

- Primal problem v.s. Dual problem

$$\min_{x \in D} f_0(x) \quad \max_{\lambda, \nu} g(\lambda, \nu)$$

$$\text{s.t.} \quad \begin{aligned} f_i(x) &\leq 0 \\ h_i(x) &= 0 \\ \lambda &\geq 0 \end{aligned}$$

$$\min_{x \in D} \max_{\lambda, \nu} L(x, \lambda, \nu) = \max_{\lambda, \nu} \min_{x \in D} L(x, \lambda, \nu)$$

↙ minimax theorem

- Minimax property:

ex:

		z	
	1	-1	3
w	2	2	-1
	3	1	-2
	↓	↓	↓
	1	-1	-2

⇒ ^① maximize then ^② minimize
seems to induce large value

Proof: for arbitrary \tilde{w}, \tilde{z}

$$\begin{aligned} \min_{w \in W} f(w, \tilde{z}) &\leq f(\tilde{w}, \tilde{z}) \leq \max_{z \in Z} f(\tilde{w}, z) \\ \Rightarrow \min_{w \in W} f(w, \tilde{z}) &\leq \max_{z \in Z} f(\tilde{w}, z) \\ \Rightarrow \max_{z \in Z} \left(\min_{w \in W} f(w, z) \right) &\leq \min_{w \in W} \left(\max_{z \in Z} f(w, z) \right) \end{aligned}$$

- Lagrange dual problem:

- Properties

- * This is a concave problem

- * The opt solution $d^* \Rightarrow p^* - d^* = \text{gap} \geq 0$

- Slater's Condition

Given that the primal problem is convex. If $f_i(x) < 0 \quad \forall i=1, \dots, m, \exists x \in \text{relint } D$ the strong duality holds, i.e. $\text{gap} = 0$.

- Define set

$$g = \{f_1(x), \dots, f_n(x), h_1(x), \dots, h_p(x), f_0(x) \mid x \in D\}$$

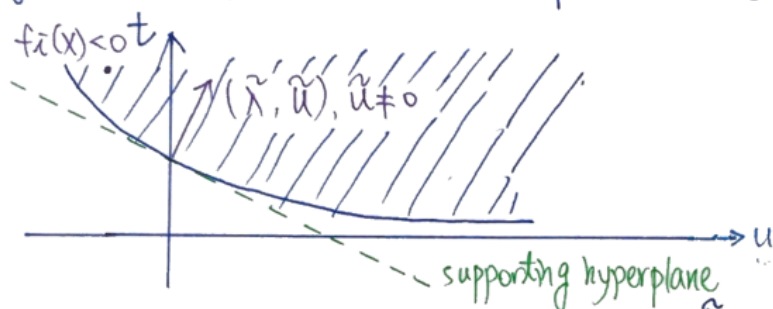
$$p^* = \inf \{ \lambda \mid (u, v, \lambda) \in g, u \leq 0, v = 0 \}$$

- Lagrangian

$$L = (\lambda, \nu, 1)^T \quad (u, v, t) = \sum_{i=1}^n \lambda_i u_i + \sum_{i=1}^p \nu_i v_i + t$$

- Dual Problem

$$g(\lambda, \nu) = \inf \{ (\lambda, \nu, 1)^T (u, v, t) \mid (u, v, t) \in g \}$$



$$\{(u, t) \mid f_0 \leq t, f_i(x) \leq u, \exists x \in D\}$$

Since $\tilde{\alpha} \neq 0$, we can have $(\lambda, \nu, 1) = (\frac{\tilde{\lambda}}{\tilde{\alpha}}, \frac{\tilde{\nu}}{\tilde{\alpha}}, 1)$

- Example: Conjugate Function

$$\begin{aligned} \min f_0(x) \\ \text{s.t. } \begin{cases} Ax = b \\ Cx = d \end{cases} \end{aligned}$$

- Dual Function

$$\begin{aligned} g(\lambda, \nu) &= \inf_{x \in D} [f_0(x) + \lambda^T (Ax - b) + \nu^T (Cx - d)] \\ &= \inf_{x \in D} [f_0(x) + (A^T \lambda + C^T \nu)^T x - b^T \lambda - d^T \nu] \\ &= -f_0^*(y) - b^T \lambda - d^T \nu, \text{ where } y = -(A^T \lambda + C^T \nu) \end{aligned}$$

- Example: Entropy Maximization

$$\begin{aligned} \min f_0(x) &= \sum_{i=1}^n x_i \log x_i \\ \text{s.t. } \begin{cases} Ax \leq b \\ 1^T x = 1 \end{cases} \end{aligned}$$

- Dual Function

$$\begin{aligned} g(\lambda, \nu) &= -f_0^*(y) - b^T \lambda - d^T \nu, \text{ where } y = -(A^T \lambda + \nu \cdot 1) \\ &= -b^T \lambda - \nu - \sum_{i=1}^n e^{-a_i^T \lambda - \nu - 1} \end{aligned}$$