## Continuous optimization, an introduction

Exercises (22th Nov. 2016)

1. We recall that for a convex function $f: X \rightarrow \mathbb{R}$,

$$
\operatorname{prox}_{\tau f}(x)=\arg \min _{y} f(y)+\frac{1}{2 \tau}\|y-x\|^{2}
$$

Evaluate $\operatorname{prox}_{\tau f}(x)$ for $\tau>0$, and

- $x \in \mathbb{R}^{N}, f(x)=\frac{1}{2}\left\|x-x^{0}\right\|^{2}$ : what does Moreau's identity give in this case, for $x^{0}=0$ ?;
- $x \in \mathbb{R}^{N}, f(x)=\delta_{\{\|x\| \leq 1\}}{ }^{1}$;
- $x \in \mathbb{R}^{N}, f(x)=\langle p, x\rangle-\sum_{i} g_{i} \log x_{i}\left(g_{i}>0\right)$ if $x_{i}>0$ for all $i=1, \ldots, n$ and $f(x)=+\infty$ else;
- $x \in \mathbb{R}^{N}, f(x)=\delta_{\left\{\left|x_{i}\right| \leq 1: i=1, \ldots, N\right\}}(x)+\varepsilon\|x\|^{2} / 2$.

2. Evaluate the convex conjugate of:

- $f(x)=\delta_{\left\{\left|x_{i}\right| \leq 1: i=1, \ldots, N\right\}}(x)+\varepsilon\|x\|^{2} / 2, x \in \mathbb{R}^{N}$;
- $f(x)=\sum_{i=1}^{N} x_{i} \log x_{i}, x \in \mathbb{R}^{N}$, where $x \mapsto x \log x$ is $+\infty$ for $x<0$ and extended by continuity (that is, with the value 0 ) in $x=0$;
- $f(x)=\sqrt{1+\|x\|_{2}^{2}}, x \in \mathbb{R}^{N}$.

In each case of the three cases above, describe $\partial f$ and $\partial f^{*}$.
3. Show that if $\|x\|$ is a norm and $\|y\|^{\circ}=\sup _{\|x\| \leq 1}\langle x, y\rangle$ is the polar or dual norm, then

$$
\|\cdot\|^{*}(y)=\delta_{B_{\|\cdot\| 0}(0,1)}(y)= \begin{cases}0 & \text { if }\|y\|^{\circ} \leq 1, \\ +\infty & \text { else. }\end{cases}
$$

Hint: $\operatorname{write}_{\sup }^{x} 2\langle x, y\rangle-\|x\|$ as $\sup _{t>0}\left(\sup _{\|x\| \leq t}\langle x, y\rangle\right)-t$.
What is $\|\cdot\|^{00}$ ?
4. (Schatten norms) Let $X \in \mathbb{R}^{n \times p}$ be a matrix.
a. Show that $X^{T} X$ and $X X^{T}$ are a symmetric $p \times p$ and $n \times n$ (respectively) matrix and that they have the same nonzero eigenvalues $\left(\lambda_{1}, \ldots, \lambda_{k}\right)(k \leq \min \{p, n\})$. The values $\mu_{i}=\sqrt{\lambda_{i}}$ are the "singular values" of $X$.
b. Show that if $\left(e_{1}, \ldots, e_{p}\right)$ is an orthonormal basis of eigenvectors of $X^{T} X$ (associated to the eigenvalues $\lambda_{i}$, or 0 if $\left.i>k\right)$, then $\left(X e_{i}\right)_{i}$ are orthogonal. Show that one can write, for $\mu_{i}>0, X e_{i}=\mu_{i} f_{i}$ where $f_{i}$ are also orthonormal. Completing $f_{i}$ into an orthonormal basis of $\mathbb{R}^{n}$, deduce that

$$
X=\sum_{i=1}^{k} \mu_{i} f_{i} \otimes e_{i}=V D^{t} U
$$

[^0]where $U$ is the column vectors $\left(e_{i}\right)_{i=1}^{p}, V$ the column vectors $\left(f_{i}\right)_{i=1}^{n}, D$ is the $n \times p$ matrix with $D_{i i}=\mu_{i}, i=1, \ldots, k, D_{i j}=0$ for all other entries (just evaluate $X x=$ $X\left(\sum_{i=1}^{p}\left\langle x, e_{i}\right\rangle e_{i}\right)$, etc. ) What type of matrices are the matrices $U, V$ ? This is called the "singular value decomposition" (SVD) of $X$ (one usually orders the $\mu_{i}$ by nonincreasing values).
c. One defines the $p$-Schatten norm of $X, p \in[1, \infty]$, as $\|X\|_{p}^{p}=\sum_{i=1}^{k} \mu_{i}^{p},\|X\|_{\infty}=$ $\max _{i} \mu_{i}$. Show that
$$
\|X\|_{2}^{2}=\sum_{i, j} x_{i, j}^{2}=\operatorname{Tr}\left({ }^{t} X X\right) ; \quad\|X\|_{\infty}=\sup _{\|x\| \leq 1}\|X x\|
$$
(where in the latter $\|x\|$ is the 2 -norm). $\|\cdot\|_{\infty}$ is called the spectral norm or operator norm.
d. [Exercice 3. is necessary for this question.] Why do we have that
$$
\left\{X:\|X\|_{1} \leq 1\right\}=\operatorname{conv}\left\{f \otimes e: f \in \mathbb{R}^{n}, e \in \mathbb{R}^{p},\|f\| \leq 1,\|e\| \leq 1\right\} ?
$$

Deduce that

$$
\|X\|_{\infty}=\sup _{\left\{\|Y\|_{1} \leq 1\right\}}\langle Y, X\rangle
$$

where we use the Frobenius (or Hilbert-Schmidt) scalar product $\langle Y, X\rangle=\sum_{i, j} Y_{i, j} X_{i, j}=$ $\operatorname{Tr}\left({ }^{t} Y X\right)$. Deduce that

$$
\|X\|_{1}=\sup _{\left\{\|Y\|_{\infty} \leq 1\right\}}\langle Y, X\rangle
$$

(One can also show that $\|\cdot\|_{p}^{\circ}=\|\cdot\|_{p^{\prime}}, 1 / p+1 / p^{\prime}=1$.)
e. We want to compute

$$
\bar{Y}=\arg \min _{\|X\|_{\infty} \leq 1}\|X-Y\|_{2}^{2}=\operatorname{prox}_{\delta_{\{\|X\| \infty \leq 1\}}}(Y)
$$

Show first that it is equivalent to estimate $\min _{\|X\|_{\infty} \leq 1}\|X-D\|_{2}^{2}$ where $Y=V D^{t} U$ is the SVD decomposition of $Y$. Show that the matrix $X$ which optimizes this last problem is diagonal, and satisfies $X_{i, i}=\max \left\{D_{i, i}, 1\right\}$. Deduce the solution $\bar{Y}$ of $\left(P_{\infty}\right)$. Deduce the proximity operator $\operatorname{prox}_{\tau\|\cdot\|_{1}}$.
f. A company rents movies and has a file of clients $X_{i, j} \in\{-1,0,1\}$ which states for each client $i=1, \ldots, p$ whether he/she has already rented the film $j=1, \ldots, n$ (otherwise $\left.X_{i, j}=0\right)$ and has liked it $\left(X_{i, j}=1\right)$, or not $\left(X_{i, j}=-1\right)$. It wants to determine a matrix of "tastes" for all the clients $Y \in\{-1,1\}^{p \times n}$. Assuming that the clients can be grouped into few categories, this matrix should have low rank. One could look therefore for an approximation of $Y$ by minimising

$$
\min _{Y}\|Y\|_{1}+\frac{\lambda}{2} \sum_{i, j: X_{i, j} \neq 0}\left(X_{i, j}-Y_{i, j}\right)^{2}+\frac{\varepsilon}{2} \sum_{i, j: X_{i, j}=0} Y_{i, j}^{2}
$$

where $\lambda \gg \varepsilon>0$ are parameters.
Design an iterative algorithm to solve this problem.


[^0]:    ${ }^{1} \delta_{C}(x)=0$ if $x \in C,+\infty$ if $x \notin C$

