CS265, Winter 2021-2022

Class 7: Agenda, Questions, and Links

1 Announcements

- HW4 is out, due next Wednesday.
- Solutions for HW2 are posted (or will be posted very soon).

2 Lecture Recap and Questions?

Any questions from the mini-lectures or pre-class-quiz? (Metric Embeddings; Bourgain's Embedding)

3 Warm-Up

Group Work

Let G = (V, E) be a weighted, undirected graph, on *n* vertices with edge weights w_{uv} on the edge $\{u, v\} \in E$. Let $d: V \times V \to \mathbb{R}$ be the associated graph metric.

Explain how to efficiently find and apply a map $f: V \to \mathbb{R}^k$, for $k = O(\log^2 n)$, so that

$$\frac{\sum_{\{u,v\}\in E} \|f(u) - f(v)\|_1}{\sum_{\{u,v\}\in \binom{V}{2}} \|f(u) - f(v)\|_1} \le O(\log n) \frac{\sum_{\{u,v\}\in E} d(u,v)}{\sum_{\{u,v\}\in \binom{V}{2}} d(u,v)}$$

holds with high probability. Above, $\binom{V}{2}$ refers to the set of all unordered pairs $\{u, v\}$ for $u, v \in V$ and $u \neq v$.

4 Minimum Cuts

[Will present on the whiteboards, summary is below]

For a graph G = (V, E), define

$$\phi(G,S) = \frac{|E(S,S)|}{|S||\bar{S}|},$$

and

$$\phi(G) = \min_{S \subset V, S \neq \emptyset, V} \phi(G, S),$$

where above $\overline{S} := V \setminus S$ denotes the complement of S, and $E(S, \overline{S})$ denotes the set of edges that have one endpoint in S and one endpoint in \overline{S} .

Intuitively, if $\phi(G, S)$ is small, then S is pretty "disconnected" from \overline{S} . Notice that the denominator, $|S||\overline{S}|$, is the number of edges that would be between S and \overline{S} in the complete graph, so $\phi(G, S)$ is the fraction of possible edges between S and \overline{S} that actually exist in G.

Finding S to minimize $\phi(G, S)$ is useful, for example, in clustering applications. However, it's also NP-hard. Today we'll see a randomized algorithm to find an S so that $\phi(G, S)$ is *approximately* minimized. More precisely, we'll find S so that $\phi(S, G) \leq O(\log n)\phi(G)$.

Question: How is this definition of $\phi(G)$ different/better than simply asking for the sparsest cut? (Recall we saw a randomized algorithm for the sparsest cut back in Week 1...)

4.1 Connection to metrics

Group Work

In this group work, you will show that

$$\phi(G) = \min_{f} \frac{\sum_{\{u,v\} \in E} \|f(u) - f(v)\|_{1}}{\sum_{\{u,v\} \in \binom{V}{2}} \|f(u) - f(v)\|_{1}},\tag{1}$$

where the minimum is over all functions $f: V \to \mathbb{R}^k$ for some k, so that f takes on at least two distinct values. (This last bit is needed so that the denominator doesn't vanish).

1. Show that

$$\phi(G) = \min_{f:V \to \{0,1\}} \frac{\sum_{\{u,v\} \in E} |f(u) - f(v)|}{\sum_{\{u,v\} \in \binom{V}{2}} |f(u) - f(v)|},$$

where the minimum is over all functions $f: V \to \{0, 1\}$ so that f takes on both values 0 and 1. (The difference between this and the expression above is that f maps to $\{0, 1\}$ instead of \mathbb{R}^k for some k).

Hint: Consider mapping functions f to sets S by the relationship $S = \{u : f(u) = 1\}$.

2. Think about why the above extends to show that

$$\phi(G) = \inf_{f:V \to \mathbb{R}} \frac{\sum_{\{u,v\} \in E} |f(u) - f(v)|}{\sum_{\{u,v\} \in \binom{V}{2}} |f(u) - f(v)|},$$

where now the minimum is over $f: V \to \mathbb{R}$ instead of $f: V \to \{0, 1\}$.

(Don't worry about a formal proof here, just kind of convince yourself intuitively that this is true).

Hint: Using part (a), it suffices to show that the infimum over all $f : V \to \mathbb{R}$ is actually attained by some f that maps vertices in V to $\{0,1\}$. To see this, consider the following steps:

• Suppose that $f: V \to \mathbb{R}$ takes on three distinct values, a < b < c. Consider a new function $f_x: V \to \mathbb{R}$, so that $f_x(u) = x$ if f(u) = b, and $f_x(u) = f(u)$ otherwise. That is, $f_x(u)$ just replaces the value b with x. Show that either

$$R(f_a) \le R(f)$$
 or $R(f_c) \le R(f)$,

where

$$R(f) = \frac{\sum_{\{u,v\}\in E} |f(u) - f(v)|}{\sum_{\{u,v\}\in \binom{V}{2}} |f(u) - f(v)|}.$$

(That is, by sliding the middle value b towards either a or c, you can decrease this quantity.)

Sub-hint: when you vary $x \in [a, c]$, you can get rid of the absolute values in $R(f_x)$. Looking at a small example might be helpful.

- Argue that the above logic implies that there's an f that attains the infemum that takes on only two values.
- Argue that those two values may as well be 0 and 1.
- 3. Think about why the above extends to show that

$$\phi(G) = \min_{f: V \to \mathbb{R}^k} \frac{\sum_{\{u,v\} \in E} \|f(u) - f(v)\|_1}{\sum_{\{u,v\} \in \binom{V}{2}} \|f(u) - f(v)\|_1},$$

where the minimum is over all functions $f: V \to \mathbb{R}^k$ for any k. *Hint*: You may want to use the inequality that $\frac{\sum_i a_i}{\sum_i b_i} \ge \min_i \frac{a_i}{b_i}$ for $a_i, b_i > 0$.

4.2 A randomized algorithm

Group Work

1. First, all quietly read the following: Based on the result that we got in the first group work, we might think of the following approach:

Find $f: V \to \mathbb{R}^k$ to minimize

$$R(f) := \frac{\sum_{\{u,v\} \in E} \|f(u) - f(v)\|_1}{\sum_{\{u,v\} \in \binom{V}{2}} \|f(u) - f(v)\|_1}$$

Unfortunately, this doesn't turn out to be an easy optimization problem to solve. Instead, we'll consider the optimization problem:

Find values $d_{u,v} \in \mathbb{R}$ for all $u \neq v \in V$ to minimize

$$Q(d) := \sum_{\{u,v\}\in E} d_{u,v}$$

subject to:

- $d_{u,v} = d_{v,u} \ge 0$ for all u, v
- $d_{u,v} + d_{v,w} \ge d_{u,w}$ for all u, v, w
- $\sum_{\{u,v\}\in\binom{V}{2}} d_{u,v} = 1$

It turns out that this problem *can* be solved efficiently, using linear programming. (If you don't know what that is, it's okay, all that matters now is that we can find \vec{d} to minimize this efficiently).

- 2. Suppose that d^* is the minimizer of the problem above. Explain why $Q(d^*) \leq \phi(G)$.
- 3. Find a randomized algorithm to approximate $\phi(G)$. More precisely, give a randomized algorithm that finds $f: V \to \mathbb{R}^k$ so that, with high probability,

$$\frac{\sum_{\{u,v\}\in E} \|f(u) - f(v)\|_1}{\sum_{\{u,v\}\in \binom{V}{2}} \|f(u) - f(v)\|_1} \le O(\log n)\phi(G).$$

Hint: Your warm-up exercise might be relevant.

Hint: If it comes up, you may assume that Bourgain's embedding works just fine on pseudo-metrics, which are functions d(u, v) that obey all of the axioms of metrics except that maybe d(u, v) = 0 for $u \neq v$.

4. Given f as in the previous part, explain how to efficiently find a set $S \subset V$ so that

 $\phi(G, S) \le O(\log n)\phi(G).$

Hint: Our proof in the first group-work was somewhat algorithmic...