

## Math 650 Fall 2011 Homework #5

Due Nov. 9, Wed. in class

- P.1 Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a G-differentiable function. Show that  $f$  is convex if and only if  $\langle \nabla f(y) - \nabla f(x), y - x \rangle \geq 0$ ,  $\forall x, y \in \mathbb{R}^n$ . (*Hint*: consider the convexity condition  $f(y) \geq f(x) + \langle \nabla f(x), y - x \rangle$ .)
- P.2 Show that the following statements are equivalent:
- (1)  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is sublinear;
  - (2)  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is convex and positively homogeneous;
  - (3)  $f(\lambda x + \mu y) \leq \lambda f(x) + \mu f(y)$  for all  $x, y \in \mathbb{R}^n$  and all  $\lambda \geq 0, \mu \geq 0$ . (*Hint*: for positive homogeneity, show that  $f(x/\lambda) \leq f(x)/\lambda$  for any  $x \in \mathbb{R}^n$  and  $\lambda > 0$ .)
- P.3 Let  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a convex function. It has been shown that the one-sided directional derivative  $f'_+(x; d)$  exists. Fix  $x \in \mathbb{R}^n$ , define  $h : \mathbb{R}^n \rightarrow \mathbb{R}$  as  $h(d) := f'_+(x; d)$ , where  $d \in \mathbb{R}^n$ .
- (1) Show that  $h$  is convex. (*Hint*: use  $f(x + t(\lambda d^1 + (1-\lambda)d^2)) = f(\lambda(x + td^1) + (1-\lambda)(x + td^2))$  for all  $\lambda \in [0, 1]$ ,  $t \in \mathbb{R}$ , and  $d^1, d^2 \in \mathbb{R}^n$ .)
  - (2) Show that  $f'_+(x; d)$  is sublinear in  $d$ . (You may assume the positive homogeneity of  $h$  proved in HW #1.)
- P.4 For a given nonempty set  $S \subseteq \mathbb{R}^n$ , define its support function  $\sigma_S : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\pm\infty\}$  as  $\sigma_S(x) := \sup\{\langle x, z \rangle \mid z \in S\}$ .
- (1) Show that  $\sigma_S$  is convex, sublinear, and lower semicontinuous.
  - (2) Show that if  $S$  is bounded, then  $\sigma_S$  is continuous. And give an example of a set  $S$  whose support function is *not* continuous on  $\mathbb{R}^n$ .
- P.5 Given a function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  and a vector  $x^* \in \mathbb{R}^n$ .
- (1) Show that the subdifferential  $\partial f(x^*)$  is a closed convex set provided that it is nonempty.
  - (2) Show that  $x^*$  is a global minimizer of  $f$  on  $\mathbb{R}^n$  if and only if  $0 \in \partial f(x^*)$ .
- P.6 Let  $K \subseteq \mathbb{R}^n$  be a convex cone, and  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  be a G-differentiable function. Consider the convex optimization  $\min_{x \in K} f(x)$ , and let  $x^* \in K$  be a minimizer.
- (1) Show that if  $x^*$  is in the interior of  $K$ , then  $\nabla f(x^*) = 0$ .
  - (2) Show that  $\nabla f(x^*) \in K^*$ , where  $K^*$  is the dual cone of  $K$ .
  - (3) Show that  $\nabla f(x^*) \perp x^*$ .
  - (4) Show that the first order necessary condition (or the variational inequality) is equivalent to the condition (H):  $K^* \ni \nabla f(x^*) \perp x^* \in K$ .
  - (5) Find  $K^*$  and simplify the condition (H) for the following three cases: (i)  $K = \mathbb{R}^n$ ; (ii)  $K$  is a subspace of  $\mathbb{R}^n$  with dimension  $1 \leq \dim(K) < n$ ; and (iii)  $K = \mathbb{R}_+^n$ . (*Note*: these three cases correspond to unconstrained, equality constrained, and inequality constrained optimization problems, respectively.)