Optimization Techniques Lecture 8

2. Problems with equality and inequality constraints KKT conditions

3. Problems with nonnegativity constraints

2. Problems with equality and inequality constraints – KKT Multipliers

• Consider the following problem:

Min f(x) s.t. g_i(x)=0 i=1,2,...,k≤n g_i(x)≤0 j=k+1,k+2,...,N

 where f(x) and g_i(x) are continuously differentiable functions in Rⁿ.

For the above general problem, we adopt the following definitions:

Definition: An inequality constraint $g_j(x) \le 0$ is said to be **active** at x* if $g_j(x *) = 0$. It is inactive at x* if $g_j(x) < 0$.

By convention, we consider an equality constraint to be always active.

Definition: Let x^* satisfies $g_i(x^*) = 0$ for each *i* and $g_j(x^*) \le 0$. And let $J(x^*)$ be the index set of active inequality constraints, that is,

$$J(x^{*}) = \{j \in \{k_{1}^{*}, N\} \mid g_{j}(x^{*}) = 0\}$$

We again assumed that the vectors in

are linearly independent.

First order necessary condition (Karush – Kuhn – Tucker (KKT) Condition)

• $f, g_i and g_j$ are continuously differentiable functions in \mathbb{R}^n . Let x^* be a minimizer for the problem of minimizing f subject to $g_i(x) = 0$ and $g_j(x) \le 0$. Then the Lagrangian of the problem is:

$$L(x_{i},\lambda_{i},\mu) = f(x) + \sum_{j=1}^{k} \lambda_{i} \cdot 9_{j} + \sum_{j=k+1}^{n} M_{j} \cdot 9_{j}$$

$$If M_{j} \cdot 9_{j} = 0 \implies L(x_{i},\lambda_{j},\mu) = f(x^{i})$$

$$M_{j} \cdot 9_{j} = 0 \implies a) \quad 9_{j} \cdot (x^{**}) = 0 \quad 9_{j} \text{ is activ}$$

$$b) \quad M_{j} = 0 \implies 9_{j} \leq 0 \quad .$$

FONC:

 $\nabla L = \nabla f(x^{*}) + \sum_{j=1}^{k} \lambda_{j} \nabla g_{j}(x^{*}) + \sum_{j=k+1}^{N} M_{j} \nabla g_{j}(x^{*}) = 0 - \dots (1)$ $g_{i}(x) = 0$; i = 1, ..., k (2) $9_{j}(x^{*}) \leq 0$; j = k + 1 - ... N (3) $M_{j} \cdot g_{j}(x^{*}) = 0$, j = k + 1, ..., N - ...(4) $M_j \ge 0$, $\forall j \cdot \cdots \cdot (s)$

Observe that λ_i values are free for all *i*, but μ_j values are non-negative for all *j*.

XER : n veriables. Ni(i=1,..,k): k lagrange multipliers Mi((j=k+1,..,p):N-K KKT multipliers.

We search for all points satisfying (1)-(5), and treat them as candidate extremizers.

Second Order Conditions

We assume that f: $\mathbb{R}^n \rightarrow \mathbb{R}$ and g: $\mathbb{R}^n \rightarrow \mathbb{R}^k$ are twice continuously differentiable functions in \mathbb{R}^n , the set

$$\{ \nabla g_i(x), i = 1, 2, ..., k; \nabla g_j(x), j \in J(x^*) \}$$

is linearly independent, the feasible direction set is defined as:

$$H(\mathbf{x}) = \{ h \in \mathbb{R}^n | \nabla g_i(x)^T h = 0; \forall i = 1, 2, ..., k; \nabla g_j(x)^T h = 0; \forall j \in J(x^*) \}.$$

Then the second order (sufficient) condition for a local **strict minimizer** is that $\nabla^2 L(x^*, \lambda)$ with respect to x is **positive definite** over $H(x^*)$.

Then the SOSC for a local **strict maximizer** is that $\nabla^2 L(x^*, \lambda)$ with respect to x is **negative definite** over H(x*).

Example: Find the extremum points of the below problem.

min f(x) =
$$(x_1 - 1)^2 + (x_2 - 2)^2$$

s.t. $x_2 - x_1 = 1$
 $x_1 + x_2 \le 2$

3. Problems with nonnegativity constraints

• Consider the following problem:

Min f(x)

subject to $x_i \ge 0$; i=1,2,...,n.

where f(x) is continuously differentiable functions in \mathbb{R}^n . With the following arrangement

$$g_i(x): -x_i \le 0; i=1,2,...,n$$

the above problem can be converted to the following form which is a problem with inequality constraints (Title 2)

Min f(x)

s.t. g_i(x) <= 0 ; i=1,2,...,n

• For the above problem, we adapt the FONC and SOSC in title 2: 11

Observe that
$$L(x,\mu) = f(x) + \sum_{i=1}^{n} \mu_i g_i(x)$$

FONC:

$$\nabla L = \nabla f + \sum_{i=1}^{n} \mu_i \cdot \nabla g_i = 0 \dots (1)$$

$$g_i(x) \le 0 \dots (2)$$

$$M_i \cdot g_i(x) = 0 = \dots (3)$$

$$M_i > 0 \dots (4)$$

$$\begin{array}{rcl} g_{i}(x) &= -X_{i} &= j &= 1, 2, ..., n \\ \hline \frac{\partial(-x_{i})}{\partial x_{i}} &= -J &= j &= 1, 2, ..., n \\ \hline \frac{\partial(-x_{i})}{\partial x_{i}} &= 0 &= j &= 1, 2, ..., n \\ \hline \frac{\partial(-x_{i})}{\partial x_{i}} &= 0 &= j &= 1, 2, ..., n \\ \hline \frac{\partial(-x_{i})}{\partial x_{i}} &= 0 &= j &= 1, 2, ..., n \\ \hline \end{array}$$

$$\frac{\partial L}{\partial x_i} = \frac{\partial f}{\partial x_i} - M_i = 0 \quad \dots \quad (\Lambda) \quad \forall I.$$

We search for points satisfying (1)-(4), and treat these points as candidate extremizers.

(1)
$$M_i = \frac{\partial f}{\partial x_i}$$

Considering the above equality, the last form of FONC can be constructed as follows:

FONC:

$$\frac{\partial f}{\partial x_i} = 0; i=1,2,...,n \dots (5) \qquad \text{inequality}$$

$$\frac{\partial f}{\partial x_i} = 0; i=1,2,...,n \dots (6) \qquad \text{equality}$$

$$x_i \cdot \frac{\partial f}{\partial x_i} = 0; i=1,2,...,n \dots (7) \qquad \text{inequality}$$

$$x_i \gg 0; i=1,2,...,n \dots (7) \qquad \text{inequality}$$

We have n equations to find n unknowns (n variables x in Rⁿ). Observe that the candidate points must satisfy (5) and (7).

SOSC:

$$\nabla L = \nabla f(x) - \mu; T \qquad T = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\nabla^{2} L = \nabla^{2} f(x) \implies b \text{ and } f \text{ have the some}$$

$$Hossian$$

$$\nabla^{2} L (X^{*}/\mu) = \nabla^{2} f(x^{*}) \implies M(X^{*}).$$

Then the SOSC for a local **strict minimizer** is that $\nabla^2 L(x^*, \mu)$ with respect to x is **positive definite** over H(x*). Example: Find the extremum points of the below problem.

min f(x, y, z) =
$$2x^2 + 3y^2 + z^2 - 2xy + 2xz - 2x - 4z$$

s.t. $x \ge 0, y \ge 0, z \ge 0$

Example: Find the extremum points of the below problem.

$$f(x) = x_1^2 + x_1 x_2 + 2x_2^2 - 6x_1 - 14x_2$$

s.t. $x_1 + x_2 + x_3 = 2$
 $-x_1 + 2x_2 \le 3$
 $x_1 \ge 0, x_2 \ge 0, x_3 \ge 0$