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 gj (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 $g_i(x) \leq 0$ is said to be **active** at x^* if $g_i(x*) = 0$. It is inactive at x^* if $g_i(x) < 0$.

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

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

$$
J(x^{\star}) = \left\{ j \in \left\{ k_1^{\star}, N \right\} \middle| \quad g_j(x) = 0 \right\}
$$

We again assumed that the vectors in

$$
\{ \nabla g_{i,j} \in \{1, \ldots, k\} \setminus \nabla g_{j} \} \in \mathfrak{ICX}^{1/2}
$$

are linearly independent.

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

• f , g_i and g_j are continuously differentiable functions in 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: \sim 1

$$
L(x^*, \lambda_1 \mu) = f(x) + \sum_{i=1}^{k} \lambda_i \frac{g_i^*}{g_i^*} + \sum_{j=k+1}^{N} M_j \cdot g_j^*
$$

\nIf $\mu_j \cdot g_j = 0 \implies L(x^*, \lambda_1 \mu) = f(x^*)$
\n
$$
\mu_j \cdot g_j = 0 \implies \alpha) g_j(x^*) = 0. g_j \text{ is adim}
$$

\n
$$
\mu_j = 0 \implies g_j \le 0.
$$

FONC:

 $\nabla L = \nabla f(x^*) + \sum_{i=1}^{k} \lambda_i \nabla \mathfrak{R}_i(x^*) + \sum_{j=k+1}^{k} M_j \cdot \nabla \mathfrak{R}_j(x^*) = 0 - \cdots (1)$ $g_{\phi}(x) = 0$; $i = 1, ..., k$...(2) $9.1x^{**}$) \leq 0 ; j = k +1, ... N ... (3) $Mj \cdot g_j(x^*) = 0$, $j = k+1, ..., N - (4)$ $Mj \geqslant O$ $\forall j$. \cdots (5)

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

$$
(1) n equations
$$
\n
$$
(2) k
$$
\n
$$
(3) N-k
$$
inequality¹ equations.
\n
$$
(4) N-k
$$
lequality¹...\n
$$
(5) N-k
$$
isangularity¹...

$$
x \in \mathbb{R}^{n}
$$
 : n variables.
\n $\lambda_{i}(i_{1}:1...,k) \cdot k$ largest $\lambda_{1}:1^{k}iplies$
\n $M_{j}(i_{j}:k+1,...,k) \cdot N-k$ kkt $\lambda_{1}:1^{k}p!i\in S$

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

Second Order Conditions

We assume that f: $R^n \rightarrow R$ and g: $R^n \rightarrow R^k$ are twice continuously differentiable functions in Rⁿ, 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:

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

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 $H(x^*)$.

7 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 $x_i >=0$; i=1,2,...,n.

where $f(x)$ is continuously differentiable functions in $Rⁿ$. With the following arrangement

$$
g_i(x): -x_i \leq 0
$$
; 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
$$
L(x,\mu) = f(x) + \sum_{i=1}^{n} \mu_i g_i(x)
$$

\n**FONC:**
\n
$$
\nabla L = \nabla f + \sum_{i=1}^{n} \mu_i \nabla g_i = 0 \cdots (1)
$$
\n
$$
\nabla f(x) \leq 0 \cdots (1)
$$
\n
$$
\mu_i \cdot g_i(x) = 0 \cdots (3)
$$
\n
$$
\mu_i \gg 0 \cdots (4)
$$
\n
$$
\nabla f(x) = -x_i - \sum_{i=1}^{n} \sum_{i=1}^{n} \sum_{i=1}^{n} f_i(x_i) \cdot f(x_i)
$$
\n
$$
\frac{\partial f(x)}{\partial x_i} = -\frac{1}{2} \int_{0}^{1} \sum_{i=1}^{n} f_i(x_i) \cdot f(x_i) \cdot f(x_i)
$$
\n
$$
\frac{\partial f(x_1)}{\partial x_1} = 0 \qquad \int_{0}^{1} \sum_{i=1}^{n} f_i(x_i) \cdot f(x_i) \cdot f
$$

$$
\frac{9_{i}(x) = -x_{i} - 7i = 1, 2, ..., n}{2(-x_{i})} = -1, 3, i = 1, 2, ..., n
$$
\n
$$
\frac{2(-x_{i})}{2(x_{i})} = 0, j = 1, 2, ..., n, j \neq i
$$

$$
\frac{\partial L}{\partial x_i} = \frac{\partial L}{\partial x_i} - \mu_i = 0 \qquad (1) \quad \forall i.
$$

$$
\mu_{i} \cdot g_{i}(x) = 0 \implies \mu_{i} (-x_{i}) = 0 \implies \mu_{i} \cdot x_{i} = 0
$$

\n
$$
g_{i}(x) \leq 0 \implies x_{i} \geq 0 - \sum_{i=1,2,3,4} 0
$$

\n
$$
\mu_{i} \geq 0 - \sum_{i=1,2,4,5,6,6} 0
$$

\n
$$
\mu_{i} \geq 0 - \sum_{i=1,4,5,6,6,6} 0
$$

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

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

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

FONC:

$$
\frac{\partial f}{\partial x_i} \gg 0 \quad \text{if } f, 2, ..., n \text{ (S)} \text{ (i) } \text{ inequality } f \text{ is a function of } f \text{ (ii)}
$$
\n
$$
\frac{\partial f}{\partial x_i} = 0 \text{ if } f, 2, ..., n \text{ (ii)}
$$
\n
$$
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$$
\n
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$$

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

SOSC:
\n
$$
\nabla L = \nabla f(x) - \mu: \hat{L} = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}
$$

\n $\nabla^{2} L = \nabla^{2} f(x) \implies L = \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$
\nHessian.
\n $\nabla^{2} L = \nabla^{2} f(x) \implies L = \mu(X^{*})$
\nHessian.
\n $\nabla^{2} L(X^{*}/M) = \nabla^{2} L(X^{*}) = \mu(X^{*})$

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