

March 12, 2020

Last time: $NCUT(S) = \frac{cut(S)}{v(S)} + \frac{cut(\bar{S})}{v(\bar{S})}$

$$cut(S) = \sum_{i \in S, j \in \bar{S}} A_{ij} \quad v(S) = \sum_{i \in S} d_i$$

$$\phi(S) = \frac{cut(S)}{\min(v(S), v(\bar{S}))}$$

$$\frac{cut(S)}{v(S)} + \frac{cut(\bar{S})}{v(\bar{S})} \leq \frac{cut(S)}{\min(v(S), v(\bar{S}))} + \frac{cut(\bar{S})}{\min(v(S), v(\bar{S}))} = 2\phi(S)$$

$\rightarrow \geq \frac{cut(S)}{\min(v(S), v(\bar{S}))} = \phi(S)$

$$\lambda_2 \leq \min_S NCUT(S)$$

$$\lambda_2/2 \leq \min_S \phi(S) \leq \sqrt{2\lambda_2}$$

Charger

$$\min_x x^T L x \quad \text{s.t.} \quad \mathbf{1}^T D x = 0 \quad x^T D x = 1$$

$$z = D^{1/2} x \quad \min z^T N z \quad N = D^{-1/2} L D^{-1/2}$$

$$\text{s.t.} \quad \mathbf{1}^T D^{1/2} z = 0 \quad z^T z = 1$$

$$N z_* = \lambda_2 z_* \Rightarrow z_*^T N z_* = \lambda_2$$

$$\lambda_2 = \min_{\mathbf{1}^T D^{1/2} z = 0} \frac{z^T N z}{z^T z} \quad \text{at } z_* \quad \geq \min_S \text{NCUT}(S)$$

$$= \min_{\mathbf{1}^T D x = 0} \frac{x^T L x}{x^T D x} \quad (\text{at } x_* = D^{-1/2} z_*)$$

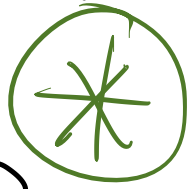
Let $\underline{1}^T D y = 0$ $S_t = \{i \mid y_i < t\}$

Claim: $\min_t \phi(S_t) \leq \sqrt{2 \frac{y^T L y}{y^T D y}} \stackrel{\Delta}{=} \sqrt{2R}$

$\min_y \frac{y^T L y}{y^T D y} \Rightarrow \lambda_2(N)$ $y_* = D^{-1/2} z_*$ $N z_* = \lambda_2 z_*$

WLOG: $y_1 \leq \dots \leq y_n$

$c = \min_k \sum_{i \in S_k} d_i \geq v(N)/2$ $z \stackrel{\Delta}{=} y - y_c \underline{1}$

$\frac{z^T L z}{z^T D z} = \frac{y^T L y}{y^T D y} \approx \frac{y^T L y}{y^T D y} = R$ 

$(y + s \underline{1})^T D (y + s \underline{1}) \Rightarrow 2 \underline{1}^T D (y + s \underline{1}) = 0$

$$z_1^2 + z_n^2 = 1 \quad (\text{re-scale})$$

Define prob. dist. on t so that

$$\mathbb{E}(\text{cut}(S_t)) \leq \sqrt{2R} \mathbb{E}(\min(v(S_t), v(\bar{S}_t)))$$

$$\Rightarrow \exists t \quad \text{cut}(S_t) \leq \sqrt{2R} \min(v(S_t), v(\bar{S}_t))$$

$$\Rightarrow \phi(S_t) \leq \sqrt{2R}$$

$$\text{Prob}(t \in [a, b] \mid z_1, z_n)$$

$$= \int_a^b 2|t| dt = \text{sgn}(b)b^2 - \text{sgn}(a)a^2$$

$$\text{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases}$$

Sub-claim: $\mathbb{E}(\min(v(S_t), v(\bar{S}_t))) \geq z^T D z$ *

$$\mathbb{E}_t(v(S_t)) = \sum_i \Pr(i \in S_t) d_i = \sum_i \Pr(z_i \leq t) d_i$$

$$t < 0 \Rightarrow v(S_t) = \min(v(S_t), v(\bar{S}_t))$$

$$t \geq 0 \Rightarrow v(\bar{S}_t) = \min(v(S_t), v(\bar{S}_t))$$

$i < c \Rightarrow i$ is in smaller-set if $t < 0$

$j \geq c \Rightarrow j$ is in smaller-set if $t \geq 0$

$$\begin{aligned} \mathbb{E}(\min(v(S_t), v(\bar{S}_t))) &= \sum_{i < c} \Pr(z_i < t < 0) d_i + \sum_{j \geq c} \Pr(0 \leq t \leq z_j) d_j \\ &= z^T D z \end{aligned}$$

Sub-claim: $\Pr(i \in S_+, j \in \bar{S}_+) \leq |z_i - z_j| (|z_i| + |z_j|)$

$= \Pr(z_i \leq t < z_j)$

$= \operatorname{sgn}(z_j) z_j^2 - \operatorname{sgn}(z_i) z_i^2$

$= \begin{cases} |z_i^2 - z_j^2| & \operatorname{sgn}(z_j) = \operatorname{sgn}(z_i) \\ z_j^2 + z_i^2 & \operatorname{sgn}(z_j) > \operatorname{sgn}(z_i) \end{cases}$

Exercise:

$$\mathbb{E}(\text{cut}(S_+)) \leq^* \sum_{(i,j) \in E} |z_i - z_j| (|z_i| + |z_j|)$$

$C \sim$
 $\sqrt{u_i u_j} \leq \dots$
 $\sqrt{v_i v_j}$

$$\leq \sqrt{\sum_{(i,j) \in E} (z_i - z_j)^2} \sqrt{\sum_{(i,j) \in E} (|z_i| + |z_j|)^2}$$

$$\leq^* \sqrt{R z^T D z} \sqrt{\sum_{(i,j) \in E} 2(z_i^2 + z_j^2)}$$

$$= \sqrt{R} \sqrt{z^T D z} \sqrt{2} \sqrt{z^T D z}$$

$$= \sqrt{2R} z^T D z$$

$$^* = \sqrt{2R} \mathbb{E}(\min(v(S_+), v(\bar{S}_+)))$$

Alg: $G = (V, E)$

$$N = D^{-1/2} L D^{-1/2}$$

$$N v_2 = \lambda_2 v_2$$

$$x = D^{-1/2} v_2$$

$\sigma = \text{sort } x \text{ by value}$

for $t = 1, \dots, n$

$$\phi_t = \phi(\overbrace{\{\sigma_1, \dots, \sigma_t\}}^{S_t})$$

return S_t that minimizes cost

guarantee: $\phi(S_t) \leq \underbrace{\sqrt{2\lambda_2}}_{\text{upper bound}} \leq \underbrace{\sqrt{2 \cdot 2\phi_*}}_{\text{lower bound}} \leq 2\sqrt{\phi_*}$

$\lambda_2/2 \leq \phi_* \leq \sqrt{2\lambda_2}$

k-way NCUT

$$\text{NCUT}(S_1, \dots, S_k) = \sum_{r=1}^k \frac{\text{cut}(S_r)}{v(S_r)}$$

test matrix



$$X_{ir} = \begin{cases} 1/\sqrt{v(S_r)} & i \in S_r \\ 0 & \text{otherwise} \end{cases}$$

Claim: $\text{tr}(X^T L X) = \text{NCUT}$ $\text{tr}(M) = \sum_i M_{ii}$

$$= \sum_{r=1}^k X_r^T L X_r \rightarrow X_r^T L X_r = \sum_{(i,j) \in E} (x_{ir} - x_{jr})^2$$

$$= \sum_{i \in S_r, j \in S_r} \left(\frac{1}{\sqrt{v(S_r)}} - 0 \right)^2$$

Claim: $X^T D X = I$

Proof: $(r, s) \quad e_r^T X^T D X e_s = x_r^T D x_s = \sum_i d_i x_{ir} x_{is}$
 $= \sum_i d_i x_{ir}^2$
 $= \sum_{i \in S_r} d_i \frac{1}{v(S_r)} = 1$

$$\min_{S_1, \dots, S_k} \text{tr}(X^T L X) = \text{NCUT}$$

S_1, \dots, S_k

$$\text{s.t. } X^T D X = I$$

$$Z = D^{-1/2} X$$

~~$$X_{ip} = \begin{cases} 1/\sqrt{|S_p|} & i \in S_p \\ 0 & \text{otherwise} \end{cases}$$~~

$$\min_Z \text{tr}(Z^T N Z) \quad \text{s.t. } Z^T Z = I$$

$$Z = \underbrace{V(:, 1:k)}_{V_k}$$

(Courant-Fischer)

$$N V_k = \Lambda_k V_k$$

$$X_* = D^{-1/2} V_k$$

\uparrow $\begin{bmatrix} | \\ | \\ | \\ | \end{bmatrix}$ (k smallest evals)