Practice Set

Course Code: CS6007 Instructor: Dr. Avishek Ghosh Date: August 5, 2025

Instructions:

- This practice set covers basic optimization concepts.
- Attempt all questions for a better understanding of optimization foundations.
- Q1. Let $C \subseteq \mathbb{R}^n$ be the solution set of a quadratic inequality,

$$C = \left\{ x \in \mathbb{R}^n \mid x^\top A x + b^\top x + c \le 0 \right\},\,$$

where $A \in \mathbb{S}^n$ (the set of symmetric $n \times n$ matrices), $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$.

- (a) Show that C is convex if $A \succeq 0$ (i.e., A is positive semidefinite).
- (b) Let $H = \{x \in \mathbb{R}^n \mid g^\top x + h = 0\}$ be a hyperplane with $g \neq 0$. Show that the intersection $C \cap H$ is convex if $A + \lambda g g^\top \succeq 0$ for some $\lambda \in \mathbb{R}$.
- **Q2.** Suppose $f: \mathbb{R}^d \to \mathbb{R}$ is convex and M-smooth. Show that

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \ge \frac{1}{M} \|\nabla f(x) - \nabla f(y)\|^2$$

Hint: Use the Descent Lemma on the following two functions:

- (a) $h_x(z) = f(z) \langle \nabla f(x), z \rangle$
- (b) $h_y(z) = f(z) \langle \nabla f(y), z \rangle$
- **Q3.** Let f be a (M, m) smooth and strongly convex function (M > m) on \mathbb{R}^d . Then, show that

$$\langle \nabla f(x) - \nabla f(y), x - y \rangle \ge \frac{mM}{m+M} \|x - y\|^2 + \frac{1}{M+m} \|\nabla f(x) - \nabla f(y)\|^2$$

Hint: Use the result from Question 2.

Q4. [Gradient Descent for Polyak Lojasiewicz (PL) functions]

Suppose $f: \mathbb{R}^d \to \mathbb{R}$ is M-smooth and possibly non-convex. However, it satisfies the PL condition (i.e., $\|\nabla f(x)\|^2 \geq 2m[f(x) - f(x^*)]$, for all x where m > 0 and x^* is any minimizer of f). Show that running Gradient Descent with initial point x^0 for T steps with step size $\alpha = 1/M$ for such functions yields

$$f(x^T) - f(x^*) \le \left(1 - \frac{m}{M}\right)^T [f(x^0) - f(x^*)].$$

Q5. Let V be a vector space. A norm on V is a function $p: V \to [0, \infty)$ satisfying the following properties:

- $p(\lambda v) = |\lambda| p(v)$ for all $v \in V$, $\lambda \in \mathbb{R}$
- $p(u+v) \le p(u) + p(v)$ for all $u, v \in V$ (Triangle inequality)
- p(v) = 0 if and only if v = 0

Now suppose $v \in V$, r > 0, and let p be a norm. Show that the set

$$B := \{ x \in V \mid p(x - v) < r \}$$

is convex.

Q6. A function $\psi : \mathbb{R}^n \to \mathbb{R}^n$ is called **monotone** if for all $x, y \in \text{dom}(\psi)$,

$$(\psi(x) - \psi(y))^{\top}(x - y) \ge 0.$$

- (a) Suppose $f: \mathbb{R}^n \to \mathbb{R}$ is a differentiable convex function. Show that its gradient ∇f is monotone.
- (b) Is the converse true? That is, is every monotone mapping the gradient of a convex function? Justify your answer.

Q7. Let $C \subseteq \mathbb{R}^n$ be the solution set of a quadratic inequality given by:

$$C = \left\{ x \in \mathbb{R}^n \mid x^\top A x + b^\top x + c \le 0 \right\},\,$$

where $A \in \mathbb{S}^n$, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$.

- (a) Show that the set C is convex if $A \succeq 0$, i.e., A is positive semidefinite.
- (b) Does the converse hold true? Justify your answer with a counterexample or reasoning.