

Midterm 1

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Q1: Normal cones to level sets.

Grade:

Suppose $h : \mathbb{R}^n \rightarrow \mathbb{R}$ is a continuously differentiable convex function, and consider the level set $L(0, h) = \{x \in \mathbb{R}^n \mid h(x) \leq 0\}$. Assuming that there exists some point $\bar{x} \in \mathbb{R}^n$ with $h(\bar{x}) < 0$, prove that, for any $x \in L(0, h)$, the normal cone $N_{L(0, h)}(x)$ to $L(0, h)$ at x is given by the formula

$$N_{L(0, h)}(x) = \{\alpha \nabla h(x) \mid \alpha \geq 0, \alpha h(x) = 0\} \begin{cases} \emptyset & \text{if } h(x) > 0 \\ \{\alpha \nabla h(x) \mid \alpha \geq 0\} & \text{if } h(x) = 0 \\ \{\mathbf{0}\} & \text{if } h(x) < 0 \end{cases}$$

Solution

Proof. We prove the statement by cases.

1. If $h(x) > 0$, then $x \notin L(0, h)$, so $N_{L(0, h)}(x) = \emptyset$, which is trivial.
2. If $h(x) = 0$, x lies on the boundary of $L(0, h)$. The function h being continuously differentiable and convex implies that at x , the gradient $\nabla h(x)$ points in a direction that is normal to the level set $L(0, h)$ (since the normal cone is the polar cone of tangent cone of level set at x). By convexity, we have

$$h(y) \geq h(x) + \langle \nabla h(x), y - x \rangle, \quad \forall y \in L(0, h).$$

With $h(y) \leq 0$ (definition of level set) and $h(x) = 0$ (case assumption), we have

$$\langle \nabla h(x), y - x \rangle \leq 0.$$

This means the vector $\nabla h(x)$ is an outward normal to the level set at x . Since h does not increase in the direction inside the level set, the normal cone at x consists of all non-negative scalar multiples of $\nabla h(x)$, i.e.

$$N_{L(0, h)}(x) = \{\alpha \nabla h(x) \mid \alpha \geq 0\}.$$

3. If $h(x) < 0$, the $x \in \text{ri } L(0, h)$. The normal cone at a point in the relative interior of a convex set is just the zero vector. Because there are directions in every neighborhood around x that stay within $L(0, h)$, and therefore no “outside” direction is associated with a decrease from x within level set. Thus,

$$N_{L(0, h)}(x) = \{\mathbf{0}\}.$$

□

Question: Is the necessity of the assumption $h(\bar{x}) < 0$ for some \bar{x} to guarantee that the level set $L(0, h)$ is nonempty?

Q2**Grade:**

(Optimality conditions for convex problems with “mixed” constraint sets.) Consider an optimization problem of the form

$$\begin{aligned} \min \quad & f(x) \\ \text{S.T.} \quad & Ax = b \\ & h_j(x) \leq 0 \quad j = 1, 2, \dots, r \\ & x \in X \end{aligned} \tag{1}$$

where

- $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$ is a convex function
- A is an $m \times n$ matrix and $b \in \mathbb{R}^m$
- For $j = 1, 2, \dots, r$, $h_j : \mathbb{R}^n \rightarrow \mathbb{R}$ is a differentiable convex function
- X is a convex set.

Let a_i denote row i of A , $i = 1, 2, \dots, m$ represented as a column vector. Suppose that there exists a point $\bar{x} \in \mathbb{R}^n$ with the following properties:

- $\bar{x} \in \text{ri dom } f$
- $A\bar{x} = b$
- For $j = 1, 2, \dots, r$, $h_j(\bar{x}) < 0$
- $\bar{x} \in \text{ri } X$.

Show that for $x^* \in \mathbb{R}^n$ to be a solution of eq. (1), it is necessary and sufficient that there exist $\lambda^* \in \mathbb{R}^m$ and $\mu^* \in \mathbb{R}^r$ such that

$$\begin{aligned} \partial f(x^*) + \sum_{i=1}^m \lambda_i^* a_i + \sum_{j=1}^r \mu_j^* \nabla h_j(x^*) + N_X(x^*) &\ni 0 \\ \sum_{j=1}^r \mu_j^* h_j(x^*) &= 0 \\ Ax^* &= b \\ h_j(x^*) &\leq 0 \quad j = 1, 2, \dots, r \\ \mu_j^* &\geq 0 \quad j = 1, 2, \dots, r. \end{aligned}$$

Solution

Proof. Solving eq. (1) is equivalent to solving the following cvx problem:

1. $f_1(x) = f(x)$
2. $f_2(x) = \delta_L(x) = \begin{cases} 0, & Ax = b \\ +\infty, & \text{otherwise} \end{cases}$
3. $f_3(x) = \delta_X(x) = \begin{cases} 0, & x \in X \\ +\infty, & \text{otherwise} \end{cases}$

$$4. f_4(x) = \delta_{h_j}(x) = \begin{cases} 0, & h_j(x) \leq 0 \\ +\infty, & \text{otherwise} \end{cases}, j=1,2,\dots,r$$

Let x^* be an optimal solution to the optimization problem. For $h_j(x^*) = 0$, we can use the result from the previous question and have normal cone $N_{L(0,h_j)}(x^*) = \{\mu_j^* \nabla h_j(x^*) \mid \mu_j^* \geq 0\}$. For $h_j(x^*) < 0$, we will have $\mu_j^* = 0$ since we can't have a positive multiplier for a strictly feasible constraint. These contribute to the condition of $f_4(x)$

$$\sum_{j=1}^r \mu_j^* h_j(x^*) = 0; \quad h_j(x^*) \leq 0 \quad j = 1, 2, \dots, r; \quad \mu_j^* \geq 0 \quad j = 1, 2, \dots, r.$$

With the proposition that we have proved in the class, we know that solving $\partial(f_1 + f_2 + f_3)(x) \ni \partial f_1(x) + \partial f_2(x) + \partial f_3(x)$ with condition $Ax = b$ implies

$$\exists \lambda^* \in \mathbb{R}^m, x^* \in \mathbb{R}^n \quad \partial f(x^*) + A^T \lambda^* + N_X(x^*) \ni 0.$$

Combine the above results (since $\bar{x} \in \text{ri dom } f_1 \cap \text{ri dom } f_2 \cap \text{ri dom } f_3 \cap \text{ri dom } f_4 \neq \emptyset$), we have (using Rockafellar-Moreau theorem)

$$\partial f(x^*) + \sum_{i=1}^m \lambda_i^* a_i + \sum_{j=1}^r \mu_j^* \nabla h_j(x^*) + N_X(x^*) \ni 0,$$

which completes the proof. □

Q3: Optimality conditions for convex cone programming.

Grade:

Below, suppose $K \subseteq \mathbb{R}^m$ be a nonempty closed convex cone,

- (a) Show that for any $x \in K$,

$$F_K(x) = \{z - \alpha x \mid z \in K, \alpha \geq 0\}.$$

- (b) Show that for any $x \in K$,

$$N_K(x) = \{y \in K^* \mid \langle x, y \rangle = 0\}.$$

Hint: you may use the results of homework 3, problem 1(c) and 5(c).

- (c) A is an $m \times n$ matrix, and $b \in \mathbb{R}^m$, and let $Z = \{x \in \mathbb{R}^n \mid Ax - b \in K\}$. Assume that Z is nonempty. Show that, for $x \in Z$,

$$N_Z(x) = \text{cl}\{A^T \lambda \mid \lambda \in K^*, \langle Ax - b, \lambda \rangle = 0\}.$$

Hint: you may use the results of homework 3, problem 5.

- (d) Show that $\text{ri } Z \supseteq \{x \in \mathbb{R}^n \mid Ax - b \in \text{ri } K\}$.

- (e) Let $f : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{+\infty\}$ be a convex function, suppose that the cone $A^T K^* = \{A^T \lambda \mid \lambda \in K^*\}$ is closed, and consider the problem

$$\begin{aligned} \min \quad & f(x) \\ \text{S.T.} \quad & Ax - b \in K. \end{aligned} \tag{2}$$

Further suppose that there exists some point $\bar{x} \in \text{ri dom } f$ such that $A\bar{x} - b \in \text{ri } K$. Show that, in order for $x^* \in \mathbb{R}^n$ to solve eq. (2), it is necessary and sufficient that there exists $\lambda^* \in \mathbb{R}^m$ such that

$$\begin{aligned} \partial f(x^*) + A^T \lambda^* &\ni 0 \\ \lambda^* &\in K^* \\ \langle Ax^* - b, \lambda^* \rangle &= 0. \end{aligned}$$

Solution

(a) *Proof.* By definition 4.6.1, given $x \in K$, we have

$$F_K(x) = \{ y \in \mathbb{R}^m \mid x + \alpha y \in K, \forall \alpha \in [0, \bar{\alpha}], \bar{\alpha} > 0 \},$$

where y is a feasible direction. Here, to show that

$$F_K(x) = \{ z - \alpha x \mid z \in K, \alpha \geq 0 \},$$

we need to show $y = z - \alpha x$ is a feasible direction and every feasible direction can be represented as $y = z - \alpha x$.

Let $y = z - \alpha x$ where $z \in K$ and $\alpha \geq 0$. Consider $x + ty$ for $t > 0$,

$$x + ty = x + t(z - \alpha x) = x + tz - t\alpha x = (1 - t\alpha)x + tz.$$

Since K is a convex cone, it is closed under positive linear combinations. For sufficiently small t , $1 - t\alpha$ remains positive, and hence $(1 - t\alpha)x + tz$ is a positive linear combination of points in K , which means $x + ty \in K$ for all sufficiently small $t > 0$. Therefore, y is a feasible direction at x .

Let y be any feasible directions in $F_K(x)$. By definition, for all small $t > 0$, $x + ty \in K$. By the convexity of K , the line segment connecting x and $x + ty$ must entirely lie in K . For a sufficiently small t , this implies that y can be represented as

$$y = \frac{1}{t}(x + ty) - \frac{1}{t}x \Rightarrow (x + ty) - x = z - \alpha x,$$

where $z = x + ty \in K$. We can set $\alpha = 1$ to match the form required. So, $y = z - \alpha x$ with $x \in K$ and $\alpha = 1 \geq 0$. \square

(b) *Proof.* The proof contains two parts.

(a) $N_K(x) \subseteq \{ y \in K^* \mid \langle x, y \rangle = 0 \}$. Take any $y \in N_K(x)$. By definition of the normal cone, for all $z \in K$

$$\langle y, z - x \rangle \leq 0.$$

Since K is a cone, for $\lambda > 0$, λx is also in K . Replace z by λx and get

$$\langle y, \lambda x - x \rangle \leq 0,$$

which simplifies to

$$\lambda \langle y, x \rangle - \langle y, x \rangle \leq 0 \Rightarrow (\lambda - 1) \langle y, x \rangle \leq 0.$$

Since λ is arbitrary, we must have $\langle y, x \rangle = 0$. Besides, $\langle y, x \rangle \leq 0$ implies $y \in K^*$. Therefore, $N_K(x) \subseteq \{ y \in K^* \mid \langle x, y \rangle = 0 \}$.

(b) $\{ y \in K^* \mid \langle x, y \rangle = 0 \} \subseteq N_K(x)$. By the definition of K^* , we have that for every $y \in K^*$ and for every $z \in K$,

$$\langle y, z \rangle \leq 0.$$

And given $\langle y, x \rangle = 0$, we have

$$\langle y, z - x \rangle = \langle y, z \rangle - \langle y, x \rangle \leq 0 - 0 = 0,$$

which implies $y \in N_K(x)$. Therefore, $\{ y \in K^* \mid \langle x, y \rangle = 0 \} \subseteq N_K(x)$.

The two parts together prove the statement. \square

(c) *Proof.* For vector v that is in $N_Z(x)$, it must have

$$\langle v, z - x \rangle \leq 0 \quad \forall z \in Z.$$

To use the definition of Z , we have

$$\langle v, z - x \rangle = \langle A^T v, Az - Ax \rangle = \langle A^T v, (Az - b) - (Ax - b) \rangle.$$

For v to be in the normal cone $N_Z(x)$, the last inner product should be non-positive for all $Az - b \in K$, which means that $A^T v$ must be in the normal cone to K at the point $Ax - b$, i.e. $A^T v \in N_K(Ax - b)$. With the previous question, we can relate $N_K(Ax - b)$ to K^* by

$$N_K(Ax - b) = \{ \lambda \in K^* \mid \langle Ax - b, \lambda \rangle = 0 \}.$$

So, a vector $v \in N_Z(x)$ must correspond to a λ in the dual cone K^* such that $A^T \lambda$ has a zero inner product with $Ax - b$, hence $v = A^T \lambda$ for some λ satisfying $\langle Ax - b, \lambda \rangle = 0$. To account for the fact that the normal cone $N_Z(x)$ is a closed set, we take the closure of the set $\{ A^T \lambda \mid \lambda \in K^*, \langle Ax - b, \lambda \rangle = 0 \}$ since the image under a linear transformation of a closed set is not necessarily closed. Therefore,

$$N_Z(x) = \text{cl}\{ A^T \lambda \mid \lambda \in K^*, \langle Ax - b, \lambda \rangle = 0 \}.$$

□

- (d) *Proof.* Let x_0 be such that $Ax_0 - b \in \text{ri}(K)$. By the prolongation principle, for every point $\bar{y} \in K$, there exists $\delta > 1$ such that

$$Ax_0 - b + (\delta - 1)(Ax_0 - b - \bar{y}) \in K.$$

Now, let x be any point in Z , implying $Ax - b \in K$. Taking $\bar{y} = Ax - b$, the prolongation principle gives us

$$\begin{aligned} Ax_0 - b + (\delta - 1)((Ax_0 - b) - (Ax - b)) &\in K \\ \Rightarrow A(x_0 + (\delta - 1)(x_0 - x)) - b &\in K. \end{aligned}$$

showing that

$$x_0 + (\delta - 1)(x_0 - x) \in Z.$$

Since this is true for any $x \in Z$, x_0 must be in $\text{ri}(Z)$.

We conclude that

$$\text{ri } Z \supseteq \{x \in \mathbb{R}^n \mid Ax - b \in \text{ri } K\}.$$

□

- (e) *Proof.* Solving eq. (2) is equivalent to minimizing $f_1 + f_2$ where:

$$(a) \ f_1(x) = f(x)$$

$$(b) \ f_2(x) = \delta_K(Ax - b) = \begin{cases} 0, & Ax - b \in K \\ +\infty, & \text{otherwise} \end{cases}$$

The range of f_1 and f_2 are

$$(a) \ \text{ri dom } f_1 = \text{ri dom } f$$

$$(b) \ \text{ri dom } f_2 = \text{ri } Z \text{ (} Z \text{ is in the same form in the previous question)}$$

The condition says $\bar{x} \in \text{ri dom } f_1 \cap \text{ri } K \neq \emptyset$. So $\partial(f_1 + f_2)(x) = \partial f_1(x) + \partial f_2(x)$. Given x^* is optimal, we have

$$\begin{aligned} 0 &\in \partial(f_1 + f_2)(x^*) \\ \Rightarrow 0 &\in \partial f_1(x^*) + \partial f_2(x^*) \\ \Rightarrow 0 &\in \partial f(x^*) + N_Z(x^*) \\ \Rightarrow 0 &\in \partial f(x^*) + A^T \lambda^* \quad \text{for some } \lambda^* \in K^* \end{aligned}$$

With $A^T \lambda^*$ is closed (from statement), combining $N_Z(x) = \text{cl}\{ A^T \lambda \mid \lambda \in K^*, \langle Ax - b, \lambda \rangle = 0 \}$ from previous result, we finish the proof. □