

Iterated Randomized Rounding for STEINER TREE

$C_i :=$ component selected in iteration i
 $F_i := \bigcup_{j=1}^{i-1} E_{c_j}$
 $G_i :=$ dir full comp. in G/F_i
 $x_i :=$ opt sol. to LP in iteration i

Lemma 13.1 $\mathbb{E}[d(T')] \leq 2 \exp(-\ell/\Sigma) \cdot \text{OPT}$

Proof: $\mathbb{E}[\text{mst}(F_i \cup C_i)] = \mathbb{E}[\text{mst}(F_i) - \text{drop}_{F_i}(C_i)]$

$$= \mathbb{E}\left[\text{mst}(F_i) - \underbrace{\frac{1}{\Sigma} \sum_{C \in C_i} x_{i,C} \text{drop}_{F_i}(C)}_{\geq \text{mst}(F_i)}\right]$$

$$\leq \left(1 - \frac{1}{\Sigma}\right) \mathbb{E}[\text{mst}(F_i)]$$

$$\Rightarrow \mathbb{E}[T'] \leq \left(1 - \frac{1}{\Sigma}\right)^\ell \cdot \underbrace{\text{mst}(\emptyset)}_{\leq 2\text{OPT}} \leq 2 \exp(-\ell/\Sigma) \cdot \text{OPT} \quad \square$$

Lemma 13.2 $\mathbb{E}[d(E_{c_i})] \leq \frac{1}{\Sigma} \cdot \text{OPT}$

Proof: $\mathbb{E}[d(E_{c_i})] = \mathbb{E}\left[\frac{1}{\Sigma} \sum_{C \in C_i} x_{i,C} d_{C_i}\right] \leq \frac{1}{\Sigma} \cdot \text{OPT} \quad \square$

↑
Contracting edges does not increase cost of LP.

Theorem 12.3 Iterated Rounding is a $(1 + \ln(2) + \epsilon)$ -approximation for STEINER TREE. because we do not solve LP exactly

Proof: $\mathbb{E}[ALG] = \mathbb{E}\left[d(T') + \sum_{i=1}^{\ell} d(E_{c_i})\right] \leq 2 \exp(-\ell/\Sigma) \cdot \text{OPT} + \frac{\ell}{\Sigma} \cdot \text{OPT}$

$$= (1 + \ln 2) \text{OPT} \leq 1.694 \text{OPT} \quad \square$$

Choose $\Sigma := \frac{\lceil \ln 2 \cdot M \rceil}{\ln 2}$ and $\ell := \ln 2 \cdot \Sigma$.

(M upper bound on $\sum_{C \in C_i} x_C$, polynomial when restricting to components of constant size)

Proof of Drop Lemma (Idea): Let T be a MST in G/F . Use full comp.

to construct helper graph $H = (R, \bar{E})$. For $e = \{v, w\} \in \bar{E}$, let $\bar{d}(e) = \max_{e \in T[v, w]} d(e)$ for $\bar{e} = \{v, w\} \in \bar{E}$ represent the drop from merging v and w . Show that x induces a solution to bidirected cut relaxation.

$$\Rightarrow \sum_{C \in C_i} \text{drop}_C x_C \geq \text{cost of MST in } H \text{ w.r.t } \bar{E} \geq d(T).$$

Semi-Definite Programming for MAX CUT

Lemma 13.4: Let $x \in \{-1, 1\}^n$ and $S := \{i \in V : x_i = 1\}$.

$$\text{Then } \sum_{e \in \delta(S)} w(e) = \frac{1}{2} \cdot \sum_{\{i,j\} \in E} w_{ij} (1 - x_i x_j).$$

Proof: $\{i,j\} \in \delta(S) \iff i \in S, j \notin S \text{ or } i \notin S, j \in S \iff x_i \neq x_j$

$$\text{Also: } 1 - x_i x_j = \begin{cases} 2 & \text{if } x_i \neq x_j \\ 0 & \text{if } x_i = x_j \end{cases} \text{ for } x_i, x_j \in \{-1, 1\}.$$

$$\text{Thus: } \sum_{\{i,j\}} (1 - x_i x_j) = 2 \sum_{\{i,j\} \in \delta(S)} w_{ij} \quad \square$$

Lemma 13.5 $\text{OPT} \in \mathbb{Z}^*$

Proof: Let $x^* \in \{-1, +1\}^n$ be an optimal solution to the QP.

Define $v_i = \begin{pmatrix} x_i^* \\ 0 \\ \vdots \\ 0 \end{pmatrix}$. Then $v_i^T v_i = 1 \quad \forall i \in [n]$ and

$$\mathbb{Z}^* \geq \frac{1}{2} \sum_{\{i,j\} \in E} w_{ij} (1 - v_i^T v_j) = \frac{1}{2} \sum_{\{i,j\} \in E} (1 - x_i^* x_j^*) \geq \text{OPT}. \quad \square$$

\uparrow
Lemma 13.4

Proof of Theorem 13.6:

Consider $U := \text{span}(\{v_i^*, v_j^*\})$. Let r' be the projection of r on U .

Then $r'' := \frac{r'}{\|r'\|}$ is uniformly distributed on unit circle in U .

$$\mathbb{E}[\text{ALG}] = \sum_{\{i,j\} \in E} w_{ij} \Pr[\{i,j\} \in \delta(S)] = \sum_{\{i,j\} \in E} \frac{\arccos(v_i^{*T} v_j^*)}{\pi}$$

$$\geq 0.878 \sum_{\{i,j\} \in E} w_{ij} \frac{1}{2} (1 - v_i^{*T} v_j^*) = 0.878 \cdot \mathbb{Z}^*. \quad \square$$

Solving the SDP: Replace $v_i^T v_j$ by a_{ij} .

Then $(a_{ij})_{i,j \in [n]}$ corresponds to sol. v_i, v_j if and only if the

matrix $A := \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{pmatrix}$ is positive semidefinite.

Separation Oracle: Find smallest eigenvalue of A .

(see book for details)