



LUND
UNIVERSITY

Department of
AUTOMATIC CONTROL

Exam in Optimization for Learning

2020-10-26

Points and grading

All answers must include a clear motivation. Answers should be given in English. The total number of points is 25. The maximum number of points is specified for each subproblem. Preliminary grading scales:

Grade 3: 12 points
4: 17 points
5: 22 points

Accepted aid

All material from the course.

Results

Solutions will be posted on the course webpage, and results will be registered in LADOK. Date and location for display of corrected exams will be posted on the course webpage.

1. Which of the following functions f are convex? Prove or disprove. (Use may use convexity perserving operations.)

a. $f(x) = \frac{1}{g(x)}$ where $g : \mathbb{R} \rightarrow \mathbb{R}$ is concave and satisfies $g(x) > 0$ for all $x \in \mathbb{R}$ (1 p)

b. $f(x) = \sqrt{x^T L^T L x}$ where $x \in \mathbb{R}^n$ and $L \in \mathbb{R}^{m \times n}$ (1 p)

c. $f(x) = \begin{cases} \sqrt{x_1 x_2} & \text{if } x_1 > 0, x_2 > 0 \\ \infty & \text{otherwise} \end{cases}$, where $x = (x_1, x_2) \in \mathbb{R}^2$ (1 p)

- d. $f(x) = \sum_{i=1}^r x_{(i)} = x_{(1)} + \dots + x_{(r)}$, where r is an integer such that $1 \leq r \leq n$ and for any vector $x \in \mathbb{R}^n$, we let $x_{(i)}$ denote the i th largest component of x , i.e.

$$x_{(1)} \geq \dots \geq x_{(n)} \quad (1 \text{ p})$$

2. Which of the following sets S are convex?

a. $S = \{x \in \mathbb{R}^n : x_1 + \dots + x_n = 1\}$ (1 p)

b. $S = \{x \in \mathbb{R}^n : \|x - a\|_2 \leq \|x - b\|_2\}$, where $a \neq b$ and $a, b \in \mathbb{R}^n$ (1 p)

c. $S = \left\{x \in \mathbb{R}^3 : 2x_1 \geq \sqrt{x_2^2 + x_3^2}\right\}$ (1 p)

d. $S = \{x \in \mathbb{R}^2 : 2 \leq e^{x_1^2 + x_2^2} \leq 4\}$ (1 p)

e. $S = \{x \in \mathbb{R}^n : x^T y \leq 1, \forall y \in C\}$ where $C \subseteq \mathbb{R}^n$ (1 p)

3. Consider the closed convex function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ such that

$$f(x) = (a^T x - b)^2, \quad \forall x \in \mathbb{R}^n,$$

where $a \in \mathbb{R}^n \setminus \{0\}$, $b \in \mathbb{R}$ and $n \geq 2$.

a. Prove or disprove that f is a strongly convex function (1 p)

b. Derive the conjugate function f^* of f (2 p)

c. Derive the proximal operator $\text{prox}_{\gamma f}$ of f , where $\gamma > 0$ (1 p)

4. Let $C \subseteq \mathbb{R}^n$ be a nonempty closed convex set. Its support function $\sigma_C : \mathbb{R}^n \rightarrow \mathbb{R} \cup \{\infty\}$ is defined as

$$\sigma_C(y) = \sup_{x \in C} y^T x, \quad \forall y \in \mathbb{R}^n.$$

a. Show that the support function σ_C is convex, independent of the convexity of the set C (1 p)

b. Show that $\sigma_C^* = \iota_C$ (1 p)

- c. Find an expression for $\text{prox}_{\gamma\sigma_C}$, where $\gamma > 0$, that involves Π_C , i.e. the projection onto the set C (1 p)

5. Consider the problem

$$\underset{x \in \mathbb{R}^n}{\text{minimize}} f(x) = \frac{1}{2} \|Ax - b\|_2^2,$$

where $A \in \mathbb{R}^{n \times n}$ satisfies

$$A = \mathbf{diag}(a_1, \dots, a_n), \quad a_i \neq 0, \quad \forall i \in \{1, \dots, n\},$$

and $b = (b_1, \dots, b_n) \in \mathbb{R}^n$.

- a. Give a closed-form expression for the solution (0.5 p)
- b. Show that $\beta = \max_{i \in \{1, \dots, n\}} a_i^2$ is a smoothness constant for f (1 p)
- c. Show that $\beta_i = a_i^2$ is a coordinate-wise smoothness constants for f for each coordinate $i \in \{1, \dots, n\}$ (1 p)
- d. Consider the gradient method with step-size $1/\beta$, where β is the smoothness constant in **b.** Suppose you are given the iterate $x^k \in \mathbb{R}^n$, where $k \in \mathbb{N}$ is the iteration number. For each coordinate $i \in \{1, \dots, n\}$, provide the update formula for x_i^k . Utilize that $A = \mathbf{diag}(a_1, \dots, a_n)$ (1 p)
- e. Let $b_i = 0$ for each $i \in \{1, \dots, n\}$ and provide an exact linear convergence rate for each of the coordinates for the gradient method in **d.** This means, find the $\rho_i \in [0, 1)$ such that

$$\|x_i^{k+1}\|_2 = \rho_i \|x_i^k\|_2,$$

for each coordinate $i \in \{1, \dots, n\}$ (Each coordinate will converge linearly to $x_i^* = 0$ in this case) (1 p)

- f. Consider the coordinate gradient method (i.e. no proximal operator) with step-sizes $1/\beta_i$, where β_i are the coordinate smoothness constants in **c.** Provide an update formula for each coordinate $i \in \{1, \dots, n\}$. Utilize that $A = \mathbf{diag}(a_1, \dots, a_n)$. Show that $x_i^{k+1} = x_i^*$ with x_i^* from **a.**, independent on $x^k \in \mathbb{R}^n$ (1 p)
6. Consider minimizing a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$, with minimizer $x^* \in \mathbb{R}^n$, using a stochastic optimization algorithm, starting at some predetermined (deterministic) point $x_0 \in \mathbb{R}^n$. Analysis of the algorithm resulted in the following inequality

$$\mathbb{E} [\|x_{k+1} - x^*\|_2^2 \mid x_k] \leq \|x_k - x^*\|_2^2 - 2\gamma(f(x_k) - f(x^*)) + \gamma^2 G, \quad \forall k \in \mathbb{N},$$

where G is a deterministic positive constant and γ is a deterministic fixed positive step-size of the algorithm. In particular, $(x_k)_{k \in \mathbb{N}}$ is a stochastic process.

- a. Apply an expectation to the above inequality to derive a Lyapunov inequality for the algorithm (1 p)

b. Use the obtained Lyapunov inequality to show that

$$\sum_{i=0}^k \mathbb{E}[f(x_i) - f(x^*)] \leq \frac{\|x_0 - x^*\|_2^2 + G(k+1)\gamma^2}{2\gamma}, \quad \forall k \in \mathbb{N} \quad (1)$$

(1.5 p)

c. The upper bound (1) diverges as $k \rightarrow \infty$ unless $G = 0$. Consider the step-size $\gamma = \theta/\sqrt{K+1}$, where $K \in \mathbb{N}$ is the total number of iterations we wish to run in the algorithm and $\theta > 0$. Show that we get a $\mathcal{O}(1/\sqrt{K+1})$ convergence bound

$$\min_{i \in \{0, \dots, K\}} \mathbb{E}[f(x_i) - f(x^*)] \leq \frac{\|x_0 - x^*\|_2^2 + G\theta^2}{2\theta\sqrt{K+1}}$$

that is valid until iteration K

(1 p)