

**Reading:** Text: Vazirani, Chapter 21

*Started with min-cut, saw max-cut last lecture, now for another important cut problem, sparsest cut. We use this problem to demonstrate embedding techniques in randomized approximation algorithms.*

**Fact:**  $f^* \leq \min_{S \subseteq V} \frac{c(S)}{\text{dem}(S)}$  (one direction of min-cut/max-flow thm).

**Def:** The *sparsity* of a cut  $(S, \bar{S})$  is  $\frac{c(S)}{\text{dem}(S)}$ .

**Problem:** Sparsest cut. Given above setup, find cut  $S$  with minimum sparsity.

**Note:** Unlike single-commodity, bound is *not* tight!

**Example:**  $K_{3,2}$ , unit capacity, unit demand between each pair of non-adjacent vertices.

## Multi-commodity flow/sparest cut

**Problem:** Multi-commodity flow.

Given

- graph  $G = (V, E)$
- capacities  $c : E \rightarrow \mathbb{R}^+$
- commodities  $\{1, \dots, k\}$  with
  - demands  $\text{dem}(i)$
  - source/sink pairs  $(s_i, t_i)$

Find

- max throughput  $f^*$  s.t. for each commodity,  $f^* \times \text{dem}(i)$  flow can be routed simultaneously

**Note:** Given cut  $(S, \bar{S})$ , let

- $c(S)$  be total capacity of  $e \in \delta(S)$
- $\text{dem}(S)$  be total demand separated by cut

- sparsest cut: remove a node on lhs, sparsity is 1

- flow: can only route all lhs demands by sending 1/2 on each edge, but this saturates edges, so rhs can't route demand.

## LP Formulation

### Primal

Let  $\mathcal{P}_i = \{q_j^i\}$  be paths from  $s_i$  to  $t_i$ .

$$\begin{aligned} \max \quad & f \\ \text{s.t.} \quad & \sum_j f_j^i \geq f \cdot \text{dem}(i), \quad 1 \leq i \leq k \\ & \sum_{q_j^i: e \in q_j^i} f_j^i \leq c_e, \quad e \in E \end{aligned}$$

where  $f_j^i$  is flow from commodity  $i$  on path  $q_j^i$ .

## Dual

$$\begin{aligned} \min \quad & \sum_{e \in E} c_e d_e \\ \text{s.t.} \quad & \sum_{e \in q_j^i} d_e \geq l_i \\ & \sum_{i=1}^k l_i \cdot \text{dem}(i) \geq 1 \end{aligned}$$

where  $d_e$  is “distance” of edge  $e$ .

*[Don't actually need exponential LP, and/or can use separation oracle that looks at shortest path from  $s_i$  to  $t_i$ .]*

**Fact:** There is an optimal soln. in which the  $d_e$  form a *metric* and second ineq. is tight.

**Def:** A *metric space* is a pair  $(V, d)$  where  $d : V \times V \rightarrow \mathbb{R}^+$  s.t.

- $d(x, y) = 0 \leftrightarrow x = y$
- symmetry:  $d(x, y) = d(y, x)$
- triangle inequality:  $d(x, y) + d(y, z) \geq d(x, z)$

**Proof:** If not, can massage it to one:

- if for some  $u, v, w$ ,  $d_{uv} + d_{vw} < d_{uw}$ , can set  $d_{uw} = d_{uv} + d_{vw}$  without changing shortest path length, so still feasible
- set  $l_i = d(s_i, t_i)$  where  $d(\cdot)$  is dist. according to metric  $d_e$
- if second ineq. isn't tight, scale all  $d_e$  to make it tight

Hence optimal throughput  $f^*$  equals

$$\min_{\text{metric } d} \frac{\sum_e c_e d_e}{\sum_i \text{dem}(i) d(s_i, t_i)}.$$

**Idea:** Cuts are metrics too!

*[To find sparsest cut, write optimal metric in terms of cut metrics and hope it suggests a good one.]*

## Cut packings

**Def:** A *cut-packing* is a function  $y : 2^V \rightarrow \mathbb{R}^+$  assigning value  $y_S$  to cut  $(S, \bar{S})$  s.t. for each edge  $e$ , the amount of cut  $e$  “feels” is at most  $d_e$ :

$$\sum_{S: e \in \delta(S)} y_S \leq d_e$$

- *exact* if  $\sum_{S: e \in \delta(S)} y_S = d_e$
- $\beta$ -*approximate* for  $\beta \geq 1$  if  $\frac{d_e}{\beta} \geq \sum_{S: e \in \delta(S)} y_S \leq d_e$

**Claim:** Given a  $\beta$ -approx. cut packing for  $(V, d)$ , let  $S^*$  be the sparsest cut among those with  $y_S > 0$ . Then sparsity of this cut is at most  $\beta \cdot f^*$ .

*[Hence if we can find  $\beta$ -approximate cut packings we can get  $\beta$ -approximations to sparsest cut.]*

**Proof:** Let  $y$  be a  $\beta$ -approx. cut packing. Then

$$\begin{aligned} f^* &= \frac{\sum_e c_e d_e}{\sum_i \text{dem}(i) d(s_i, t_i)} \\ &\geq \frac{\sum_e c_e \sum_{S: e \in \delta(S)} y_S}{\sum_i \text{dem}(i) \sum_{S: (s_i, t_i) \in \delta(S)} \beta y_S} \\ &= \frac{\sum_S c(S) y_S}{\beta \sum_S \text{dem}(S) y_S} \\ &\geq \frac{1}{\beta} \left( \frac{c(S^*)}{\text{dem}(S^*)} \right) \end{aligned}$$

(recall ratio of sums at least min ratio).

*[Exact cut packings means all cuts with non-zero weight are sparsest cuts.]*

**Question:** How small can  $\beta$  be in general?

## Metric Embeddings

**Idea:** To find good cut packing, embed arbitrary metric into “simple” metric without too

much distortion, then cut-pack simple metric.

If  $m > 1$ , do this in each dimension, get  $mn$  cuts,  $l_1$  norm additive, so works.

## $l_1$ metrics and their packing

[[*Other direction true too.*]]

**Def:** A *norm* on a vector space  $\mathfrak{R}^m$  is a function  $\|\cdot\| : \mathfrak{R}^m \rightarrow \mathfrak{R}^+$  s.t. for any  $x, y \in \mathfrak{R}^m$  and  $\lambda \in \mathfrak{R}$ ,

- $\|x\| = 0 \leftrightarrow x = 0$
- $\|\lambda x\| = |\lambda| \cdot \|x\|$
- $\|x + y\| \leq \|x\| + \|y\|$

**Def:** For  $p \geq 1$ , the  $l_p$ -norm is

$$\|x\|_p = \left( \sum_{k=1}^m |x_k|^p \right)^{1/p}$$

**Def:** The associated metric is defined by  $d_{l_p}(x, y) = \|x - y\|_p$ .

[[ *$l_2$  is what you think of as Euclidian distance;  $l_1$  is grid distance in 2-d. Here we only care about  $l_1$ .*]]

**Def:** A  $\beta$ -distortion  $l_1$ -embedding for metric  $(V, d)$  is a mapping  $\sigma : V \rightarrow \mathfrak{R}^m$  for some  $m$  such that for all  $u, v \in V$ ,

$$\frac{1}{\beta} d(u, v) \leq \|\sigma(u) - \sigma(v)\|_1 \leq d(u, v).$$

**Claim:** Given  $\beta$ -distortion  $l_1$  embedding  $\sigma$  with dimension  $m$ , can construct  $\beta$ -approximate cut packing  $y$  with at most  $mn$  non-zero  $y_S$ .

**Proof:** If  $m = 1$ , suppose vertices mapped to  $u_1 \leq \dots \leq u_n$ . Define

$$y_{1, \dots, t} = u_{t+1} - u_t.$$

Then

$$\sum_{S: (i, j) \in \delta(S)} y_S = \sum_{t=i}^{j-1} y_{1, \dots, t} = u_t - u_s.$$

## Embedding into $l_1$

**Idea:** Use distances to sets:

- Pick  $S_1, \dots, S_m$
- Define  $\sigma_i(u) = \min_{t \in S_i} d(u, t)/m$
- No stretch since for dim.  $i$  and edge  $(u, v)$ ,

$$d(u, t_u) \leq d(u, t_v) \leq d(v, t_v) + d(u, v).$$

**Question:** How to choose  $S_i$  for to not over-shrink?

**Idea:** Choose randomly!

**Algorithm:** For  $1 \leq i \leq \log n$ , let  $S_i$  include each  $t \in V$  with prob.  $1/2^i$ .

**Claim:**  $O(\log n)$ -distortion embedding.

Let  $B(t, r)$  be ball of radius  $r$  around  $t$ . Bound  $d(u, v)$ :

- Let  $r_1 \geq r_2 \geq 0$
- Suppose  $S_i \cap B(u, r_1) = \emptyset$  and  $(S_i \cap B(v, r_2) \neq \emptyset)$
- Then  $|\sigma_i(u) - \sigma_i(v)| \geq (r_1 - r_2)/l$

**Claim:** Let  $A$  and  $B$  be disjoint subsets s.t.  $|A| < 2^i$  and  $|B| \geq 2^{i-1}$ . Then  $\Pr[(S_i \cap A = \emptyset) \wedge (S_i \cap B \neq \emptyset)] \geq c$  for some constant  $c$ .

**Proof:** Sets disjoint so independent, easy to calculate.

Let  $\rho_i$  be min radius s.t. both  $B(u, \rho_i)$  and  $B(v, \rho_i)$  have at least  $2^i$  points.

- Suppose  $\rho_i$  limited by  $u$
- Suppose  $\rho_i < d(u, v)/2$
- $A = B^o(u, \rho_i)$ ,  $B = B(v, \rho_{i-1})$
- Then  $S_i$  contributes  $c(\rho_i - \rho_{i-1})/l$  to  $i$ 'th coordinate in expectation
- Summing over coordinates up to  $\rho_i = d(u, v)/2$  gives result for  $(u, v)$

Get for all edges whp by running  $\log n$  times and using Chernoff, hence dimension of embedding is  $O(\log^2 n)$ .

*Really only wanted to make sure the  $k$  demand pairs not overshrunk. Can save by only selecting subsets of vertices that are source/sink pairs and re-running above analysis to conclude demand pairs not overshrunk. Gives a  $(\log k)$ -approx.*

*Also gives approx. multi-commodity max-flow/min-cut, i.e., sparsity at most  $O(\log k)$  times throughput.*

*Improved to  $O(\sqrt{\log n})$  with SDPs by Arora, Rao, Vazirani in 2004 and via a faster algorithm using “expander flows” by Arora, Hazan, and Kale.*