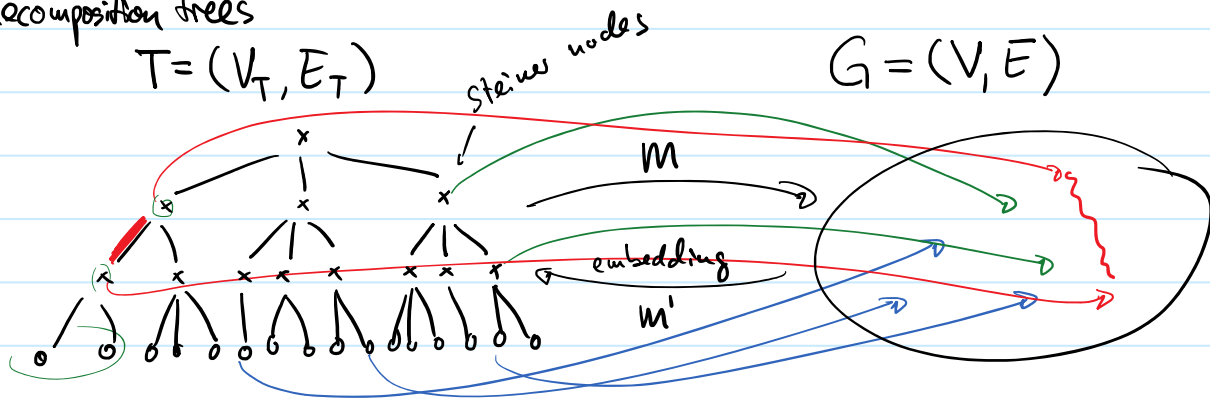


Cut-Based Tree Decompositions

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last week: distance-based tree decompositions [Räcke 2008]

decomposition trees



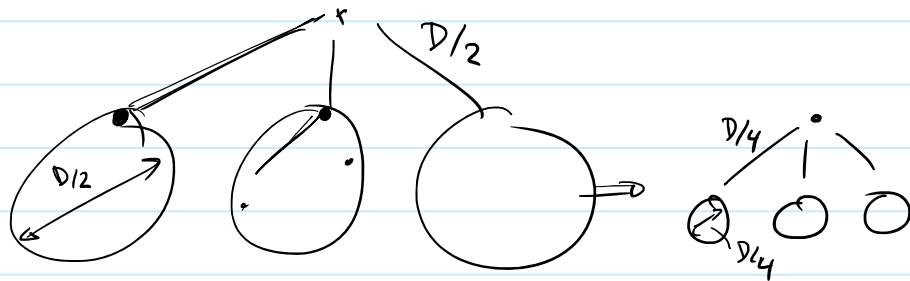
$M_V : V_T \rightarrow V$ (one-to-one mapping between the leaves of T and V)

$M_E : E_T \rightarrow 2^E$ for $\{u_t, v_t\} \in E_T$ $M_E(\{u_t, v_t\}) \rightarrow$ shortest path between $M_V(u_t)$ and $M_V(v_t)$

$M'_V : V \rightarrow V_T$ (maps to leaves in one-to-one manner)

$M'_E : E \rightarrow 2^{E_T}$ for $\{u, v\} \in E$ $M'_E(\{u, v\}) \rightarrow$ unique path between $M'_V(u)$ & $M'_V(v)$

from now on: $d_T(u_t, v_t)$: length of corresponding path in G



Mapping Multicommodity Flows

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Given $G = (V, E, c)$

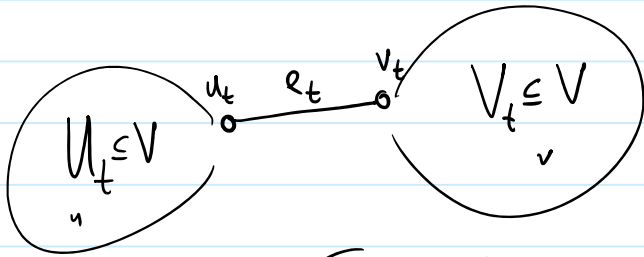
multicommod. flow instance given by requirements $r(u, v)$ for $\{u, v\} \in \binom{V}{2}$

When solving a multicommod. flow problem on T :

(requirements are only between leaves)

each comm. $\{u, v\}$ is routed on the unique path conn. the 2 leaves

Load of an edge $e \in E$ when mapping the flow from T to G



$$r(e_t) = \sum_{u \in U_t, v \in V_t} r(u, v)$$

ultimate goal:

for multicommod. flow inst.,
find tree T

s.t. $\max_e \frac{\text{load}_T(e)}{c(e)}$ is minimized

$$\text{load}_T(e) := \sum_{\substack{e_t \in E_T \\ \text{path repr. } e_t \text{ in } G}} r(e_t)$$

The Minimum Communication Cost Tree (MCCT) Problem

undir. $G = (V, E, \ell)$ $\ell(e)$: length of e $\ell(e) \geq 0$ $d_G(u, v)$: length of shortest path

$\forall \{u, v\} \in \binom{V}{2}$: $r(u, v)$: amount of traffic that has to go between u & v
↑
requirement

Goal: Find decomp. tree T that minimizes

$$\text{cost}(T) = \sum_{\{u, v\} \in \binom{V}{2}} d_T(u, v) \cdot r(u, v) \geq \sum_{\{u, v\} \in \binom{V}{2}} d_G(u, v) \cdot r(u, v)$$

Lemma: MCCT can be $O(\log n)$ -approximated.

Proof: use random tree constr. from last lecture:

$$\mathbb{E}[\text{cost}(T)] = \mathbb{E}\left[\sum_{u, v} d_T(u, v) \cdot r(u, v)\right] = \sum_{u, v} r(u, v) \cdot \underbrace{\mathbb{E}[d_T(u, v)]}_{\substack{O(\log n) \cdot d_G(u, v) \\ \text{(last lecture)}}} = O(\log n) \cdot \underbrace{\sum_{u, v} d_G(u, v) \cdot r(u, v)}_{\substack{\text{lower bd. on} \\ \text{opt. cost}}}$$

MCCT Problem

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$$\text{cost}(T) = \sum_{u,v} d_T(u,v) \cdot r_{u,v}$$

Alternative formulation of MCCT

Lemma:

$$\text{cost}(T) = \sum_{e \in E} \text{load}_T(e) \cdot l(e)$$

Proof:

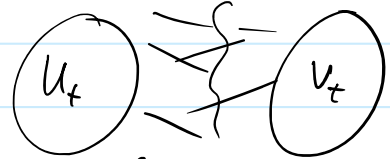
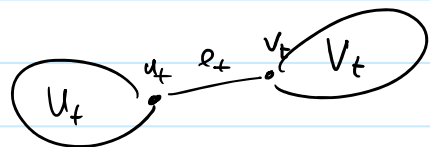
$$\begin{aligned} \sum_{u,v} d_T(u,v) r_{u,v} &= \sum_{u,v} r_{u,v} \cdot \sum_{e_t \in P_{uv}} \sum_{e \in E_T(e_t)} l(e) \\ &= \sum_e l(e) \cdot \sum_{e_t: e \in E_T(e_t)} \sum_{\substack{u,v \text{ s.t.} \\ u,v \text{ are sep. in} \\ (T \text{ by } e_t)}} r_{u,v} \\ &= \sum_e l(e) \cdot \text{load}_T(e) \end{aligned}$$

Approximating Cuts/Bottlenecks of a Graph by a Tree

Given: $G = (V, E, c)$ & $T = (V_T, E_T)$

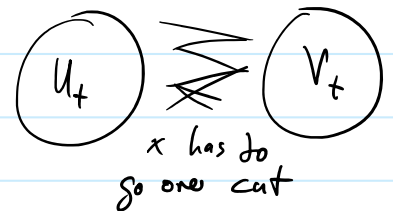
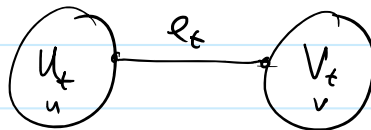
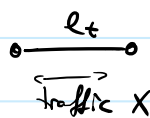
capacity of tree edge $\{u_t, v_t\} \in E_T$

cap. $C_T(u_t, v_t) := \sum_{u \in U_t, v \in V_t} c(u,v)$



$C_T(u_t, v_t) = \text{total cap. over this cut}$

Theorem: Given multicom. flow problem, let C_G be the opt. congestion on G and let C_T be the opt. cong. on T . Then, $C_T \leq C_G$.



Load on edge $e \in E$ for tree T

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Assume that each edge $e_t \in E_T$ is fully utilized

$\hookrightarrow C_T(e_t)$ units of traffic on e_t

$$\text{load}_T(e) = \sum_{e_t \in E_T: e \in M_E(e_t)} C_T(e_t)$$

\hookrightarrow the same as when routing a multicomm. flow with $r(u,v) = C(u,v)$

$$\text{rload}_T(e) := \frac{1}{C(e)} \cdot \text{load}_T(e)$$

Goal: Find a distribution over trees T s.t. \max (over all e) expected $\text{rload}_T(e)$ is minimized.

trees T_1, \dots, T_k and $0 \leq \lambda_1, \dots, \lambda_k \leq 1$ s.t. $\sum \lambda_i = 1$

$$\text{Minimize } \beta := \max_{e \in E} \left\{ \sum_{i=1}^k \lambda_i \text{rload}_{T_i}(e) \right\}$$

Claim: Given multicomm. flow f_i for each T_i s.t. congestion on T_i is ≤ 1

When mapping $\sum \lambda_i f_i$ to $G \rightarrow$ cong. on G is $\leq \beta$

Proof: f_i uses each $e_t \in E_{T_i}$ at most to its cap. $C_{T_i}(e_t)$

f_i incurs load on $e \in E$ a load of at most $\lambda_i \text{load}_{T_i}(e)$

$$\text{total load on } e \leq \sum_{i=1}^k \lambda_i \text{load}_{T_i}(e) \leq \beta$$

Why is this what we need?

Multicomm. flow instance $r(u,v)$, assume opt. cong. on G is C_G

$$\text{flow on } e \leq C_G \cdot C(e)$$

We showed that for each T_i : opt. cong. on T_i is $C_T \leq C_G$

flow on T_i has cong. $\leq C_G$

convex comb. of flows on T_i mapped to $G \Rightarrow$ cong. $\leq \beta \cdot C_G$ on G .

Finding a distribution on trees

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Goal: $\min \beta$

$$\text{s.t. } \forall e \in E: \sum_i \lambda_i \cdot \text{load}_{T_i}(e) \leq \beta \leftarrow$$

$$\sum \lambda_i \geq 1$$

$$\lambda_i \geq 0$$

think of this as a distribution over all possible trees $T_i \in \mathcal{T}$

matrix formulation $|E| \times |\mathcal{T}|$ matrix M , $M_{e,T} = \text{load}_T(e)$

edge constr. $M \cdot \vec{\lambda} \leq \beta \cdot \mathbb{1} \leftarrow$ all-1-vector

$\max(\vec{x})$: maximum component

$$\max(M\vec{\lambda}) \leq \beta$$

replace max by a smooth approx.

$$\ln_{\max}(\vec{x}) := \ln\left(\sum_{e \in E} e^{x_e}\right) \geq \max(\vec{x}) = \max_{e \in E} \{x_e\}$$

replace $\max(M\vec{\lambda}) \leq \beta$ by the stronger cond.

$$\ln_{\max}(M\vec{\lambda}) \leq \beta$$

Basic Idea

- start with $\lambda_1 = \lambda_2 = \dots = 0$, $\ln_{\max}(M\vec{\lambda}) = 0(\log n)$

- in each step, choose a tree T_i and $\delta_i > 0$ and update $\lambda_i := \lambda_i + \delta_i$

$\ln_{\max}(M\vec{\lambda})$ increases by at most $\delta_i \cdot \beta$ (for $\beta = 0(\log n)$)

- stop when $\sum \lambda_i \geq 1$

Implementing basic idea

need to understand how \ln_{\max} changes when some λ_i

$$\text{What is } \ln_{\max}(\vec{x} + \vec{\varepsilon}) \approx \ln_{\max}(\vec{x}) + \vec{\varepsilon}^T \cdot \nabla \ln_{\max}(\vec{x}) = \ln_{\max}(\vec{x}) + \sum_e \varepsilon_e \cdot \text{partial}_e(\vec{x})$$

$$\text{partial}'_e(\vec{x}) := \frac{\partial}{\partial x_e} \ln_{\max}(\vec{x}) = \frac{e^{x_e}}{\sum_e e^{x_e}}$$

