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1st lead in : Lagrange Multiplier Method

$$\min f(x) \quad \text{s.t. } y=f(x) \Rightarrow L(x, y) = f(x, y) + \lambda [y - g(x)]$$

calculate $\nabla L = 0$

generally, $\min_{x \in \mathbb{R}^n} f(x)$ $L(x, \lambda) = f(x) + \sum \lambda_i g_i(x)$
 s.t. $g_i(x) = a_i^T \cdot x + b_i \leq 0$ \Rightarrow If at (x^*, λ^*) take max \Rightarrow
 $i \in \{1, m\}$, $a_i \in \mathbb{R}^n$, $b_i \in \mathbb{R}$ $\nabla L(x^*, \lambda^*) = 0$

Remark: $\forall \lambda_i \geq 0$ $\left\{ \begin{array}{l} \lambda_i = 0, \quad g_i(x) \text{ is slack condition} \\ \lambda_i > 0, \quad g_i(x) \text{ is compact condition} \end{array} \right.$

2nd Dual problem:

$$(P): \min_{x \in \mathbb{R}^n} f_0(x) \quad L(x, \lambda, \nu) = f_0(x) + \sum \nu_i h_i(x) \quad \min_{x^*} \max_{\lambda, \nu} L(x, \lambda, \nu)$$

s.t. $g_i(x) \leq 0, i \in \{1, m\}$ $\xrightarrow{\quad} (P)$ $\text{s.t. } \lambda_i \geq 0 \Rightarrow \forall \lambda_i \geq 0$
 $h_i(x) = 0, i \in \{1, q\}$

proof for equivalence: $D = \{\text{feasible set}\}$

1st $x \in D$, $\max_{\lambda, \nu} L(x, \lambda, \nu) = f_0(x) + \begin{cases} 0 & g_i(x) \leq 0, \lambda_i \geq 0 \\ \infty & g_i(x) > 0, \lambda_i \geq 0 \end{cases}$

2nd $x \in D$, $\max_{\lambda, \nu} L(x, \lambda, \nu) \leq f_0(x)$

□



convex (can be proved)

$$x^* \triangleq \arg \min$$

dual function: $g(\lambda, \nu) = \min_x L(x, \lambda, \nu) = f(x^*) + \sum \lambda_i g_i(x^*) + \sum \nu_i h_i(x^*)$

$$(D): \max_{\lambda, \nu} g(\lambda, \nu)$$

$$\text{s.t. } \nabla_x L(x, \lambda, \nu) = 0$$

$$\lambda \geq 0$$

Compare:

$$p^* \triangleq (P): \min_x \max_{\lambda, \nu} L(x, \lambda, \nu) \quad \geq \quad (D): \max_{\lambda, \nu} \min_x L(x, \lambda, \nu) \triangleq d^*$$

weak dual "=" strong dual

3rd Lagrange - dual - function:

$$L(x, \lambda, \nu) = f_0(x) + \sum \lambda_i g_i(x) \triangleq t + \lambda^T u \quad \left(\begin{array}{l} t = f_0(x) \\ u = (g_1(x), \dots, g_m(x)) \end{array} \right)$$

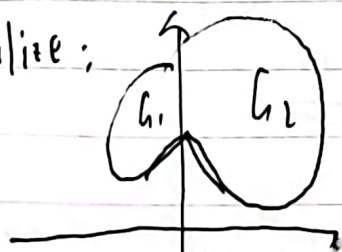
(P) feasible set:

$$\{(t, u) \mid t = f_0(x), u_i = g_i(x), x \in D\} = G_1 \quad (D): \{(t, u) \mid t = f_0(x), u_i = g_i(x), x \in D\} = G_2$$

$$D = \{x \mid f_i(x) \leq 0, h_i(x) = 0\}$$

$$\text{problem } \min_x \{t \mid (t, u) \in G_1, u \leq 0\} \quad \max_{\lambda} \min_x \{t + \lambda^T u \mid (t, u) \in G_2, \lambda \geq 0\}$$

Visualize:



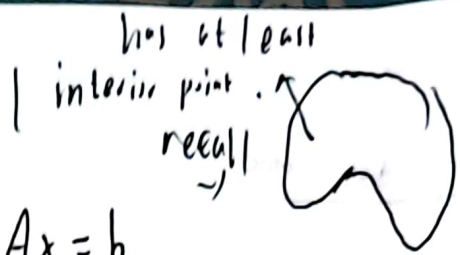
f_0 convex
constraint convex

Th. (get strong dual): If a convex problem satisfies strong dual Slater condition \Rightarrow strong dual.



Slater condition;

$$\exists x \in \text{re(interior)} \text{ s.t. } g_i(x) < 0, Ax = b.$$



The strong dual and KKT. If convex problem is strong dual \Rightarrow satisfies KKT.

4th KKT; def

① primal: $\begin{matrix} f_i(x) \leq 0 \\ h_i(x) = 0 \end{matrix}$ ② dual: $\begin{matrix} \max_x L(x, \lambda, \nu) = 0 \\ \lambda \geq 0 \end{matrix}$

③ achieve op-sol both primal and dual (strong dual)

④ $\lambda_i g_i(x^*) = 0$ $\begin{cases} \lambda_i \geq 0 \\ \lambda_i = 0 \Rightarrow \lambda_i g_i(x^*) = 0 \\ \lambda_i > 0 \Rightarrow g_i(x^*) \leq 0 \Rightarrow \lambda_i g_i(x^*) = 0 \end{cases}$

