## OR Advanced, Part 1, Final Report

- $\checkmark\,$  Answer the questions in Japanese or English.
- $\checkmark~$  The final report corresponds to 70% of the grade of the "nonlinear optimization" part, and the two small reports correspond to 30% (each one 15%) of the total grade.
- $\checkmark\,$  Submit this report on November 28's class.

**Exercise 1.** [15 points] Let  $x^* \in \mathbb{R}^n$  be a local minimizer of the following nonlinear programming problem:

$$\min_{\text{s.t.}} f(x) \\ \text{s.t.} \quad g_i(x) \le 0, \quad i = 1, \dots, m,$$
 (P1)

where  $f: \mathbb{R}^n \to \mathbb{R}$  and  $g_i: \mathbb{R}^n \to \mathbb{R}$ , i = 1, ..., m, are differentiable. Assume that  $x^*$  satisfies the linear independence constraint qualification (LICQ), and let  $\lambda^* \in \mathbb{R}^m$  be its corresponding Lagrange multiplier that satisfies the KKT conditions of (P1). Prove that  $\lambda^*$  is unique. Exercise 2. Consider the following quadratic optimization problem:

$$\min \quad \frac{1}{2} x^{\top} Q x + r^{\top} x$$
s.t.  $Ax \le b,$ 
(P2)

where  $Q \in \mathbb{R}^{n \times n}$ ,  $r \in \mathbb{R}^n$ ,  $A \in \mathbb{R}^{m \times n}$  and  $b \in \mathbb{R}^m$  are given and  $x \in \mathbb{R}^n$  is the decision variable. Assume also that Q is symmetric and positive definite.

- (a) [5 points] Prove that the objective function of (P2) is convex.
- (b) [15 points] Prove that the dual of (P2) is also a quadratic problem of the form

$$\begin{array}{ll} \max & \lambda^{\top} \tilde{Q} \lambda + \tilde{r}^{\top} \lambda + \tilde{s} \\ \text{s.t.} & \lambda \in \mathbb{R}^m_+. \end{array}$$

Write the formulas of  $\tilde{Q}$ ,  $\tilde{r}$  and  $\tilde{s}$  explicitly, using only Q, r, A and b.

Exercise 3. [15 points] Consider the following nonlinear optimization problem:

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & g(x) \leq 0, \\ & h(x) = 0, \end{array} \end{array} \tag{P3}$$

with  $f: \mathbb{R}^n \to \mathbb{R}, g: \mathbb{R}^n \to \mathbb{R}^m$  and  $h: \mathbb{R}^n \to \mathbb{R}^p$ . We say that  $(x^*, \lambda^*, \mu^*) \in \mathbb{R}^n \times \mathbb{R}^m_+ \times \mathbb{R}^p$  is a saddle point of the Lagrangian function L if the following inequalities hold:

$$L(x^*, \lambda, \mu) \le L(x^*, \lambda^*, \mu^*) \le L(x, \lambda^*, \mu^*) \quad \text{for all } (x, \lambda, \mu) \in \mathbb{R}^n \times \mathbb{R}^m_+ \times \mathbb{R}^p.$$

Assume that f and g are convex and that h is affine. Suppose also that the Slater constraint qualification holds. Prove that  $x^* \in \mathbb{R}^n$  is an optimal solution of problem (P3) if, and only if, there exists  $(\lambda^*, \mu^*) \in \mathbb{R}^m_+ \times \mathbb{R}^p$  such that  $(x^*, \lambda^*, \mu^*)$  is a saddle point of L.

Exercise 4. Consider the following optimization problem:

$$\min_{\substack{x \in \mathcal{F}_{i}}} f(x)$$
 s.t.  $g_{i}(x) \leq 0, \quad i = 1, \dots, m,$  (P4)

where  $f: \mathbb{R}^n \to \mathbb{R}, g_i: \mathbb{R}^n \to \mathbb{R}, i = 1, ..., m$ , are differentiable and convex. Let  $\phi_i: \mathbb{R} \to \mathbb{R}$ , i = 1, ..., m, be increasing, differentiable and convex functions.

(a) [10 points] Prove that the function  $q \colon \mathbb{R}^n \to \mathbb{R}$  defined below is convex:

$$q(x) := f(x) + \sum_{i=1}^{m} \phi_i(g_i(x)).$$

(b) [10 points] Assume that  $\bar{x} \in \mathbb{R}^n$  is a minimizer of q. Find a feasible point for the dual of (P4) by using  $\bar{x}$ , justifying your answer. Write out the corresponding lower bound on (P4)'s optimal value.