CS5321 Numerical Optimization Homework 4

Student: 103062624 李彥均

1. (20%) Consider the problem

(a) Write down the KKT conditions for (1).

Answer. $\vec{x} = (x_1, x_2)$

The Lagrangian function

$$\mathcal{L}(\vec{x}, \lambda) = 0.1(x_1 - 3)^2 + x_2^2 - \lambda(-x_1^2 - x_2^2 + 1)$$

The KKT conditions (First-Order Necessary Conditions) Suppose that \vec{x}^* is a local solution, and that the LICQ holds at \vec{x}^* . Stationarity

$$\nabla_{\vec{x}^*} \mathcal{L}(\vec{x}^*, \lambda^*) = 0$$

$$\Rightarrow \begin{bmatrix} (2\lambda + 0.2)x_1^* - 0.6\\ (2\lambda + 2)x_2^* \end{bmatrix} = 0$$

Primal feasibility

$$-x_1^{*2} - x_2^{*2} + 1 \ge 0$$

Dual feasibility

$$\lambda^* \ge 0$$

Complementary slackness

$$\lambda^*(-x_1^{*2} - x_2^{*2} + 1) = 0$$

Strict Complementarity

Exactly one of λ^* and $(-x_1^{*2} - x_2^{*2} + 1)$ is zero.

(b) Solve the KKT conditions and find the optimal solutions, including the Lagrangian parameters.

Answer.
$$\vec{x}^* = (1,0) \text{ and } \lambda^* = 0.2.$$

(c) Compute the reduced Hessian and check the second order conditions for the solution.

Answer. Second-Order Necessary Conditions

$$w^{T} \nabla_{\vec{x}\vec{x}}^{2} \mathcal{L}(\vec{x}^{*}, \lambda^{*}) w \geq 0$$
where
$$\begin{bmatrix} -2x_{1}^{*} \\ -2x_{2}^{*} \end{bmatrix}^{T} w = 0 \text{ with } \lambda^{*} > 0$$
or
$$\begin{bmatrix} -2x_{1}^{*} \\ -2x_{2}^{*} \end{bmatrix}^{T} w \geq 0 \text{ with } \lambda^{*} = 0$$

Hessian matrix

$$\nabla^2_{\vec{x}\vec{x}}\mathcal{L}(\vec{x}^*, \lambda^*) = \begin{bmatrix} 2\lambda^* + 0.2 & 0\\ 0 & 2\lambda^* + 2 \end{bmatrix} = \begin{bmatrix} 0.6 & 0\\ 0 & 2.4 \end{bmatrix}$$

Because $\nabla^2_{\vec{x}\vec{x}}\mathcal{L}(\vec{x}^*,\lambda^*)$ is positive-definite, satisfy the second-order conditions. \square

2. (20%) The trust region method (for unconstrained optimization problem) needs to solve a local model in each step

$$\min_{\vec{p}} \quad m(\vec{p}) = \frac{1}{2} \vec{p}^T A \vec{p} + \vec{g}^T \vec{p}$$
s.t.
$$\vec{p}^T \vec{p} \le \Delta^2.$$

Prove that the optimal solution \bar{p}^* of the local model satisfies

$$\begin{split} \left(A + \lambda I\right) \vec{p}^* &= -\vec{g} \\ \lambda \left(\Delta - \|\vec{p}^*\|\right) &= 0 \\ \left(A + \lambda I\right) \text{ is positive semidefinite.} \end{split}$$

(Hint: to prove the last statement, you only need to consider the directions in the *critical cone*.)

Answer. The Lagrangian function

$$\begin{split} \mathcal{L}(\vec{p},\lambda) &= m(\vec{p}) - \frac{\lambda}{2}(\Delta^2 - \vec{p}^T \vec{p}) \\ &= m(\vec{p}) - \frac{\lambda}{2}\Delta^2 + \frac{1}{2}\vec{p}^T(\lambda I)\vec{p} \\ &= \frac{1}{2}\vec{p}^T(A + \lambda I)\vec{p} + \vec{g}^T\vec{p} - \frac{\lambda}{2}\Delta^2 \end{split}$$

Suppose that \vec{p}^* is a local solution, and that the LICQ holds at \vec{p}^* . Then KKT conditions are hold.

Stationarity
$$\nabla_{\vec{p}^*} \mathcal{L}(\vec{p}^*, \lambda^*) = 0$$

Complementary slackness $\lambda(\Delta^2 - \vec{p}^T \vec{p}) = 0$

Equivalently,

$$(A + \lambda I) \vec{p}^* = -\vec{g},$$

$$\lambda (\Delta - ||\vec{p}^*||) = 0.$$

Also, the second-order necessary conditions are satisfied.

$$w^T \nabla^2_{\vec{p}\vec{p}} \mathcal{L}(\vec{p}^*, \lambda^*) w \ge 0 \text{ for all } w \in \mathcal{C}(\vec{p}^*, \lambda^*).$$

Equivalently,

$$w^T(A + \lambda I)w \ge 0$$
 for all $w \in \mathcal{C}(\vec{p}^*, \lambda^*)$.

Hence $(A + \lambda I)$ is positive semidefinite.

3. (60%) Implement the Interior Point Method (IPM), as shown in Figure 1, to solve linear programming problem.

$$\min_{\vec{x}} \quad \vec{c}^T \vec{x}$$

s.t.
$$A\vec{x} - \vec{s} = \vec{b}$$

$$\vec{s} \ge 0$$

You can assume $\vec{x}_0 = 0$ is a feasible interior point.

- (1) Given \vec{x}_0 , $\vec{\lambda}_0$, and \vec{s}_0 , in which $\vec{\lambda}_0$, $\vec{s}_0 \ge 0$.
- (2) For k = 0, 1, ...
- (3) Choose $\sigma_k \in [0, 1]$ and solve

$$\begin{pmatrix} 0 & -A^T & 0 \\ -A & 0 & I \\ 0 & S^k & \Lambda^k \end{pmatrix} \begin{pmatrix} \Delta x_k \\ \Delta \lambda_k \\ \Delta s_k \end{pmatrix} = \begin{pmatrix} A^T \vec{\lambda}_k - \vec{c} \\ A\vec{x}_k - \vec{s}_k - \vec{b} \\ \sigma_k \mu_k e - \Lambda^k S^k e \end{pmatrix},$$

where
$$\mu_k = \frac{\vec{\lambda}_k^T \vec{s}_k}{m}$$
, $\Lambda^k = \text{diag}(\vec{\lambda}_k)$, $S^k = \text{diag}(\vec{s}_k)$.

(4) Compute α_k such that

$$(\vec{x}_{k+1}, \vec{\lambda}_{k+1}, \vec{s}_{k+1}) = (\vec{x}_k, \vec{\lambda}_k, \vec{s}_k) + \alpha(\Delta x_k, \Delta \lambda_k, \Delta s_k)$$

is in the region $N(\gamma) = \{(\vec{x}, \vec{\lambda}, \vec{s}) | \lambda_i s_i \ge \gamma \mu_k, \forall i = 1, 2, \dots, n \}$ for some $\gamma = 10^{-3}$.

Figure 1: The interior point method for solving linear programming