

Problem Set 3

Due Date: September 15, 2016

1. **Alternatives.** The Theorem of Alternatives (proved in lecture 6) states that for a given matrix $A \in \mathbb{R}^{m \times n}$ and a given vector $b \in \mathbb{R}^m$, exactly one of the following two statements holds:

- (a) $\exists x \in \mathbb{R}^n$ such that $Ax \leq b$.
- (b) $\exists y \in \mathbb{R}^m$ such that $y \geq 0$, $A^T y = 0$, and $b^T y < 0$.

Use the Theorem of Alternatives to prove

- **Farkas' Lemma:** Given a matrix $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^m$, exactly one of the following hold:
 - $\exists x \in \mathbb{R}^n$ such that $Ax = b$ and $x \geq 0$.
 - $\exists y \in \mathbb{R}^m$ such that $A^T y \geq 0$ and $b^T y < 0$.
- **Mixed Theorem of Alternatives.** Given $A \in \mathbb{R}^{m_1 \times n}$, $C \in \mathbb{R}^{m_2 \times n}$, and $b \in \mathbb{R}^{m_1}$, $d \in \mathbb{R}^{m_2}$, exactly one of the following hold:
 - $\exists x \in \mathbb{R}^n$ such that $Ax \leq b$ and $Cx = d$.
 - $\exists z \in \mathbb{R}^{m_1}, y \in \mathbb{R}^{m_2}$ such that $z \geq 0$, $A^T z + C^T y = 0$, and $b^T z + d^T y < 0$.

2. **Normal Cones and Strong Duality.** Given $A, \bar{A}, \hat{A}, \tilde{A}, b, \bar{b}, \tilde{b}, c, \bar{c}$:

(a) for all $z = [x \ \bar{x}]^T$, compute $N_P(z)$, where

$$P = \left\{ \begin{bmatrix} x \\ \bar{x} \end{bmatrix} \mid Ax + \bar{A}\bar{x} \leq b, \hat{A}x + \tilde{A}\bar{x} = \tilde{b}, x \geq 0 \right\}.$$

(b) for all $w = [y \ \bar{y}]^T$, compute $N_D(w)$, where

$$D = \left\{ \begin{bmatrix} y \\ \bar{y} \end{bmatrix} \mid A^T y + \hat{A}^T \bar{y} \geq c, \bar{A}^T y + \tilde{A}^T \bar{y} = \bar{c}, y \geq 0 \right\}.$$

(c) Using the descriptions of the above normal cones, and **without using the strong duality theorem we proved in class**, prove the following variant of the strong duality theorem: suppose that both of the linear programs

$$\begin{array}{ll} \max & c^T x + \bar{c}^T \bar{x} \\ & \begin{bmatrix} x \\ \bar{x} \end{bmatrix} \in P \end{array} \qquad \begin{array}{ll} \min & b^T y + \bar{b}^T \bar{y} \\ & \begin{bmatrix} y \\ \bar{y} \end{bmatrix} \in D \end{array}$$

have finite optimal values, which we denote by p^* and d^* , respectively. Then $p^* = d^*$.

3. **Subgradients.** Let $f : \mathbb{R}^n \rightarrow \mathbb{R}$ be a continuous, convex function, i.e., f satisfies

$$(\forall \lambda \in [0, 1]) (\forall x, y \in \mathbb{R}^n) \quad f(\lambda x + (1 - \lambda)y) \leq \lambda f(x) + (1 - \lambda)f(y).$$

Define the *epigraph* of f :

$$\mathbf{epi}(f) := \{(x, t) \in \mathbb{R}^{n+1} \mid f(x) \leq t\}.$$

- Prove that $\mathbf{epi}(f)$ is closed and convex.
- Prove that $[v \quad -1]^T \in N_{\mathbf{epi}(f)}(x, f(x))$ if, and only if,

$$(\forall z \in \mathbb{R}^n) \quad f(z) \geq f(x) + (z - x)^T v.$$

Such vectors $v \in \mathbb{R}^n$ are called *subgradients* f at x , and the set of all such v is denoted by $\partial f(x)$.

- Prove Fermat's rule: x minimizes f if, and only if, $0 \in \partial f(x)$.
- Let $f : \mathbb{R} \rightarrow \mathbb{R}$ be the absolute value function $f(x) = |x|$. Draw the following normal cones: $N_{\mathbf{epi}(f)}(-1, 1)$, $N_{\mathbf{epi}(f)}(0, 0)$, and $N_{\mathbf{epi}(f)}(1, 1)$.

4. Vertices of Dual Problems.

- Prove the following lemma: consider the polyhedron $Q := \{x \mid x \geq 0, Cx = d\}$. Then
 - $\bar{x} \in Q$ is an extreme point if

$$\text{rank}([c_{i_1} \quad c_{i_2} \quad \dots \quad c_{i_k}]) = k$$

where c_j is column j of C and $\{i_1, i_2, \dots, i_k\} = \{i \mid \bar{x}_i > 0\}$.

- any extreme point of Q has at most $\text{rank}(C)$ nonzero elements.
- Suppose that the following linear program has a solution:

$$\begin{aligned} & \text{minimize } b^T y \\ & \text{subject to: } A^T y = c \\ & \quad y \geq 0 \end{aligned}$$

Using Problem 4 from homework 2, conclude that at least one solution to this problem is a vertex. Use the first part of this exercise to show that there exists a solution y^* with at most $\text{rank}(A^T)$ nonzero elements.

- Using part 2, prove **Carathéodory's Theorem**: if $x \in \mathbb{R}^n$ is the convex combination of k vectors, v_1, \dots, v_k , then x is also the convex combination of at most $n + 1$ of the vectors v_1, \dots, v_k .