

Relation between Primal and the Dual problem.

$$\begin{array}{c} x^* \rightarrow \\ \min_x \left[\max_{\lambda \geq 0} L(x, \lambda) \right] \end{array}$$

Primal

$$\begin{array}{c} \max_{\lambda \geq 0} \min_x L(x, \lambda) \end{array}$$

DUAL

$\leftarrow \lambda^*$

$$J(x) = \begin{cases} \frac{\beta(x)}{\infty} & \text{if } \underline{h(x)} \leq 0 \\ \infty & \text{otherwise} \end{cases}$$

$$\text{For any } \underline{\lambda \geq 0} \\ \underline{L(x, \lambda)} = \underline{\beta(x) + \underline{\lambda} \underline{h(x)}} \leq \underline{\beta(x)} \quad \text{if } h(x) \leq 0 \\ \leq \infty$$

Fix $\lambda \geq 0$

$$\underline{L(x, \lambda)} \leq \underline{J(x)} \quad \forall x$$

$$\min_x L(x, \lambda) \leq \min_x J(x) = \beta(x^*)$$

solution of the primal problem

$$\boxed{\max_{\lambda \geq 0} \min_x L(x, \lambda) \leq \beta(x^*)}$$

Primal objective.

$$\max_{\lambda \geq 0} [g(\lambda)] = \boxed{g(\lambda^*) \leq \beta(x^*)}$$

Value at dual optimum \leq value at primal optimum.

WEAK-DUALITY

If f, h are convex, then STRONG-DUALITY holds!
 [upto some regularity]
 $\uparrow \quad \uparrow$
 Objective Constraint

$$\min_z \left[\max_{\lambda \geq 0} L(x, \lambda) \right] \quad (\text{or}) \quad \max_{\lambda \geq 0} \left[\min_x L(x, \lambda) \right]$$

Assume f, h are convex \Rightarrow Strong duality holds.

Let x^*, λ^* are the primal and dual optimal solutions

$$x^* = \operatorname{argmin}_x \left[\max_{\lambda \geq 0} f(x) + \lambda h(x) \right] \quad ; \quad \lambda^* = \operatorname{argmax}_{\lambda \geq 0} \left[\min_x \underbrace{f(x) + \lambda h(x)}_{g(\lambda)} \right]$$

By strong duality.

$$\begin{aligned} \underline{f(x^*)} &= g(\lambda^*) \\ &= \min_x \left[\underbrace{f(x) + \lambda^* h(x)} \right] \end{aligned}$$

$$\Rightarrow \boxed{\nabla f(x^*) + \lambda^* \nabla h(x^*) = 0} \quad \text{--- c1}$$

$$\underline{f(x^*)} = g(\lambda^*) \quad [\text{by strong duality}]$$
$$= \min_x \underbrace{f(x) + \lambda^* h(x)}$$

$$f(x^*) \leq \underbrace{f(x^*) + \lambda^* h(x^*)} \leq \underline{f(x^*)}$$

$$\Rightarrow \boxed{\lambda^* h'(x^*) = 0} \rightarrow C2$$

Putting it all together

f, h are convex \Rightarrow Strong duality

\Downarrow

x^*, λ^* must satisfy. [modulo Regularity conditions]

(a) $\nabla f(x^*) + \lambda^* \nabla h(x^*) = 0$ [Stationarity condition]. ✓

(b) $\lambda^* h(x^*) = 0$ [Complementary slackness condition]. ✓

(c) $h(x^*) \leq 0$ [Primal feasibility]. ✓

(d) $\lambda^* \geq 0$ [Dual feasibility]. ✓

[Sufficiency part] In general
 If (x^*, λ^*) satisfies the above conditions. \Rightarrow Local optima.
 [and some regularity conditions]

KKT Conditions [Karush-Kuhn-Tucker]

$$\min f(x)$$

$$h_i(x) \leq 0 \quad \forall i=1, \dots, m$$

$$l_j(x) = 0 \quad \forall j=1, \dots, n$$

$$\mathcal{L}(x, u, v) =$$

$$\begin{array}{c} \uparrow \\ \text{vector} \end{array} \quad \begin{array}{c} \sim \\ \uparrow \end{array} \quad \begin{array}{c} \uparrow \end{array}$$

$$\begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_m \end{bmatrix} \quad \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$$

$$f(x) + \sum_{i=1}^m u_i h_i(x) + \sum_{j=1}^n v_j l_j(x)$$

- (a) $\nabla f(x^*) + \sum_{i=1}^m u_i^* \nabla h_i(x^*) + \sum_{j=1}^n v_j^* \nabla l_j(x^*) = 0 \in \text{vector.}$
 \hookrightarrow [Stationarity]
- (b) $u_i^* h_i(x^*) = 0 \quad \forall i$ [C.S. condition]
- (c) $h_i(x^*) \leq 0 \quad \forall i ; \quad l_j(x^*) = 0 \quad \forall j$ [Feasibility]
- (d) $u_i^* \geq 0 \quad \forall i$ [Dual feasibility]
- Primal