

Problem 1

Consider the problem of minimizing

$$f(x) = 4x - \ln(x), \quad x > 0,$$

by using the Newton's method with the step-size $\gamma = 1$.

- (a) What is the minimizer x^* of f ?
- (b) Find an interval $I \in \mathbb{R}$ such that for any $x^0 \in I$, the Newton's method converges to x^* . Show that the order of convergence is at least quadratic.

Problem 2

Consider a set of $m + 1$, possibly nonconvex, functions $\{f_0(\mathbf{x}), f_1(\mathbf{x}), \dots, f_m(\mathbf{x})\}$ defined over the whole \mathbb{R}^n and the function $L : \mathbb{R}^n \times \mathbb{R}^m \rightarrow \mathbb{R}$ defined as

$$L(\mathbf{x}, \boldsymbol{\theta}) = f_0(\mathbf{x}) + \sum_{i=1}^m \theta_i f_i(\mathbf{x}).$$

Show that the following function over $\boldsymbol{\theta} \in \mathbb{R}^m$ is always convex

$$g(\boldsymbol{\theta}) = \sup_{\mathbf{x} \in \mathbb{R}^n} \{L(\mathbf{x}, \boldsymbol{\theta})\}.$$

Hint: You may rely on the definition of convexity and/or the properties of convex functions.

Problem 3

Consider the problem of minimizing the following function over \mathbb{R}^3

$$f(\mathbf{x}) = \frac{1}{2} \exp \left(\frac{1}{2} \mathbf{x}^\top \mathbf{Q} \mathbf{x} - \mathbf{c}^\top \mathbf{x} + d \right), \quad \text{where} \quad \mathbf{Q} = \begin{bmatrix} 2 & -1 & \theta \\ -1 & 2 & -1 \\ \theta & -1 & 2 \end{bmatrix}, \quad \mathbf{c} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \quad \text{and} \quad d = 5.$$

- (a) For what values of $\theta \in \mathbb{R}$ is the problem strictly convex?
- (b) Is $\mathbf{g} = \mathbf{c} - \mathbf{Q}\mathbf{x}$ a descent direction for f at any $\mathbf{x} \in \mathbb{R}^3$?
- (c) What is the minimizer \mathbf{x}^* of f for $\theta = 0$?

Problem 4

Consider the problem of minimizing the following function over \mathbb{R}^n :

$$f(\mathbf{x}) = \frac{1}{2} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|^2 \quad \text{where} \quad \mathbf{A} \in \mathbb{R}^{m \times n} \quad \text{and} \quad \mathbf{b} \in \mathbb{R}^m.$$

- (a) Provide the expressions for the gradient and the Hessian of f . Is f a convex function?
- (b) Find the minimizer $\mathbf{x}^* \in \mathbb{R}^n$ of f , when $\mathbf{A}^\top \mathbf{A}$ is nonsingular.
- (c) Assume that $\mathbf{A}^\top \mathbf{A}$ is nonsingular. Find a matrix $\mathbf{M} \in \mathbb{R}^{n \times n}$ such that for any $\mathbf{x}^0 \in \mathbb{R}^n$ the following single iteration

$$\mathbf{x}^1 = \mathbf{x}^0 - \mathbf{M} \nabla f(\mathbf{x}^0),$$

converges to the minimizer $\mathbf{x}^* \in \mathbb{R}^n$.

Hint: Note this result must be valid for any starting point $\mathbf{x}^0 \in \mathbb{R}^n$.

Bonus Problem

Consider a function $\mathbf{y} = \mathbf{G}(\mathbf{x})$ that takes in a vector $\mathbf{x} \in \mathbb{R}^n$ and produces another vector $\mathbf{y} \in \mathbb{R}^n$.

- We say that \mathbf{G} is *Lipschitz continuous* with constant $L > 0$, when

$$\|\mathbf{G}(\mathbf{x}_1) - \mathbf{G}(\mathbf{x}_2)\| \leq L\|\mathbf{x}_1 - \mathbf{x}_2\|, \quad \forall \mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^n.$$

When $L < 1$, we say that \mathbf{G} is *contractive*.

- We say that \mathbf{G} is *strongly monotone* with constant $M > 0$, when

$$(\mathbf{G}(\mathbf{x}_1) - \mathbf{G}(\mathbf{x}_2))^T(\mathbf{x}_1 - \mathbf{x}_2) \geq M\|\mathbf{x}_1 - \mathbf{x}_2\|^2, \quad \forall \mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^n$$

- (a) Show that for $f \in \mathcal{S}_{M,L}^1(\mathbb{R}^n)$, the gradient $\nabla f(\mathbf{x})$ is strongly monotone with constant M .

Hint: Use the definition of strong convexity at two different points $\mathbf{x}_1 \in \mathbb{R}^n$ and $\mathbf{x}_2 \in \mathbb{R}^n$.

- (b) Show that for $f \in \mathcal{S}_{M,L}^1(\mathbb{R}^n)$ there exists $\gamma > 0$, such that the function $\mathbf{G}(\mathbf{x}) = \mathbf{x} - \gamma \nabla f(\mathbf{x})$ is contractive.

Hint: Use the fact that ∇f is both Lipschitz continuous and strongly monotone.

- (c) Show that when $\mathbf{G}(\mathbf{x}) = \mathbf{x} - \gamma \nabla f(\mathbf{x})$ is contractive with a Lipschitz constant $0 < c < 1$, the iterates generated by the gradient method converge linearly to the minimizer $\mathbf{x}^* \in \mathbb{R}^n$ as follows

$$\|\mathbf{x}^t - \mathbf{x}^*\| \leq c^t \|\mathbf{x}^0 - \mathbf{x}^*\|, \quad \forall t \geq 1.$$