EECS 127

Lecture 14, March 5 2020

Today: More duality.

Minimax Thro.

Slaters Conditions

LP duals.

"Shadow "prices

$$p^* = \min_{f_0(\vec{x}) \leq 0} f_0(\vec{x})$$

$$f_1(\vec{x}) \leq 0 \quad |\leq i \leq m$$

$$h_1(\vec{x}) = 0 \quad |\leq i \leq p$$

$$d^* = \max_{\vec{\lambda} \geq 0} g(\vec{\lambda}, \vec{z})$$

$$g(\vec{\lambda},\vec{z}) = \min_{\vec{z}}$$

$$= \min_{\overrightarrow{X}} L(\overrightarrow{X}, \overrightarrow{X}, \overrightarrow{D})$$

$$= \min_{\overrightarrow{X}} f_0(\overrightarrow{X}) + \sum_{i=1}^{m} \lambda_i f_i(\overrightarrow{X}) + \sum_{i=1}^{p} 2j_i h_i(\overrightarrow{X})$$

$$= \min_{\overrightarrow{X}} f_0(\overrightarrow{X}) + \sum_{i=1}^{m} \lambda_i f_i(\overrightarrow{X}) + \sum_{i=1}^{p} 2j_i h_i(\overrightarrow{X})$$

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= 6 = 9,2,+ 9222

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Thm: Mimax theorem.
       For any sets X, Y and any function F.
                  min max F(x,y) \ge \max \min F(x,y)
                                                yey xex
                  XEX YEY
          Fine xo EX, yo EY.
    Proof:
           Define: h(y_0) := \min_{x \in X} F(x, y_0)
                       g(x_0) := \max_{y \in Y} F(x_0, y)
h(y_0) = \min_{x \in X} F(x, y_0) \le F(x_0, y_0) \le \max_{y \in Y} F(x_0, y) = g(x_0)
                               specific
realization
    \Rightarrow \forall x_0, y_0 \Rightarrow h(y_0) \leq g(x_0)
                          max h(y) < min g(xo)
                                         x Ex
                          yey
                    \max_{x \in \mathcal{X}} \min_{x \in \mathcal{X}} F(x,y) \leq \min_{x \in \mathcal{X}} \max_{x \in \mathcal{X}} F(x,y)
                    yey xex
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$$p \neq = \min_{f(x) \leq 0} f(x)$$

Consider: max
$$L(x, \lambda) = \max_{\lambda \geq 0} \left(f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) \right)$$

$$= \begin{cases} \infty & \text{if } f_i(x) \geq 0 \end{cases}$$

$$= \begin{cases} f_0(x) & \text{if } f_i(x) \leq 0 \end{cases}$$

$$p^{+} = \min_{\lambda \geq 0} \max_{\lambda \geq 0} L(x, \lambda)$$

$$d^{+} = \max_{\lambda \neq 0} g(\lambda) = \max_{\lambda \neq 0} \min_{\lambda \neq 0} L(x_{i}\lambda)$$

. Strong duality.

Pt = dt (Only sometimes).

CONVEX

CONVEX

Slater's condition.

 $min fo(x) = p^{*}$ $fi(x) \leq 0$

hi(x)=0.

I a print 26 such that. 20 & relint (D) AND.

fi(x) <0 for all 1sism (strictly feasible)

then strong duality holds

Refined Slaters condition.

fi, fz. fk are affine conditions. Strong duality holds if 7 260 st.

 $f_i(\chi_0) \leq 0$ $i=1,\dots,k$

fi(x.) < 0 1= kel, ...m.

Dual of an LP Linear program

$$L(\vec{z}, \vec{\lambda}) = \vec{c} \vec{x} + \vec{\lambda} \vec{r} (A\vec{z} - \vec{b})$$

$$= (A\vec{\lambda} + \vec{c}) \vec{z} - \vec{\lambda} \vec{b}$$

$$g(\vec{\lambda}) = \min_{\vec{\lambda}} L(\vec{\lambda}, \vec{\lambda})$$

$$= \begin{cases} -\infty & AT_{\lambda+c\neq 0} \\ -\vec{b}T_{\lambda} & AT_{\lambda+c=0} \end{cases}$$

Dual: max.
$$g(\vec{x}) = \max_{\vec{\lambda} \geq 0} -\vec{b}^{T} \vec{\lambda}$$
 dual. $\vec{\lambda} \geq 0$ $\vec{s} + A^{T} \vec{\lambda} + \vec{c} = 0$.

Economic/Pricing interpretation of duality.

Winemaking business.

Maximize:
$$202, + 1592$$
 $49, + 292 \le 200$
 $49, + 392 \le 300$

Total merlot

 $49, + 392 \le 300$

What it you wanted to just sell off the grape?

1: for merlot grapes

12: for shiraz grapes.

$$\max_{q_1,q_2}$$
 $20q_1 + 15q_2 + \lambda_1(200 - 4q_1 - 2q_2) + \lambda_2(300 - q_1 - 3q_2)$

=
$$\max_{q_1q_2}$$
 $(200 + 4\lambda_1 - \lambda_2)q_1 + \max_{q_1q_2} (15 - 2\lambda_2 - 3\lambda_2) \cdot q_2$
+ $200 \cdot \lambda_1 + 300 \cdot \lambda_2$

If
$$20-4\lambda_1-\lambda_2=0$$
, $15-2\lambda_1-3\lambda_2=0$

Profit lower bound:
$$\min_{\lambda_1 \lambda_2}$$
 $200\lambda_1 + 300\lambda_2$ $3+2=0$ $15-2\lambda_1-3\lambda_2=0$

Dual

min forx). s-1. fi(x) =0 Change of variable. G: { (f,(x), fo(x)) ER23 $p^*=\min \left\{t \mid (u,t) \in G, u \leq 0\right\}.$ $L(u,t,\lambda) = t + \lambda u = b$

Line: y=mx+c

(u,t) EG u=0

min x^2 fo(u)

st. x+3 = 0. f(n)

 χ (χ_{+5} , χ^2) (u, t)

> 4=2+3 40 t= x2