

Some Theorems on LPP

$$\begin{array}{l} \text{maximize } z = cX \\ \text{subject to } AX = b, X \geq 0 \end{array} \quad (*)$$

$$A \text{ is } m \times n, \quad b \text{ is } m \times 1, \quad C \text{ is } 1 \times n, \quad X_B^T \in \mathbb{R}^m, \quad C_B \in \mathbb{R}^m$$

$$\Downarrow \quad \Downarrow \quad \Downarrow$$

$$B^T \in \mathbb{R}^m \quad C_B \in \mathbb{R}^m \quad (X_B) \text{ is } m \times 1$$

$B \rightarrow$ Basis matrix $X = [X_B, 0]$ $X_B = B^{-1}b$

$C_B \rightarrow$ cost coefficients of basis variables X_B

$a_j \in A$ (i.e., a_j are columns of A)

$b_j \in B$ (" b_j " " " B)

Theorem: (Replacement Basis Vector): Let LPP (*) have a BFS. If we drop one of the basis vectors and introduce a non-basis vector in basic set, the new solution obtained is also BFS.

Proof: Let $f(A) = m$. Suppose there exists BFS X_B so that $BX_B = b, X_B \geq 0$ — (1)

where B is basis set for columns vectors of A . Hence for any vector $a_j \in A$, we have

$$a_j = y_{1j}b_1 + y_{2j}b_2 + \dots + y_{mj}b_m$$

$$= [b_1 \ b_2 \ \dots \ b_m] \begin{bmatrix} y_{1j} \\ y_{2j} \\ \vdots \\ y_{mj} \end{bmatrix} = B y_j$$

(as a_j can be written as l.c. of elements of B (basis))

where $b_i \in B$ and y_{ij} are suitable scalars.

Let b_r be basis vector for which $y_{rj} \neq 0$. Then

$$b_r = \frac{a_j}{y_{rj}} - \sum_{\substack{i=1 \\ i \neq r}}^m \left(\frac{y_{ij}}{y_{rj}} \right) b_i \quad (2)$$

From (1) & (2) we have

$$b = Bx_B = \sum_{i=1}^m x_{Bi} b_i = \sum_{\substack{i=1 \\ i \neq r}}^m x_{Bi} b_i + x_{Br} \left[\frac{a_j}{y_{rj}} - \sum_{\substack{i=1 \\ i \neq r}}^m \left(\frac{y_{ij}}{y_{rj}} \right) b_i \right]$$

$$= \sum_{\substack{i=1 \\ i \neq r}}^m \left[x_{Bi} - x_{Br} \left(\frac{y_{ij}}{y_{rj}} \right) \right] b_i + \left[\frac{x_{Br}}{y_{rj}} \right] a_j$$

Thus, new B.S. \hat{x}_B has components

$$\hat{x}_{Bi} = \begin{cases} x_{Bi} - x_{Br} \left(\frac{y_{ij}}{y_{rj}} \right) & i \neq r \\ \frac{x_{Br}}{y_{rj}} & i = r \end{cases}$$

To prove: \hat{x}_B is Feasible. (i.e., $\hat{x}_B \geq 0$)

Case I: $x_{Br} = 0 \Rightarrow \hat{x}_B = x_B$ and hence feasible
(as x_B is BFS).

Case II: $x_{Br} \neq 0$. In this case we must have $y_{rj} > 0$ ^(*)
(why??)

Remaining y_{ij} ($i \neq r$) are either zero or $\left[x_{Bi} - x_{Br} \left(\frac{y_{ij}}{y_{rj}} \right) \right] > 0$

$$\Rightarrow \frac{x_{Bi}}{y_{ij}} > \frac{x_{Br}}{y_{rj}} \text{ for } y_{ij} > 0 \text{ \& } \frac{x_{Bi}}{y_{ij}} < \frac{x_{Br}}{y_{rj}} \text{ for } y_{ij} < 0 \text{ (} i \neq r \text{)}$$

Select index i^* ($y_{i^*r} \neq 0$) in such a way that

$$\frac{x_{Br}}{y_{rj}} = \min_i \left\{ \frac{x_{Bi}}{y_{ij}} : y_{ij} > 0, i \neq r \right\}$$

Then $\hat{x}_B \geq 0$, hence feasible.

Therefore \hat{x}_B is BFS //

Note: $B = (b_1, b_2, \dots, b_{r-1}, a_j, b_{r+1}, \dots, b_m)$

$$\therefore \hat{x}_B = B^{-1} b$$

(*) $\nexists y_{rj} < 0$ ~~then~~ $\hat{x}_{Br} = \frac{x_{Br}}{y_{rj}} < 0$ hence ^{not} feasible)

Net evaluation $a_j = \sum_{i=1}^m y_{ij} b_i$ (seen in above theorem)

Then the number $z_j = \sum_{i=1}^m C_{B_i} y_{ij}$

is called evaluation corresponding to a_j and the number $C_j - z_j$ is called net evaluation corresponding to a_j

Theorem (Improved BFS): Let X_B be a B.F.S to LPP (*)

Let \hat{X}_B be another BFS obtained by admitting a non-basis column vector a_j in the basis, for which the net evaluation $C_j - z_j$ is positive. Then \hat{X}_B is an improved BFS to the problem - i.e., $C_B \hat{X}_B > C_B X_B$

Proof: Consider LPP (*)

Given X_B is BFS.

Let $z_0 = C_B X_B$. Let a_j be the column vector introduced in basis such that $C_j - z_j > 0$. Let b_r be vector removed from basis (outgoing variable) from the basis and let \hat{X}_B be new BFS, then

$$\hat{X}_{Bi} = \begin{cases} x_{Bi} - x_{Br} \frac{y_{ij}}{y_{rj}} & i \neq r \\ \frac{x_{Br}}{y_{rj}} & i = r \end{cases} \quad \text{(Previous theorem (thm 2))}$$

Hence, new value of objective function is

$$\hat{z} = \sum_{i=1}^m \hat{C}_{B_i} \hat{X}_{Bi} = \sum_{i=1}^m \hat{C}_{B_i} \left(x_{Bi} - x_{Br} \frac{y_{ij}}{y_{rj}} \right) + \hat{C}_{B_r} \left(\frac{x_{Br}}{y_{rj}} \right)$$

$$= \sum_{i=1}^m C_{B_i} \left(x_{Bi} - x_{Br} \frac{y_{ij}}{y_{rj}} \right) + C_j \frac{x_{Br}}{y_{rj}}$$

$$= z_0 - \sum_{i=1}^m C_{B_i} x_{Br} \frac{y_{ij}}{y_{rj}} + C_j \frac{x_{Br}}{y_{rj}}$$

$$= z_0 - \frac{x_{Br}}{y_{rj}} \sum_{i=1}^m C_{B_i} y_{ij} + C_j \frac{x_{Br}}{y_{rj}}$$

$$\left. \begin{aligned} \hat{C}_{B_i} &= C_{B_i} & i \neq r \\ \hat{C}_{B_r} &= C_j & i = r \end{aligned} \right\} \begin{array}{l} \text{Cost coeff. associated} \\ \text{with entering column} \\ a_j \end{array}$$

$$= z_0 - z_j \frac{x_{Br}}{y_{rj}} + c_j \frac{x_{Br}}{y_{rj}} \quad (\text{defn of } z_j = \sum c_i b_i y_{ij})$$

$$= z_0 + \underbrace{(c_j - z_j)}_{> 0} \frac{x_{Br}}{y_{rj}} > z_0$$

Hence new BFS \hat{x}_0 gives improved value of objective fn z .

Remark (1) If a given B.S. happens to be non-degenerate one, then $\frac{x_{Br}}{y_{rj}} > 0$ and there is increase in value of z_0 .

(2) If given feasible solution happens to be degenerate one, then an increase in value of z_0 depends on $\frac{x_{Br}}{y_{rj}}$. But in any case $\hat{z} \geq z_0$. ($\because c_j - z_j \geq 0$).

Corollary: If $c_j - z_j = 0$ for at least one j for which $y_{rj} > 0$, $i = 1, 2, \dots, m$, then another BFS is obtained which gives an unchanged value of objective fn.

Proof: $\hat{z} = z_0 + (c_j - z_j) \frac{x_{Br}}{y_{rj}}$, $y_{rj} > 0$
 $= z_0$ ($\because c_j - z_j = 0$)

Theorem 4: (Unbounded Solution): Let there exist a BFS to given LPP(*). If for at least one j , for which $y_{ij} \leq 0$ ($i=1, 2, \dots, m$) and $g_j - z_j$ is positive, then there does not exist any optimum solution to this LPP.

Proof: Let X_B be BFS to LPP(*), so $BX_B = b$ & $X_B \geq 0$
and value of objective function $z_0 = CBX_B = \sum_{i=1}^m x_{Bi} c_{Bi}$

Now, $b = BX_B + \xi a_j - \xi a_j$ $a_j \in A, \xi$ is a scalar
 $= \sum_{i=1}^m x_{Bi} b_i + \xi a_j - \xi \sum_{i=1}^m y_{ij} b_i$ ($\because a_j$ can be written as L.C. of columns of basis matrix B)
 $= \sum_{i=1}^m (x_{Bi} - \xi y_{ij}) b_i + \xi a_j$

If $\xi > 0$, then $x_{Bi} - \xi y_{ij} \geq 0$ ($\because y_{ij} \leq 0$).
 $\Rightarrow \exists$ a F.S. whose $(m+1)$ components may be strictly positive. But in general, it may not be basic solution.
 For these $(m+1)$ variables, objective function is

$$z = \sum_{i=1}^m c_{Bi} (x_{Bi} - \xi y_{ij}) + \xi c_j = \sum_{i=1}^m c_{Bi} x_{Bi} + \xi (c_j - \sum_{i=1}^m c_{Bi} y_{ij})$$

$$= z_0 + \xi (g_j - z_j) \rightarrow \infty \text{ as } \xi \rightarrow \infty$$

Hence, unbounded solution to given LPP(*)

Theorem 5: (Conditions of Optimality): A sufficient condition for a BFS of an LPP(*) to be an optimum (maximum) is that $g_j - z_j \leq 0$ for all j for which column vector $a_j \in A$ is not in basis B .

Proof: Let $|A| = m$ and $B_{m \times m}$ be basis matrix. Let X_B be BFS to LPP(*), then $BX_B = b, X_B \geq 0$
 & $z_0 = CBX_B$.

Given: $g_j - z_j \leq 0 \forall a_j \in A$ j 's st. $a_j \notin B$.

Let $a_j = b_j$ for all such j for which $a_j \in B$. Then

$$y_j = B^T b_j \quad (\text{since } y_j = B^T a_j) \quad (\text{see Thm 2}) \\ = e_j, \text{ the unit vector}$$

$$\& g - z_j = c_B e_j - g = c_B j - g = 0 \quad (\because a_j \in B \therefore c_B j = g)$$

Thus $g - z_j \leq 0 \quad \forall j$ for which $a_j \in A$.

Now, let X be F.S. Then $\sum_{j=1}^n (g - z_j) x_j \leq 0 \quad \because x_j \geq 0$

$$\Rightarrow \sum_{j=1}^n g_j x_j \geq \sum_{j=1}^n g x_j$$

$$\Rightarrow \sum_{j=1}^n c_B y_j x_j \geq \sum_{j=1}^n g x_j \quad (\because z_j = c_B y_j)$$

$$\text{or, } \sum_{i=1}^m c_{B_i} \sum_{j=1}^n y_{ij} x_j \geq \sum_{j=1}^n g x_j \quad (\because c_B y_j = \sum_{i=1}^m c_{B_i} y_{ij})$$

(U) for all j for which $a_j \notin B$.

Now, as $x_B = B^T (AX) = (\because AX = b)$

$$= (B^T A) X = YX$$

$$\text{or, } x_{B_i} = \sum_{j=1}^n y_{ij} x_j \quad i=1, 2, \dots, m \quad (2)$$

\therefore From (U) & (2)

$$\sum_{i=1}^m c_{B_i} x_{B_i} \geq \sum_{j=1}^n g x_j \quad \text{or, } c_B X_B \geq c X \\ \text{or, } z_0 \geq z^*$$

where z^* is value of objective ~~fn~~ for feasible soln.

Hence z_0 is optimum ~~value~~ for \forall BFS for which $g - z_j \leq 0$ $\forall j$ such that $a_j \notin B$.

Corollary: A n.a.s.c. for a BFS to LPP(*) to be an optimum (maximum) is that $g - z_j \leq 0$ for all j for which $a_j \notin B$.

P.S. For necessary: Thm 3 & 4. For sufficient: Thm 5

Theorem 6: Any convex combination of k different optimum solutions to a LPP is again an optimum solution to the problem.

Proof 1. Let x_1, x_2, \dots, x_k be k -different optimum solutions to LPP(*). Let z_0 be optimum value of z .

$$\text{Obviously } z_0 = Cx_1 = Cx_2 = \dots = Cx_k$$

$$\& b = Ax_1 = Ax_2 = \dots = Ax_k$$

$$\text{where } x_i \geq 0 \quad 1 \leq i \leq k.$$

Let x be any combination of x_1, x_2, \dots, x_k i.e.,
 $x = \sum_{i=1}^k d_i x_i$ d_i 's are positive scalars s.t. $\sum_{i=1}^k d_i = 1$

$$\begin{aligned} \therefore Ax &= A\left(\sum_{i=1}^k d_i x_i\right) = \sum_{i=1}^k d_i (Ax_i) = \sum_{i=1}^k d_i b \\ &= \sum_{i=1}^k d_i b = b \quad \left(\because \sum_{i=1}^k d_i = 1\right). \end{aligned}$$

Since $x_i \geq 0$ & $d_i \geq 0 \quad \forall i=1, 2, \dots, k$, therefore every component of x will be non-negative.

Thus, x is a F.S. to LPP(*).

$$\text{Again } Cx = C\left(\sum_{i=1}^k d_i x_i\right) = \sum_{i=1}^k d_i Cx_i = \sum_{i=1}^k d_i z_0 = z_0.$$

Hence, convex combination of k different optimum solutions to a LPP is also optimum solution to LPP.