

Linear Programming LP

optimize linear objective function
under linear ^{inequality} constraints

STANDARD FORM

$$\underline{x} \geq \underline{0}$$

$$A \underline{x} \leq \underline{b}$$

$$\max x \leftarrow \underline{c}^T \underline{x}$$

PRIMAL

$$A \in \mathbb{R}^{k \times n}$$

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n$$

$$b = \begin{bmatrix} b_1 \\ \vdots \\ b_k \end{bmatrix} \in \mathbb{R}^k$$

$$c = \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \in \mathbb{R}^n$$

LP STANDARD FORM

$$\begin{array}{l} \underline{x} \geq \underline{0} \\ A \underline{x} \leq \underline{b} \\ \hline \max \leftarrow \underline{c}^T \underline{x} \end{array} \quad \left. \vphantom{\begin{array}{l} \underline{x} \geq \underline{0} \\ A \underline{x} \leq \underline{b} \\ \hline \max \leftarrow \underline{c}^T \underline{x} \end{array}} \right\} \text{PRIMAL}$$

$$\begin{aligned} A &\in \mathbb{R}^{k \times n} \\ x &= \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^n \\ b &= \begin{bmatrix} b_1 \\ \vdots \\ b_k \end{bmatrix} \in \mathbb{R}^k \\ c &= \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \in \mathbb{R}^n \\ y &\in \mathbb{R}^k \end{aligned}$$

$$\begin{array}{l} \underline{y} \geq \underline{0} \\ A^T \underline{y} \geq \underline{c} \\ \hline \min \leftarrow \underline{b}^T \underline{y} \end{array} \quad \left. \vphantom{\begin{array}{l} \underline{y} \geq \underline{0} \\ A^T \underline{y} \geq \underline{c} \\ \hline \min \leftarrow \underline{b}^T \underline{y} \end{array}} \right\} \text{DUAL}$$

Weak duality

$$\max_{\text{PR}} \leq \min_{\text{DL}}$$

DUALITY THM

$$\max = \min$$

$$\Leftarrow \left\{ \begin{array}{l} \text{if each is feasible} \\ \rightarrow \exists \max, \min \end{array} \right.$$



Weak duality means

for $\forall$ sol x of primal
 and $\forall$ sol y of dual

$$c^{\text{tr}} x \leq b^{\text{tr}} y$$

$$Ax \leq b \quad x \geq 0$$

$$A^{\text{tr}} y \geq c$$

$$y^{\text{tr}} A \geq c^{\text{tr}}$$

$$(AB)^{\text{tr}} = B^{\text{tr}} A^{\text{tr}}$$

Pf

$$\underline{c^{\text{tr}} x} \leq (y^{\text{tr}} A) x = y^{\text{tr}} A x = y^{\text{tr}} (Ax) \leq y^{\text{tr}} b = (y^{\text{tr}} b)^{\text{tr}} = \underline{\underline{b^{\text{tr}} y}}$$

$\begin{matrix} k & k \times n & n & k & k \end{matrix}$

ν^*
 τ^*

fractional matching makes
" covering "

$$\tau^* = \min \left\{ \sum_{i=1}^n x_i \mid (\forall j) (\sum_{i \in E_j} x_i \geq 1), (\forall i) (x_i \geq 0) \right\}$$

$\underline{x} \geq \underline{0} \quad x \in \mathbb{R}^n$

$$\underline{M} \underline{x} \geq \underline{1} \quad \underline{m} \in \mathbb{R}^m$$

$$\min \underline{1}_n^T \underline{x}$$

M: incidence matrix
m x n
#edges } # vxs

$$\nu^* = \max \left\{ \sum_{j=1}^m y_j \mid (\forall i) (\sum_{j \in E_i} y_j \leq 1), (\forall j) (y_j \geq 0) \right\}$$

$$\underline{M}^T \underline{y} \leq \underline{1} \quad \underline{y} \geq \underline{0}$$
$$\max \underline{1}_m^T \underline{y}$$

DUAL

Str. duality $\nu \leq \nu^* = \tau^* \leq \tau$

$$\tau^* \leq \tau \leq \tau^* \cdot \underbrace{\quad}_{\text{?}}$$

trivial

↑
INTEGRALITY GAP

(5)

LÁSZLÓ LOVÁSZ

$$\tau \leq \tau^* (1 + \ln \deg_{\max})$$

Greedy cover algorithm

{ pick vertex of max degree
remove, along with all incident edges
repeat



Size of Greedy cover: t

$$t \geq \tau$$

$$t \leq \tau^* (1 + \ln \deg_{\max})$$

ν_k : max k -matching : $\forall$ vertex in at most selected edges
multiset

$\tilde{\nu}_k$: max Simple k -matching
set (not multi)

Do !

$$\tilde{\nu}_k \leq \nu_k$$

Do !

$$\nu \leq \frac{\nu_k}{k}$$

$$k \cdot \nu \leq \nu_k$$

Do !

$$\frac{\nu_k}{k} \leq \nu^*$$

THEOREM 2.

$$t \leq \frac{\tilde{\gamma}_1}{1 \cdot 2} + \frac{\tilde{\gamma}_2}{2 \cdot 3} + \dots + \frac{\tilde{\gamma}_{d-1}}{(d-1)d} + \frac{\tilde{\gamma}_d}{d}$$

$d = \deg_{\max}$ [7]

• $\tilde{\gamma}_d = m = |\Sigma|$

COROLLARY previous thm

Pf of THM 2. t_k : #times $\deg_{\max} = k$

$$t = t_d + t_{d-1} + \dots + t_1$$

after $t_d + \dots + t_{i+1}$ steps: $\mathcal{H}_i$ residual hyper
 $\deg_{\max}(\mathcal{H}_i) \leq i$ $|\Sigma_i| = \tilde{\gamma}_i(\mathcal{H}_i) \leq \tilde{\gamma}_i$

LHS $\leq$ RHS

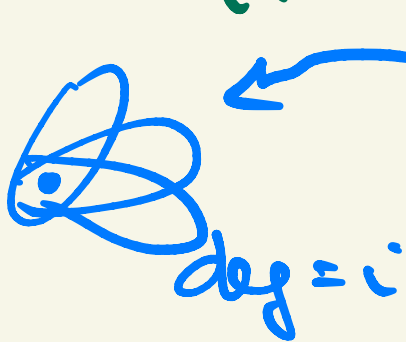
Pf of THM 2. t_k : #times $\deg_{\max} = k$ (8)

$$t = t_d + t_{d-1} + \dots + t_1$$

after $t_d + \dots + t_{i+1}$ steps: $\mathcal{H}_i$ residual hypergraph

$$\deg_{\max}(\mathcal{H}_i) \leq i \quad |\mathcal{E}_i| = \tilde{\gamma}_i(\mathcal{H}_i) \leq \tilde{\gamma}_i$$

$$|\mathcal{E}_i| = i \cdot t_i + (i-1) \cdot t_{i-1} + \dots + t_1 \leq \tilde{\gamma}_i$$



NTS $t \leq \frac{\tilde{y}_1}{1 \cdot 2} + \frac{\tilde{y}_2}{2 \cdot 3} + \dots + \frac{\tilde{y}_{d-1}}{(d-1) \cdot d} + \frac{\tilde{y}_d}{d} \quad \cdot \quad \boxed{9}$

WE KNOW $\left\{ \begin{aligned} i \cdot t_i + (i-1) \cdot t_{i-1} + \dots + t_1 &\leq \tilde{y}_i && \times \frac{1}{i(i+1)} \\ &&& i=1 \dots d-1 \end{aligned} \right.$

NTS: in this lin comb.

$(\forall i) (\text{coeff}(t_i) = 1)$

$\times \frac{1}{d}$
 $i=d$

$$\text{coeff}(t_i) = i \left(\underbrace{\frac{1}{i(i+1)} + \frac{1}{(i+1)(i+2)} + \dots + \frac{1}{(d-1)d}}_{\frac{1}{i} - \frac{1}{i+1} + \frac{1}{i+1} - \frac{1}{i+2} + \dots + \frac{1}{d-1} - \frac{1}{d} + \frac{1}{d}} + \frac{1}{d} \right)$$

$= i \cdot \frac{1}{i} = 1$ telescoping sum 

THM 2

$$t \leq \frac{\tilde{v}_1}{1 \cdot 2} + \frac{\tilde{v}_2}{2 \cdot 3} + \dots + \frac{\tilde{v}_{d-1}}{(d-1) \cdot d} + \frac{\tilde{v}_d}{d}$$

(10)

THM 1

$$t \leq \tau^* \cdot (1 + \ln d)$$

def max

actually

$$t \leq \tau^* \cdot H_d$$

$$H_d = 1 + \frac{1}{2} + \dots + \frac{1}{d} < 1 + \ln d$$

harmonic
number

$$\int \frac{dx}{x}$$

$$\tilde{v}_k \leq v_k$$

$$\frac{v_k}{k} \leq v^*$$

THM 2 $\Rightarrow$

$$t \leq v^* \left(\frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{d} + 1 \right)$$

H_d



$m(r)$: min # edges of a non-2-colorable
 r -unif hypergraph

$$m(r) > 2^{r-1} \quad \text{was tw}$$

THM (ERDŐS) $m(r) = O(r^2 \cdot 2^r)$
if probabilistic method

SEMI-CONSTRUCTIVE PF:
follows from greedy cover