

# Discrete Extension and Selection Problems

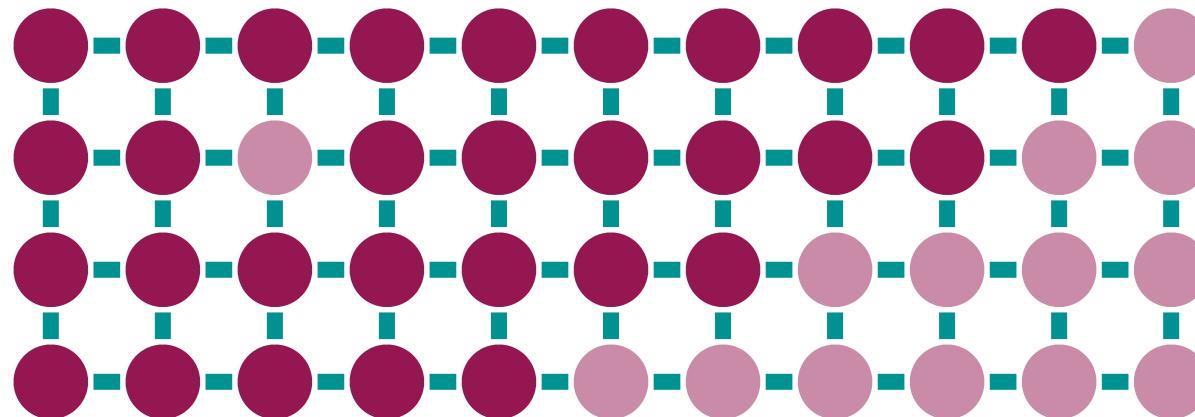
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## motivation – image segmentation [KT '99]

Input: a raster image degraded by noise.

Output: a restored image.

Assumption: small spatial discontinuity.



Homogeneous Markov random fields with pairwise interactions.

## motivation - Lipschitz extension

finite  $X \subset Y$ , Banach spaces  $Y, Z$ ,  $\varphi: X \rightarrow Z$   
 $\varphi': Y \rightarrow Z$  extends  $\varphi$

$$e(X, Y, Z) = \sup_{\varphi} \inf_{\varphi'} \{ \| \varphi' \|_{\text{Lip}} / \| \varphi \|_{\text{Lip}} \}$$

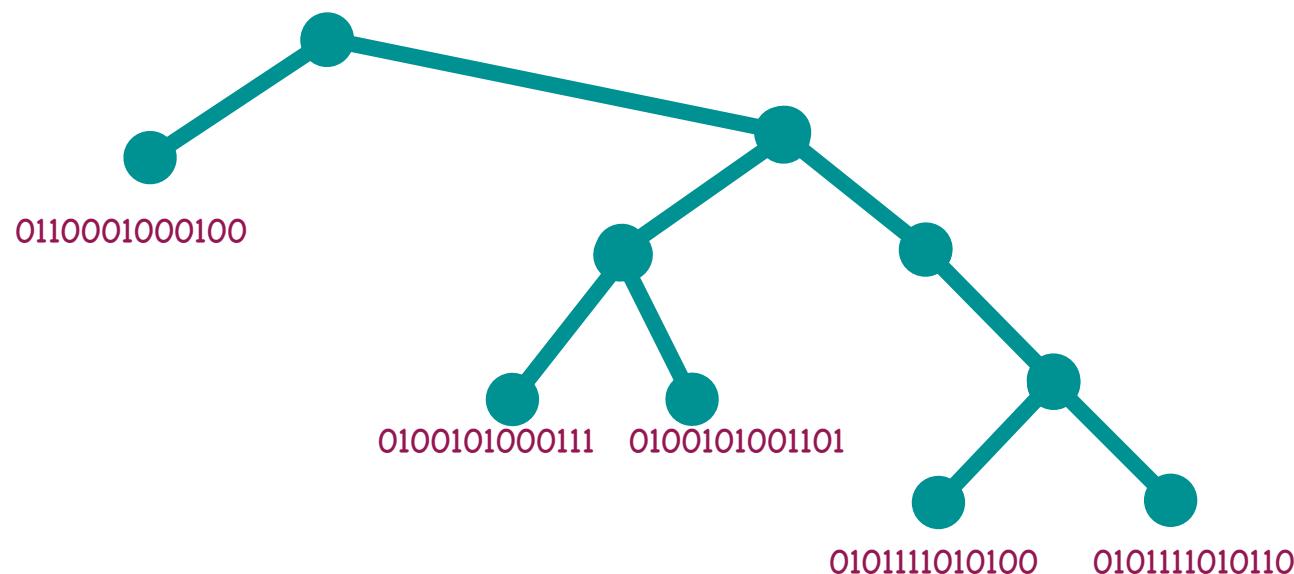
Problem: what's  $e_n(Y, Z) = \sup_{|X|=n} \{ e(X, Y, Z) \}$  ?

$$e_n(Y, L_2) = O(\sqrt{\log n}) \quad [\text{JL '84}]$$

$$\begin{aligned} e_n(Y, Z) &= O(\log n) \\ e_n(Y, Z) &= \Omega(\sqrt{\log n / \log \log n}) \end{aligned} \quad \left. \right\} [\text{JLS '86}]$$

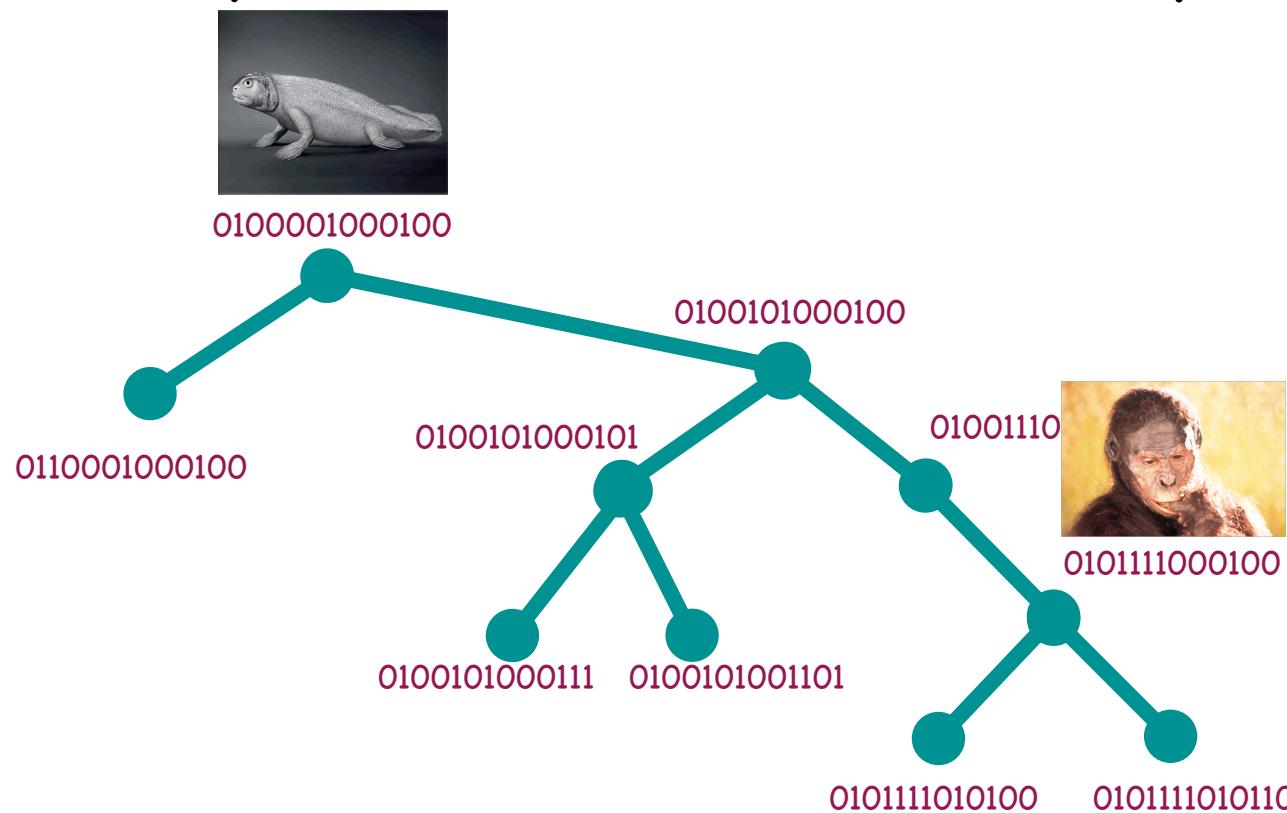
## motivation - DNA multiple sequence alignment

Input: evolutionary tree, DNA seq on leaves  
Output: hypothesized ancestors sequences



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## multiway cut

Input: graph  $G=(V,E)$ , terminal set  $T \subset V$

$$k = |T|$$

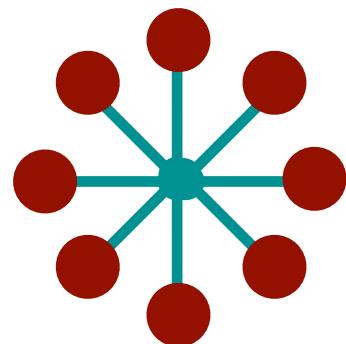
Output:  $\varphi: V \rightarrow T$  extending  $\text{id}: T \rightarrow T$

Objective: min #edges  $uv$  w/  $\varphi(u) \neq \varphi(v)$

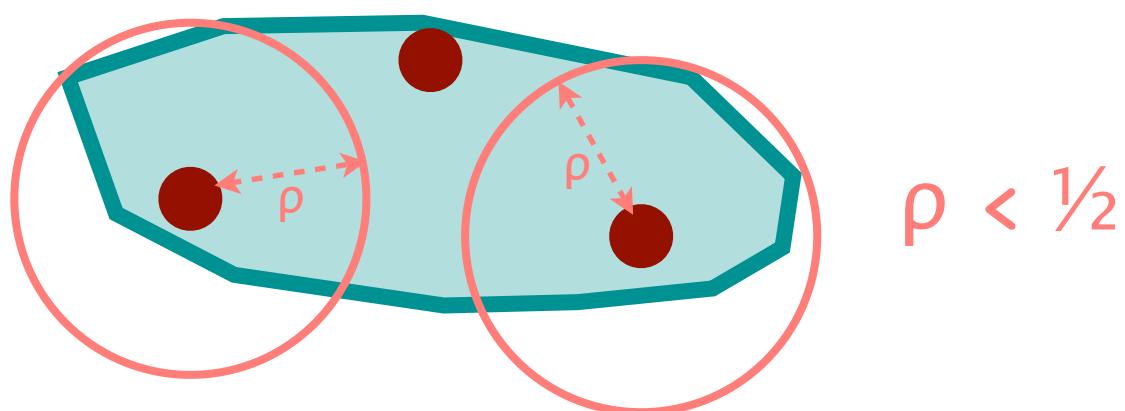
metric relaxation: minimize  $\sum_{uv \in E} d(u,v)$  s.t.

$d$  is a metric on  $V$  and  $d$  is uniform on  $T$ .

$\Rightarrow (2-2/k)$ -approx., matching [DJPSY '94].



bad example



rounding algorithm

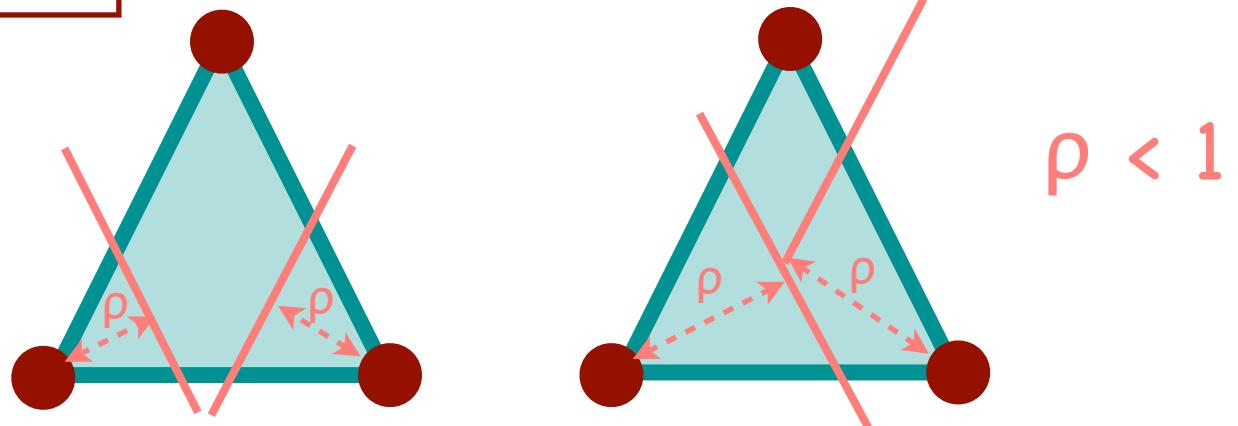
## multiway cut (cont.)

transportation relaxation [CKR '98]

minimize  $\sum_{uv \in E} \frac{1}{2} \cdot \|\theta(u) - \theta(v)\|_1 \leftarrow$  statistical distance

s.t.  $\theta: V \rightarrow \Delta^k$  maps  $T$  to the vertices

(k-1)-simplex



ratio in  $[8/7-o(1), 1.349]$  [FK '00, KKSTY '99]  
for  $k=3$  ratio is  $12/11$  [KKSTY '99, CT '99]

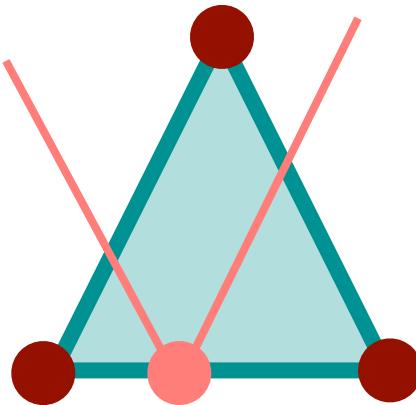
## uniform labeling

Input: graph  $G=(V,E)$ , label set  $L$ ,  $a:V \rightarrow 2^L$

$$k = |L|$$

Output:  $\varphi:V \rightarrow L$  s.t.  $\varphi(u) \in a(u)$

Objective:  $\min \# \text{edges } uv \text{ w/ } \varphi(u) \neq \varphi(v)$



ratio in  $[2 - 2/k, 2]$  [KT '99]

for  $k=3$  ratio is  $4/3$  [Chuzhoy '00]

## 0-extension [Karzanov '98]

Input:  $G=(V,E)$ ,  $T \subset V$ , metric  $d$  on  $T$

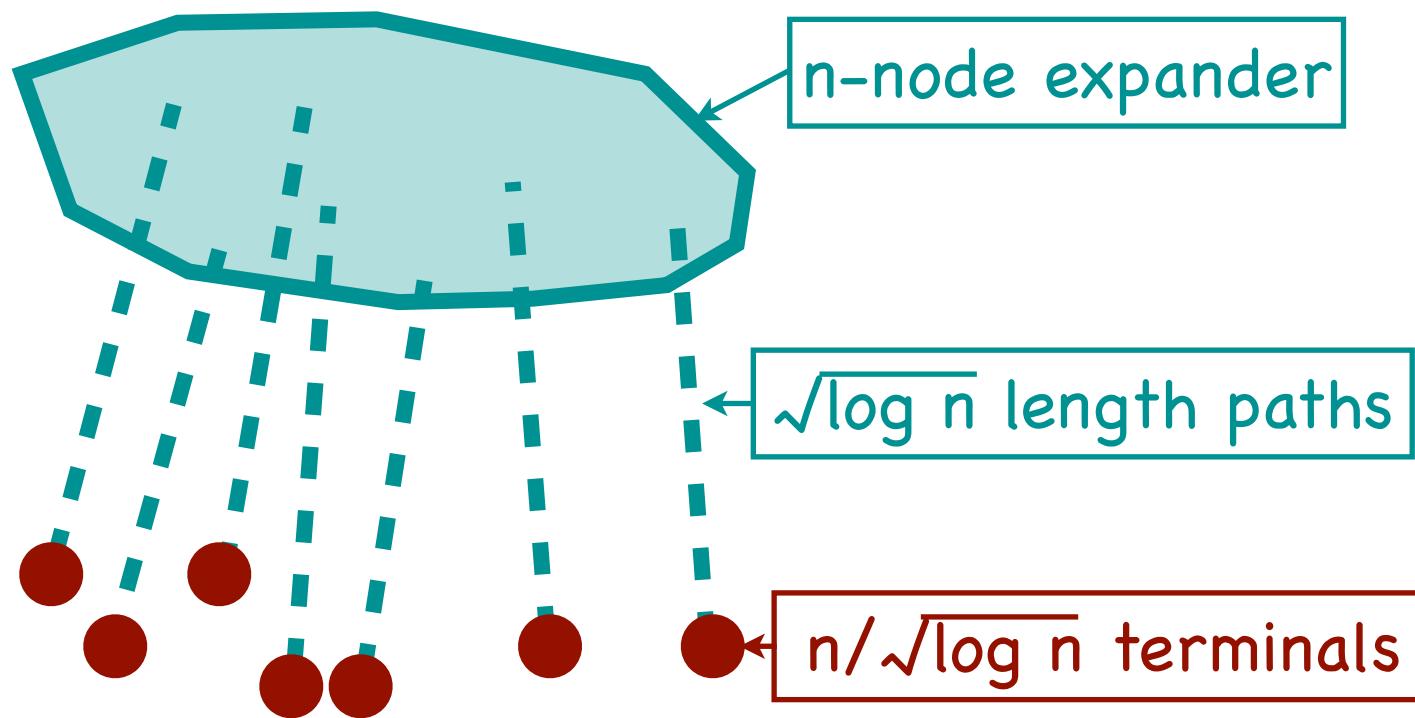
Output:  $\varphi: V \rightarrow T$  extending  $\text{id}: T \rightarrow T$

Objective: minimize  $\sum_{uv \in E} d(\varphi(u), \varphi(v))$

metric relaxation: minimize  $\sum_{uv \in E} d'(u, v)$  s.t.

$d'$  is a metric on  $V$  that extends  $d$ .

[CKR '00]:  
 $\Omega(\sqrt{\log |T|})$



## padded decompositions (graph version)

graph  $G=(V,E)$ , shortest path metric  $d_G$

distribution  $\Pr$  over injections  $\varphi: V \rightarrow V$

$$\text{diam}(\varphi, u) = \text{diam}(\varphi^{-1}(u))$$

$$\text{diam}(\varphi) = \max_{u \in V} \text{diam}(\varphi, u)$$

Objective 1:  $T \subset V$ ,  $|T| = k$ ,  $\varphi: V \rightarrow T$  (id on  $T$ )

$$\min \max_{uv \in E} E[\chi(\varphi(u) \neq \varphi(v)) \cdot \text{diam}(\varphi, u)]$$

CKR decompositions [CKR '00]:

pick u.a.r perm.  $\sigma$  on  $T$ , factor  $\rho \in [1, s]$

$$\varphi(u) = \text{first } t \in T \text{ s.t. } d_G(u, t) \leq \rho \cdot \Delta_u$$

Thm [FHRT '03]:  $E[\chi(\varphi(u) \neq \varphi(v)) \cdot \text{diam}(\varphi, u)]$

$$= O(\log k / \log \log k) \text{ (for } s = \log k / \log \log k\text{)}$$

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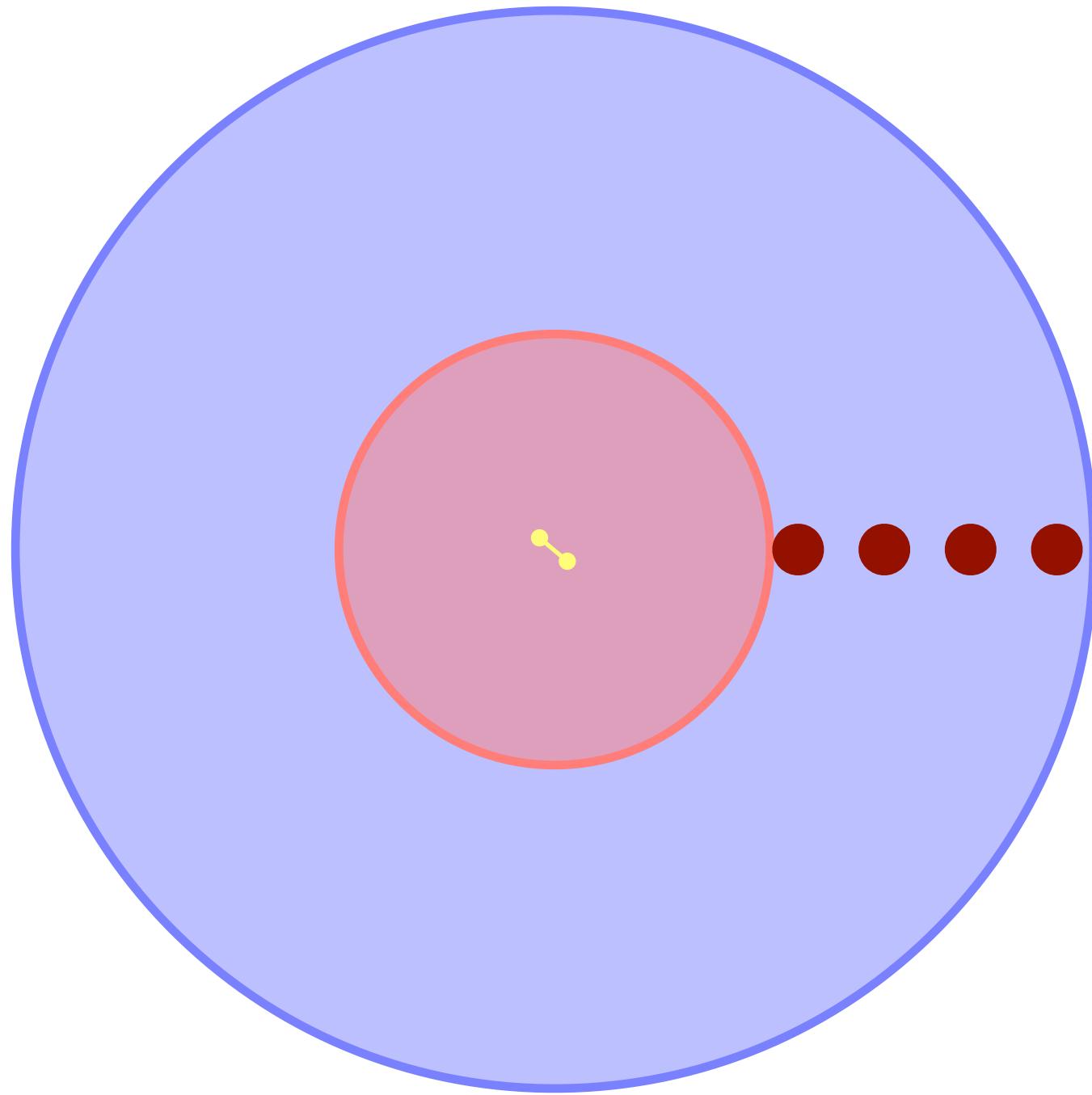
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$$\varphi(u) = \text{first } t \in T \text{ s.t. } d_G(u, t) \leq \rho \cdot \Delta_u \quad \boxed{\Delta_u = d_G(u, T)}$$

Thm [FHRT '03]:  $E[\chi(\varphi(u) \neq \varphi(v)) \cdot \text{diam}(\varphi, u)]$

$$= O(\log k / \log \log k) \text{ (for } s = \log k / \log \log k\text{)}$$

# the idea in a nutshell



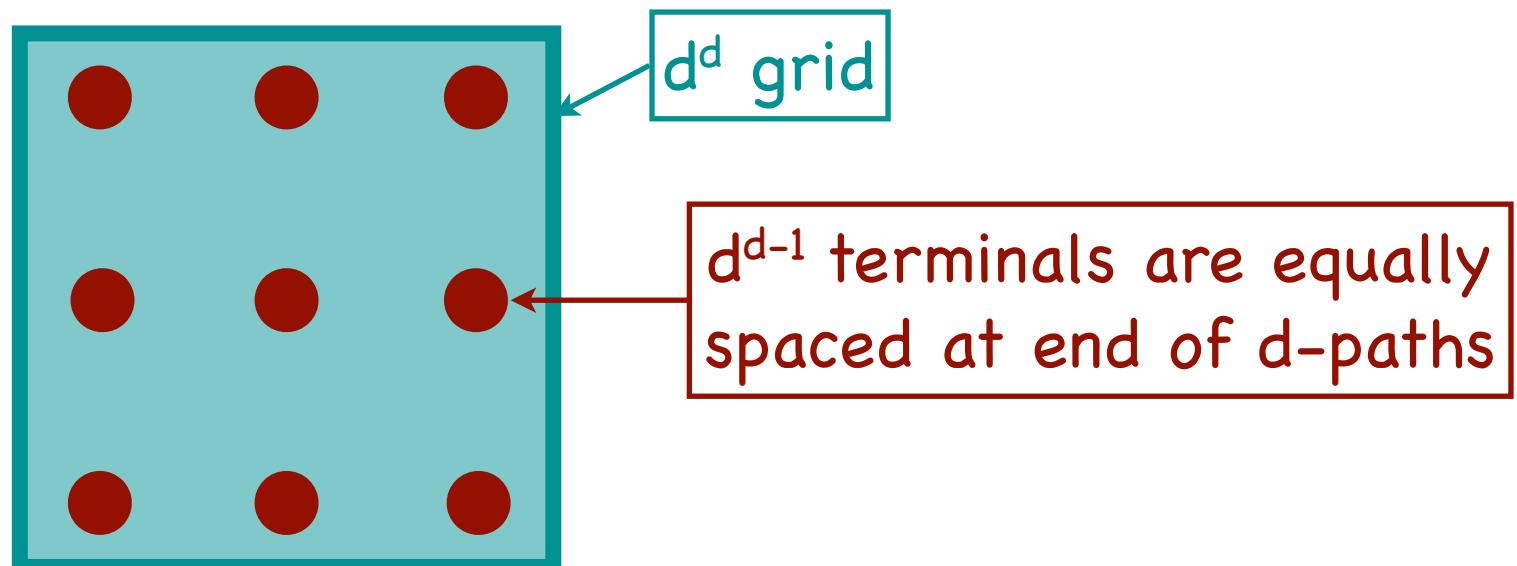
## further observations on 0-extension

- $O(\sqrt{\text{diam}(\mathcal{T})})$ -approximation [CKR '00]:

pick u.a.r  $\rho \in [\sqrt{\text{diam}(\mathcal{T})}, 2 \cdot \sqrt{\text{diam}(\mathcal{T})}]$

$$\varphi(u) = \begin{cases} u & \text{if } u \in \mathcal{T} \\ \text{closest terminal} & \text{if } d_G(u, \mathcal{T}) < \rho \\ \text{terminal 1} & \text{otherwise} \end{cases}$$

- $O(\log k / \log \log k)$  is tight for minimizing  $\sum_{\text{cut}} [\text{diam}(\varphi, u) + \text{diam}(\varphi, v)]$ :



## further observations on 0-extension

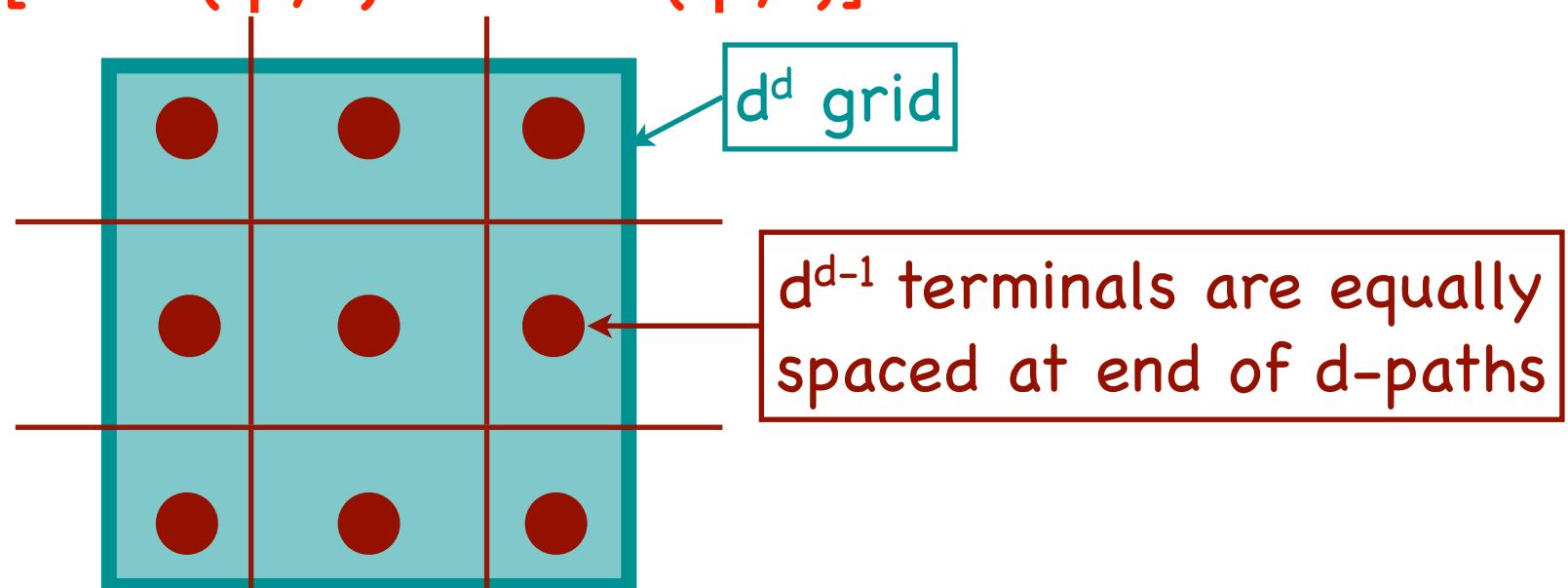
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- $O(\log k / \log \log k)$  is tight for minimizing

$\sum_{\text{cut}} [\text{diam}(\varphi, u) + \text{diam}(\varphi, v)]$ :



## more on decompositions

Objective 2:  $\varphi: V \rightarrow V$

$\min \max_{uv \in E} \Pr[\varphi(u) \neq \varphi(v)]$  s.t.  $\text{diam}(\varphi) \leq r$

$\max \min_u \Pr[N(u) \subset \varphi^{-1}(\varphi(u))]$  s.t.  $\text{diam}(\varphi) \leq r$

$\min \text{diam}(\varphi)$  s.t.  $\forall u, \Pr[N(u) \subset \varphi^{-1}(\varphi(u))] \geq \frac{1}{2}$

Thm [MN '06]:

$$\Pr[N(u) \subset \varphi^{-1}(\varphi(u))] \geq (|B(u, r/8)| / |B(u, r)|)^{16/r}$$

\* Improves  $1 - (1/r) \cdot \log(|B(u, r)| / |B(u, r/8)|)$

$\Rightarrow$  Thm [FRT '04]: any finite metric  $(X, d)$  embeds into a convex combination of dominating HSTs with distortion  $O(\log |X|)$ .

## metric labeling [KT '99]

Input:  $G=(V,E)$ , metric space  $(L,d)$ ,  $a:V \rightarrow 2^L$   $k = |L|$

Output:  $\varphi:V \rightarrow L$  s.t.  $\varphi(u) \in a(u)$

Objective: minimize  $\sum_{uv \in E} d(\varphi(u), \varphi(v))$

$O(\log k)$  approximation [KT '99, FRT '04]

embeds  $(L,d)$  into HSTs, then const. factor approximation for HSTs

## transportation relaxations

### transportation relaxation [CKNZ '01]

minimize  $\sum_{uv \in E} \text{Tran}_d(\theta(u), \theta(v))$  transportation metric

s.t.  $\theta: V \rightarrow \Delta^k$  maps  $u$  to  $\text{span}(a(u))$

bad example [KKMR '06]:

$L$  = nodes of a  $k$ -node expander  $H$ ,  $d = d_H$

$V(G) = \{uv : u, v \in L, u \neq v\}$

$E(G) = \{uv - uv' : vv' \in E(H)\}$

$\theta(uv)$  = uniform distribution on  $\{u, v\}$

$\Rightarrow \Omega(\log |L|)$  integrality gap

similar construction  $\Rightarrow \Omega(\sqrt{\log |L|})$

integrality gap for 0-extension

## hardness results

### metric labeling:

$\Omega(\sqrt{\log |L|})$  unless  $NP \subset \text{quasi-P}$  [CN '04]

$k$  provers,  $\forall$  pair  $\{i,j\}$ ,  $i$  gets a clause  $C_{ij}$  and  $j$  gets a variable  $x_{ij} \in C_{ij}$

### 0-extension:

$\Omega(\sqrt[4]{\log |L|})$  (similar argument) [KKMR '06]

### all problems:

unique games-hard to approximate beyond the transportation relaxation integrality gap [MNRS '08]

## label extension [RK '98]

Input: tree  $T=(V,E)$ , leaf labels in  $\{0,1\}^k$

Output:  $L:V \rightarrow \{0,1\}^k$  (unchanged on leaves)

Objective: minimize  $\max_{uv \in E} H(L(u), L(v))$

Trivial lower bound:

$\max\{1, \max\{H(L(u), L(v))/d_T(u,v) : u, v \text{ leaves}\}\}$

Thm [Matoušek '90]:  $e(d_T, Z) = O(1)$

(in particular, for  $Z = \{0,1\}^k$ )

$\Rightarrow O(1)$  approximation [RSS '08]

## label completion/selection [RSS '08]

Input:  $G=(V,E)$ ,  $L:V \rightarrow \{0,1,*\}^k$

Output:  $L':V \rightarrow \{0,1\}^k$  consistent with  $L$

Objective: minimize  $\max_{uv \in E} H(L'(u), L'(v))$

obvious relaxation:

minimize  $\max\{1, \max_{uv \in E} \|L'(u) - L'(v)\|_1\}$  s.t.

$L': V \rightarrow [0,1]^k$  is consistent with  $L$

$O(\log^2 k)$ -approx. for trees

$\Omega(\log k)$  integrality gap for trees

$O(\log |E| / \log \log |E|)$ -approx.

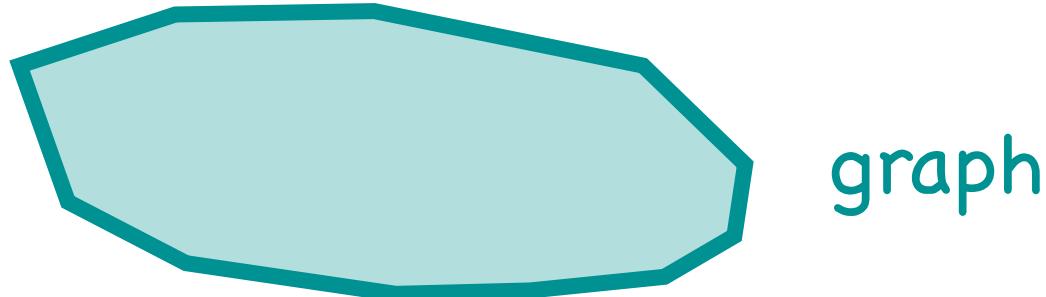


[RSS '08]

## applications of padded decompositions

- measured descent [KLMN '04]:  
an  $n$ -point  $\lambda$ -doubling metric embeds into  
 $\ell_2$  w/distortion  $O(\sqrt{\lambda \log n})$
- Lipschitz extension [LN '05]:  
 $e_n(Y, Z) = O(\log n / \log \log n)$
- metric Ramsey properties [MN '06]:  
an  $n$ -point metric has an  $n^{1-\varepsilon}$ -point subset  
that embeds into  $\ell_2$  w/distortion  $O(1/\varepsilon)$
- local-global tradeoffs [CMM '07]:  
every  $m$ -point subset of an  $n$ -point metric  
 $M$  embeds into  $\ell_1$  w/distortion  $c$   
 $\Rightarrow M$  embeds into  $\ell_1$  w/dist.  $O(c \cdot \log(n/m))$

## vertex sparsifiers [Moitra '09, LM '10]



graph

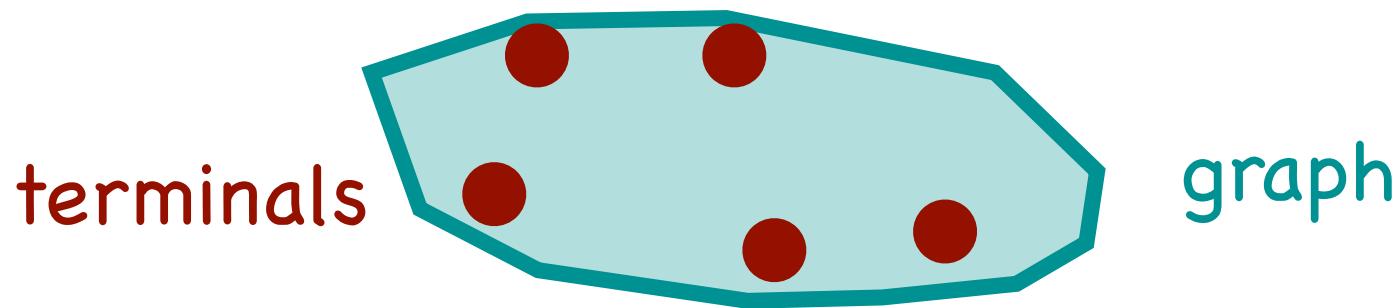
$O(\log k / \log \log k)^*$  cut (also flow) sparsifiers  
[CLLM '10, MM '10, EGKRTT '10]

$\Omega(\sqrt{\log k} / \log \log k)$  lower bound [MM '10]

does  $e_n(l_2, l_1) = \text{const.}$ ? [Ball '92]  $\Rightarrow$   
 $e_n(l_1, l_1) = \tilde{O}(\sqrt{\log n}) \Rightarrow \tilde{O}(\sqrt{\log n})$  cut spars.

\* integrality gap for the metric relaxation  
for 0-extension

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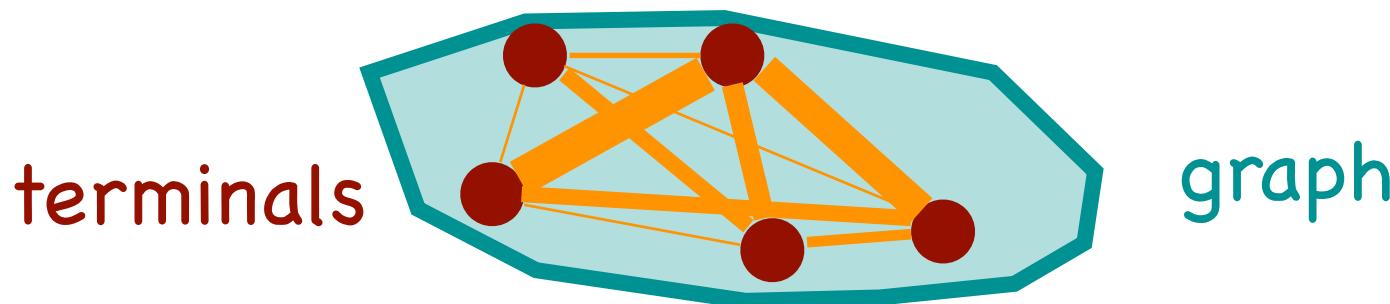
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cut sparsifier

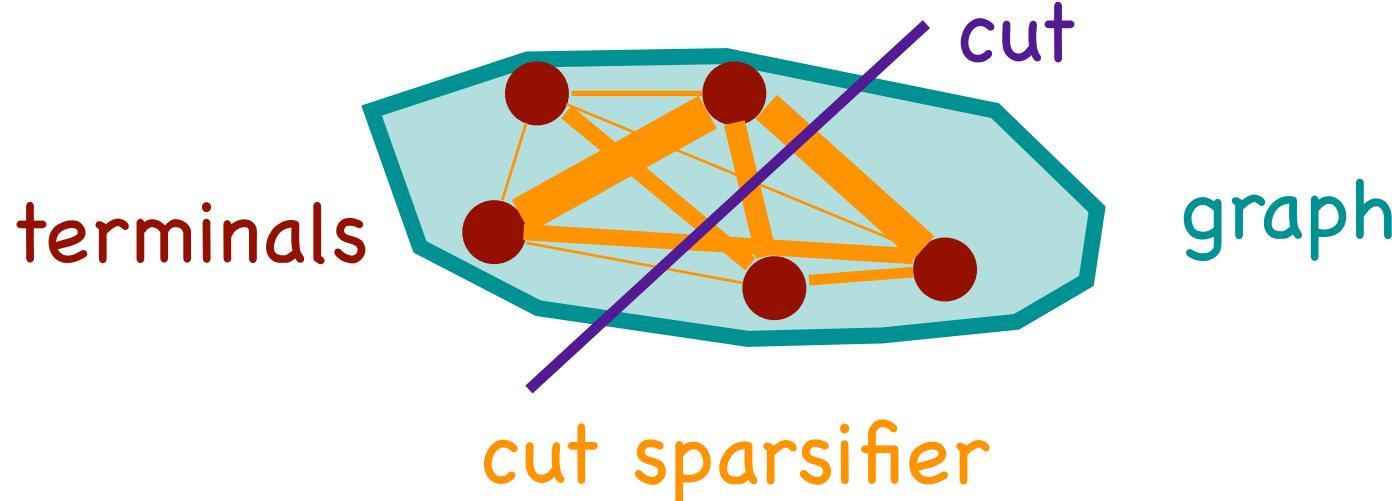
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