

1. (25 points) **Familiarity with Euclidean Norms.** In the following exercise, you will familiarize yourself with Euclidean metrics. For any  $n$  points  $X = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$  where each  $\mathbf{x}_i \in \mathbb{R}^d$ , define  $d(\mathbf{x}_i, \mathbf{x}_j) = \|\mathbf{x}_i - \mathbf{x}_j\|_p$ . Here,  $\|\mathbf{x}\|_p = \left(\sum_{\ell=1}^d (x_\ell)^p\right)^{1/p}$  for any  $\mathbf{x} = (x_1, x_2, \dots, x_d)^\top$  is any vector in  $\mathbb{R}^d$  and  $p \geq 1$ .

- (a) (5 points) Show that  $(X, d)$  is a metric space for any  $p = 1$  and  $p = 2$ . In fact, it is a metric space for all  $p \geq 1$ , but you don't need to prove this.

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

- (b) (5 points) Consider the 4-point metric space formed by  $d(1, 2) = 1, d(1, 3) = 2, d(1, 4) = 1, d(2, 3) = 1, d(2, 4) = 2, d(3, 4) = 1$ . Of course,  $d(i, i) = 0$  and  $d(i, j) = d(j, i)$  for all  $i, j \in \{1, 2, 3, 4\}$  hold. Does this embed into  $\ell_1$  metrics? If so, how many dimensions do you need in your embedding?

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

- (c) (10 points) Consider the same 4-point metric space as above. Does this embed into  $\ell_2$  metrics? If so, how many dimensions do you need in your embedding? Conclude that  $\ell_1$  metrics do not embed isometrically into  $\ell_2$  metrics.

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

- (d) (5 points) For any vector  $\mathbf{x}$ , show that  $\|\mathbf{x}\|_2 \leq \|\mathbf{x}\|_1 \leq \sqrt{n} \|\mathbf{x}\|_2$ . Using this, show that any finite  $\ell_1$  metric trivially embeds into an  $\ell_2$  metric with distortion at most  $\sqrt{n}$ .

2. (20 points) **Finding the Best Embeddings.** Here, we see algorithmic problems involving embeddings. Indeed, given a metric  $(X, d)$ , we want to see the best possible embedding into  $\ell_2$  metrics with minimum distortion. Show that this can be formulated as an SDP.

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

3. (30 points) **Cut Metrics and  $\ell_1$  metrics.** Recall that given a graph  $G = (V, E)$ , a cut metric  $\delta_S(\cdot, \cdot)$  is defined for  $S \subseteq V$ , and is of the form  $\delta_S(u, v) = 1$  if and only if

$S \cap \{u, v\} = 1$ , and  $\delta_S(u, v) = 0$  otherwise. Also recall that an  $\ell_1$  metric associates a vector  $f(u) \in \mathbb{R}^d$  for all  $u \in V$ .

- (a) (10 points) Suppose the  $\ell_1$  metric is in 1 dimension, i.e., it is a line. Then show that you can obtain weights  $w_S \geq 0$  for all  $S \subseteq V$  such that, for all  $u \in V, v \in V$ , the distance  $\|f(u) - f(v)\|_1$  can be expressed as  $\sum_{S \subseteq V} w_S \delta_S(u, v)$ . (Hint: consider the line embedding and assign non-zero weights only to the subsets which arise as prefixes on this line.)

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

- (b) (5 points) Extend the above proof for an  $\ell_1$  embedding  $f$  in dimension  $d$  (Hint: just separately do this over all the co-ordinates).

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

- (c) (15 points) Using the above idea, show that if we have an  $\ell_1$  metric  $d(\cdot, \cdot)$  which has sparsity<sup>1</sup>  $\frac{\sum_{(u,v) \in E} d(u,v)}{\sum_{u \in V, v \in V} d(u,v)} = \lambda$ , then we can actually find a cut  $(S, \bar{S})$  such that  $\frac{|E(S, \bar{S})|}{|S||\bar{S}|} \leq \lambda$ . This completes the  $O(\log n)$  approximation to sparsest cut using metric embeddings discussed in class.

4. (0 points) **Difficulty Level.** How difficult was this homework? How much time would you have spent on these questions?

**Solution:**

*Proof.*  $1 + 1 = 2$ . □

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<sup>1</sup>Here the denominator sums over all pairs  $(u, v)$  without double counting any pair. In other words, we are summing over all the edges of the complete graph  $K_n$ .