Convex Optimization for Machine Learning and Computer Vision

Lecture: Dr. Tao Wu Computer Vision Group Exercises: Zhenzhang Ye Institut für Informatik Winter Semester 2019/20 Technische Universität München

## Weekly Exercises 8

Room: 02.09.023

Wednesday, 15.01.2020, 12:15-14:00

Submission deadline: Monday, 13.01.2020, 16:15, Room 02.09.023

## Exact Line Search

(14+6 Points)

**Exercise 1** (6 Points). Let  $Q \in \mathbb{R}^{n \times n}$  be a positive definite symmetric matrix. Prove the following inequality for any vector  $x \in \mathbb{R}^n$ 

$$\frac{(x^\top x)^2}{(x^\top Q x)(x^\top Q^{-1} x)} \ge \frac{4\lambda_n \lambda_1}{(\lambda_n + \lambda_1)^2},$$

where  $\lambda_n$  and  $\lambda_1$  are, respectively, the largest and smallest eigenvalues of Q.

**Exercise 2** (6 Points). Let  $Q \in \mathbb{R}^{n \times n}$  be symmetric positive definite, and  $b \in \mathbb{R}^n$ . As in the previous exercise, denote the eigenvalues of Q as  $0 < \lambda_1 \le \lambda_2 \le \ldots \le \lambda_n$ . Consider the quadratic function  $f : \mathbb{R}^n \to \mathbb{R}$ ,  $x \mapsto \frac{1}{2}x^\top Qx - b^\top x$  and show gradient descent with exact line search has the following convergence property:

$$||x^{k+1} - x^*||_Q^2 \le \left(\frac{\lambda_n - \lambda_1}{\lambda_n + \lambda_1}\right)^2 ||x^k - x^*||_Q^2,$$

where  $x^* \in \mathbb{R}^n$  denotes the global minimizer of f.

Hint: use the inequality from exercise 1.

## Image Denoising (Due Date: 13.01) (10 Points)

Given a noisy input image, we want to remove the noises by solving following minimization problem:

$$\operatorname{argmin}_{u} \frac{1}{2} \|u - f\|^{2} + \rho H_{\varepsilon}(Ku).$$

where  $f \in \mathbb{R}^N$  is the input image with N pixels,  $\rho$  is a scalar weighting the smooth regularizor,  $H_{\varepsilon}$  is the Huber function defined as before and K is the gradient operator.

Your task is using gradient descent with line search to solve it.

For detailed line search, you can refer to Algorithm 3.5 and 3.6 (Page 79) in Numerical Optimization

http://www.apmath.spbu.ru/cnsa/pdf/monograf/Numerical\_Optimization2006.pdf. For zoom function, you can directly use bisection.