# Math 450-558: Smooth and Nonsmooth Optimization 

Instructor: Emre Mengi

Fall Semester 2015
Final Exam
Tuesday January 5th, 2016
Duration: 180 minutes

NAME $\quad$ STUDENT ID $\quad$| $\# 1$ | 20 |  |
| :--- | :--- | :--- |
| $\# 2$ | 20 |  |
| $\# 3$ | 20 |  |
| $\# 4$ | 20 |  |
| $\# 5$ | 20 |  |
| $\Sigma$ | 100 |  |

## Signature

- Please put your name, student ID and signature in the space provided above.
- You may use the lecture notes and/or your own notes, but you should not be using any textbooks.

Question 1 (20 points) Express the dual problem of

$$
\operatorname{minimize}_{x \in \mathbb{R}^{n}} c^{T} x \quad \text { subject to } f(x) \geq 0
$$

with $c \neq 0$, in terms of the Fenchel conjugate $f^{*}$.

Question 2 Let $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ be a Lipschitz continuous function with Lipschitz constant $\gamma$, that is

$$
|f(x)-f(y)| \leq \gamma\|x-y\|_{2}
$$

for all $x, y \in \mathbb{R}^{n}$.
(a) (10 points) Prove the following regarding the generalized directional derivative $f^{(0)}$ of $f$ :

$$
\left|f^{\circ}(x ; p)-f^{\circ}(y ; q)\right| \leq \gamma\left(\|x-y\|_{2}+\|p-q\|_{2}\right) \quad \forall x, y \in \mathbb{R}^{n}, \quad \forall p, q \in \mathbb{R}^{n}
$$

(b) (10 points) Prove the following regarding the generalized gradient $\partial f(x)$ of $f$ (at every $x$ ):

$$
\|\Psi\|_{2} \leq \gamma \quad \forall \Psi \in \partial f(x)
$$

Question 3 Let $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ be a convex Lipschitz continuous (but not necessarily differentiable) function. The penalized bundle method to find the global minimizer of $f$ keeps track of two sequences $\left\{x^{(k)}\right\}$ and $\left\{y^{(k)}\right\}$ in $\mathbb{R}^{n}$. It requires the solution of the nonsmooth optimization problem

$$
\begin{equation*}
\operatorname{minimize}_{x \in \mathbb{R}^{n}} P_{k}(x):=\phi_{k}(x)+\frac{\mu}{2}\left\|x-x^{(k)}\right\|_{2}^{2} \tag{1}
\end{equation*}
$$

where $\mu>0$ is a penalty parameter, and

$$
\phi_{k}(x):=\max \left\{f\left(y^{(j)}\right)+s_{j}^{T}\left(x-y^{(j)}\right) \mid j=0, \ldots, k\right\}
$$

for some $s_{j} \in \partial f\left(y^{(j)}\right)$ for $j=0, \ldots, k$, repeatedly. The point $y^{(k+1)}$ is defined as the global minimizer of $P_{k}(x)$. Furthermore, $x^{(k+1)}:=y^{(k+1)}$ if $f\left(y^{(k+1)}\right)$ satisfies a sufficient decrease condition compared to $f\left(x^{(k)}\right)$, otherwise $x^{(k+1)}:=$ $x^{(k)}$.
(a) (10 points) Express (1) as a convex optimization problem with a quadratic objective function subject to linear constraints.
(b) (10 points) Write down the centrality conditions (that is the KKT conditions but with the complementarity condition replaced by a centering equation in the primal-dual space) for the convex optimization problem in part (a).
(Bonus) (5 points) Write down one iteration of Newton's method for the solution of the centrality conditions in part (b).

Question 4 Let $A$ be a matrix-valued function defined by

$$
A(x):=A_{0}+x_{1} A_{1}+\cdots+x_{d} A_{d}
$$

where $A_{0}, A_{1}, \ldots, A_{d}$ are given $n \times n$ symmetric positive semidefinite matrices, and let $\lambda_{\max }: \mathbb{R}^{d} \rightarrow \mathbb{R}, \quad \lambda_{\max }(x):=\lambda_{\max }(A(x))$. Furthermore, assume $A_{0} \neq 0$.
(a) (10 points) Express the unconstrained eigenvalue optimization problem

$$
\begin{equation*}
\operatorname{minimize}_{x \in \mathbb{R}^{d}} \lambda_{\max }(x) \tag{2}
\end{equation*}
$$

as a constrained optimization problem with a linear objective subject to a positive semidefiniteness constraint.
(b) (10 points) Derive a semidefinite program that yields an upper bound for (2). State also conditions that guarantee that this semidefinite program is equivalent to (2).
(Hint: Try to view the constrained optimization problem in part (a) as the dual of a semidefinite program.)

Question 5 (20 points) Let $A \in \mathbb{R}^{m \times n}$ and $b \in \mathbb{R}^{m}$ with $m>n$ be given. Write down a necessary and sufficient condition for a point to be a global minimizer for the following problem using generalized gradients:

$$
\operatorname{minimize}_{x \in \mathbb{R}^{n}}\|b-A x\|_{\infty}
$$

For simplicity, assume the following:
(i) $\operatorname{rank}(A)=n$;
(ii) every set consisting of $n$ rows of $A$ is linearly independent;
(iii) letting $r(x):=b-A x$, at every $x \in \mathbb{R}^{n}$ no more than $n$ components of $r(x)$ are identical in absolute value.

Note that the function $f(x):=\|b-A x\|_{\infty}$ is differentiable everywhere excluding a set $\Omega$ of (Lebesgue) measure zero; you can use this fact in your answer.

