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Local Global Tradeoffs in Metric Embeddings

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Abstract

Suppose that every k points in a n point metric space X are D-distortion embeddable into ℓ_1. We give upper and lower bounds on the distortion required to embed the entire space X into ℓ_1. This is a natural mathematical question and is also motivated by the study of relaxations obtained by lift-and-project methods for graph partitioning problems. In this setting, we show that X can be embedded into ℓ_1 with distortion $O(D \times \log(n/k))$. Moreover, we give a lower bound showing that this result is tight if D is bounded away from 1. For $D = 1+\delta$ we give a lower bound of $\Omega(\log(n/k)/\log(1/\delta))$; and for $D = 1$, we give a lower bound of $\Omega(\log n/(\log k + \log\log n))$. Our bounds significantly improve on the results of Arora, Lovász, Newman, Rabani, Rabinovich and Vempala, who initiated a study of these questions.

1 Introduction

In this paper we study the following question raised by Arora, Lovász, Newman, Rabani, Rabinovich and Vempala [4]:

> Suppose that every k points in a metric space X are D-distortion embeddable into ℓ_1. What is the least distortion with which we can embed the entire space X into ℓ_1?

In other words, what do *local* properties (embeddability of subsets) of the space tell us about *global* properties (embeddability of the entire space)? This is a natural question about metric spaces and our research is motivated by numerous applications of low distortion metric embeddings in computer science and mathematics[1].

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[1] A good introduction to the area of low distortion metric embeddings and their applications in computer science is Matoušek's book [19, Section 15].

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The study of embeddings of metric spaces into normed spaces has played an important role in the development of approximation algorithms. In particular, finite metrics arise naturally in mathematical programming relaxations of graph partitioning problems and the distortion required for embedding into ℓ_1 is directly related to the approximation factor achievable using this approach. The challenge here is to find computationally tractable metrics that admit low distortion embeddings into ℓ_1. The classical theorem due to Bourgain [7] states that any n point metric is embeddable into ℓ_1 with distortion $O(\log n)$. Linial, London and Rabinovich [15] and independently Aumann and Rabani [6] showed that this result is tight and exploited it to design an $O(\log n)$ approximation for sparsest cut.

Considering tighter relaxations is one potential route to improved results. Indeed the study of SDP relaxations and the so called ℓ_2^2 metrics that arise from them have given rise to better approximations for sparsest cut [5, 3]. One avenue for further improvement is the application of lift-and-project methods (such as those given by Lovász–Schrijver [16] and Sherali–Adams [23]) which are systematic ways to design a sequence of increasingly tighter relaxations. The metrics that arise from k rounds of lift-and-project satisfy the property that every subset of size k is isometrically embeddable into ℓ_1. This naturally leads to the question of how such local embeddability affects global embeddability of the metric.

Independent of the motivation from combinatorial optimization, the question of the relationship between local and global properties of metric spaces is fairly natural. It has been studied before in the context of other properties of metric spaces. Menger's theorem [21] states that the embeddability of a metric into ℓ_2^n is characterized by embeddability of all subsets of size $n+3$ into ℓ_2^n. Similarly, it is known that metric is a tree metric if and only if every subset of size four is a tree metric.

Analogous local-global questions have been studied in other realms, including analysis, combinatorics, geometry, topology, and mathematical logic. One such example is Helly's theorem [14] on intersections of bounded convex sets. The influential theory of graph minors studies global graph properties that arise from the local property of subgraphs excluding a given set of minors. Other examples are numerous compactness theorems that state that if some property holds for every finite subset of elements, then the property holds for the entire set (e.g. if every finite subtheory is consistent, then the entire theory is consistent). In functional analysis, many properties of a Banach space are deduced from properties of its finite dimensional subspaces. In particular, one important parameter is the largest Banach–Mazur distance between a k dimensional subspace of a Banach space and the k dimensional Euclidean space (see e.g. [25, Section 6]). In computer science, such local-global considerations arise in property testing and in the study of PCPs.

1.1 Our results

We show that if every k point subset of n point metric space X can be embedded into ℓ_1 with distortion D, then X can be embedded into ℓ_1 with distortion[2] $O(D \times \log(n/k))$. Moreover, we give a lower bound showing that this result is tight if D is bounded away from 1. For

[2]We also generalize this result to all ℓ_p spaces.

$D = 1 + \delta$ we give a lower bound of $\Omega(\log(n/k)/\log(1/\delta))$; and for $D = 1$, we give a lower bound of $\Omega(\log n/(\log k + \log\log n))$. We summarize our results and compare them with the results obtained by Arora, Lovász, Newman, Rabani, Rabinovich and Vempala [4] in the table below.

Upper Bounds

	This paper	**Arora et al [4]**
D	$O(D\log(n/k))$	$O\left(D\,(n/k)^2\right)$

Lower Bounds

1	$\Omega\left(\frac{\log n}{\log k + \log\log n}\right)$	$(\log n)^{\Omega(1/k)}$
$1+\delta$	$\Omega\left(\frac{\log(n/k)}{\log(1/\delta)}\right)$	
$D \geq 3/2$	$\Omega(D\log(n/k))$	$\Omega\left(D\frac{\log^2(n/k)}{\log n}\right)$ for $D \sim C\frac{\log^2 n}{\log^2(n/k)}$

The local distortion (the distortion with which every k points are embeddable into ℓ_1) is given in the first column. In the last row we assume that $D \leq \log n/\log(n/k)$.

Our results significantly improve the results obtained in [4]. We completely solve the problem for every D bounded away from 1. We also answer the main open question posed by Arora, Lovász, Newman, Rabani, Rabinovich, and Vempala [4]: we construct a metric space that requires large distortion to embed into ℓ_1, such that every subset of size $n^{o(1)}$ embeds *isometrically* into ℓ_1. There is still a gap between our lower and upper bounds for metric spaces locally embeddable into ℓ_1 isometrically. Closing this gap is an interesting open question.

We also show that even if a small fraction α (say 1%) of all subsets of size k embeds into ℓ_p with distortion at most D, then we still can embed the entire space into ℓ_p with distortion at most

$$D \cdot O(\log(n/k) + \log\log(1/\alpha) + \log p).$$

In subsequent work [11], we show that our results imply strong lower bounds for Sherali–Adams relaxations of the Sparsest Cut, MAX CUT and Vertex Cover problems. Namely, we prove that the integrality gap for the Sparsest Cut problem is at least

$$\Omega\left(\max\left(\sqrt{\frac{\log n}{\log r + \log\log n}}, \frac{\log n}{r + \log\log n}\right)\right)$$

after r rounds of the Sherali–Adams lift-and-project. The integrality gap for the MAX CUT and Vertex Cover problems remains $2-\varepsilon$ even after n^γ rounds (for every positive ε and some γ that depends on ε).

1.2 Overview

Before we describe the technical details of our results, we give a brief (and imprecise) overview of our techniques.

Our upper bound is based on combining two embeddings, one that handles large distances and the other that handles small distances. In order to construct the first embedding, we construct a hitting set S of size k such that the local neighborhood of every point contains a point in S. The local embeddability property guarantees that S is embeddable into ℓ_1 with small distortion. We extend this embedding to an embedding of the entire set. In order to do this, we construct a random clustering of the points in the space such that nearby points are likely to fall in the same cluster; each cluster is then mapped to a point in the hitting set S. We show that this embedding does not stretch any pair of points by a large amount and is a good embedding for pairs of points at large distances. The second embedding is obtained by taking the first $O(\log(n/k))$ densities in Bourgain's embedding. Again, this does not stretch any pair of points by a large amount. On the other hand, it is a good embedding for small distances.

Our lower bounds are based on constant degree expander graphs used in previous work [2]. Instead of the commonly used shortest path metric however, we define a different metric particularly convenient for the purpose of constructing embeddings into ℓ_1. Our choice of this metric was inspired by the papers of de la Vega and Kenyon-Mathieu [12] and Schoenebeck, Trevisan, and Tulsiani [24], who used a similar metric (distribution of cuts) in their integrality gap examples. We exploit the fact that subgraphs of constant degree expander graphs are sparse and show that such sparse graphs equipped with the new metric embed well into ℓ_1. All short distances are preserved exactly (which is convenient in our iterative construction) and long distances are distorted by a small factor. By appropriately choosing parameters, we are able to construct embeddings with distortion at most $1 + \delta$. However the metric on the entire expander still requires high distortion for embedding into ℓ_1. In order to obtain examples with high global distortion where the metric on subsets is isometrically embeddable into ℓ_1, we show that obtaining distortion sufficiently close to 1 is enough. In this case, we guarantee that a slightly different metric (obtained by adding a small constant to all distances) is in fact isometrically embeddable into ℓ_1. This changes all distances by a factor of at most 2 and still has high global distortion.

2 Embedding Theorem

In this section, we prove the following theorem.

Theorem 2.1. *Let k be a positive integer and $p \geq 1$. Suppose that every subset of size k of a finite metric space (X, d) is embeddable into ℓ_p with distortion D. Then the metric space (X, d) is embeddable into ℓ_p with distortion $O(D \cdot \log(|X|/k))$.*

For simplicity of presentation, we assume throughout the proof that all distances in our metric space are distinct. This is a standard assumption and we may make it without loss of generality. We denote the ball of radius R about x by $\mathrm{B}(x, R) = \{y : d(x, y) \leq R\}$. Finally, we define the local radius for every point as follows.

Definition 2.2. *For every point x of the metric space X, define radius $R_{x,m}$ to be the minimum radius R for which the ball* $\mathrm{B}(x, R)$ *contains m points:*

$$R_{x,m} = \min(R : |\,\mathrm{B}(x, R)| = m).$$

Note that for a point x, the local neighborhood (mentioned in the overview) is the ball $\mathrm{B}(x, R_{x,m})$.

2.1 Hitting Set

In this section we describe a greedy algorithm for finding a set S of size at most k that intersects with every ball $\mathrm{B}(x, 2R_{x,m})$. The following lemma first appeared in the paper of Chan, Dinitz and Gupta [10].

Lemma 2.3. *For every finite metric space (X, d) and every positive integer m there exists a subset $S \subset X$ of size at most $\lfloor |X|/m \rfloor$ such that for every point x in X the ball about x of radius $2R_{x,m}$ contains at least one point from S. In other words, for every x in X*

$$\mathrm{B}(x, 2R_{x,m}) \cap S \neq \varnothing.$$

Moreover, for every x and y in S the balls $\mathrm{B}(x, R_{x,m})$ *and* $\mathrm{B}(y, R_{y,m})$ *do not intersect.*

We need the following simple observation.

Lemma 2.4. *For every finite metric space (X, d), every positive integer m and every two points x and y in X, the following inequality holds:*

$$|R_{x,m} - R_{y,m}| \leq d(x, y).$$

Proof. Notice, that the ball $\mathrm{B}(x, R_{y,m} + d(x, y))$ contains the ball $\mathrm{B}(y, R_{y,m})$. Therefore, $|\,\mathrm{B}(x, R_{y,m} + d(x, y))| \geq |\,\mathrm{B}(y, R_{y,m})| = m$ and

$$R_{x,m} \leq R_{y,m} + d(x, y).$$

Similarly, $R_{y,m} \leq R_{x,m} + d(x, y)$. □

Proof of Lemma 2.3. We give an explicit (deterministic) algorithm for finding the set S. The algorithm maintains three sets: a set of "active" points A, a set of "unsatisfied" balls $\mathcal{B}$, and a set of selected points S. Initially the set A contains all points of the metric space X, the set $\mathcal{B}$ contains all balls $\mathrm{B}(x, R_{x,m})$:

$$\mathcal{B} = \{\mathrm{B}(x, R_{x,m}) : x \in X\};$$

and the set S is empty. At each iteration we pick the ball $\mathrm{B}(x, R_{x,m})$ of smallest radius from $\mathcal{B}$ and add the center of this ball, the point x, to S. Then we remove all points of the ball $\mathrm{B}(x, R_{x,m})$ from the set of active points A:

$$A = A \setminus \mathrm{B}(x, R_{x,m});$$

we also remove all balls that intersect with $\mathrm{B}(x, R_{x,m})$ from $\mathcal{B}$:

$$\mathcal{B} = \{\mathrm{B}(y, R_{y,m}) \in \mathcal{B} : \mathrm{B}(y, R_{y,m}) \cap \mathrm{B}(x, R_{x,m}) = \varnothing\}.$$

When the set $\mathcal{B}$ becomes empty, the algorithm stops and returns the set S.

Let us analyze the algorithm. Observe that after every iteration all balls in $\mathcal{B}$ contain points only from the set A. Hence at every step we remove exactly m points from A (recall that every ball $\mathrm{B}(x, R_{x,m})$ contains exactly m points from X by the definition of $R_{x,m}$). Therefore, after $\lfloor |X|/m \rfloor$ iterations A will contain less than m elements and thus the set $\mathcal{B}$ will be empty. Hence the set S contains at most $\lfloor |X|/m \rfloor$ points.

We now need to check that S intersects with every ball $\mathrm{B}(y, 2R_{y,m})$. Consider an arbitrary point y and the step at which $\mathrm{B}(y, R_{y,m})$ was removed from $\mathcal{B}$. Let x be the point that was added to the set S at this step. Since $\mathrm{B}(y, R_{y,m})$ was removed from $\mathcal{B}$, the ball $\mathrm{B}(y, R_{y,m})$ intersects with the ball $\mathrm{B}(x, R_{x,m})$. Hence

$$d(x, y) \leq R_{x,m} + R_{y,m}.$$

Notice that $R_{x,m} \leq R_{y,m}$, since at every step we choose the ball of smallest radius. Thus x lies in the ball of radius $2R_{y,m}$ about y. This concludes the proof. □

Corollary 2.5. *For every finite metric space (X, d) and every positive integer m there exists a subset $S \subset X$ of size at most $\lfloor |X|/m \rfloor$ and a mapping $g : X \to S$ such that for every point x in X,*

$$d(x, g(x)) \leq 2R_{x,m}.$$

2.2 Partitioning

In this section, we describe a randomized mapping of the metric space X into itself that "glues" together points at small distances with high probability. Our algorithm is based on the clustering technique of Calinescu, Karloff and Rabani [9] and Fakcharoenphol, Rao, and Talwar [13].

Lemma 2.6. *For every finite metric space (X, d) and every positive integer m there exists a random mapping $f : X \to X$ such that for every x and y in X,*

1. *$d(x, f(x)) \leq R_{x,m}$ (always);*
2. *$\Pr(f(x) \neq f(y)) \leq O(\log m) \times \frac{d(x,y)}{R_{x,m} + R_{y,m}}$.*

Proof. We present a probabilistic algorithm that finds the mapping f.

1. Pick a random number α uniformly distributed in $(0, 1)$.
2. Pick a random (uniform) total order $<_\pi$ on the elements of the space X.
3. Now define the mapping $f\colon X \to X$ as follows: For every point x, let $f(x)$ be the minimal point z in the ball $\mathrm{B}(x, \alpha \cdot R_{x,m})$ with respect to the order $<_\pi$.
4. Return the mapping f.

Clearly, the mapping returned by the algorithm always satisfies the first property:

$$d(x, f(x)) \leq \alpha \cdot R_{x,m} \leq R_{x,m}.$$

To verify the second property, consider two points x and y in X. We will show that

$$\Pr\Big(f(x) <_\pi f(y)\Big) \leq (2\log m + O(1)) \times \frac{d(x,y)}{R_{y,m}}.$$

Enumerate all points in the ball $\mathrm{B}(x, R_{x,m})$ in the order of increasing distance from the point x: $z_1, \dots, z_m$. Write

$$\Pr\left(f(x) <_\pi f(y)\right) = \sum_{i=1}^{m} \Pr\left(f(x) = z_i \text{ and } f(y) >_\pi z_i\right). \tag{1}$$

Observe that if $f(y) >_\pi z_i$, then z_i does not belong to the ball $\mathrm{B}(y, \alpha \cdot R_{y,m})$. Therefore,

$$\begin{aligned}\Pr(f(x) = z_i \text{ and } f(y) >_\pi z_i) &= \Pr\left(f(x) = z_i \mid z_i \in \mathrm{B}(x, \alpha R_{x,m}) \text{ and } z_i \notin \mathrm{B}(y, \alpha R_{y,m})\right)\\ &\quad \times \Pr\left(z_i \in \mathrm{B}(x, \alpha R_{x,m}) \text{ and } z_i \notin \mathrm{B}(y, \alpha R_{y,m})\right).\end{aligned}$$

Let us estimate the probabilities in the right hand side. We have

$$\begin{aligned}\Pr(z_i \in \mathrm{B}(x, \alpha R_{x,m}) \text{ and } z_i \notin \mathrm{B}(y, \alpha R_{y,m})) &= \Pr\left(d(x, z_i) \leq \alpha R_x \text{ and } d(y, z_i) > \alpha R_{y,m}\right)\\ &= \Pr\left(\frac{d(z_i,x)}{R_{x,m}} \leq \alpha < \frac{d(z_i,y)}{R_{y,m}}\right)\\ &\leq \max\left(\frac{d(z_i,y)}{R_{y,m}} - \frac{d(z_i,x)}{R_{x,m}}, 0\right).\end{aligned}$$

Applying the triangle inequality $d(z_i, y) \leq d(z_i, x) + d(x, y)$ and the inequality $R_{x,m} - R_{y,m} \leq d(x, y)$ we get

$$\begin{aligned}\frac{d(z_i,y)}{R_{y,m}} - \frac{d(z_i,x)}{R_{x,m}} &\leq \frac{d(z_i,x) + d(x,y)}{R_{y,m}} - \frac{d(z_i,x)}{R_{x,m}}\\ &= \frac{d(z_i,x)}{R_{x,m}} \cdot \frac{R_{x,m} - R_{y,m}}{R_{y,m}} + \frac{d(x,y)}{R_{y,m}} \leq \frac{2d(x,y)}{R_{y,m}}.\end{aligned}$$

We now show that

$$\Pr\left(f(x) = z_i \mid z_i \in \mathrm{B}(x, \alpha R_{x,m}) \text{ and } z_i \notin \mathrm{B}(y, \alpha R_{y,m})\right) \le \frac{1}{i}.$$

Indeed for any fixed $\alpha = \alpha_0$, if z_i lies in the ball $\mathrm{B}(x, \alpha_0 R_{x,m})$, then the points $z_1, \dots, z_{i-1}$ also lie in this ball. Therefore, conditionally on $\alpha = \alpha_0$ the probability that z_i is the minimal point with respect to the order $<_\pi$ is at most $1/i$.

Now we can bound (1) as follows:

$$\Pr\left(f(x) <_\pi f(y)\right) = \sum_{i=1}^{m} \frac{1}{i} \times \frac{2d(x,y)}{R_{y,m}} \le (2\log m + O(1)) \times \frac{d(x,y)}{R_{y,m}}.$$

Hence

$$\Pr\left(f(x) \ne f(y)\right) \le (2\log m + O(1)) \times d(x,y) \times \left(\frac{1}{R_{x,m}} + \frac{1}{R_{y,m}}\right).$$

We are almost done. Assume without loss of generality that $R_{x,m} \le R_{y,m}$. If $R_{x,m} \ge d(x,y)$, then $R_{y,m} \le 2R_{x,m}$ and hence

$$\Pr\left(f(x) \ne f(y)\right) \le (2\log m + O(1)) \times d(x,y) \times \left(\frac{1}{R_{x,m}} + \frac{1}{R_{y,m}}\right) \le (9\log m + O(1)) \times \frac{d(x,y)}{R_{x,m} + R_{y,m}}.$$

If $R_{x,m} \le d(x,y)$, then

$$\Pr\left(f(x) \ne f(y)\right) \le 1 \le 3\frac{d(x,y)}{R_{x,m} + R_{y,m}}.$$

$\square$

2.3 Embedding for Large Scales

In this section, we combine the results of the previous two sections and obtain an embedding of X into ℓ_p that separates points at large distances.

Lemma 2.7. *For every finite metric space (X, d) and every positive integer m there exists a subset $S \subset X$ of size at most $\lfloor |X|/m \rfloor$ and a probabilistic mapping $h : X \to S$ such that for every two points x and y in X the following conditions hold:*

1. $d(x, h(x)) \le 5R_{x,m}$ *(always);*
2. $\Pr\left(h(x) \ne h(y)\right) \le O(\log m) \times \frac{d(x,y)}{R_{x,m}+R_{y,m}}$;
3. $\mathbb{E}\left[d(h(x), h(y))\right] \le O(\log m) \times d(x,y)$;
4. $\mathbb{E}\left[d(h(x), h(y))\right] \ge d(x,y) - 5(R_{x,m} + R_{y,m})$.

Proof. Choose the set S as in Corollary 2.5 and let f and g be mappings from Lemma 2.6 and Corollary 2.5. Define $h(x) = g(f(x))$. Let us verify that conditions 1-4 are satisfied.

1. We have

$$d(x, h(x)) \leq d(x, f(x)) + d(f(x), g(f(x))) \leq R_{x,m} + 2R_{f(x),m} \leq R_{x,m} + 4R_{x,m} = 5R_{x,m}.$$

Here we used the following simple observation:

$$R_{f(x),m} \leq R_{x,m} + d(x, f(x)) \leq 2R_{x,m}.$$

2. The probability of the event $h(x) \neq h(y)$ is not greater than the probability of the event $f(x) \neq f(y)$. Therefore, the second condition follows from Lemma 2.6.

3. Verify the third condition:

$$\begin{aligned}
\mathbb{E}\left[d(h(x), h(y))\right] &= \mathbb{E}\left[d(h(x), h(y)) \mid h(x) \neq h(y)\right] \ \Pr\left(h(x) \neq h(y)\right) \\
&\leq \mathbb{E}\left[d(x, y) + d(x, h(x)) + d(y, h(y)) \mid h(x) \neq h(y)\right] \ \Pr\left(h(x) \neq h(y)\right) \\
&\leq d(x, y) + 5(R_{x,m} + R_{y,m}) \times O(\log m) \times \frac{d(x, y)}{R_{x,m} + R_{y,m}} \\
&= O(\log m) \times d(x, y).
\end{aligned}$$

4. Finally,

$$\mathbb{E}\left[d(h(x), h(y))\right] \geq d(x, y) - \mathbb{E}\left[d(x, h(x)) + d(y, h(y))\right] \geq d(x, y) - 5(R_{x,m} + R_{y,m}).$$

□

We are ready to finish the construction of the embedding that handles large distances.

Lemma 2.8. *Let (X, d) be a finite metric space and let k be a positive integer. Suppose that every subset $S \subset X$ of size k is embeddable into a normed space $(V, \|\cdot\|)$ with distortion D. Then there exists an embedding $\varphi : X \hookrightarrow V$ such that for all x and y,*

1. $\|\varphi(x) - \varphi(y)\| \leq D \cdot O(\log(|X|/k)) \times d(x, y)$;
2. $\|\varphi(x) - \varphi(y)\| \geq d(x, y) - (7D + 2) \times (R_{x,m} + R_{y,m})$.

Proof. Set $m = \lceil |X|/k \rceil$. Pick a set S and a random mapping h as in Lemma 2.7. Since the size of S is at most k there exists a distortion D embedding $\nu : S \hookrightarrow V$. By rescaling it we may assume that for every x and y in S:

$$d(x, y) \leq \|\nu(x) - \nu(y)\| \leq D \times d(x, y).$$

Define φ as follows:

$$\varphi(x) = \mathbb{E}\left[\nu(h(x))\right].$$

Verify that it satisfies condition 1:

$$\begin{aligned}\|\varphi(x)-\varphi(y)\| &= \|\mathbb{E}\left[\nu(h(x))-\nu(h(y))\right]\| \le \mathbb{E}\|\nu(h(x))-\nu(h(y))\| \\ &\le \mathbb{E}\left[D\times d(h(x),h(y))\right] \le D\times O(\log(|X|/k))\times d(x,y).\end{aligned}$$

Consider an arbitrary x' in the intersection $S\cap \mathrm{B}(x,2R_{x,m})$ and y' in $S\cap \mathrm{B}(y,2R_{y,m})$. Then

$$\begin{aligned}\|\varphi(x)-\nu(x')\| &\le \mathbb{E}\,\|\nu(h(x))-\nu(x')\| \le \mathbb{E}\left[D\times d(h(x),x')\right] \\ &\le \mathbb{E}\left[D\times (d(h(x),x)+d(x,x'))\right] \le 7D\times R_{x,m},\end{aligned}$$

and similarly $\|\varphi(y)-\nu(y')\|\le 7D\times R_{y,m}$. Therefore,

$$\begin{aligned}\|\varphi(x)-\varphi(y)\| &\ge \|\nu(x')-\nu(y')\|-\|\varphi(x)-\nu(x')\|-\|\varphi(y)-\nu(y')\| \\ &\ge d(x',y')-7D\times(R_{x,m}+R_{y,m}) \\ &\ge d(x,y)-(7D+2)\times(R_{x,m}+R_{y,m}).\end{aligned}$$

□

2.4 Bourgain's Embedding for Small Scales

In this section, we show that Bourgain's embedding applied at the first $\log(n/k)$ scales preserves short distances and does not expand long distances. The proof is a slight modification of Bourgain's original argument [7].

Lemma 2.9. *For every finite metric space (X,d), every real $p\ge 1$ and every positive integer m there exists an embedding $\psi : X\hookrightarrow \ell_p$ such that for every x and y in X*

1. $\|\psi(x)-\psi(y)\|_p\le d(x,y)$;
2. $\|\psi(x)-\psi(y)\|_p\ge \Omega(1/\log m)\times \min(d(x,y),R_{x,m}+R_{y,m})$.

Proof. Let $\ell=\lceil \log m\rceil$. Pick a random integer number r from 1 to ℓ. Then choose a random subset $W_r\subset X$, where each point of X belongs to W_r with probability 2^{-r} (the choices are independent for distinct points). Now, for every x in X, define $\psi(x)$ to be the distance from x to the set W_r:

$$\psi(x)=d(x,W_r)\equiv \min_{w\in W_r} d(x,w).$$

Note that $\psi(x)$ is a random variable. The ℓ_p norm is defined in the standard way:

$$\|\psi(x)-\psi(y)\|_p=\left(\mathbb{E}\,|\psi(x)-\psi(y)|^p\right)^{1/p}.$$

Fix two arbitrary points x and y in X and verify that ψ satisfies conditions 1 and 2. By the triangle inequality, $|\psi(x)-\psi(y)|$ is always less than or equal to $d(x,y)$. Hence the first condition holds.

By Lyapunov's inequality,

$$\|\psi(x) - \psi(y)\|_p \geq \|\psi(x) - \psi(y)\|_1.$$

Therefore, we need to prove the second condition only for $p = 1$. Let $\Delta = \min(d(x, y), R_{x,m} + R_{y,m})/2$. We will show that for every $0 < t < \Delta$,

$$\Pr\left(\psi(x) \leq t \leq \psi(y) \text{ or } \psi(y) \leq t \leq \psi(x)\right) \geq \Omega(1/\log m); \tag{2}$$

and hence,

$$\|\psi(x) - \psi(y)\|_1 = \int_0^\infty \Pr\left(\psi(x) \leq t \leq \psi(y) \text{ or } \psi(y) \leq t \leq \psi(x)\right) dt \geq \Omega(1/\log m) \times \Delta.$$

Fix an arbitrary t in the segment $[0, \Delta]$. Let m' be the size of the smallest of the balls $\mathrm{B}(x, t)$ and $\mathrm{B}(y, t)$. Without loss of generality assume that $|\mathrm{B}(x, t)| = m'$ and $|\mathrm{B}(y, t)| \geq m'$. Note that $m' \leq m$, since $t \leq \max(R_{x,m}, R_{y,m})$. Hence there exists a "scale" $i \in \{1, \ldots, \ell\}$ such that $2^{i-1} \leq m' \leq 2^i$. Assume that $r = i$, then with a constant probability the set W_i contains no points from $\mathrm{B}(x, t)$ and with a constant probability W_i contains at least one point from $\mathrm{B}(y, t)$. Moreover, since the balls $\mathrm{B}(x, t)$ and $\mathrm{B}(y, t)$ are disjoint, with a constant probability (conditional on $r = i$) both events happen:

$$\Pr\left(\mathrm{B}(x, t) \cap W_r = \varnothing \text{ and } \mathrm{B}(y, t) \cap W_r \neq \varnothing \mid r = i\right) \geq \Omega(1),$$

which implies

$$\Pr\left(\psi(x) \geq t \text{ and } \psi(y) \leq t\right) \geq \Omega(1/\log m).$$

□

Remark 2.10. *A similar statement was independently proved by Abraham, Bartal, and Neiman [1, Theorem 2]. Our lemma is a generalization of the result of Mendel and Naor [20, Lemma 3.4], stating that every metric space that* has an m-center *(which means, in our terms, that all balls* $\mathrm{B}(x, R_{x,m})$ *have a nonempty intersection) is embeddable into* ℓ_1 *with distortion* $\log m$. *Notice that if a metric space has an* m *center, then* $d(x, y) \leq R_{x,m} + R_{y,m}$ *for every* x *and* y. *Therefore, in this case, our embedding works for all distances. Mendel and Naor also used first* $\log m$ *scales of Bourgain's embedding in their proof.*

2.5 Proof of Theorem 2.1

In this section, we finish the proof of Theorem 2.1 .

Proof of Theorem 2.1. Let φ and ψ be the embeddings from Lemmas 2.8 and 2.9. After appropriate rescaling we get that

- for all x and y,

$$\|\varphi(x) - \varphi(y)\|_p \leq O(D \log(|X|/k) \times d(x,y));$$
$$\|\psi(x) - \psi(y)\|_p \leq O(D \log(|X|/k) \times d(x,y));$$

- for all x and y with $d(x,y) \geq 10D \times (R_{x,m} + R_{y,m})$,

$$\|\varphi(x) - \varphi(y)\|_p \geq d(x,y);$$

- for all x and y with $d(x,y) \leq (R_{x,m} + R_{y,m})$,

$$\|\psi(x) - \psi(y)\|_p \geq 10D \times d(x,y) \geq d(x,y);$$

- finally, for all x and y with $d(x,y) \geq (R_{x,m} + R_{y,m})$,

$$\|\psi(x) - \psi(y)\|_p \geq 10D \times (R_{x,m} + R_{y,m}).$$

Notice that ψ expands all distances by a factor at least $10D$. The desired embedding is the direct sum of the embeddings φ and ψ. It is easy to see that it is expanding, but does not increase distances more than $D \cdot O(\log(|X|/k))$ times. □

2.6 Embedding using random samples

Suppose that only an α fraction of all subsets of size k embeds into ℓ_p with distortion at most D. We show that the entire space embeds into ℓ_p with distortion at most

$$D \cdot O(\log(|X|/k) + \log\log(1/\alpha) + \log p).$$

Lemma 2.11. *Let (X,d) be a metric space and $\gamma \in (0,1)$. Consider a probabilistic distribution $\mathcal{D}_\gamma$ of subsets $Y \subset X$ with measure $\Pr(\{Y\}) = \gamma^{|Y|}(1-\gamma)^{|S\setminus Y|}$, that is, each x in X belongs to Y with probability γ. Denote the event "Y* embeds into ℓ_p with distortion D*" by $\mathcal{E}$. Then the entire space X embeds into ℓ_p with distortion at most*

$$O(D \times (\log(1/\gamma) + \log\log(1/\Pr(\mathcal{E})) + \log p)). \tag{3}$$

Proof sketch. We use the same embedding as in Theorem 2.1 with

$$k = \left\lfloor \frac{\gamma|X|}{\log(1/\Pr(\mathcal{E})) + 2p} \right\rfloor.$$

The distortion of this embedding is at most $O(D \log(|X|/k)) = (3)$. The only property of X we used in the proof of Theorem 2.1 is that the set S from Lemma 2.3 embeds into ℓ_p with distortion D (see Lemma 2.8). We shall prove a slightly weaker statement which is still sufficient for the proof. Namely, we show that there exists an embedding ν of S into ℓ_p such that for all x and y in S, A: $\|\nu(x) - \nu(y)\|_p \leq O(D) \times d(x, y)$;

B: $\|\nu(x) - \nu(y)\|_p \geq \Omega(1) \times (d(x, y) - (R_{x,m} + R_{y,m}))$.

As before, let $m = \lceil |X|/k \rceil$. Let T_Y be the set of those points x in S for which there exists a point y in Y at distance at most $R_{x,m}$. Since each ball $\mathrm{B}(x, R_{x,m})$ contains m points, the probability that x belongs to T_Y is equal to $1 - \delta$, where

$$\delta = (1-\gamma)^m \leq \frac{\Pr(\mathcal{E})}{e^{2p}}.$$

Moreover, since for every distinct x and y in S, the balls $\mathrm{B}(x, R_{x,m})$ and $\mathrm{B}(y, R_{y,m})$ are disjoint, the events $x \in T_Y$ and $y \in T_Y$ are independent.

Let $\mathcal{E}'$ be the event "*Y embeds into ℓ_p with distortion D and T_Y is not empty*". Then $\Pr(\mathcal{E}') \geq \Pr(\mathcal{E}) - \Pr(T_Y = \varnothing) > 4\Pr(\mathcal{E})/5$. Let $\tilde{Y}$ be a random set distributed according to $\mathcal{D}_\gamma$ conditional on the event $\mathcal{E}'$; denote the random set $T_{\tilde{Y}}$ by $\tilde{T}$.

Fix now a subset Y of X that embeds into ℓ_p with distortion D. Consider the embedding $\nu_Y : T_Y \hookrightarrow \ell_p$ that maps each x in T_Y to the closest point y in Y and then embeds Y into ℓ_p (using a non-contracting embedding). Notice that ν_Y satisfies properties A and B. Below we describe an algorithm that *extends* ν_Y to the set S: for every nonempty set T and every point x in S it returns a point $q_T(x)$ in T. We show that the mapping of x to the random variable $\nu_{\tilde{Y}}(q_{\tilde{T}}(x))$ is an embedding of S into ℓ_p satisfying properties A and B.

Input: a nonempty set T;
Output: mapping $q_T : S \to T$;

1. Enumerate all points in S with numbers 1 to k:
   - Pick an arbitrary starting point x_1 in S;
   - For all $i < k$, let x_{i+1} be the closest point to x_i in the set $S \setminus \{x_1, \ldots, x_i\}$.

   Remark: the ordering of points $x_1, \ldots, x_k$ does not depend on the set T.

2. Consider the following *random walk*: x_i goes to x_{i+1} unless there is a point y_i in T at distance less than $d(x_i, x_{i+1})$, in which case x_i goes to y_i. More precisely, at every step, x_i goes to

   $$N(x_i) = \begin{cases} y_i, & \text{if } d(x_i, y_i) \leq d(x_i, x_{i+1}); \\ x_{i+1}, & \text{otherwise}; \end{cases}$$

   where y_i is the closest point to x_i in T. Note that $N(x_k) = y_k$. Continue to move x_i till it hits the set T:

   $$x_i \mapsto x_{i+1} \mapsto \cdots \mapsto x_{i+t} \mapsto y_{i+t} \in T.$$

   Denote the number of steps needed to reach T by t_i:

   $$t_i = \min\left\{t : N^t(x_i) \in T\right\};$$

and let $q_T(x_i)$ be the last point of the random walk:

$$q_T(x_i) = N^{t_i}(x_i).$$

3. Return the mapping q_T.

Notice that the algorithm does not move elements of the set T. If $i < j$ then

$$d(N(x_i), x_j) \le d(x_i, N(x_i)) + d(x_i, x_j) \le 2d(x_i, x_j);$$

and if $x_i \in T$ then similarly $d(x_i, N(x_j)) \le 2d(x_i, x_j)$. Hence

$$d(q_T(x_i), q_T(x_j)) \le 2^{t_i + t_j} d(x, y).$$

Estimate the probability of the event $t_i \ge t$ (for a random Y). If $t_i \ge t$ then $x_i, \dots, x_{i+t-1}$ do not belong to T_Y. Hence, this probability is at most δ^t and the probability that $t_i + t_j \ge t$ is at most $2\delta^{\lceil t/2 \rceil}$. We have for positive t,

$$\Pr\left(t_i + t_j \ge t \mid \mathcal{E}'\right) = \frac{2\delta^{\lceil t/2 \rceil}}{\Pr\left(\mathcal{E}'\right)} \le \frac{5}{2} e^{-pt};$$

and

$$\Pr\left(q_{\tilde{T}}(x) = x \text{ and } q_{\tilde{T}}(y) = y\right) = \Pr\left(t_i + t_j = 0 \mid \mathcal{E}'\right) \ge 1 - \frac{5}{2e} = \Omega(1).$$

Therefore,

$$\begin{aligned}
\|\nu_{\tilde{Y}}(q_{\tilde{T}}(x)) - \nu_{\tilde{Y}}(q_{\tilde{T}}(y))\|_p &= \mathbb{E}\left[\|\nu_Y(q_{T_Y}(x)) - \nu_Y(q_{T_Y}(y))\|_p^p \mid \mathcal{E}'\right]^{1/p} \\
&\le O(D\, d(x, y)) \times \left(1 + \sum_{t=1}^{\infty} 2^{tp} \Pr\left(t_i + t_j \ge t \mid \mathcal{E}'\right)\right)^{1/p} \\
&\le O(D\, d(x, y)).
\end{aligned}$$

and

$$\begin{aligned}
\|\nu_{\tilde{Y}}(q_{\tilde{T}}(x)) - \nu_{\tilde{Y}}(q_{\tilde{T}}(y))\|_p &= \mathbb{E}\left[\|\nu_Y(q_{T_Y}(x)) - \nu_Y(q_{T_Y}(y))\|_p^p \mid \mathcal{E}'\right]^{1/p} \\
&\ge \Omega(1) \times (d(x, y) - R_{x,m} - R_{y,m}) \Pr\left(q_{\tilde{T}}(x) = x \text{ and } q_{\tilde{T}}(y) = y\right) \\
&\ge \Omega(1) \times (d(x, y) - R_{x,m} - R_{y,m}).
\end{aligned}$$

$\square$

The following theorem is an easy corollary of the lemma we proved.

Theorem 2.12. *Let (X, d) be a metric space of size n. Suppose that an α fraction of all subsets of size k embeds into ℓ_p with distortion at most D. Then entire space (X, d) embeds into ℓ_p with distortion at most*

$$D \cdot O(\log(n/k) + \log\log(1/\alpha) + \log p).$$

Proof. Let $\gamma = k/(2n)$. Then a random set Y distributed as $\mathcal{D}_\gamma$ contains at most k elements with probability at least half. Therefore, Y embeds into ℓ_p with distortion D with probability at least $\alpha/2$. $\square$

Remark 2.13. *In the bound above, one can replace* $\log p$ *with* $\log D$. *The proof of the new bound is similar to the previous one.*

3 Lower Bound Constructions

3.1 Embedding Sparse Graphs into ℓ_1

Now we present our lower bounds. We will construct metric spaces that embed locally into ℓ_1 with small distortion, but whose global distortion is large. In this section, we prove that every sparse graph with high girth equipped with an appropriate metric embeds into ℓ_1 with very small distortion. Later we will use this to show that the metric spaces we construct locally embed into ℓ_1 with small distortion.

Definition 3.1. *A graph G is α-sparse, if every subgraph on k vertices contains at most αk edges.*

To embed a sparse graph, we will decompose it to several pieces, embed them separately, and then combine the embeddings. We will need the following definition, which was implicitly introduced in [2].

Definition 3.2. *We say that a graph G is l-path decomposable if every 2-connected subgraph H of G contains a path of length l such that every vertex of the path has degree 2 in H.*

Every l-path decomposable graph is either
1. an edge; or
2. the union of (more than one) connected components, each of which is also l-path decomposable; or
3. a one vertex union of l-path decomposable (proper) subgraphs; or
4. the union of an l-path decomposable subgraph and a path of length l (that do not have common vertices except for the endpoints of the path).

Arora, Bollobás, Lovász, and Tourlakis [2] proved that every $1+\eta$ sparse graph with girth $\Omega(1/\eta)$ is $\Omega(1/\eta)$-path decomposable.

Theorem 3.3. *Suppose $G = (V, E)$ is an l-path decomposable graph. Let $d(\cdot,\cdot)$ be the shortest path distance on G, and $L = \lfloor l/9 \rfloor$; $\mu \in [1/L, 1]$. Then there exists a distribution on multicuts of G (i.e. partitions into two or more disjoint pieces) such that the following properties hold.*
1. The probability that two points u and v are separated by the multicut equals

$$\rho(u,v) = \rho_\mu(u,v) = 1 - (1-\mu)^{d(u,v)},$$

if $d(u,v) \le L$; and this probability is at least $1-(1-\mu)^L$ if $d(u,v) > L$.
2. Every piece of the multicut partition is a tree.

Proof idea. Each multicut is a subset S of edges (i.e. the edges removed to obtain the partition): the multicut S separates two vertices if every path between them intersects S. We will ensure that every edge belongs to S with probability μ. Additionally, if the distance between two edges e_1, e_2 is less than L, the events that $e_1 \in S$, and $e_2 \in S$ will be independent. We will also ensure that if there is more than one simple path between u and v, all but one path will be cut with probability 1. Our proof will be by induction: using the path-decomposability of G, we will reduce the problem to smaller subproblems. In order to argue about paths of length l which we will encounter during the decomposition we need the following lemma.

Lemma 3.4. *Suppose a graph H is a path of length at least $3L$. Then there exists a distribution of multicuts S of H that satisfies the condition of the theorem. Moreover, the endpoints of the path are separated with probability* 1.

Proof. Let us subdivide the path into three paths P_1, P_2, and P_3, each of length at least L. We now add every edge to S with probability μ. However, our decisions are not independent, and we add edges so that: all decisions for P_1 and P_2 are independent; all decisions for P_2 and P_3 are independent; we add to S at least one edge either from P_1 or from P_3. This coupling is possible since the probability that we do not add any edge from P_1 plus the probability that we do not add any edge from P_3 is at most $(1-\mu)^L + (1-\mu)^L \leq 2/e < 1$.

First assume that both vertices u and v lie in the same path P_i or they lie in the neighboring paths P_i and P_{i+1}. Then all our choices for the edges between u and v are independent. Therefore, the probability that S separates u and v is $1-(1-\mu)^{d(u,v)} = \rho(u,v)$. Hence S satisfies condition 1 in this case. Now assume that u lies in P_1 and v lies in P_3 (or vice versa). Then $d(u,v) > L$. If S contains an edge from P_2 then u and v are separated, so

$$\Pr(u \text{ and } v \text{ are separated}) \geq \Pr\left(S \cap E(P_2) \neq \varnothing\right) = 1-(1-\mu)^{|E(P_2)|} \geq 1-(1-\mu)^L.$$

Finally, since S contains either an edge from P_1 or from P_3, the endpoints of H are always separated. □

Proof of Theorem 3.3. We prove by induction that there exists the required distribution on multicuts $S \subset E$. We first verify the base case. If G consists of two vertices connected by an edge then let S contain this edge with probability μ. Otherwise, G is decomposable into the union of smaller l-path connected subgraphs. Consider three cases. 1. The graph G is the union of connected components C_i. Since each C_i has less vertices than G, by the induction hypothesis, there exists a probability distribution on multicuts S_i in each C_i. Let $S = \cup_i S_i$, where all S_i are drawn independently. Then if u and v lie in the same connected component C_i then $\Pr(S \text{ separates } u \text{ and } v) = \Pr(S_i \text{ separates } u \text{ and } v)$; if u and v lie in distinct connected components $\Pr(S \text{ separates } u \text{ and } v) = 1 \geq 1-(1-\mu)^L$ whereas $d(u,v) = \infty > L$.
2. The graph G has a cut vertex c. Represent G as the union of subgraphs C_i that have only one common vertex c. Construct a distribution of multicuts S_i for each C_i. Let $S = \cup_i S_i$, where all S_i are drawn independently. Assume first that u and v lie in the same subgraph

C_i. Then every simple path between them lies entirely in C_i. Therefore, S separates u and v if and only if S_i separates them. Therefore, by the induction hypothesis, the probability that the multicut S separates u and v satisfies condition 1. Now assume that u and v lie in distinct subgraphs: $u \in C_i$, $v \in C_j$. Then each path between u and v must visit c. We have

$$\begin{aligned}\Pr(S \text{ separates } u \text{ and } v) &= \Pr(S \text{ separates } u \text{ and } c \text{ or } S \text{ separates } c \text{ and } v)\\ &= 1-(1-\Pr(S \text{ separates } u \text{ and } c))(1-\Pr(S \text{ separates } c \text{ and } v))\\ &= 1-(1-\Pr(S_i \text{ separates } u \text{ and } c))(1-\Pr(S_j \text{ separates } c \text{ and } v)).\end{aligned}$$

Now if $d(u,c) \leq L$ and $d(v,c) \leq L$, then

$$\begin{aligned}\Pr(S \text{ separates } u \text{ and } v) &= 1-(1-\rho(u,c))(1-\rho(c,v))\\ &= 1-(1-\mu)^{d(u,c)}(1-\mu)^{d(c,v)} = 1-(1-\mu)^{d(u,c)+d(c,v)} = \rho(u,v).\end{aligned}$$

Here we used that $d(u,v) = d(u,c) + d(c,v)$. Now consider the case when either $d(u,c) \geq L$ or $d(v,c) \geq L$. Assume without loss of generality $d(u,c) \geq L$. Note that $d(u,v) = d(u,c) + d(c,v) > L$. Hence we have to show that u are v are separated with probability at least $1-(1-\mu)^L$. Indeed,

$$\begin{aligned}\Pr(S \text{ separates } u \text{ and } v) &= 1-(1-\Pr(S_i \text{ separates } u \text{ and } c))(1-\Pr(S_j \text{ separates } c \text{ and } v))\\ &\geq 1-(1-\Pr(S_i \text{ separates } u \text{ and } c))\cdot 1\\ &= \Pr(S_i \text{ separates } u \text{ and } v) \geq 1-(1-\mu)^L.\end{aligned}$$

Finally, since each piece of every multicut partition S_i is a tree, every piece of S is also a tree.

3. Finally, assume that G is the union of a subgraph H and a path P of length l. Denote the endpoints of the path by x and y. Let S_H be a distribution on multicuts in H that satisfies condition 1. Subdivide P into three pieces A_1, A_2 and A_3, each of length at least $3L$. Let S_i be the multicut whose existence is guaranteed by Lemma 3.4 for the path A_i (we choose multicuts S_H, S_1, S_2, S_3 independently). Let $S = S_H \cup S_1 \cup S_2 \cup S_3$. Consider two vertices u and v. Note that either both of them lie in $H \cup A_1 \cup A_2$, or in $H \cup A_2 \cup A_3$, or in $H \cup A_1 \cup A_3$ (of course, these possibilities are not mutually exclusive). First, assume that u and v lie in $H \cup A_1 \cup A_2$. Since A_3 is always cut by S, the multicut S separates u and v in G if and only if the multicut $S_H \cup S_1 \cup S_2$ separates them in $H \cup A_1 \cup A_2$. Additionally, if $d_G(u,v) \leq L$ then $d_{H\cup A_1 \cup A_2}(u,v) = d_G(u,v)$, and if $d_G(u,v) > L$ then $d_{H\cup A_1\cup A_2}(u,v) > L$. Therefore, it suffices to verify that condition 1 holds for $H \cup A_1 \cup A_2$. Indeed, the graph $H \cup A_1 \cup A_2$ is a one vertex union of graphs H and $A_1 \cup A_2$; in turn, the graph $A_1 \cup A_2$ is a one vertex union of graphs A_1 and A_2. We already proved that a one vertex union of graphs satisfying condition 1 satisfies condition 1. Therefore, the multicut $S_H \cup S_1 \cup S_2$ of the graph $H \cup A_1 \cup A_2$ satisfies condition 1. Similarly, condition 1 holds when u and v lie in $H \cup A_2 \cup A_3$, or u and v lie in $H \cup A_1 \cup A_3$.

Finally, we know that every cycle in H is cut by the multicut (by the induction hypothesis) and the path P is cut by the multicut. Therefore, every piece of the constructed multicut partition is a tree. □

Corollary 3.5. *Let $G = (V, E)$, L, μ and ρ be as in Theorem 3.3. Then the metric space (V, ρ) embeds into ℓ_1 with distortion $1+O(e^{-\mu L})$. Moreover, if $d(u, v) \le L$ then the embedding preserves the distance between u and v; if $d(u, v) > L$ then the distance between images of u and v lies between $1 - (1 - \mu)^L$ and 1.*

Proof. The distribution of multicuts from Theorem 3.3 defines the desired embedding: the distance between images of u and v equals the probability that the multicut separates u and v. If $d(u, v) \le L$ then the distance between u and v is preserved by the embedding. If $d(u, v) > L$ then the distance between u and v in the cut metric lies between $1 - (1 - \mu)^L$ and 1. Hence the distortion is at most

$$\frac{1}{1 - (1 - \mu)^L} = 1 + O(e^{-\mu L}).$$

□

3.2 Lower Bound for Non-Isometric Case

In this section, we construct a metric space that locally embeds into ℓ_1 almost isometrically, but the minimum distortion with which the entire space embeds into ℓ_1 is high. The metric space will be based on a 3-regular expander graph whose k vertex subgraphs are sparse. The underlying expander graph was used by Arora, Lovász, Newman, Rabani, Rabinovich, and Vempala [4] in their construction of such metric space. However, we equip this graph with a different metric.

We need the following lemma that was proved by Arora, Bollobás, Lovász, and Tourlakis [2].

Lemma 3.6 ([2], Lemma 2.8, Lemma 2.12; see also [4], Lemma 3.3)**.** *There exists a 3-regular expander graph on n vertices with girth $\Omega(\log n)$ such that every subset of k points has sparsity $1 + O(\frac{1}{\log(n/k)})$. Therefore, this expander is $\Omega(\log(n/k))$-path decomposable.*

We are ready to prove the following theorem.

Theorem 3.7.
I. For every n, $k < n$ and $\delta \in (0, 1/2]$, there exists a metric space (X, ρ) on n points such that

- *every embedding of (X, ρ) into ℓ_1 requires distortion $\Omega\left(\frac{\log(n/k)}{\log 1/\delta}\right)$;*
- *every subset of X of size k embeds into ℓ_1 with distortion $1 + \delta$.*

Moreover, the aspect ratio of X (i.e. the ratio between the diameter of X and the minimal distance between two points) is $O(\log(n/k))$.
II. For every n, $k < n$ and $D \in (1, \frac{\log n}{\log(n/k)})$, there exists a metric space (X, ρ) on n points such that

- *every embedding of (X, ρ) into ℓ_1 requires distortion $\Omega(D \log(n/k))$;*

- *every subset of X of size k embeds into ℓ_1 with distortion $O(D)$.*

Proof.
I. Let G be the expander from Lemma 3.6. Denote the set of its vertices by X. We know that every subgraph of G on $k \cdot 3 \cdot 2^l$ vertices (for every l) is $\Omega(\log(n/(k \cdot 3 \cdot 2^l)))$-path decomposable. Choose $l = \Theta(\log(n/k))$ so that every subgraph on $k \cdot 3 \cdot 2^l$ vertices is l-path decomposable. Let $\mu = c \log(1/\delta)/l$, where c is a sufficiently large constant.

Let us equip X with the metric ρ defined as

$$\rho(u, v) = \rho_\mu(u, v) = 1 - (1 - \mu)^{d(u,v)},$$

where $d(u, v)$ is the shortest path distance between u and v in G. We will now prove that every subset of X of size k embeds into ℓ_1 with distortion at most $1 + \delta$. Let Y be a subset of X of size k. Consider the set of vertices $B_d(Y, l)$ whose distance to Y is at most l: $B_d(Y, l) = \{x : d(x, Y) \le l\}$. Let H be the graph induced by $B_d(Y, l)$ on G. Since degree of each vertex in G is at most 3, the size of $B_d(Y, l)$ is at most $k \cdot 3 \cdot 2^l$. Therefore, H is l-path decomposable. By Corollary 3.5, there exists an embedding $\psi : B_d(Y, l) \to \ell_1$ such that for every $u, v \in B_d(Y, l)$ (for $L = \lfloor l/9 \rfloor$):

1. if $d_H(u, v) \le L$ then $\|\psi(u) - \psi(v)\|_1 = 1 - (1 - \mu)^{d(u,v)}$;
2. if $d_H(u, v) > L$ then $1 \ge \|\psi(u) - \psi(v)\|_1 \ge 1 - (1 - \mu)^L$.

Note that since H is a subgraph of G, the shortest path distance between two vertices in H, $d_H(u, v)$, is at least the shortest path distance between them in G, $d_G(u, v) \equiv d(u, v)$. However, if $u, v \in Y$, and $d_G(u, v) \le l$ then the shortest path between them lies in H. Hence $d_H(u, v) = d_G(u, v)$. Therefore, for $u, v \in Y$, if $d_G(u, v) \le L$ then $\|\psi(u) - \psi(v)\|_1 = \rho(u, v)$; if $d_G(u, v) > L$ then $1 \ge \|\psi(u) - \psi(v)\|_1 \ge 1 - (1 - \mu)^L$. Hence the distortion of the embedding $\psi : (Y, \rho) \hookrightarrow \ell_1$ is at most $1 + O(e^{-\mu L}) = 1 + O(e^{-c/9 \cdot \log(1/\delta)}) < 1 + \delta$ (if we choose c sufficiently large).

As was shown by Linial, London and Rabinovich [15] and Aumann and Rabani [6], the distortion with which a bounded degree expander graph is embeddable into ℓ_1 is at least (up to a constant factor) the ratio of the average distance between all vertices in the graph to the average length of an edge:

$$\frac{2}{n(n-1)} \sum_{u,v \in V(G)} \rho(u, v) \Bigg/ \frac{1}{|E(G)|} \sum_{(u,v) \in E(G)} \rho(u, v) .$$

Therefore, the least distortion with which (X, ρ) embed into ℓ_1 is

$$\frac{\Omega(1)}{(1 - (1 - \mu))} = \Omega\left(\frac{\log(n/k)}{\log(1/\delta)}\right). \tag{4}$$

Finally, the diameter of X is at most 1; the minimal distance between two points is μ. Hence the aspect ratio is $O(\log(n/k))$.

II. Consider the metric space $(X, \rho \equiv \rho_\mu)$ constructed in part I for $\delta = 1/2$. Recall that $\mu = \Theta(1/\log(n/k))$.

Let us equip X with a new distance function $\rho_{\mu/D}(u,v) = 1-(1-\mu/D)^{d(u,v)}$ (where $d(u,v)$ is the shortest path metric in the underlying expander). Note that since

$$\frac{1}{D}\left(1-(1-\mu)^{d(u,v)}\right) \leq 1-(1-\mu/D)^{d(u,v)} \leq 1-(1-\mu)^{d(u,v)},$$

and every k point subspace of (X,ρ_μ) embeds into ℓ_1 with a constant distortion, then every k point subspace of $(X,\rho_{\mu/D})$ embeds into ℓ_1 with distortion at most $O(D)$. On the other hand, the entire space $(X,\rho_{\mu/D})$ embeds into ℓ_1 with distortion at least (similarly to (4))

$$\frac{\Omega(1)}{(1-(1-\mu/D))} = \Omega\left(D\log\frac{n}{k}\right).$$

(The average distance in X with respect to $\rho_{\mu/D}$ is a constant, since if $d(u,v)=\Omega(\log n)$ then $\rho_{\mu/D}(u,v) = 1-e^{-\Omega(\mu\log n/D)}$. Recall that $D < \log n/\log(n/k)$. Hence $\rho_{\mu/D}(u,v) = \Omega(1)$.) □

3.3 Lower Bound for Isometric Case

In this section, we present a metric space such that every subset of size k isometrically embeds into ℓ_1, whereas every embedding of the entire space into ℓ_1 requires distortion at least $\Omega(\log n/(\log\log n+\log k))$. Our construction will be a perturbation of the metric space we presented in Section 3.2.

Theorem 3.8. *Consider a metric space (X,ρ) on n points. Let $k<n$; let M be the aspect ratio (i.e. the ratio between the diameter of X and the shortest distance). Suppose now that every subspace of (X,ρ) of size k embeds into ℓ_1 with distortion at most $1+1/(2kM)$. Then there exists a 2-Lipschitz equivalent metric $\hat{\rho}$ on X such that every subspace of $(X,\hat{\rho})$ of size k embed isometrically into ℓ_1.*

We need the following definition and lemma.

Definition 3.9. *Let $S(u,v)$ be the metric defined by $S(u,v)=1$, if $u\neq v$; and $S(u,v)=0$, if $u=v$. This metric is often called the discrete metric.*

Lemma 3.10. *Consider a metric space (Y,ρ) on k points. If for every two points u and v from Y:*

$$|\rho(u,v)-S(u,v)| \leq \frac{1}{2k},$$

then (Y,ρ) is isometrically embeddable into ℓ_2.

Proof. We will prove that the matrix

$$G_{uv} = 1-\rho(u,v)^2/2$$

is positive semidefinite and, therefore, there exists a set of unit vectors z_u in ℓ_2 such that

$$\langle z_u, z_v\rangle = 1-\rho(u,v)^2/2.$$

This implies that the mapping $u \mapsto z_u$ is an isometric embedding, since

$$\|z_u - z_v\|_2 = \sqrt{\|z_u\|^2 + \|z_v\|^2 - 2\langle z_u, z_v\rangle} = \rho(u, v).$$

Express the matrix G as the sum of three matrices:

$$G = \frac{1}{2} I + \begin{pmatrix} \frac{1}{2} & \cdots & \frac{1}{2} \\ \vdots & \ddots & \vdots \\ \frac{1}{2} & \cdots & \frac{1}{2} \end{pmatrix} + Q.$$

Observe, that the eigenvalues of the matrix $I/2$ are equal to $1/2$; the second matrix is positive semidefinite. Then $|Q_{uv}| \le 1/(2k) + 1/(8k^2)$ and $Q_{uu} = 0$ for all u and v. Therefore, the eigenvalues of Q are bounded in absolute value by

$$(k-1) \times \left[\frac{1}{2k} + \frac{1}{8k^2}\right] = \frac{4k^2 - 3k - 1}{8k^2} \le \frac{1}{2}.$$

Hence G is positive semidefinite. $\square$

Corollary 3.11. *Consider a metric space (Y, ρ) on k points. If for every two points u and v from Y:*

$$|\rho(u, v) - S(u, v)| \le \frac{1}{2k},$$

then (Y, ρ) is isometrically embeddable into ℓ_2.

Proof. Every finite subset of ℓ_2 is isometrically embeddable into ℓ_1. $\square$

Remark 3.12. *The condition in this corollary cannot be significantly strengthened: there exists a metric space (Y, ρ) such that $|\rho(u, v) - S(u, v)| = O(1/k)$, however, the space (Y, d) is not isometrically embeddable into ℓ_1.*

Proof of Theorem 3.8. Denote the minimal distance between two distinct vertices of X by δ. Define a new metric $\hat{\rho}$ on X as follows:

$$\hat{\rho}(u, v) = \rho(u, v) + \delta S(u, v).$$

First, the metric $\hat{\rho}$ is 2-Lipschitz equivalent to the metric ρ. Indeed, for $u \ne v$ we have $\rho(u, v) \le \hat{\rho}(u, v) = \rho(u, v) + \delta \le 2\rho(u, v)$. Now let Y be a subset of X of size k. By the condition, there is an embedding $\varphi : Y \hookrightarrow \ell_1$ with distortion at most $1 + 1/(2kM)$. Without loss of generality we may assume that

$$\rho(u, v) \le \|\varphi(u) - \varphi(v)\|_1 \le (1 + 1/(2kM))\rho(u, v).$$

Since the distance $\rho(u, v)$ is at most $M\delta$ (by the definition of M), we have

$$0 \le \|\varphi(u) - \varphi(v)\|_1 - \rho(u, v) \le \delta/(2k).$$

This bound and Corollary 3.11 imply that the set Y equipped with the metric

$$(u,v) \mapsto S(u,v) - (\|\varphi(u) - \varphi(v)\|_1 - \rho(u,v))/\delta$$

embeds into ℓ_1 isometrically. Denote the embedding by ψ. We have

$$\begin{aligned}\hat\rho(u,v) &= \|\varphi(u) - \varphi(v)\|_1 + \delta\,(S(u,v) - (\|\varphi(u) - \varphi(v)\|_1 - \rho(u,v))/\delta) \\ &= \|\varphi(u) - \varphi(v)\|_1 + \delta\,\|\psi(u) - \psi(v)\|_1.\end{aligned}$$

Therefore, $\varphi \oplus \delta\psi$ is an isometric embedding of $(Y, \hat\rho)$ into $\ell_1 \oplus \ell_1 \cong \ell_1$. □

Theorem 3.13. *For every n and $k < n$, there exists a metric space (X, ρ) on n points such that*

- *every embedding of (X,ρ) into ℓ_1 requires distortion $\Omega\left(\frac{\log n}{\log k + \log\log n}\right)$;*
- *every subset of X of size k embeds isometrically into ℓ_1.*

Proof. Let $\delta = \frac{c}{k \log n}$ (where c is sufficiently small). By Theorem 3.7, there exists a metric space (X,ρ) such that X embeds into ℓ_1 with distortion at least $\Omega(\frac{\log(n/k)}{\log(1/\delta)}) = \Omega(\frac{\log n}{\log k + \log\log n})$; every subset of X of size k embeds into ℓ_1 with distortion $1+\delta$; the aspect ratio of X is $O(\log n)$. Applying Theorem 3.8 to (X,ρ), we get that there exists a 2-Lipschitz equivalent metric $\hat\rho$ on X such that every subspace of $(X,\hat\rho)$ of size k embeds into ℓ_1 isometrically. Since $(X,\hat\rho)$ is 2-Lipschitz equivalent to (X,ρ), every its embedding into ℓ_1 has distortion at least $\Omega(\frac{\log n}{\log k + \log\log n})$. This concludes the proof. □

3.4 Lower Bounds for Spaces ℓ_p

In this section, we present analogs of the results from Sections 3.2 and 3.3 for spaces ℓ_p.

Notice that if a metric space (X,ρ) embeds isometrically into ℓ_1, then the metric space $(X, \rho^{1/p})$ embeds isometrically into ℓ_p. Therefore, if (X,ρ) embeds into ℓ_1 with distortion D then $(X,\rho^{1/p})$ embeds into ℓ_p with distortion $D^{1/p}$. We can upper bound the (global) distortion of an embedding $(X,\rho^{1/p})$ into ℓ_p using a theorem by Matoušek [17], which states that every embedding of en expander into ℓ_p has distortion $\Omega(1/p \times \frac{\text{average distance}}{\text{length of edge}})$.

This observation allow us to generalize Theorems 3.7 and 3.13 for ℓ_p spaces.

Theorem 3.14.
I. For every n, $k < n$, $p \geq 1$ and $\delta \in (0, 1/2]$, there exists a metric space (X,ρ) on n points such that

- *every embedding of (X,ρ) into ℓ_1 requires distortion $\Omega\left(\frac{\log(n/k)}{\log 1/\delta}\right)^{1/p}$;*
- *every embedding of (X,ρ) into ℓ_p requires distortion $\frac{1}{p} \cdot \Omega\left(\cdot \frac{\log(n/k)}{\log 1/\delta}\right)^{1/p}$;*
- *every subset of X of size k embeds into ℓ_p with distortion $1+\delta$.*

II. For every n, $k < n$, $p \geq 1$, and $D \in (1, \frac{\log n}{\log(n/k)})$, there exists a metric space (X, ρ) on n points such that

- *every embedding of (X, ρ) into ℓ_1 requires distortion $\Omega(D \log \frac{n}{k})^{1/p}$;*
- *every embedding of (X, ρ) into ℓ_p requires distortion $\frac{1}{p} \cdot \Omega(D \log \frac{n}{k})^{1/p}$;*
- *every subset of X of size k embeds into ℓ_p with distortion $O(D)$.*

III. For every n, $k < n$ and $p \geq 1$, there exists a metric space (X, ρ) on n points such that

- *every embedding of (X, ρ) into ℓ_1 requires distortion $\Omega\left(\frac{\log n}{\log k + \log\log n}\right)^{1/p}$;*
- *every embedding of (X, ρ) into ℓ_p requires distortion $\frac{1}{p} \cdot \Omega\left(\frac{\log n}{\log k + \log\log n}\right)^{1/p}$;*
- *every subset of X of size k embeds isometrically into ℓ_p.*

We can also obtain a result with a better global distortion guarantee but with a local distortion $\Omega(\log\log n)^{\min(1/2, 1/p)}$.

Theorem 3.15. *For every n, $k < n$, there exists a metric space (X, ρ) on n points such that for every $p \geq 1$*

- *every embedding of (X, ρ) into ℓ_1 (and, therefore, into ℓ_p) requires distortion $\Omega(\log(n/k))$;*
- *every subset of X of size k embeds into ℓ_p with distortion $O(\log\log(n/k))^{\min(1/2,1/p)}$.*

Proof idea. We claim that the expander graph from Section 3.2 equipped with the shortest distance metric truncated at level $\log(n/k)$ satisfies the desired properties. It is immediate that it requires distortion at least $\log(n/k)$ for embedding into ℓ_1.

We show that every k points embed into ℓ_1 with distortion $(\log\log(n/k))^{\min(1/2,1/p)}$. Our proof relies on ideas from papers of Bourgain [8] and Matoušek [18] that study low distortion tree embeddings. We omit the details from this extended abstract.

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