

18/11/2021

Lecture - 15

Motivation for studying duality (in the context of linear programming);

- (1) Finding lower bounds on the optimal value.
- (2) Finding certificate for easy verification of a proposed/submitted optimal solⁿ.

($\boxed{x^2 + \dots + 4x^2 + x + 1 = 0}$) (x) (x^2) (x^3) x^4 (x^5)

Use your favourite method to find a solⁿ.

Is the submitted set of roots of the above polynomial accurate?

Checking feasibility of proposed optimal solⁿ is easy

$$\boxed{A\bar{x} \leq \bar{b}}$$

Checking optimality is not so straightforward.
(3) Potentially having a simpler LP to solve and inferring the optimal solⁿ to original LP from this simpler LP.

It's not the n in $\mathbb{R}^n$ that causes the simplex algorithm to be complicated, rather it is the number of constraints (in the case of LPs)

$$A\bar{x} \leq \bar{b} \quad A_{nm}, \bar{x} \geq \bar{1}$$

PRIMAL

$$\boxed{\vec{x} \in \mathbb{R}^n}$$

[constraint 1] $\langle \vec{a}_1, \vec{x} \rangle \geq b_1$

[constraint 2] $\langle \vec{a}_2, \vec{x} \rangle = b_2$

var 1 $x_1 \geq 0$

var 2 $\boxed{x_2 \geq 0}$

min $\langle \vec{c}, \vec{x} \rangle$

$\vec{x} \in \mathbb{R}^n$

$$\boxed{m, n}$$

DUAL

$$\boxed{y_i \geq 0}$$

$$y_i \geq 0$$

$$\boxed{(A^T \vec{y})_j = c_j}$$

$$\boxed{(A^T \vec{y})_j \leq c_j}$$

min. $\langle \vec{b}, \vec{y} \rangle$
 $\vec{y} \in \mathbb{R}^m$

If PRIMAL has a large number of constraints compared to the number of variables, then DUAL has a small number of constraints compared to the number of variables.

Duality theorem:

Theorem, (Strong duality) If a linear program has an optimal solⁿ (feasible and bounded), then so does its dual, that is, DUAL is also feasible and bounded, and their optimal costs are identical.

Theorem (Weak duality)

Let $\bar{x}$ be a feasible solⁿ to PRIMAL, $\bar{y}$ be a feasible solⁿ to DUAL, then

$$\underline{\underline{\langle \bar{c}, \bar{x} \rangle \geq \langle \bar{b}, \bar{y} \rangle.}}$$

Proof: PRIMAL

min $\langle \bar{c}, \bar{x} \rangle$
s.t. $\boxed{(A)^i \bar{x} = b_i} \quad (\langle \bar{c}_i, \bar{x} \rangle = b_i)$
 $1 \leq i \leq h$

$$(A)^i \bar{x} \geq b_i, \quad h+1 \leq i \leq m$$

$$\underbrace{x_j \geq 0}_{x_j \geq 0}, \quad 1 \leq j \leq l$$
$$x_j \geq 0, \quad l+1 \leq j \leq n.$$

DUAL :

$$\max \langle \vec{b}, \vec{y} \rangle$$

$$y_i \geq 0$$

$$, 1 \leq i \leq h$$

$$y_i \geq 0 ,$$

$$\underline{h+1} \leq i \leq \underline{m}$$

$$(A^T)^j \vec{y} \leq c_j , 1 \leq j \leq l$$

$$(A^T)^j \vec{y} = c_j , l+1 \leq j \leq n.$$

$$\langle \vec{c}, \vec{x} \rangle \geq \sum_{j=1}^l (\vec{A}^T \vec{y})^j \underbrace{(x_j)} + \sum_{j=l+1}^n (\vec{A}^T \vec{y})^j x_j$$

$$\left(\sum_{j=1}^n c_j x_j \right)$$

$$= \sum_{j=1}^n \left(\sum_{i=1}^m a_{ij} y_i \right) x_j + \sum_{j=l+1}^n$$

$$= \sum_{i=1}^m y_i \left[\sum_{j=1}^n a_{ij} x_j \right]$$

$$= \sum_{i=1}^m y_i \left[\sum_{j=1}^n a_{ij} x_j \right]$$

$$+ \sum_{j=l+1}^n \underbrace{(y_j)} \left[\sum_{i=1}^m a_{ij} x_i \right]$$

$$\geq \sum_{i=1}^m b_i y_i = \langle \vec{b}, \vec{y} \rangle \quad \text{Q.E.D.}$$

Strong duality theorem

If PRIMAL is ~~infeasible~~ has an optimal solution, then DUAL has an optimal solⁿ, and the optimal value coincides.

Pf.: PRIMAL $\min \langle \vec{c}, \vec{x} \rangle$
 s.t. $A\vec{x} = \vec{b}, \vec{x} \geq \vec{0}.$

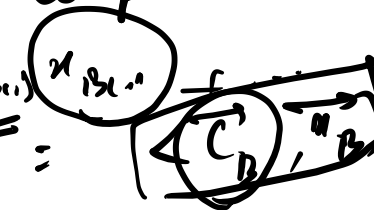
DUAL $\max \langle \vec{b}, \vec{y} \rangle$
 s.t. $\vec{y} \geq \vec{0}, A^T \vec{y} \leq \vec{c}$

Let $\vec{v}^k$ be an optimal bfs for PRIMAL.
 discovered by the Simplex Algorithm,
 and $B(1), \dots, B(m)$ be the basis corresponding
 to $\vec{v}^k$.

$$\begin{bmatrix} A \\ B(1) \dots B(m) \end{bmatrix}, \quad \textcircled{B_2} [A_{B(1)} \quad A_{B(2)} \quad \dots \quad A_{B(m)}]$$

$m \times m$

$\vec{c}_B \rightarrow$ vector in $\mathbb{R}^m$ whose i th component is $c_{B(i)}$. $(\vec{c}, \vec{x}) = \sum_{i=1}^m c_{B(i)} x_{B(i)}$



$$\boxed{\vec{c} - \vec{z}} \quad \boxed{\vec{z}^T \quad C_B^T \quad B^T \quad A}$$

$$B^T \begin{bmatrix} | & A & | \end{bmatrix}$$

At termination, 0th row of $\vec{z}^T$ is non-negative.

$$\vec{c} - \vec{z} \geq \vec{0} \Rightarrow \boxed{\vec{c}^T \geq \cancel{C_B^T} \cancel{B^T} A}$$

$$A^T (B^{-1})^T \vec{c}_B$$

Let,

$$\vec{u} := (B^{-1})^T \vec{c}_B$$

$$\boxed{\vec{c} - A^T \vec{u} \geq \vec{0}}$$

$\vec{u}$ is feasible from DUAL.

$\underbrace{\langle \vec{c}, \vec{v}^* \rangle}_{\substack{\text{optimal value} \\ \text{of PRIMAL}}} = \vec{c}_B^T \cdot (\text{column 0 of final table})$
 $\vec{c}_B^T \vec{b} \rightarrow \pi_0$
 $= \vec{c}_B^T B^{-1} \vec{b}$
 $= \vec{u}^T \vec{b}$
 $= \langle \vec{u}^*, \vec{b} \rangle$

From weak duality, $\langle \vec{c}_B, \vec{b} \rangle \leq \langle \vec{c}, \vec{v}^* \rangle$
 $\forall \vec{u}$ the DUAL feasible sol.
 Hence, $\vec{u}^*$ must be DUAL optimal.

Corollary: If we run simplex on LPS₂
at termination, $(B^{-1}) \begin{bmatrix} \bar{b} \\ \bar{c} \end{bmatrix}$ is dual optimal.

Corollary: Exactly one of these four cases happens.

(1) PRIMAL and DUAL are both infeasible.

(2) PRIMAL is unbounded, DUAL is infeasible.

(3) PRIMAL is infeasible, DUAL is unbounded.

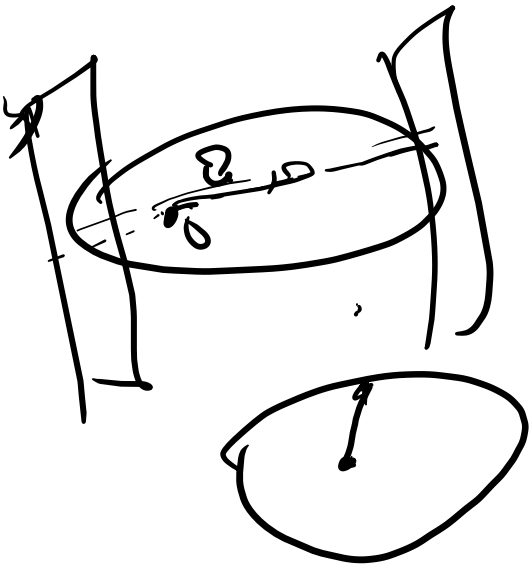
(4) PRIMAL and DUAL both have optimal
paths with equal optimal value.

If DUAL is easier to solve (by simplex)
 than PRIMAL, find optimal solⁿ of dual
 (optimal obj)
 and corresponding basis. This will give you an optimal
 solⁿ of the primal.

(geometric proof of strong duality)

$$h_K(\vec{u}) = \frac{1}{p_K(\vec{u})}$$

Main example - $\vec{0} \in K$.



If $\vec{0} \notin \mathbb{F}$, we have already shown the result

$$\boxed{A\vec{x} \leq \vec{b}} \quad \Leftarrow$$

$$\boxed{A^T \vec{y} = \vec{c}, \quad \vec{y} \geq \vec{0},}$$

$$\begin{aligned} \langle \vec{b}, \vec{y} \rangle &\leq \langle A\vec{x}, \vec{y} \rangle = \langle \vec{x}, \underbrace{A^T \vec{y}}_{\vec{c}} \rangle \\ &= \langle \vec{x}, \vec{c} \rangle \end{aligned}$$

Let PRIMAL be feasible and bounded.

$\vec{x}_0 \in \mathbb{F}$. Translate $\mathbb{F}$ to

$$\boxed{\mathbb{F} - \langle \vec{x}_0 \rangle}$$

$$b_i' = b_i \leq \langle \vec{x}, \vec{a}_i \rangle \quad \vec{b}' = \vec{b} - A\vec{x}$$

$$A\vec{x} \leq \vec{b} \quad (\Leftrightarrow) \quad A\vec{x} - A\vec{x} \leq \vec{b} - A\vec{x}$$

$$\Leftrightarrow A\vec{x}' \leq \vec{b}'$$

$$\vec{x}' \in \mathbb{R}^n - \langle \vec{x}_0 \rangle$$

$$\text{and } \vec{0} \in \mathbb{R}^n - \langle \vec{x}_0 \rangle$$

$$\begin{aligned} (\text{DUAL}) \quad \langle \vec{b}, \vec{y} \rangle &\leq \langle \vec{b}, \vec{x}' \rangle \quad \forall \vec{y} \in \mathbb{R}^m, \vec{y} \geq 0 \\ &= \langle \vec{b}, \vec{y} \rangle - \sum_{i=1}^m \langle \vec{a}_i, \vec{y}_i \rangle \\ &= \langle \vec{b}, \vec{y} \rangle - \langle \vec{A}^T \vec{y}, \vec{x}' \rangle \leq \langle \vec{b}, \vec{y} \rangle - \langle \vec{A}^T \vec{y}, \vec{x}_0 \rangle \\ &= \langle \vec{b}, \vec{y} \rangle - \langle \vec{A}^T \vec{y}, \vec{x}_0 \rangle \leq \langle \vec{b}, \vec{y} \rangle - \langle \vec{A}^T \vec{y}, \vec{x}_0 \rangle \end{aligned}$$

$$\langle \bar{b}, \bar{a} \rangle - \langle \bar{c}, \bar{a} \rangle \leq \langle \bar{b}, \bar{a} \rangle - \langle \bar{c}, \bar{a} \rangle$$

$$\Rightarrow \langle \bar{b}, \bar{a} \rangle \leq \langle \bar{c}, \bar{a} \rangle$$

Q.E.D.