## Optimierung I

## Problem Sheet 8

Due date: 3. June 2014

## Problem 8.1: [Convexity]

i) Let $K_{1}$ and $K_{2}$ be two convex subsets of $\mathbb{R}^{n}$, let $\lambda \in \mathbb{R}$. Prove that the following subsets are convex:
a) $K_{1} \cap K_{2}$
b) $K_{1}+K_{2}$, defined by: $\left\{x+y \mid x \in K_{1}, y \in K_{2}\right\}$.
c) $\lambda K_{1}$, defined by: $\left\{\lambda x \mid x \in K_{1}\right\}$.
ii) Let $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ and $g: \mathbb{R}^{n} \rightarrow \mathbb{R}$ be two convex functions, prove that $\max (f, g)$ is also convex.
iii) Let $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$. We define its epigraph as the following subset of $\mathbb{R}^{n+1}$ :

$$
\begin{equation*}
\operatorname{Epi}(f)=\left\{(x, y) \in \mathbb{R}^{n} \times \mathbb{R} \mid y \geq f(x)\right\} \tag{1}
\end{equation*}
$$

Prove that $f$ is convex if and only if $\operatorname{Epi}(f)$ is a convex subset of $\mathbb{R}^{n+1}$.

## Problem 8.2: [Positive matrices of dimension 2]

i) Let $S$ be a symmetric matrix of dimension 2. Prove that $S$ is positive semi-definite if and only if:

$$
\begin{equation*}
\operatorname{tr}(S) \geq 0 \quad \text { and } \quad \operatorname{det}(S) \geq 0 \tag{2}
\end{equation*}
$$

To this purpose, we recall the spectral theorem: for all symmetric matrix, there exist an invertible matrix $B$ and a diagonal matrix $D$ such that $S=B D B^{-1}$.
ii) Using the above characterization of positive semi-definite matrices, check if the following functions are convex on the open subset $(0,+\infty) \times(0,+\infty)$ of $\mathbb{R}^{2}$ :
a) $f\left(x_{1}, x_{2}\right)=x_{1} x_{2}$
b) $f\left(x_{1}, x_{2}\right)=\frac{1}{x_{1} x_{2}}$
c) $f\left(x_{1}, x_{2}\right)=\frac{x_{1}}{x_{2}}$
d) $f\left(x_{1}, x_{2}\right)=\frac{x_{1}^{2}}{x_{2}}$.
iii) Let $A \in \mathbb{R}^{n \times n}$ be a positive definite symmetric matrix, $b \in \mathbb{R}^{n}$ and

$$
\begin{equation*}
f(x)=x^{\top} A x+b^{\top} x, \tag{3}
\end{equation*}
$$

for $x \in \mathbb{R}^{n}$. With $x^{*}$ denoting the global minimum of $f$, show that, if $x_{0}-x^{*}$ is colinear to an eigenvector of $A$, then the steepest descent method starting at $x_{0}$ and using exact line search converges in one step.

## Problem 8.3: [Stationary points]

i) Let $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$ be a continuous function satisfying the following property: for all sequence $\left(x_{k}\right)_{k}$,

$$
\begin{equation*}
\text { if }\left\|x_{k}\right\| \rightarrow+\infty, \text { then } f\left(x_{k}\right) \rightarrow+\infty \tag{4}
\end{equation*}
$$

Prove the existence of (at least) one global minimizer.
ii) We consider the following function:

$$
\begin{equation*}
f(x)=x_{1}^{4}+2 x_{1}^{3}+2 x_{1}^{2}-2 x_{1} x_{2}+x_{2}^{2} . \tag{5}
\end{equation*}
$$

Compute the stationary points. Compute the Hessian of $f$ at these points, deduce which of them are local minimizers or local maximizers.
iii) Using the identity $f(x)=x_{1}^{2}\left(x_{1}+1\right)^{2}+\left(x_{1}-x_{2}\right)^{2}$, prove that property (4) is satisfied. Compute the global minimizer(s).

## Problem 8.4: [Linear regression]

For given data points $\left(x_{1}, y_{1}\right), \ldots,\left(x_{n}, y_{n}\right)$ in $\mathbb{R}^{2}$, the linear regression problem problem consists in fitting the line $y=d+k x$ such that to minimize the residuals:

$$
\begin{equation*}
\min _{(d, k) \in \mathbb{R}^{2}} \sum_{i=1}^{n}\left(d+k x_{i}-y_{i}\right)^{2} . \tag{6}
\end{equation*}
$$

We assume that there exist $i$ and $j$ such that $x_{i} \neq x_{j}$.
i) Rewrite the problem in the form of the following unconstrained problem:

$$
\begin{equation*}
\min _{z \in \mathbb{R}^{2}}(A z-b)^{\top}(A z-b) \tag{7}
\end{equation*}
$$

where $A \in \mathbb{R}^{n \times 2}$ and $b \in \mathbb{R}^{n}$.
ii) Compute $A^{\top} A$, its determinant, and check that this last matrix is invertible.
iii) Compute the value of the unique stationary point (in function of $\left.\left(x_{1}, y_{1}\right), \ldots,\left(x_{n}, y_{n}\right)\right)$.

## Problem 8.5: [Programming exercise: gradient descent with Armijo and Wolfe rules]

We consider a gradient descent method in order to minimize a differentiable function $f: \mathbb{R}^{n} \rightarrow \mathbb{R}$. The parameters are the following: $x_{0} \in \mathbb{R}^{n}, \sigma_{1}$ and $\sigma_{2} \in(0,1)$ such that $\sigma_{1}<\sigma_{2}, \gamma>1, \varepsilon>0$, $R>0, N \in \mathbb{N}$. The method generates the sequence $\left(x_{k}\right)_{k}$ starting at $x_{0}$ and defined by:

$$
\begin{equation*}
x_{k+1}=x_{k}+\alpha_{k} d_{k} \tag{8}
\end{equation*}
$$

where $d_{k}=-\nabla f\left(x_{k}\right)$. For a given $\alpha>0$, we say that Armijo rule (resp. Wolfe rule) holds if

$$
\begin{equation*}
f\left(x_{k}+\alpha_{k} d_{k}\right) \leq f\left(x_{k}\right)-\sigma_{1} \alpha_{k}\left\|d_{k}\right\|^{2} \quad\left(\text { resp. } \nabla f\left(x_{k}+\alpha_{k} d_{k}\right) d_{k} \geq-\sigma_{2}\left\|d_{k}\right\|^{2}\right) \tag{9}
\end{equation*}
$$

We use a bisection method to find a step $\alpha_{k}$ satisfying these two rules. If we know that $\alpha_{k}$ belongs to an interval $\left[\beta_{0}, \beta_{1}\right]$, then, setting $\beta=\left(\beta_{0}+\beta_{1}\right) / 2$,
i) if $\beta$ satisfies both rules, stop and set $\alpha_{k}=\beta$
ii) if $\beta$ satisfies Armijo's rule (but not Wolfe's rule), investigate $\left[\beta, \beta_{1}\right]$
iii) if $\beta$ does not satisfy Armijo's rule, investivate $\left[\beta_{0}, \beta\right]$.

Start with the interval $\left[0, \alpha_{k}^{\prime}\right]$, where $\alpha_{k}^{\prime}$ is defined as follows:

$$
\begin{equation*}
\alpha_{k}^{\prime}=\min _{i \in \mathbb{N}}\left\{\gamma^{i} \mid f\left(x_{k}+\gamma^{i} d_{k}\right)>f\left(x_{k}\right)-\sigma_{1} \gamma^{i}\left\|d_{k}\right\|^{2}\right\} . \tag{10}
\end{equation*}
$$

As a result, you should have the following function:

$$
\begin{equation*}
\text { [x e]= hollerm(xinit, sigma1, sigma2, gamma, epsilon, } R, N \text { ) } \tag{11}
\end{equation*}
$$

Your method should stop according to the following criterion:
i) if $\left\|\nabla f\left(x_{k}\right)\right\| \leq \varepsilon$, then $x=x_{k}$ and $e=0$
ii) if the total number of iterations is greater than $N$, then $e=1$ and $x$ is the last computed value of the sequence $\left(x_{k}\right)_{k}$ (too many iterations)
iii) if $\left\|x_{k}\right\| \geq R$, then $x=x_{k}$ and $e=2$ (the problem may be unbounded).

Use the Euclidean norm. Your program should use the following functions:

$$
\begin{equation*}
y=\operatorname{func}(x) \text { and } y=\operatorname{gradient}(x) \tag{12}
\end{equation*}
$$

which give the value of $f(x)$ and $\nabla f(x)$, respectively. We will specify them when we will test your program. Your program should also use a column vector for xinit; the result of the function gradient will also be a column vector.
Test your program with the different functions:

- the Rosenbruck function (try different values of $\varepsilon$ )
- a quadratic function of the form: $x^{\top} A x+b^{\top} x$, with $A \in \mathbb{R}^{n \times n}$ symmetric, $b \in \mathbb{R}^{n}$, for example:

$$
A=\left(\begin{array}{ccc}
14 & 9 & -1  \tag{13}\\
9 & 18 & 6 \\
-1 & 6 & 5
\end{array}\right), \quad A=\left(\begin{array}{ccc}
2 & 27 & -7 \\
27 & -5 & -46 \\
-7 & -46 & 9
\end{array}\right)
$$

- $f(x)=-\exp \left(-\|x\|^{2}\right)$, for different starting points.

Follow the rules of the previous exercises, in particular send a mail with subject Optimierung 1, Abgabe 8.5. If your are using Octave, please indicate this by additionally writing Octave in the subject.

