

$$\begin{cases} \text{maximize} & f(x) \\ \text{s.t.} & h(x) = 0 \\ & g(x) \leq 0 \end{cases}$$

KKT condition

1. $\mu^* \geq 0$
2. $-Df(x^*) + \lambda^{*T} Dh(x^*) + \mu^{*T} Dg(x^*) = 0^T$
3. $\mu^{*T} g(x^*) = 0$
4. $h(x^*) = 0$
5. $g(x^*) \leq 0$

Thm 21.3 SOSC Suppose that $f, g, h \in C^2$ and there exists a feasible point $x^* \in \mathbb{R}^n$ and vectors $\lambda^* \in \mathbb{R}^m$ and $\mu^* \in \mathbb{R}^p$ such that

1. $\mu^* \geq 0$, $Df(x^*) + \lambda^{*T} Dh(x^*) + \mu^{*T} Dg(x^*) = 0^T$, $\mu^{*T} g(x^*) = 0$
2. $\forall y \in \tilde{T}(x^*, \mu^*)$, $y \neq 0$, we have $y^T L(x^*, \lambda^*, \mu^*) y > 0$

Then x^* is a strict local minimizer of f s.t. $h(x) = 0$, $g(x) \leq 0$.

$$\begin{cases} \tilde{T}(x^*, \mu^*) = \{y : Dh(x^*)y = 0, Dg_i(x^*)y = 0, i \in \tilde{J}(x^*, \mu^*)\} \\ \tilde{J}(x^*, \mu^*) = \{i : g_i(x^*) = 0, \mu_i^* > 0\} \end{cases}$$

Exercise 21.7

(a) Suppose it is minimization.

$$\begin{aligned} \min & (x_1 - 2)^2 + (x_2 - 1)^2 \\ \text{s.t.} & x_1^2 - x_2 \leq 0 \\ & x_1 + x_2 - 2 \leq 0 \\ & -x_1 \leq 0 \end{aligned}$$

$$Df(x^*) + \lambda^{*T} Dh(x^*) + \mu^{*T} Dg(x^*) = \begin{pmatrix} 2x_1 - 4 \\ 2x_2 - 2 \end{pmatrix} + \mu_1^* \begin{pmatrix} 2x_1 \\ -1 \end{pmatrix} + \mu_2^* \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \mu_3^* \begin{pmatrix} -1 \\ 0 \end{pmatrix} = 0$$

$$(\mu_1^* \quad \mu_2^* \quad \mu_3^*) \begin{pmatrix} x_1^2 - x_2 \\ x_1 + x_2 - 2 \\ -x_1 \end{pmatrix} = 0$$

$$\begin{cases} 2x_1 - 4 + 2\mu_1^* x_1 + \mu_2^* - \mu_3^* = 0 \\ 2x_2 - 2 - \mu_1^* + \mu_2^* = 0 \\ \mu_1^*(x_1^2 - x_2) + \mu_2^*(x_1 + x_2 - 2) + \mu_3^*(-x_1) = 0 \end{cases}$$

Let $(x_1, x_2) = (0, 0)$. Then

$$\begin{cases} -4 + \mu_2^* - \mu_3^* = 0 \\ -2 - \mu_1^* + \mu_2^* = 0 \\ -2\mu_2^* = 0 \end{cases}$$

$\Rightarrow \mu_2^* = 0, \mu_1^* = -2, \mu_3^* = -4$. Since $\mu_3^*, \mu_1^* < 0$, not feasible.

Consider maximization.

$$\begin{array}{ll} \min & -(x_1-2)^2 - (x_2-1)^2 \\ \text{s.t.} & x_1^2 - x_2 \leq 0 \\ & x_1 + x_2 - 2 \leq 0 \\ & -x_1 \leq 0 \end{array}$$

From KKT,

$$\begin{pmatrix} -2x_1 + 4 \\ -2x_2 + 2 \end{pmatrix} + \mu_1^* \begin{pmatrix} 2x_1 \\ -1 \end{pmatrix} + \mu_2^* \begin{pmatrix} 1 \\ 1 \end{pmatrix} + \mu_3^* \begin{pmatrix} -1 \\ 0 \end{pmatrix} = 0$$

$$\mu_1^*(x_1^2 - x_2) + \mu_2^*(x_1 + x_2 - 2) + \mu_3^*(-x_1) = 0$$

Let $(x_1, x_2) = (0, 0)$,

$$\begin{pmatrix} 4 + \mu_2^* - \mu_3^* = 0 \\ 2 - \mu_1^* + \mu_2^* = 0 \\ \mu_2^* = 0 \end{pmatrix} \Rightarrow \begin{array}{l} \mu_3^* = 4 \\ \mu_1^* = 2 \\ \mu_2^* = 0 \end{array}$$

All positive, thus feasible.

(b) $T(x^*, \mu^*) = \{i : g_i(x^*) = 0, \mu_i^* > 0\} = \{1, 3\}$

$$\begin{aligned} \tilde{T}(x^*, \mu^*) &= \{y : Dh(x^*)y = 0, Dg_i(x^*)y = 0, i \in \{1, 3\}\} \\ &= \{y : \begin{pmatrix} 0 \\ 1 \end{pmatrix}y = 0, \begin{pmatrix} -1 \\ 0 \end{pmatrix}y = 0\} = \{0\} \end{aligned}$$

From (a), SOSC (1) holds. Since $\tilde{T}(x^*, \mu^*) = \{0\}$, SOSC (2) is vacuously true. \square

Exercise 21.12

$$\min \frac{1}{2} x^T Q x$$

$$\text{s.t. } Ax \leq b$$

where $Q = Q^T > 0, A \in \mathbb{R}^{m \times n}, b \geq 0$. Find all points satisfying the KKT condition.

$$\begin{aligned} Df(x^*) + A^T Dh(x^*) + \mu^{*T} Dg(x^*) &= 0 & f(x) + \mu^T (Ax - b) \\ \mu^{*T} g(x^*) &= 0 & \nabla f(x) + A^T \mu \end{aligned}$$

$$\begin{aligned} Qx^* + A^T \mu^* &= 0 \\ \mu^{*T} (Ax^* - b) &= 0 \end{aligned}$$

$$\begin{cases} x^* = -Q^{-1}A^T\mu^* \\ \mu^{*T}(-AQ^{-1}A^T\mu^* - b) = 0 \end{cases}$$

Exercise 21.19

$$\begin{aligned} \min \quad & x_1^2 + x_2^2 \\ \text{s.t.} \quad & 4 - x_1 - x_2^2 \leq 0 \\ & -x_1 + 3x_2 \leq 0 \\ & -x_1 - 3x_2 \leq 0 \end{aligned}$$

From KKT,

$$\begin{cases} \begin{pmatrix} 2x_1 \\ 2x_2 \end{pmatrix} + \mu_1^* \begin{pmatrix} -1 \\ -2x_2 \end{pmatrix} + \mu_2^* \begin{pmatrix} 1 \\ 3 \end{pmatrix} + \mu_3^* \begin{pmatrix} -1 \\ -3 \end{pmatrix} = 0 \\ \mu_1^*(4 - x_1 - x_2^2) + \mu_2^*(-x_1 + 3x_2) + \mu_3^*(-x_1 - 3x_2) = 0 \end{cases}$$

From Figure 22.3, $(3, -1)$, $(3, 1)$ are minima.

Let $x^* = (3, 1)$. Then

$$\begin{cases} \begin{pmatrix} 6 \\ 2 \end{pmatrix} + \mu_1^* \begin{pmatrix} -1 \\ -2 \end{pmatrix} + \mu_2^* \begin{pmatrix} 1 \\ 3 \end{pmatrix} + \mu_3^* \begin{pmatrix} -1 \\ -3 \end{pmatrix} = 0 \\ \mu_1^*(-6) - 6\mu_3^* = 0 \\ \mu_1^* + \mu_3^* = 0 \end{cases}$$

$$\begin{cases} 6 - \mu_1^* - \mu_2^* - \mu_3^* = 0 \\ 2 - 2\mu_1^* + 3\mu_2^* - 3\mu_3^* = 0 \\ \mu_1^* + \mu_3^* = 0 \end{cases}$$

$$\mu_1^* = -\mu_3^* \Rightarrow 6 - \mu_2^* = 0 \Rightarrow \mu_2^* = 6$$

$$2 - 5\mu_1^* + 18 = 0 \Rightarrow \mu_1^* = 4$$

SOSC (1) is satisfied at $(3, 1)$.

* Checking SOSC (2)

$$f(x^*, \mu^*) = \{1, 2\}$$

$$f(x^*, \mu^*) = \{y : \begin{pmatrix} -1 \\ -2 \end{pmatrix} y = 0, \begin{pmatrix} -1 \\ 3 \end{pmatrix} y = 0\} = \{0\}$$

Thus, SOSC (2) is vacuously true. \square

§ Chapter 22

Def 22.1 The graph of $f: J \rightarrow \mathbb{R} \cup \{-\infty\}$, is the set of points in $J \times \mathbb{R} \cup \{\infty\}$ given by

$$\left\{ \begin{bmatrix} x \\ f(x) \end{bmatrix} : x \in J \right\}$$

Def 22.2 The epigraph of $f: J \rightarrow \mathbb{R} \cup \{-\infty\}$, $\text{epi}(f)$, is the set of points in $J \times \mathbb{R}$ given by

$$\text{epi}(f) = \left\{ \begin{bmatrix} x \\ \beta \end{bmatrix} : x \in J, \beta \in \mathbb{R}, \beta \geq f(x) \right\}$$

Def 22.3 $f: J \rightarrow \mathbb{R} \cup \{-\infty\}$ is convex on J if $\text{epi}(f)$ is a convex set.

Thm 22.1 If $f: J \rightarrow \mathbb{R} \cup \{-\infty\}$ is convex on J , then J is a convex set.

(proof) Suppose J is not convex set. Then, there are y_1, y_2 s.t.

$$\alpha y_1 + (1-\alpha) y_2 \notin J \quad \text{for some } \alpha \in (0, 1)$$

$$\alpha \begin{bmatrix} y_1 \\ f(y_1) \end{bmatrix} + (1-\alpha) \begin{bmatrix} y_2 \\ f(y_2) \end{bmatrix} = \begin{bmatrix} \alpha y_1 + (1-\alpha) y_2 \\ \alpha f(y_1) + (1-\alpha) f(y_2) \end{bmatrix} \notin \text{epi}(f)$$

since $\alpha y_1 + (1-\alpha) y_2 \notin J \Rightarrow \text{epi}(f)$ is not convex and hence f is not convex which is a contradiction. \square

Thm 22.4 Let $f: J \rightarrow \mathbb{R}$, $f \in C$ be defined on an open convex set $J \subset \mathbb{R}^n$.

Then f is convex on J iff

$$f(y) \geq f(x) + Df(x)(y-x) \quad \text{for all } x, y \in J.$$

Def: A vector $g \in \mathbb{R}^n$ is said to be a **subgradient** of f at point $x \in \mathcal{S}$

$$f(y) \geq f(x) + g^T(y-x) \quad \text{for all } y \in \mathcal{S}$$

Thm 22.8 Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$, $f \in C^1$ be a convex function on the set of feasible points

$$\mathcal{S} = \{x \in \mathbb{R}^n : h(x) = 0\}$$

where $h: \mathbb{R}^n \rightarrow \mathbb{R}^m$, $h \in C^1$, and \mathcal{S} is convex. Suppose there exist $x^* \in \mathcal{S}$ and $\lambda^* \in \mathbb{R}^m$ such that

$$Df(x^*) + \lambda^{*T} Dh(x^*) = 0^T$$

Then, x^* is a global minimizer of f over \mathcal{S} .

Exercise 22.12

$$\min \frac{1}{2} x^T Q x$$

$$\text{s.t. } Ax = b$$

where $Q \in \mathbb{R}^{n \times n}$, $Q = Q^T \geq 0$, $A \in \mathbb{R}^{m \times n}$ and $\text{rank}(A) = m$.

a) Find all points satisfying the Lagrange condition.

$$Df(x^*) + \lambda^{*T} Dh(x^*) = 0^T$$

$$Qx^* + A^T \lambda^* = 0 \Rightarrow x^* = -Q^{-1}A^T \lambda^*$$

$Q \geq 0$ thus invertible

$$Ax^* = b \Rightarrow -A Q^{-1} A^T x^* = b$$

$\text{rank}(A) = m$ and $Q > 0$, thus $AQ^{-1}A^T$ is invertible

$$\Rightarrow \lambda^* = -(AQ^{-1}A^T)^{-1}b$$

$$\Rightarrow x^* = -Q^{-1}A^T(AQ^{-1}A^T)^{-1}b$$

b) f is a convex function and $\mathcal{S} = \{x \in \mathbb{R}^n : h(x) = 0\}$ is convex.

By Thm 22.8, x^* is a global minimizer of f over \mathcal{S} . □

Exercise 22.19

$\mathcal{S} \subset \mathbb{R}^n$ nonempty closed convex set and $z \in \mathbb{R}^n$ $z \notin \mathcal{S}$.

Consider

$$\min \|x - z\|$$

$$\text{s.t. } x \in \mathcal{S}$$

• Show the problem has an optimal solution.

Define $d = \inf_{x \in J^2} \|x - z\|$.

Since J^2 is closed, there exists $x^* \in J^2$ that satisfies

$$\|x^* - z\| = \inf_{x \in J^2} \|x - z\|$$

• Show $x^* \in J^2$. ← You can ignore this part for the proof.

Suppose x^* is in the interior of J^2 . Then exists $r > 0$ such that

$$x \in J^2 \text{ if } Br(x^*) = \{x \in J^2 : \|x - x^*\| < r\}$$

We can find $\alpha > 0$ such that $\alpha x^* + (1-\alpha)z \in Br(x^*)$.

$$\|\alpha x^* + (1-\alpha)z - z\| = \|\alpha x^* - \alpha z\| = \alpha \|x^* - z\| < \|x^* - z\|$$

This is a contradiction to x^* being the minimizer. \square

• Show the solution is unique.

Suppose x_1 and x_2 are two distinct solutions.

$$\|x_1 - z\| = \|x_2 - z\|$$

Since J^2 is convex, $\frac{x_1+x_2}{2} \in J^2$. Using the triangle inequality,

$$\left\| \frac{x_1+x_2}{2} - z \right\| = \left\| \frac{x_1-z}{2} + \frac{x_2-z}{2} \right\| \leq \frac{1}{2} \|x_1 - z\| + \frac{1}{2} \|x_2 - z\| = \|x_1 - z\|$$

Since $\|x_1 - z\|$ is the minimum, it follows that

$$\left\| \frac{x_1+x_2}{2} - z \right\| = \|x_1 - z\|.$$

From the hint, the equality holds iff $x = \alpha y$ for some $\alpha \geq 0$ or $x = 0$ or $y = 0$.

$$\text{let } x = \frac{x_1 - z}{2}, \quad y = \frac{x_2 - z}{2}.$$

$x \neq 0$ $y \neq 0$ since $z \notin J^2$.

Suppose $x = \alpha y$ for some $\alpha \geq 0$.

$$\text{Then } \frac{x_1 - z}{2} = \alpha \frac{x_2 - z}{2} \Rightarrow x_1 - z = \alpha x_2 - \alpha z.$$

$$\|x_1 - z\| = \alpha \|x_2 - z\|$$

Since $\|x_1 - z\| = \|x_2 - z\|$, $\alpha = 1$.

If $\alpha \neq 1$, then $x_1 - z = x_2 - z$

$\Rightarrow x_1 = x_2$ which is a contradiction.

Thus, the minimizer is unique. \square