

# Lagrange function

Let us consider

$$(P) \quad \min_{x \in C} f_0(x) \text{ subject to } f_1(x) \leq 0$$

We may look at a family  $(P_\gamma)_{\gamma \geq 0}$  of auxiliary problems:

$$(P_\gamma) \quad \min_{x \in C} [f_0(x) + \gamma f_1(x)]$$

where  $\gamma$  plays the role of "weighting" the constraint:

Let  $x^*(\gamma)$  be optimal solution of  $(P_\gamma)$ .

Extreme cases:

- $x^*(0)$  may violate  $f_1(x^*(0)) \leq 0$  unless  $f_1(x) \leq 0$  was unnecessary.
- $\gamma$  sufficiently large guarantees  $f_1(x^*(\gamma)) \leq 0$  but  $x^*(\gamma)$  may be far from optimal

→ It is desired to find an intermediate value  $\bar{\gamma}$  s.t.  $\bar{\gamma} f_1(x^*(\bar{\gamma})) = 0$  so that  $x^*(\bar{\gamma})$  is also a solution of  $(P)$ .

DEF: i) Let  $D = \{\gamma \in \mathbb{R}^m \mid \gamma_i \geq 0 \ i=1..p\}$

We call  $L: C \times D \rightarrow \mathbb{R}$  Lagrange function of  $(P)$ :

$$L(x, \gamma) := f_0(x) + \sum_{i=1}^m \gamma_i f_i(x)$$

(ii) We call  $(x, \bar{\gamma}) \in C \times D$  saddle point of  $L$  if  $\forall x \in C, \gamma \in D$ :

$$L(x, \bar{\gamma}) \geq L(x, \bar{\gamma}) \geq L(x, \gamma)$$

Thm: Let (P) fulfil (Aconvex). Then:

i)  $(\bar{x}, \bar{y}) \in C \times D$  saddle point of  $L$   
 $\Rightarrow \bar{x}$  optimal for (P) and  
 $\bar{y}_i: f_i(\bar{x}) = 0$ , i.e.,  $L(\bar{x}, \bar{y}) = f_0(\bar{x})$

ii) If  $\bar{x}$  is optimal for (P) and (Astar)  $\wedge$   
 $\Rightarrow \exists \bar{y} \in D$  such that  $(\bar{x}, \bar{y})$  saddle  
point of  $L$

iii) If  $\alpha = \inf_{x \in S} f_0(x) \in \mathbb{R}$  and (Astar)  $\wedge$   
 $\Rightarrow \exists \bar{y} \in D$  such that  
$$\alpha = \inf_{x \in C} L(x, \bar{y}) = \max_{y \in D} \inf_{x \in C} L(x, y)$$

REM Under differentiability  
 $(\bar{x}, \bar{y})$  saddle point of  $L$   
 $\Leftrightarrow$  KKT conditions hold for  $(\bar{x}, \bar{y})$

For this note that  $L(x, \bar{y}) \geq L(\bar{x}, \bar{y})$   
implies local min. of  $L$ , and hence,  
KKT (I).

Proof: i)  $(\bar{x}, \bar{y})$  saddle point of  $L$   
 $\Leftrightarrow \forall x \in C, y \in D$ :

$$L(x, \bar{y}) \stackrel{(1)}{\geq} L(\bar{x}, \bar{y}) \stackrel{(2)}{\geq} L(\bar{x}, y)$$

$$\hookrightarrow f_0(\bar{x}) + \sum_{i=1}^p y_i f_i(\bar{x}) + \sum_{j=p+1}^m y_j f_j(\bar{x})$$

From  $\bar{x} \in C, y \in D$  and (2) it follows

for  $i=1 \dots p$ :  
 $y_i \rightarrow +\infty \Rightarrow f_i(\bar{x}) \leq 0$

for  $j = p+1 \dots m$

$$\left. \begin{array}{l} y_j \rightarrow +\infty : f_j(x) \leq 0 \\ y_j \rightarrow -\infty : f_j(x) \geq 0 \end{array} \right\} \Rightarrow f_j(x) = 0$$

$$\begin{aligned} & \cancel{f_0(x)} + \sum_{i=1}^p \bar{y}_i f_i(x) + \sum_{j=p+1}^m \bar{y}_j f_j(x) \\ & \stackrel{(2)}{\geq} \cancel{f_0(x)} + \sum_{i=1}^p \bar{y}_i f_i(x) + \sum_{j=p+1}^m \bar{y}_j f_j(x) \stackrel{(1)}{=} 0 \end{aligned}$$

$$\Rightarrow \bar{y}_i f_0(x) = 0$$

From (1) we get and  $\forall x \in S$

$$f_0(x) + \sum_{i=1}^p \bar{y}_i f_i(x) + \sum_{j=p+1}^m \bar{y}_j f_j(x) \geq f_0(x)$$

$$f(x) \geq \text{because } \left. \begin{array}{l} f_0(x) = 0 \\ f_i(x) \leq 0 \end{array} \right\} \forall x \in S$$

hence  $\bar{x}$  optimal solution on  $S$ .

ii)  $\bar{x}$  optimal solution of (P)

$$\Leftrightarrow \forall x \in S : f_0(x) \leq f_0(\bar{x})$$

$$f_i(x) \leq 0 \quad \forall i = 1 \dots p$$

$$f_j(x) = 0 \quad \forall j = p+1 \dots m$$

(A convex)  $\wedge$  (A Slater)  $\stackrel{L(\bar{x}, \bar{y})}{\Rightarrow}$

$\exists \bar{y} \in D$  s.t.  $\forall x \in C$

$$\begin{aligned} L(x, \bar{y}) &= f_0(x) + \sum_{i=1}^p \bar{y}_i f_i(x) + \sum_{j=p+1}^m \bar{y}_j f_j(x) \\ &\geq f_0(x) \end{aligned}$$

for  $x = \bar{x} \Rightarrow \sum \bar{y}_i f_i(\bar{x}) \geq 0$  but

$$\bar{y}_i \geq 0, f_i(\bar{x}) \leq 0 \Rightarrow \bar{y}_i f_i(\bar{x}) = 0$$

$$\begin{aligned} \Rightarrow L(x, \bar{y}) &\geq f_0(\bar{x}) = L(\bar{x}, \bar{y}) \\ &\geq f_0(\bar{x}) + \sum_{i=1}^p \bar{y}_i f_i(\bar{x}) + \sum_{j=p+1}^m \bar{y}_j f_j(\bar{x}) \\ &= L(\bar{x}, \bar{y}). \end{aligned}$$

$$(99) \quad \alpha := \inf_{x \in S} f(x) \in \mathbb{R}$$

$$(A_{\text{convex}}) \wedge (A_{\text{skalar}}) \stackrel{\text{LEM 2}}{\Rightarrow} \exists \bar{y} \in D$$

$$\forall x \in C: L(x, \bar{y}) \geq \alpha$$

Hence:

$$\bullet \inf_{x \in C} L(x, \bar{y})$$

$$= \inf_{x \in C} \left[ f_0(x) + \sum_{i=1}^p \bar{y}_i f_i(x) + \sum_{i=1}^m \bar{y}_i g_i(x) \right]$$

$$= \alpha$$

Furthermore:

$$\bullet \sup_{y \in D} L(x, y) = \begin{cases} f_0(x) & \text{for } x \in S \\ \infty & \text{else} \end{cases}$$

$$\Rightarrow \inf_{x \in C} \sup_{y \in D} L(x, y) = \inf_{x \in S} f(x) = \alpha$$

Therefore:

$$\alpha = \inf_{x \in C} \sup_{y \in D} L(x, y) \geq \sup_{y \in D} \inf_{x \in C} L(x, y)$$

$$\geq \inf_{x \in C} L(x, \bar{y}) = \alpha$$

$$\Rightarrow \alpha = \inf_{x \in C} L(x, \bar{y})$$

$$= \sup_{y \in D} \inf_{x \in S} L(x, y)$$

$$= \max_{y \in D} \inf_{x \in S} L(x, y)$$

□

Summary: The take away of the above theorem for us is:

① Optimality can be encoded by means of saddle points of Lagrange functions

② For (P) fulfilling (Acover) & (Aslater) and  $\alpha = \inf_{x \in S} f_0(x) \in \mathbb{R}$

$\Rightarrow \exists \bar{y} \in D$  such that

$$\alpha = \inf_{x \in C} L(x, \bar{y}) = \max_{y \in D} \inf_{x \in C} L(x, y)$$

$\rightarrow$  gives rise to a "dual program".

Duality  $S, C, D$  as above

Primal form

$$L(x, y) = f_0(x) + \sum_{i=1}^p y_i f_i(x) + \sum_{i=p+1}^m y_i f_i(x)$$

Dual form

$$\tilde{L}(y) := \inf_{x \in C} L(x, y)$$

Say  $\alpha = \inf_{x \in S} f_0(x) = f_0(x^*)$  then

$$\tilde{L}(y) = \inf_{x \in C} L(x, y) \leq L(x^*, y) \leq f_0(x^*) = \alpha$$

Hence, optimal values of the dual form

$$\delta := \sup_{y \in D} \tilde{L}(y) \text{ fulfil}$$

$\delta \leq \alpha$ ,  $\delta - \alpha$  is called duality gap which vanishes (Aslater).