$  for all  $v \geq 0$  implies that  $z^T A \geq 0$ , which would conclude the proof (as this is precisely Statement 2). Suppose, to the contrary, that there exists a coordinate of the vector  $z^T A$  that is negative. Say the coordinate is  $i$ , i.e.,  $(z^T A)_i < 0$ . Then we set  $v = L e_i \geq 0$  ( $e_i$  is the  $i$ -th unit vector) for some  $L > 0$ . Then  $z^T A v = L(z^T A)_i < 0$ . By making  $L > 0$  sufficiently large,  $z^T A v = L(z^T A)_i < q$ . This contradicts  $z^T A v > q$ . Thus Statement 2 is proved.

Technically, we also have to prove that the following cannot happen. (i) Both Statements 1 and 2 are not satisfied; (ii) Statement 2 does not hold implies Statement 1 holds. However (i) and (ii) are easy to deduce from the fact that “Statements 1 and 2 cannot hold simultaneously” and “Statement 1 does not hold implies Statement 2 must hold”. Please convince yourself of this.

3. The *polar* of an arbitrary set  $C \subset \mathbb{R}^n$  is defined as the set

$$C^\circ := \{y \in \mathbb{R}^n : y^T x \leq 1 \text{ for all } x \in C\}$$

- (a) (3 points) Let  $C \subset \mathbb{R}^n$  be any set, not necessarily convex. Is  $C^\circ$  convex? Justify your answer carefully.

**Solution:** Yes  $C^\circ$  is convex. It can be written as

$$C^\circ = \bigcap_{x \in C} \{y \in \mathbb{R}^n : y^T x \leq 1\}$$

Each set  $\{y \in \mathbb{R}^n : y^T x \leq 1\}$  parametrized by  $x \in C$  is a halfspace hence convex. Intersection of convex sets is convex.

- (b) (5 points) Recall that a *cone*  $K$  is such that if  $x \in K$  and  $\lambda \geq 0$ , then  $\lambda x \in K$ . Recall that the *dual cone* is defined as

$$K^* := \{y \in \mathbb{R}^n : y^T x \geq 0 \text{ for all } x \in K\}$$

It is known that the polar of the cone  $K$ , denoted as  $K^\circ$ , and the dual cone, denoted as  $K^*$ , are related as follows:

$$K^\circ = -cK^*$$

for some *positive* number  $c > 0$ . Find  $c$ .

**Solution:** The answer is  $c = 1$ . We prove this in two parts first noting that

$$-K^* := \{y : y^T x \leq 0 \text{ for all } x \in K\}$$

$K^\circ \subset -K^*$ : Take  $y \in K^\circ$ . This means that  $y^T x \leq 1$  for all  $x \in K$ . Since  $K$  is a cone, if  $x \in K$ , we have  $\lambda x \in K$  for all  $\lambda \geq 0$ . This means that  $y^T x \leq 1/\lambda$  for all  $x \in K$  and all  $\lambda \geq 0$ . Now take  $\lambda \rightarrow \infty$ . Then we conclude that  $y^T x \leq 0$  for all  $x \in K$ . This means that  $y \in -K^*$ .

$-K^* \subset K^\circ$ : Take  $y \in -K^*$ . This means that  $y^T x \leq 0$  for all  $x \in K$ . Clearly  $y^T x \leq 1$  for all  $x \in K$ . This means that  $y \in K^\circ$  as desired.

- (c) (2 points) Show carefully that the polar of the unit ball  $\mathcal{B}(0, 1) := \{x \in \mathbb{R}^n : \|x\|_2 \leq 1\}$  is the unit ball. You may find the Cauchy-Schwarz inequality (i.e.,  $x^T y \leq \|x\|_2 \|y\|_2$ ) useful.

**Solution:** We need to show that  $\mathcal{B}(0, 1)^\circ = \mathcal{B}(0, 1)$ .

Take  $x \in \mathcal{B}(0, 1)^\circ$ . This means that  $x^T y \leq 1$  for all  $y \in \mathcal{B}(0, 1)$ . Suppose  $\|x\|_2 > 1$ . Now let  $y = x/\|x\|_2$ . Then the inner product  $y^T x = \|x\|_2 > 1$ , which contradicts  $x^T y \leq 1$ . This means that  $\|x\|_2 \leq 1$ , i.e.,  $x \in \mathcal{B}(0, 1)$ .

Now take  $x \in \mathcal{B}(0, 1)$ . This means that  $\|x\|_2 \leq 1$ . Fix  $y \in \mathcal{B}(0, 1)$ . We have

$$x^T y \leq \|x\|_2 \|y\|_2 \leq \|y\|_2 \leq 1$$

This means that  $x \in \mathcal{B}(0, 1)^\circ$ .

4. (a) For  $x, y$  both positive scalars, show that

$$ye^{x/y} = \sup_{\alpha > 0} \alpha(x + y) - y\alpha \log \alpha.$$

(log here refers to the natural logarithm.) Use the above result to prove that the function  $f : \mathbb{R}_{++}^n \rightarrow \mathbb{R}$  defined as

$$f(x, y) = ye^{x/y}$$

is convex.

**Solutions:** Let  $g(\alpha) = \alpha(x + y) - y\alpha \log \alpha$ . Then

$$g'(\alpha) = (x + y) - y\alpha \cdot \frac{1}{\alpha} - y \log \alpha.$$

Setting this derivative to zero, we obtain

$$x - y \log \alpha = 0$$

or

$$\alpha^* = e^{x/y}$$

Since  $\alpha^* > 0$ , it satisfies the constraint automatically, and hence

$$g(\alpha^*) = e^{x/y} (x + y) - y e^{x/y} \log(e^{x/y}) = y e^{x/y}$$

as desired.

Since  $f$  is the pointwise supremum of a bunch of affine, hence convex, functions, it is also convex.

(b) Show that the function  $f : \mathbb{R}_{++}^2 \rightarrow \mathbb{R}$

$$f(x) = (\sqrt{x_1} + \sqrt{x_2})^2$$

is concave by examining the definiteness of its Hessian.

**Solution:** We can write  $f(x) = x_1 + x_2 + 2\sqrt{x_1 x_2}$ . The gradient vector is

$$\nabla f(x) = \begin{bmatrix} 1 + \sqrt{\frac{x_2}{x_1}} & 1 + \sqrt{\frac{x_1}{x_2}} \end{bmatrix}^T.$$

The Hessian is

$$\nabla^2 f(x) = \begin{bmatrix} -\frac{1}{2} \sqrt{\frac{x_2}{x_1^3}} & \frac{1}{2} \frac{1}{\sqrt{x_1 x_2}} \\ \frac{1}{2} \frac{1}{\sqrt{x_1 x_2}} & -\frac{1}{2} \sqrt{\frac{x_1}{x_2^3}} \end{bmatrix}.$$

We check the definiteness of  $\nabla^2 f$ . We can write  $\nabla^2 f$  as

$$\nabla^2 f(x) = -\frac{1}{2\sqrt{x_1 x_2}} vv^T$$

where

$$v = \begin{bmatrix} \sqrt{\frac{x_2}{x_1}} & \sqrt{\frac{x_1}{x_2}} \end{bmatrix}^T.$$

Hence  $\nabla^2 f(x)$  is negative semidefinite.

Another way to prove that  $\nabla^2 f(x)$  is negative semidefinite is to show that  $-\nabla^2 f(x)$  is positive semidefinite. That is, we want to show that

$$A = -\nabla^2 f(x) = \begin{bmatrix} \frac{1}{2} \sqrt{\frac{x_2}{x_1^3}} & -\frac{1}{2} \frac{1}{\sqrt{x_1 x_2}} \\ -\frac{1}{2} \frac{1}{\sqrt{x_1 x_2}} & \frac{1}{2} \sqrt{\frac{x_1}{x_2^3}} \end{bmatrix}$$

is PSD. We check all the all the principal minors are nonnegative. The (1,1) and (2,2) entries  $\frac{1}{2} \sqrt{\frac{x_2}{x_1^3}}$  and  $\frac{1}{2} \sqrt{\frac{x_1}{x_2^3}}$  are clearly positive. The determinant is

$$\det(A) = \frac{1}{2} \sqrt{\frac{x_2}{x_1^3}} \cdot \frac{1}{2} \sqrt{\frac{x_1}{x_2^3}} - \left( -\frac{1}{2} \frac{1}{\sqrt{x_1 x_2}} \right)^2 = 0.$$

Hence  $A = -\nabla^2 f(x)$  is positive semidefinite showing that  $f$  is concave. Note that you need to check that *all* the principal minors are nonnegative; it is not enough to check that the upper left minors are nonnegative.