

# Convex Optimization

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## 2 Convex Sets

### 2.1 Definition of convexity

1.

*Proof.* For  $k = 2$ ,  $\theta_1 x_1 + \theta_2 x_2 \in C$  holds by definition. We argue by induction on  $k$  and assume that the inclusion holds for  $k < m$ . When  $k = m$ , denoting  $\sum_{i=1}^{m-1} \theta_i$  by  $s$ ,

$$\sum_{i=1}^m \theta_i x_i = s \sum_{i=1}^{m-1} \frac{\theta_i x_i}{s} + \theta_m x_m.$$

Since  $\sum_{i=1}^{m-1} \theta_i / s = 1$ , by the induction hypothesis,  $\sum_{i=1}^{m-1} \theta_i x_i / s \in C$ . Meanwhile, as  $s + \theta_m = 1$ ,  $\sum_{i=1}^m \theta_i x_i \in C$ , completing the proof.  $\square$

2.

*Proof.* Clear that the intersection of two convex sets is still convex. Hence, the intersection of  $C \subset \mathbb{R}^n$  and any line is convex as long as  $C$  is convex.

Now we suppose that the intersection of  $C$  and any line is convex. For any  $x_1, x_2 \in C$ ,  $C_l = C \cap \{\theta x_1 + (1 - \theta)x_2 : \theta \in \mathbb{R}\}$  is convex and therefore  $\theta x_1 + (1 - \theta)x_2 \in C_l \subset C$  for every  $0 \leq \theta \leq 1$ . Thus,  $C$  is convex.

The above argument, *mutatis mutandis*, gives the second result.  $\square$

3.

*Proof.* For every  $\theta \in [0, 1]$ , the process of bisecting the interval implies there exists a series  $\langle \delta_n \rangle$  whose sum is  $\theta$ . Hence, for every  $a, b \in C$ ,  $x_n = a + (b - a) \sum_{n=1}^{\infty} \delta_n$  converges to  $a + \theta(b - a)$ . Meanwhile, the midpoint convexity implies  $x_n \in C$  for every  $n$ . And since  $C$  is closed,  $a + \theta(b - a) \in C$ . Thus,  $C$  is convex.  $\square$

4.

*Proof.* Let  $D$  be the intersection of all convex sets containing  $C$ . If  $x \in C$ , then it is a convex combination of some points in  $C$ . Hence, for every convex set containing  $C$ , it contains  $x$ . Therefore,  $\mathbf{conv} C \subset D$ . For the converse, since  $\mathbf{conv} C$  itself is a convex set containing  $C$ ,  $D \subset \mathbf{conv} C$ . Thus,  $\mathbf{conv} C = D$ .  $\square$

### 2.2 Examples

5.

*Solution.*  $|b_2 - b_1| / \|a\|_2$ .  $\square$

7.

*Proof.*  $\|x - a\|_2 \leq \|x - b\|_2$  iff  $\langle x - a, x - a \rangle \leq \langle x - b, x - b \rangle$  iff  $2\langle x, b - a \rangle \leq \langle b, b \rangle - \langle a, a \rangle$ . Namely,  $2(b - a)^T x \leq \|b\|_2^2 - \|a\|_2^2$ .  $\square$

## 2.8

*Proof.*

(a) It is trivial when  $a_1$  and  $a_2$  are linearly dependent, so we assume that  $a_1$  and  $a_2$  are linearly independent. We first tackle the problem for orthonormal  $a_1$  and  $a_2$  and then reduce the general situation to it.

Suppose that  $a_1$  and  $a_2$  are orthonormal. Let  $S_0 = \text{span}(a_1, a_2)$  and  $(b_1, \dots, b_{n-2})$  a basis of  $S_0^\perp$ . Then

$$x \in S_0 \iff \begin{bmatrix} b_1^T \\ \vdots \\ b_{n-2}^T \end{bmatrix} x = Bx = 0.$$

For  $y = y_1 a_1 + y_2 a_2 \in S_0$ ,  $y_1 \leq 1$  iff  $a_1^T y \leq 1$  as  $(a_1, a_2)$  is an orthonormal basis of  $S_0$ . Hence,

$$-1 \leq y_1, y_2 \leq 1 \iff \begin{bmatrix} a_1^T \\ a_2^T \\ -a_1^T \\ -a_2^T \end{bmatrix} y = Ay \preceq \mathbf{1}.$$

Thus, for orthonormal  $a_1$  and  $a_2$ ,  $S = \{x : Bx = 0, Ax \preceq \mathbf{1}\}$ , a polyhedron.

Now we only assume the linear independence of  $a_1$  and  $a_2$ . We know that there exists some invertible  $n$ -by- $n$  matrix<sup>1</sup>  $R$  such that  $[\tilde{a}_1, \tilde{a}_2] = R[a_1, a_2]$  and  $\tilde{a}_1$  and  $\tilde{a}_2$  are orthonormal. Denoting the set described in the problem with respect to  $u_1$  and  $u_2$  by  $S(u_1, u_2)$ ,  $x \in S(a_1, a_2)$  iff  $Rx \in S(\tilde{a}_1, \tilde{a}_2)$  iff  $Rx \in \{x : \tilde{B}x = 0, \tilde{A}x \preceq \mathbf{1}\}$  where the meaning of  $\tilde{A}$  and  $\tilde{B}$  are described in the previous passage. Hence,

$$S(a_1, a_2) = \{x : \tilde{B}Rx = 0, \tilde{A}Rx \preceq \mathbf{1}\}.$$

(b) Yes, and the provided form has already satisfied the requirement.

(c) No. Note that  $\langle x, y \rangle_2 \leq 1$  for all  $y$  with 2-norm 1 implies

$$\|x\|_2 = \langle x, x/\|x\| \rangle_2 \leq 1.$$

And by the Cauchy-Schwarz inequality, for every  $\|x\| \leq 1$ ,  $\langle x, y \rangle_2$  holds for every  $\|y\|_2 = 1$ . Hence,  $S$  is the intersection of the unit ball and  $\{x : x \succeq 0\}$ , which is not a polyhedron.

(d) Yes. Let  $\tilde{S} = \{x \in \mathbb{R}^n : x \succeq 0, \|x\|_\infty \leq 1\}$ , which is clearly a polyhedron since when  $x \succeq 0$ ,  $\|x\|_\infty \leq 1$  is equivalent to  $[e_1, \dots, e_n]x \preceq \mathbf{1}$  where  $e_i$  is the  $i$ -th vector in the standard basis of  $\mathbb{R}^n$ .

Now we show that  $S = \tilde{S}$ . Suppose that  $x \succeq 0$ . If  $\langle x, y \rangle_2 \leq 1$  for all  $y$  with 1-norm 1, then  $x_i = \langle x, e_i \rangle_2 \leq 1$ . Namely,  $\|x\|_\infty \leq 1$ . Meanwhile, if  $\|x\|_\infty \leq 1$ ,

$$\langle x, y \rangle \leq \sum_{i=1}^n x_i |y_i| \leq 1$$

as it is just the weighted average of  $x_1, \dots, x_n$ . Hence,  $S = \tilde{S}$ , completing the proof.  $\square$

<sup>1</sup>We can use  $QR$  factorization to construct the matrix explicitly

## 2.9

*Proof.*

(a) By the definition,

$$\begin{aligned}
x \in V &\Leftrightarrow \|x - x_0\|_2^2 - \|x - x_i\|_2^2 \leq 0 \\
&\Leftrightarrow 2\langle x, x_i - x_0 \rangle \leq \langle x_i, x_i \rangle - \langle x_0, x_0 \rangle \quad \text{for } i = 1, \dots, K \\
&\Leftrightarrow 2 \begin{bmatrix} \langle x, x_1 - x_0 \rangle \\ \vdots \\ \langle x, x_K - x_0 \rangle \end{bmatrix} \preceq \begin{bmatrix} \|x_1\|_2^2 - \|x_0\|_2^2 \\ \vdots \\ \|x_K\|_2^2 - \|x_0\|_2^2 \end{bmatrix} \\
&\Leftrightarrow 2 \begin{bmatrix} (x_1 - x_0)^T \\ \vdots \\ (x_K - x_0)^T \end{bmatrix} x \preceq \begin{bmatrix} \|x_1\|_2^2 - \|x_0\|_2^2 \\ \vdots \\ \|x_K\|_2^2 - \|x_0\|_2^2 \end{bmatrix}
\end{aligned}$$

Hence,  $V$  is a polyhedron. Intuitively, the border of a Voronoi set are the lines with the same distances to  $x_0$  and  $x_i$ .

(b) Suppose that  $P = \{x : \alpha_k^T x \leq b_k, k = 1, \dots, K\}$ . Let  $x_0$  be any point of  $P$  and we construct the other points by reflection. For each  $k$ , let  $\tilde{x}_k$  be any point of  $\{x : \alpha_k^T x = b_k\}$ ,  $U_k = I - 2\alpha_k\alpha_k^T/\|\alpha_k\|_2^2$ , the Householder matrix, and

$$R_k(x) = U_k(x - \tilde{x}_k) + \tilde{x}_k = x + 2\frac{\alpha_k}{\|\alpha_k\|_2^2}(b_k - \alpha_k^T x).$$

It is easy to verified that  $P$  is the Voronoi region of  $x_0$  with respect to  $R_1(x_0), \dots, R_K(x_0)$ .  $\square$

## 10.

*Proof.*

(a) Suppose  $x_1, x_2 \in C$  and  $\theta \in (0, 1)$ . Let  $x = \theta x_1 + (1 - \theta)x_2$ . Since  $A$  is symmetric,  $x_2^T A x_1 = x_1^T A x_2$ . Thus,

$$\begin{aligned}
f(x) &= x^T A x + b^T x + c \\
&= \theta^2 x_1^T A x_1 + 2\theta(1 - \theta)x_1^T A x_2 + (1 - \theta)^2 x_2^T A x_2 \\
&\quad + \theta b^T x_1 + (1 - \theta)b^T x_2 + \theta c + (1 - \theta)c.
\end{aligned}$$

Note that

$$\begin{aligned}
\theta^2 x_1^T A x_1 + \theta b_1^T x_1 + \theta c &= \theta(x_1^T A x_1 + b_1^T x_1 + c) - \theta(1 - \theta)x_1^T A x_1 \\
&\leq -\theta(1 - \theta)x_1^T A x_1
\end{aligned}$$

and we can get a similar inequality for  $x_2$ . Hence,

$$\begin{aligned}
f(x) &\leq -\theta(1 - \theta)(x_1^T A x_1 - 2x_1^T A x_2 + x_2^T A x_2) \\
&= -\theta(1 - \theta)(x_1 - x_2)^T A (x_1 - x_2) \leq 0
\end{aligned}$$

as  $A \succeq 0$ . Hence,  $C$  is convex.

(b) Put  $H = \{x : g^T x + h = 0\}$ ,  $B = A + \lambda g g^T$  and

$$C_B = \{x \in \mathbb{R}^n : x^T B x + b^T x + c - \lambda h^2 \leq 0\}.$$

By (a),  $C_B$  is convex and so does  $C_B \cap H$ . Suppose  $x \in H$ , then  $x^T B x = x^T A x + \lambda h^2$ . Therefore,  $C_B \cap H = C$ . Thus,  $C$  is convex.  $\square$

## 2.3 Operations that preserve convexity

### 2.16

*Proof.* For every  $(a, b_1 + b_2), (c, d_1 + d_2) \in S$  and  $0 \leq \theta \leq 1$ , let

$$z_\theta = \theta(a, b_1 + b_2) + (1 - \theta)(c, d_1 + d_2) = (x, y_1 + y_2)$$

where

$$x = \theta a + (1 - \theta)c, \quad y_i = \theta b_i + (1 - \theta)d_i \quad \text{for } i = 1, 2.$$

Since  $S_i$  is convex and  $(a, b_i), (c, d_i) \in S_i$ ,

$$(x, y_i) = \theta(a, b_i) + (1 - \theta)(c, d_i) \in S_i.$$

Hence,  $S$  is convex. □

### 18.

*Proof.* By Remark 2.2,  $f^{-1} = \mathcal{P}^{-1} \circ Q^{-1} \circ \mathcal{P}$ . □

### 19.

*Proof.*

(a)  $f^{-1}(C) = \{x \in \mathbf{dom} f : (g^T A - hc^T)x \leq dh - g^T b\}$ , the intersection of a halfspace and  $\mathbf{dom} f$ .

(b)  $f^{-1}(C) = \{x \in \mathbf{dom} f : (GA - hc^T)x \preceq dh - Gb\}$ , the intersection of a polyhedron and  $\mathbf{dom} f$ .

(c) □