

(1)

Special case when strong duality holds

Slater condn: $\exists \hat{x} \in \text{int}(D)$

$$h(\hat{x}) < 0 \quad \& \quad l(\hat{x}) = 0$$

then strong duality holds P=d

(Primal) barrier problem

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} - \tau \sum_{i=1}^n \log(x_i)$$

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

$$L(\mathbf{x}, \mathbf{y}) = \mathbf{c}^T \mathbf{x} - \tau \sum \log(x_i) + \mathbf{y}^T (\mathbf{b} - \mathbf{A}\mathbf{x})$$

Dual problem

$$\max_{\mathbf{y}} \min_{\mathbf{x}} (c - \bar{A}^T \mathbf{y})^T \mathbf{x} - \tau \sum \log(x_i) + b^T \mathbf{y}$$

$$\min_{\mathbf{x}} \underbrace{(c - \bar{A}^T \mathbf{y})^T \mathbf{x} - \tau \sum \log(x_i)}_{S := c - \bar{A}^T \mathbf{y}} \quad \begin{matrix} \uparrow \\ \text{decouples into} \end{matrix}$$

$$\min_{\mathbf{x}} \sum_x \underbrace{(S_i x_i - \tau \log(x_i))}_{\text{minimized at } x_i = \frac{\tau}{S_i}}$$

Dual Problem:

$$\max_{y, s} b^T y + n\tau - \tau \sum \log(\frac{\tau}{s_i})$$

$$A^T y + s = c$$

$$\Leftrightarrow \max_{y, s} b^T y + \tau \sum \log s_i + n\tau - n\tau \log \tau$$

Observe: If $(x^*(\tau), u^*(\tau), v^*(\tau))$ solve KKT condns for barrier problem

(slide 12)

Duality gap $f(x^*(\tau)) - \min_x L(x, u^*(\tau), v^*(\tau))$

dual function eval
at $(u^*(\tau), v^*(\tau))$

$$= f(x^*(\tau)) - L(x^*(\tau), u^*(\tau), v^*(\tau))$$

$$= f(x^*(\tau)) - \left[f(x^*(\tau)) + u^*(\tau)^T h(x^*(\tau)) + v^*(\tau)^T (-b - Ax^*(\tau)) \right]$$

$$= m\tau$$

Fenchel duality

$$\text{Primal: } \cdot f(x) + g(z)$$

$$Ax = z$$

$$L(x, z, v) = f(x) + g(z) + v^T(z - Ax)$$

Dual

$$\max_v \min_{x, z} \left[v^T z + g(z) - (A^T v)^T x + f(x) \right]$$

$$\text{Recall } f^*(s) := \max_x (s^T x - f(x))$$

$$\text{Dual } \max_v -f^*(A^T v) - g^*(-v)$$

Conic Programming

$$\text{Primal } \min_x c^T x \quad \Leftrightarrow \quad \min_x f(x) + g(Ax)$$

$$\begin{array}{c} \\ \text{subject to} \\ Ax = b \\ x \in K \end{array}$$

$$\text{for } f(x) = c^T x + I_K(x)$$

$$g(z) = I_{\{b\}}(z)$$

$$\text{Observe: } f(x) + g(Ax) = \begin{cases} c^T x & \text{if } Ax = b \\ +\infty & \text{o.w.} \end{cases}$$

$$\text{Recall: } \mathcal{I}_K^*(s) = \max_x s^T x - \mathcal{I}_K(x)$$

$$\text{If } K \text{ closed convex cone} = \max_{x \in K} s^T x$$

$$= \begin{cases} 0 & s \in -K^* \\ +\infty & s \notin -K^* \end{cases}$$

$$= \mathcal{I}_{-K^*}(s)$$

Strong duality may fail in SDP

$$\min 2x_{12}$$

$$\begin{bmatrix} 0 & x_{12} \\ x_{12} & x_{22} \end{bmatrix} \succeq 0$$

$$\min C \cdot X$$

$$\begin{array}{l} A \cdot X = b \\ X \succeq 0 \end{array}$$

$$C = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \quad A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, \quad b = 0$$

Dual

$$\max 0 \cdot y$$

$$\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} y + S = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$$

$$\text{Constraint} \Leftrightarrow \begin{bmatrix} -y & 1 \\ 1 & 0 \end{bmatrix} \succeq 0$$