# Exam Continuous Optimization 

22 January 2024, 14.00-17.00

This closed-book exam consists of 5 questions. Please start each question on a new page, write legibly, and hand in your work with the solutions in the correct order. In total, you can obtain 90 points. The final grade is $1+$ \#points/10 rounded to the nearest integer. Good luck!

1. Let $\phi(y)=-\sum_{i=1}^{m} \log \left(y_{i}\right)$ and consider the optimization problem

$$
\begin{array}{ll}
\operatorname{minimize} & \phi(y) \\
\text { subject to } & y=b-A x .
\end{array}
$$

in the variables $x \in \mathbb{R}^{n}$ and $y \in \mathbb{R}^{m}$.
(a) (5 points) Show this problem is convex.
(b) (15 points) Derive and simplify the Lagrange dual problem.
2. Consider the optimization problem

$$
\begin{array}{ll}
\operatorname{minimize} & \sum_{i=1}^{n} u_{i}\left(x_{i}\right) \\
\text { subject to } & \sum_{i=1}^{n} x_{i} \leq B \\
& x_{i} \geq 0, i=1, \ldots, n,
\end{array}
$$

where $B$ is a positive scalar and the functions $u_{i}: \mathbb{R} \rightarrow \mathbb{R}, i=1, \ldots, n$, are convex and twice continuously differentiable.
(a) (15 points) Suppose $x^{*}$ is an optimal solution. Use the KKT conditions to show that the value of $u_{i}^{\prime}\left(x_{i}^{*}\right)$ is the same for each $i$ with $x_{i}^{*} \neq 0$. Here $u_{i}^{\prime}$ is the derivative of $u_{i}$.
(b) (5 points) Suppose we apply the barrier method to solve this optimization problem. Why do we not need to use the Phase I problem here?
3. (15 points) Consider the function

$$
F\left(x_{1}, x_{2}\right)=x_{1}^{3} e^{x_{1}^{2}+x_{2}}
$$

where we view addition, multiplication, the exponential function, and taking the second or third power as elementary functions. Show how $\nabla F(2,-4)$ is computed using reverse-mode automatic differentiation by drawing the appropriate diagrams.
4. (a) (10 points) Apply Fibonacci search to the function $f(x)=|x-e|$, where $e=2.7182 \ldots$, with initial bracket $[0,4]$ and $k=5$ evaluations. At which points is $f$ evaluated and in what order? What is the final bracket you obtain?
(b) (5 points) Suppose we start golden section search with a bracket of size 1 . How many function evaluations do you need (roughly) to reach machine precision; that is, after how many function evaluations is the bracket size approximately $10^{-16}$ ?
5. Let $f$ be a twice continuously differentiable function. Fix $\alpha \in(0,1 / 2)$ and $\beta \in(0,1)$. Let $x$ be the current point and $\Delta x$ a descent direction at $x$. Recall that with backtracking line search we find the step size by first trying $t=\beta$, then $t=\beta^{2}$, then $t=\beta^{3}$, etc., until the following inequality holds: z

$$
f(x+t \Delta x) \leq f(x)+\alpha \nabla f(x)^{\top}(t \Delta x) .
$$

(a) (10 points) Use Taylor's theorem to show that backtracking line search terminates after finitely many iterations, and show that the objective value never increases when we use a descent method with backtracking line search to minimize $f$.
(b) (10 points) We now assume that there are strictly positive scalars $m$ and $M$ with

$$
m I \preceq \nabla^{2} f(x) \preceq M I
$$

for all $x$. It can be shown that

$$
f(y) \geq f(x)-\frac{1}{2 m}\|\nabla f(x)\|_{2}^{2}
$$

for all $x$ and $y$ and that at each point backtracking line search will terminate with either $t=1$ or $t \geq \beta / M$. Use this to show that gradient descent with backtracking line search converges at least linearly with rate

$$
1-\min \{2 \alpha m, 2 \alpha \beta m / M\} .
$$

