## 1 Demands Multicommodity Flow

Problem definition: We are given a weighted graph $G=(V, E)$, where each edge $e$ has a capacity of $c(e)$. We have $k$ different goods; each good $i$ travels the graph from $s_{i}$ to $t_{i}$, and has demand $\operatorname{dem}(i)$.
Our goal: to find and maximize $f$ so that each good $i$ has a flow of $f * \operatorname{dem}(i)$ units.
For any cut $S$, we define $c(S)=\sum_{e \in(S, \bar{S})} c(e)$, and $\operatorname{dem}(S)$ is the summation of $\operatorname{dem}(i)$ for every $i$ whose flow the cut S disrupts (i.e. flow is not possible from $s_{i}$ to $t_{i}$ after the cut). By these definitions, we immediately find:

$$
f \leq \frac{c(S)}{\operatorname{dem}(S)}
$$

We will refer to $\frac{c(S)}{\operatorname{dem}(S)}$ as the sparsity of cut $S$.
Last lesson, we showed that the optimal (fractional) answer can be viewed as a metric over the vertices $V$. In the LP problem, $d_{e}$ is a variable representing whether or not $e$ is in the cut; after relaxation $d_{e} \in[0,1]$. For each two vertices $u, v \in V, d(u, v)$ is the sum of all $d_{e} \mathrm{~S}$ on the shortest path from $u$ to $v$.

Definition $1 A$ function $y: 2^{V} \rightarrow \mathbb{R}$ is said to be a $\beta$-approximate-cut-packing if for every $e \in E$, where $d_{e}$ is e's distance in the metric,

$$
\frac{d_{e}}{\beta} \leq \sum_{S \mid e \in S} y(S) \leq d_{e}
$$

Theorem 2 Let $(V, d)$ be the metric determined by LP, as seen last lesson. Let y be a $\beta$-approximate-cut-packing for $(V, d)$. Of all the cuts $S$ where $y(S) \neq 0$, let $S^{\prime}$ be the cut with minimal sparsity $\left(\frac{c(S)}{\operatorname{dem}(S)}\right)$. Then:

$$
\beta O P T \leq \frac{c\left(S^{\prime}\right)}{\operatorname{dem}\left(S^{\prime}\right)}
$$

Lemma 3 Let $\sigma: V \rightarrow \mathbb{R}^{m}$ be a mapping. Then there exists a cut-packing $y$ so the weight each edge e 'feels' $\left(\sum_{S \mid e \in S} y(S)\right)$ is e's length in the metric $l_{1}$ under $\sigma$.
In other words, for $e=(u, v)$ :

$$
\sum_{S \mid e \in S} y(S)=\|\sigma(u)-\sigma(v)\|_{l_{1}}
$$

Theorem 4 There exists an $O(\operatorname{logn})$ approximation to the SPARSEST-CUT problem.

Proof: We will find a $\beta$-approximation-cut-packing ( $\beta$-approx-CP) for $\beta=O(\log n)$; this suffices to prove the theorem.
We will embed our metric $(V, d)$ in $l_{1}$, using mapping $\sigma$. By Bourgain, we have a distortion of $O(\log n)$, which we will denote $\beta$. So for every $e$, we find for $e=(u, v)$

$$
\frac{d_{e}}{\beta} \leq\|\sigma(u)-\sigma(v)\|_{l_{1}} \leq d_{e}
$$

Using the lemma, there exists a cut-packing $y$ so that $\sum_{S \mid e \in S} y(S)=\|\sigma(u)-\sigma(v)\|_{l_{1}}$, and so we find

$$
\frac{d_{e}}{\beta} \leq \sum_{S \mid e \in S} y(S) \leq d_{e}
$$

which is precisely a $\beta$-approx-CP, as required.

Proof: We prove the lemma for $m=1$.
We have a mapping $\sigma$ from our $n$ vertices to $u_{1} \leq u_{2} \leq \ldots \leq u_{n} \in \mathbb{R}$ (in order, without loss of generality). We define:
$y\left(\left\{v_{1}\right\}\right)=u_{2}-u_{1}$
$y\left(\left\{v_{1}, v_{2}\right\}\right)=u_{3}-u_{2}$
$y\left(\left\{v_{1}, \ldots, v_{k}\right\}\right)=u_{k+1}-u_{k}$
For any set $K \subseteq V$ not of the form $\left\{v_{1}, v_{2}, \ldots, v_{k}\right\}$, we'll define $y(K)=0$.
For any cut S where $\left(u_{1}, u_{n}\right) \in S$, we find:
$\sum_{S \mid e \in S} y(S)=\sum_{S \mid v_{1} \in S, v_{n} \notin S} y(S)=\sum_{1 \leq k<n} y\left(\left\{v_{1}, v_{2}, \ldots, v_{k}\right\}\right)=u_{n}-u_{n-1}+u_{n-1}-u_{n-2}+\ldots+u_{2}-u_{1}=u_{n}-u_{1}$
And so we have found that $\left(u_{1}, u_{n}\right)$ feels $u_{n}-u_{1}=\left\|v_{n}-v_{1}\right\|_{l_{1}}$ Similarly, for any $\left(u_{i}, u_{j}\right) \in S$, $i \leq j$, we find

$$
\sum_{S \mid e \in S} y(S)=u_{j}-u_{i}=\left\|v_{j}-v_{i}\right\|_{l_{1}}
$$

since the first cut of the $\left\{v_{1}, \ldots, v_{k}\right\}$ form that contains $v_{i}$ is $\left\{v_{1}, \ldots, v_{i}\right\}$, and the last that does not contain $v_{j}$ is $\left\{v_{1}, \ldots v_{j-1}\right\}$.
Thus, we have proved the lemma for $m=1$.
It is simple to generalize to $m$ dimensions - simply project onto each dimension separately, and repeat the process to find the distance along that dimension. $l_{1}$ distance is found by summation of the distances found along each dimension.

