Mathematical Optimization

Exam April 19, 2022, 9:00 - 12:00

No additional materials may be used during this exam (no notes, calculators, etc.). With this exam a list of theorems and lemmata is provided. In your proofs, you may use definitions from the lecture notes and the theorems and lemmata from the list without providing a proof (reference the theorem/lemma that you use). In addition, you may use all results from Appendix A and all theorems, lemmata, corollaries and propositions from Chapters 6 (Convex Sets), 7 (Convex Functions) and 9 (Iterative Optimization Methods) in the Lecture Notes (v. January 31, 2022) with a reference like "We know that."."

This exam has 8 exercises.

- 1. Let $\mathbf{A} = (a_{ij}) \in \mathbb{S}^{n \times n}$ be a positive definite matrix.
 - (a) Show that if $\mathbf{M} \in \mathbb{R}^{n \times n}$ is invertible, then $\mathbf{M}\mathbf{A}\mathbf{M}^T$ is also a positive definite matrix.
 - (b) Apply the Diagonalization Algorithm to

$$\mathbf{A} = \begin{pmatrix} 2 & 8 & 12 \\ 8 & 35 & 49 \\ 12 & 49 & 76 \end{pmatrix}$$

to find an invertible matrix $\mathbf{Q} \in \mathbb{R}^{3 \times 3}$ such that $\mathbf{Q} \mathbf{A} \mathbf{Q}^\mathsf{T}$ is diagonal.

2. Let W be a linear subspace of \mathbb{R}^n . Consider the problem of finding the best approximation $\hat{\mathbf{x}} \in W$ of $\mathbf{x} \in \mathbb{R}^n$. That is,

$$\|\mathbf{x} - \hat{\mathbf{x}}\|_2 = \min_{\mathbf{y} \in W} \|\mathbf{x} - \mathbf{y}\|_2.$$

(a) Suppose we found $\mathbf{y} \in W$ such that $\mathbf{x} - \mathbf{y}$ is orthogonal to every $\mathbf{w} \in W$. Prove that \mathbf{y} is the unique best approximation of \mathbf{x} in \mathbb{R}^n .

Let $W^{\perp} = \{ \mathbf{v} \in \mathbb{R}^n \, | \, \mathbf{v}^{\mathsf{T}} \mathbf{w} = 0, \, \forall \mathbf{w} \in W \}$ be the linear subspace of \mathbb{R}^n consisting of all vectors that are orthogonal to all vectors in W. Denote the best approximation of $\mathbf{x} \in \mathbb{R}^n$ in W^{\perp} by \mathbf{z} .

(b) Proof that

$$z = x - y$$
.

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3. Apply the Fourier-Motzkin procedure to find a solution to the system:

4. Consider the primal linear program

$$\begin{array}{ll}
\max & \mathbf{c}^\mathsf{T} \mathbf{x} \\
\text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b}
\end{array} \tag{P}$$

and its corresponding dual

$$\begin{array}{lll}
\min & \mathbf{b}^\mathsf{T} \mathbf{y} \\
\text{s.t.} & \mathbf{A}^\mathsf{T} \mathbf{y} &= \mathbf{c} \\
& \mathbf{y} &\geq \mathbf{0},
\end{array} \tag{D}$$

where $\mathbf{A} = (a_{ij}) \in \mathbb{R}^{m \times n}$, $\mathbf{b} = (b_i) \in \mathbb{R}^m$, and $\mathbf{c} = (c_j) \in \mathbb{R}^n$. Let $\mathbf{x} \in \mathbb{R}^n$ and $\mathbf{y} \in \mathbb{R}^m$ be feasible solutions of (P) and (D), respectively, and let $\mathbf{s} = \mathbf{b} - \mathbf{A}\mathbf{x}$.

Prove that $s_i y_i = 0$ for all $i \in \{1, ..., m\}$ if and only if \mathbf{x} and \mathbf{y} are optimal solutions of (P) and (D), respectively.

- 5. (a) Let $f: \mathbb{R}^n \to \mathbb{R}$ be a convex function on \mathbb{R}^n and $\bar{\mathbf{x}}$ a local minimizer. Prove that $\bar{\mathbf{x}}$ is a global minimizer (without using the theorem that states exactly this fact).
 - (b) Prove that the function $f(\mathbf{x}) = ||\mathbf{x}||$ is convex for any norm ||.|| on \mathbb{R}^n .
 - (c) Show that $f(x) = e^x$ is convex on \mathbb{R} and derive that $1 + x \leq e^x$ holds for all $x \in \mathbb{R}$.
- 6. Given the function $f(\mathbf{x}) = \frac{1}{2}x_1^4 5x_1^2 + 2x_1x_2 x_2^2$.

Determine the critical points of f on \mathbb{R}^n and investigate which of these are local minimizer(s).

7. Consider the function $f: \mathbb{R}^n \to \mathbb{R}$ given by

$$f(\mathbf{x}) = \|\mathbf{x}\|_2^2.$$

- (a) Given conjugate directions d_0, \ldots, d_k and the point \mathbf{x}_k , give \mathbf{d}_{k+1} , the direction of the Conjugate Gradient Method for f in iteration k+1.
- (b) Argue that the Steepest Descent Method with exact line minimization finds the minimizer $(\mathbf{x} = \mathbf{0})$ of f in at most n steps independent of the starting point \mathbf{x}_0 .
- 8. Can the Subgradient Method be applied to a function $f: \mathbb{R}^n \to \mathbb{R}$ that is *not* convex? Argue why or why not.

Points: 90 + 10 = 100

- 1. (a) : 7 pt.
 - (b) : 8 pt.
- 2. (a) : 7 pt.
 - $(a) \quad . \quad f p t.$
- (b) : 5 pt.
- 3. : 10 pt.
- 4. : 10 pt.

- 5. (a) : 7 pt.
 - (b) : 4 pt.
 - (c) : 8 pt.
- 6. : 8 pt.
- 7. (a) : 5 pt.
 - (b) : 5 pt.
- 8. : 6 pt.