| Seminar on Algorithms and Geometry |  |  |
| :--- | :--- | :--- |
|  | Lecture 2 |  |
|  | March 26, 2009 |  |
| Lecturer: Robert Krauthgamer | Scribe by: Liah Kor | Updated: April 1, 2009 |

## 1 Embedding into $\ell_{\infty}$

Theorem 1 (Matousek 96', based on Bourgain 85') Let $q \geq 1$ be an integer, then any $n$-point metric space, $(X ; d)$ embeds with distortion $2 q-1$ into $\ell_{\infty}^{k}$, where $k=O\left(q n^{\frac{1}{q}} \log n\right)$.

Proof Let $p=n^{-\frac{1}{q}}$. For each $j \in\{1 \ldots q\}$ let $p_{j}=\min \left\{p^{j}, \frac{1}{2}\right\}$. Let $\left\{A_{j, 1} \ldots A_{j, m}\right\} \subseteq X$ where $m=24 \cdot n^{\frac{1}{q}} \ln n$, be chosen at random by including each element with probability $p_{j}$. Consider $f$, the corresponding Frechet embedding:

$$
\mathrm{f}: \mathrm{X} \hookrightarrow \ell_{\infty}^{q \cdot m} \text { such that } f_{j, i}=d\left(x, A_{j, i}\right)
$$

We'll show using the following lemmas, that $f$ embeds $(X ; d)$ into $\ell_{\infty}^{k}$ where $k=q \cdot m=$ $q n^{\frac{1}{q}} \log n$ with distortion $2 q-1$.
Note that: $\forall x, y \in X, \| f(x)-f\left(y \| \leq \max _{i \in[1 \ldots m], j \in[1 \ldots q]}\left|f_{j, i}(x)-f_{j, i}(y)\right| \leq d(x, y)\right.$ (the last inequality is implied by Fact 5 in lecture 1).
Define $\Delta \stackrel{\text { def }}{=} \frac{1}{2 q-1} d(x, y)$
Lemma 2 For every $x, y \in X$ exists $j \in[1 \ldots q]$ s.t $\forall i \in[1 \ldots m]$ with probability $\frac{P}{12}$

$$
\left|d\left(x, A_{j, i}\right)-d\left(y, A_{j, i}\right)\right| \geq \Delta
$$

Assuming the lemma, for every $x, y \in X$ exist $i, j$ s.t with probability $1-\frac{1}{n^{2}}$ :

$$
\|f(x)-f(y)\|_{\infty} \geq\left|f_{j, i}(x)-f_{j, i}(y)\right| \geq \Delta
$$

Applying union bound over all $\binom{n}{2}$ pairs $(x, y)$, we get that with probability $\geq \frac{1}{2}$ for all $x, y \in X,\|f(x)-f(y)\|_{\infty} \geq \Delta=\frac{1}{2 q-1} d(x, y)$.

Proof of Lemma 2 Define $B(x, r)$ the ball of radius $r$ around $x \in X$. Consider the sequence $B_{0}=B(x, 0), B_{1}=B(y, \Delta), B_{2}=B(x, 2 \Delta), B_{3}=B(y, 3 \Delta) \ldots B_{q}=B(x$ or $y, q \Delta)$.

Claim 3 Exist $j \in[1 \ldots m]$ and $t \in[0 \ldots q-1]$ such that $\left|B_{t}\right| \geq n^{\frac{j-1}{q}}$ and $\left|B_{t+1}\right| \leq n^{\frac{j}{q}}$

Proof Idea Note that $1 \leq\left|B_{i}\right| \leq n$. Consider the partitioning of $[1, n]$ into $q$ intervals $1, n^{\frac{1}{q}}, n^{\frac{2}{q}}, \ldots n^{\frac{q-1}{q}}, n$. Use counting argument for the case $\left|B_{i}\right|$ is increasing. Otherwise, use the existence of $t$ s.t $\left|B_{t}\right|>\left|B_{t+1}\right|$.

Let $B_{t}$ and $B_{t+1}$ as in the claim. For $\left|d\left(x, A_{j, i}\right)-d\left(y, A_{j, i}\right)\right|$ to be at least $\Delta$ it suffices that $A_{j, i}$ contains at least one point from $B_{t}$ and no points from the open ball $\stackrel{\circ}{B}_{t+1}$. By using the claim, we can bound the probabilities of the events to be at least $\frac{P}{3}$ and $\frac{1}{4}$ respectively. Using the fact the events are independent we get:

$$
\operatorname{Pr}\left[\left|d\left(x, A_{j, i}\right)-d\left(y, A_{j, i}\right)\right| \geq \Delta\right] \geq \frac{P}{12}
$$

Corollary 4 Every n-point metric $(X ; d)$ embeds into $l_{2}$ (and $l_{1}$ ) with distortion $O\left(\log ^{2} n\right)$
Proof Idea Consider the same embedding $f$ as embedding into $l_{2}^{k}$ with $q=\log n$ which implies $k=O\left(\log ^{2} n\right)$

Remark In general $l_{2} \subseteq l_{1}$, i.e every n-point metric that embeds isometrically into $l_{2}$ also embeds isometrically into $l_{1}$.

An optimal bound is obtained in the following theorem:
Theorem 5 (Bourgain 85') Every n-point metric ( $X ; d$ ) embeds into $l_{2}$ with distortion $O(\log n)$

## 2 Sparsest Cut

The input of the Sparsest Cut problem is a graph $G=(V, E)$ s.t $|V|=n$, and k pairs of vertices called demand pairs $\left\{s_{1}, t_{1}\right\}, \ldots,\left\{s_{k}, t_{k}\right\} \subseteq V$.
Given such a graph and $S \subseteq V$ we can define the notion of sparsity for the cut $(S, \bar{S})$.

## Definition 6

sparsity $\stackrel{\text { def }}{=} \frac{|\{(\mathrm{u}, \mathrm{v}) \in \mathrm{E}:|(\mathrm{u}, \mathrm{v}) \cap \mathrm{S}|=1\}|}{\mid\left\{\mathrm{i}:\left|\left(\mathrm{s}_{\mathrm{i}}, \mathrm{t}_{\mathrm{i}}\right) \cap \mathrm{S}\right|=1\right\}}=\frac{\text { number of edges crossing the cut }}{\text { number of demand pairs separated by the cut }}$
The objective of the Sparsest Cut problem is to find a cut $S$ that minimizes the sparsity.
Remark A special case of the sparsest cut problem is uniform demand in which there are $\binom{n}{2}$ demand pairs (demand pair for each pair of vertices).
Denote by $e(S, \bar{S})$ the number of edges crossing a cut S .
sparsity uniform demand $=\frac{e(S, \bar{S})}{|S| \cdot|\bar{S}|}$
Without loss of generality $|S| \leq \frac{|V|}{2}=\frac{n}{2}$ and $\frac{n}{2} \leq|\bar{S}| \leq n$ thus after scaling the problem is equivalent to minimizing $\frac{e(S, \bar{S})}{|S|}$ (up to a factor of 2 ).

### 2.1 Formulation as a Linear Program

Definition 7 A given cut $(S, \bar{S})$ may be thought of as a Cut Metric $d(\cdot, \cdot)$ defined by:

$$
\begin{gathered}
f(x)= \begin{cases}1 & x \in S \\
0 & x \notin S\end{cases} \\
\forall u, v \in V, d(u, v)=|f(u)-f(v)|
\end{gathered}
$$

The sparsest cut problem can be formulated as the following optimization problem:

$$
O P T=\min \frac{\sum_{(u, v) \in E} d(u, v)}{\sum_{i=1}^{k} d\left(s_{i}, t_{i}\right)}
$$

subject to: $d(\cdot, \cdot)$ is a cut metric

### 2.1.1 Relaxation to a linear program

$$
L P=\min \sum_{(u, v) \in E} d(u, v) \text { s.t: }\left\{\begin{array}{l}
\sum_{i=1}^{k} d\left(s_{i}, t_{i}\right)=1 \\
\mathrm{~d}(\cdot, \cdot) \text { is a metric }
\end{array}\right.
$$

Since the relaxation allows also solutions which are not a cut-metric LP $\leq \mathrm{OPT}$.
The relaxation of the sparsest set problem is a linear program, hence it can be solved in polynomial time.

### 2.1.2 Approximation of Sparsest Cut using LP relaxation

An interesting question is can we "round" a solution of the LP to a solution of the sparsest cut problem (i.e find the corresponding cut)?
A first step of the rounding will be given by Bourgain's theorem which establishes an embedding of the metric $d$ found by the LP into $l_{1}$ with distortion $O(\log n)$.
So exists $f: V \rightarrow l_{1}$ s.t $\forall u, v \in V, \quad d(u, v) \leq\|f(u)-f(v)\|_{1} \leq O(\log n) \cdot d(u, v)$
We get: $\sum_{(u, v) \in E}\|f(u)-f(v)\|_{1} \leq O(\log n) \cdot L P$ where $L P$ is the solution found by the linear program relaxation. By normalization we can also meet the condition $\sum_{i=1}^{k}\left\|f\left(s_{i}\right)-f\left(t_{i}\right)\right\|_{1}=1$

Theorem 8 For every n-point metric $(X, d)$ that embeds isometrically to $l_{1}$, there exist $\alpha_{i} \geq 0$ and cut metrics $\tau_{i}$ s.t $\forall x, y \in X d(x, y)=\sum_{i} \alpha_{i} \tau_{i}(x, y)$.

