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How to Play Unique Games on Expanders

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Abstract

In this note we improve a recent result by Arora, Khot, Kolla, Steurer, Tulsiani, and Vishnoi on solving the Unique Games problem on expanders.

Given a $(1-\varepsilon)$-satisfiable instance of Unique Games with the constraint graph G, our algorithm finds an assignments satisfying at least a $1 - C\varepsilon/h_G$ fraction of all constraints if $\varepsilon < c\lambda_G$ where h_G is the edge expansion of G, λ_G is the second smallest eigenvalue of the Laplacian of G, and C and c are some absolute constants.

We refer the reader to [1, 2, 3, 4, 7] for the motivation and an overview of related work.

1 Preliminaries: Expanders, Unique Games and SDP

1.1 Unique Games and Expanders

In this note we study the Unique Games problem on regular expanders.

Definition 1.1 (Unique Games Problem). *Given a constraint graph $G = (V, E)$ and a set of permutations π_{uv} on the set $[k] = \{1, \ldots, k\}$ (for all edges (u, v)), the goal is to assign a value (state) x_u from $[k]$ to each vertex u so as to satisfy the maximum number of constraints of the form $\pi_{uv}(x_u) = x_v$. The cost of a solution is the fraction of satisfied constraints.*

We assume that the underlying graph $G = (V, E)$ is a d-regular expander. The two key parameters of the expander G are the edge expansion h_G and the second eigenvalue of the Laplacian λ_G. The edge expansion gives a lower bound on the size of every cut: for every subset of vertices $X \subset V$, the size of the cut between X and $|V \setminus X|$ is at least

$$h_G \times \frac{\min(|X|, |V \setminus X|)}{|V|}|E|.$$

It is formally defined as follows:

$$h_G = \min_{X \subset V} \left(\frac{|\delta(X, V \setminus X)|}{|E|} \Big/ \frac{\min(|X|, |V \setminus X|)}{|V|} \right),$$

here $\delta(X, V \setminus X)$ denotes the cut — the set of edges going from X to $V \setminus X$. One can think of the second eigenvalue of the Laplacian

$$L_G(u, v) = \begin{cases} 1, & \text{if } u = v \\ -1/d, & \text{if } (u, v) \in E \\ 0, & \text{otherwise.} \end{cases}$$

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as of continuous relaxation of the edge expansion. Note that the smallest eigenvalue of L_G is 0; and the corresponding eigenvector is a vector of all 1's, denoted by $\mathbf{1}$. Thus

$$\lambda_G = \min_{x \perp \mathbf{1}} \frac{\langle x, L_G x\rangle}{\|x\|^2}.$$

Cheeger's inequality,

$$h_G^2/8 \leq \lambda_G \leq h_G,$$

shows that h_G and λ_G are closely related; however λ_G can be much smaller than h_G (the lower bound in the inequality is tight).

1.2 Results of Arora, Khot, Kolla, Steurer, Tulsiani, and Vishnoi

In a recent work [1], Arora, Khot, Kolla, Steurer, Tulsiani, and Vishnoi showed how given a $(1-\varepsilon)$ satisfiable instance of Unique Games (i.e. an instance in which the optimal solution satisfies at least a $(1-\varepsilon)$ fraction of constraints), one can obtain a solution of cost

$$1 - C\frac{\varepsilon}{\lambda_G}\log\left(\frac{\lambda_G}{\varepsilon}\right)$$

in polynomial time, here C is an absolute constant. We improve their result and show that, if the ratio ε/λ_G is less than some universal positive constant c, one can obtain a solution of cost

$$1 - C'\frac{\varepsilon}{h_G}$$

in polynomial time. As mentioned above, λ_G can be significantly smaller than h_G, then our result gives much better approximation guarantee. However, even if $\lambda_G \approx h_G$, our bound is asymptotically stronger, since

$$1 - C'\frac{\varepsilon}{h_G} \geq 1 - C'\frac{\varepsilon}{\lambda_G}$$

(our bound does not have a $\log(\lambda_G/\varepsilon)$ factor). It is an interesting open question, if one can replace the condition $\varepsilon/\lambda_G < c$ with $\varepsilon/h_G < c$.

1.3 Semidefinite Relaxation

We use the standard SDP relaxation for the Unique Games problem.

$$\text{minimize } \frac{1}{2|E|}\sum_{(u,v)\in E}\sum_{i=1}^{k}\|u_i - v_{\pi_{uv}(i)}\|^2$$

subject to

$$\forall u \in V\ \forall i,j \in [k], i \neq j \qquad \langle u_i, u_j\rangle = 0 \tag{1}$$

$$\forall u \in V \qquad \sum_{i=1}^{k}\|u_i\|^2 = 1 \tag{2}$$

$$\forall u,v,w \in V\ \forall i,j,l \in [k] \qquad \|u_i - w_l\|^2 \leq \|u_i - v_j\|^2 + \|v_j - w_l\|^2 \tag{3}$$

$$\forall u,v \in V\ \forall i,j \in [k] \qquad \|u_i - v_j\|^2 \leq \|u_i\|^2 + \|v_j\|^2 \tag{4}$$

$$\forall u,v \in V\ \forall i,j \in [k] \qquad \|u_i\|^2 \leq \|u_i - v_j\|^2 + \|v_j\|^2 \tag{5}$$

For every vertex u and state i we introduce a vector u_i. In the intended integral solution $u_i = 1$, if u has state i; and $u_i = 0$, otherwise. All SDP constraints are satisfied in the integral solution; thus this is a valid relaxation. The objective function of the SDP measures what fraction of all Unique Games constraints is *not satisfied*.

2 Algorithm

We define the *earthmover distance* between two sets of orthogonal vectors $\{u_1, \dots, u_k\}$ and $\{v_1, \dots, v_k\}$ as follows:

$$\Delta(\{u\}_i, \{v\}_i) \equiv \min_{\sigma(i) \in \mathcal{S}_k} \sum_{i=1}^{k} \|u_i - v_{\sigma(i)}\|^2,$$

here $\mathcal{S}_k$ is the symmetric group, the group of all permutations on the set $[k] = \{1, \dots, k\}$. Given an SDP solution $\{u_i\}_{u,i}$ we define the earthmover distance between vertices in a natural way:

$$\Delta(u, v) = \Delta(\{u_1, \dots, u_k\}, \{v_1, \dots, v_k\}).$$

Arora et al. [1] proved that if an instance of Unique Games on an expander is almost satisfiable, then the average earthmover distance between two vertices (defined by the SDP solution) is small. We will need the following corollary from their results:

For every $R \in (0, 1)$, there exists a positive c, such that for every $(1 - \varepsilon)$ satisfiable instance of Unique Games on an expander graph G, if $\varepsilon/\lambda_G < c$, then the expected earthmover distance between two random vertices is less than R i.e.

$$\mathbb{E}_{u,v \in V}[\Delta(u, v)] \leq R.$$

In fact, Arora et al. [1] showed that $c \geq \Omega(R/\log(1/R))$, but we will not use this bound. Moreover, in the rest of the paper, we fix the value of $R < 1/4$. We pick c_R, so that if $\varepsilon/\lambda_G < c_R$, then

$$\mathbb{E}_{u,v \in V}[\Delta(u, v)] \leq R/4. \tag{6}$$

Our algorithm transforms vectors $\{u_i\}_{u,i}$ in the SDP solution to vectors $\{\tilde{u}_i\}_{u,i}$ using a *normalization* technique introduced by Chlamtac, Makarychev and Makarychev [3]:

Lemma 2.1. *[3] For every SDP solution $\{u_i\}_{u,i}$, there exists a set of vectors $\{\tilde{u}_i\}_{u,i}$ satisfying the following properties:*

1. *Triangle inequalities in ℓ_2^2: for all vertices u, v, w in V and all states i, p, q in $[k]$,*

$$\|\tilde{u}_i - \tilde{v}_p\|_2^2 + \|\tilde{v}_p - \tilde{w}_q\|_2^2 \geq \|\tilde{u}_i - \tilde{w}_q\|_2^2.$$

2. *For all vertices u, v in V and all states i, j in $[k]$,*

$$\langle \tilde{u}_i, \tilde{v}_j \rangle = \frac{\langle u_i, v_j \rangle}{\max(\|u_i\|^2, \|v_j\|^2)}.$$

3. *For all non-zero vectors u_i, $\|\tilde{u}_i\|_2^2 = 1$.*

4. For all u in V and $i \neq j$ in $[k]$, the vectors $\tilde{u}_i$ and $\tilde{u}_j$ are orthogonal.

5. For all u and v in V and i and j in $[k]$,

$$\|\tilde{v}_j - \tilde{u}_i\|_2^2 \leq \frac{2\,\|v_j - u_i\|^2}{\max(\|u_i\|^2, \|v_j\|^2)}.$$

The set of vectors $\{\tilde{u}_i\}_{u,i}$ can be obtained in polynomial time.

Now we are ready to describe the rounding algorithm. The algorithm given an SDP solution, outputs an assignment of states (labels) to the vertices.

Approximation Algorithm

Input: an SDP solution $\{u_i\}_{u,i}$ of cost ε.

Initialization

1. Pick a random vertex u (uniformly distributed) in V. We call this vertex *the initial vertex.*
2. Pick a random state $i \in [k]$ for u; choose state i with probability $\|u_i\|^2$. Note that $\|u_1\|^2 + \cdots + \|u_k\|^2 = 1$. We call i *the initial state.*
3. Pick a random number t uniformly distributed in the segment $[0, \|u_i\|^2]$.
4. Pick a random r in $[R, 2R]$.

Normalization

5. Obtain vectors $\{\tilde{u}_i\}_{u,i}$ as in Lemma 2.1.

Propagation

6. For every vertex v,
   - Find all states $p \in [k]$ such that $\|v_p\|^2 \geq t$ and $\|\tilde{v}_p - \tilde{u}_i\|^2 \leq r$. Denote the set of p's by S_v:
   $$S_v = \left\{p : \|v_p\|^2 \geq t \text{ and } \|\tilde{v}_p - \tilde{u}_i\|^2 \leq r\right\}.$$
   - If S_v contains exactly one element p, then assign the state p to v.
   - Otherwise, assign an arbitrary (say, random) state to v.

Denote by σ_{vw} the partial mapping from $[k]$ to $[k]$ that maps p to q if $\|\tilde{v}_p - \tilde{w}_q\|^2 \leq 4R$. Note that σ_{vw} is well defined i.e. p cannot be mapped to different states q and q': if $\|\tilde{v}_p - \tilde{w}_q\|^2 \leq 4R$ and $\|\tilde{v}_p - \tilde{w}_{q'}\|^2 \leq 4R$, then, by the ℓ_2^2 triangle inequality (see Lemma 2.1(1)), $\|\tilde{w}_q - \tilde{w}_{q'}\|^2 \leq 8R$, but $\tilde{w}_q$ and $\tilde{w}_{q'}$ are orthogonal unit vectors, so

$$\|\tilde{w}_q - \tilde{w}_{q'}\|^2 = 2 > 8R.$$

Clearly, σ_{vw} defines a partial matching between states of v and states of w: if $\sigma_{vw}(p) = q$, then $\sigma_{wv}(q) = p$.

Lemma 2.2. *If $p \in S_v$ and $q \in S_w$ with non-zero probability, then $q = \sigma_{vw}(p)$.*

Proof. If $p \in S_v$ and $q \in S_w$ then for some vertex u and state i, $\|\tilde{v}_p - \tilde{u}_i\|^2 \le 2R$ and $\|\tilde{w}_q - \tilde{u}_i\|^2 \le 2R$, thus by the triangle inequality $\|\tilde{v}_p - \tilde{w}_q\|^2 \le 4R$ and by the definition of σ_{vw}, $q = \sigma_{vw}(p)$. □

Corollary 2.3. *Suppose, that $p \in S_v$, then the set S_w either equals $\{\sigma_{vw}(p)\}$ or is empty (if $\sigma_{vw}(p)$ is not defined, then S_w is empty). Particularly, if u and i are the initial vertex and state, then the set S_w either equals $\{\sigma_{uw}(i)\}$ or is empty. Thus, every set S_w contains at most one element.*

Lemma 2.4. *For every choice of the initial vertex u, for every $v \in V$ and $p \in [k]$ the probability that $p \in S_v$ is at most $\|v_p\|^2$.*

Proof. If $p \in S_v$, then $i = \sigma_{vu}(p)$ is the initial state of u and $t \le \|v_p\|^2$. The probability that both these events happen is

$$\Pr(i \in S_u) \times \Pr\left(t \le \|v_p\|^2\right) = \|u_i\|^2 \times \min(\|v_p\|^2/\|u_i\|^2, 1) \le \|v_p\|^2$$

(recall that t is a random real number on the segment $[0, \|u_i\|^2]$). □

Denote the set of those vertices v for which S_v contains exactly one element by X. First, we show that on average X contains a constant fraction of all vertices (later we will prove a much stronger bound on the size of X).

Lemma 2.5. *If $\varepsilon/\lambda_G \le c_R$, then the expected size of X is at least $|V|/4$.*

Proof. Consider an arbitrary vertex v. Estimate the probability that $p \in S_v$ given that u is the initial vertex. Suppose that there exists q such that $\|v_p - u_q\|^2 \le \|v_p\|^2 \cdot R/2$, then

$$\|\tilde{u}_q - \tilde{v}_p\|^2 \le \frac{2\|u_q - v_p\|^2}{\max(\|u_q\|^2, \|v_p\|^2)} \le R.$$

Thus, $q = \sigma_{vu}(p)$ and $\|\tilde{u}_q - \tilde{v}_p\|^2 \le r$ with probability 1. Hence, if q is chosen as the initial state and $\|v_p\|^2 \ge t$, then $v_p \in S_v$. The probability of this event is $\|u_q\|^2 \times \min(\|v_p\|^2/\|u_q\|^2, 1)$. Notice that

$$\|u_q\|^2 \times \min(\|v_p\|^2/\|u_q\|^2, 1) = \min(\|v_p\|^2, \|u_q\|^2) \ge \|v_p\|^2 - \|u_q - v_p\|^2 \ge \frac{\|v_p\|^2}{2}.$$

Now, consider all p's for which there exists q such that $\|v_p - u_q\|^2 \le \|v_p\|^2 \cdot R/2$. The probability that one of them belongs to S_v, and thus $v \in X$, is at least

$$\begin{aligned}
\frac{1}{2} \sum_{p:\min_q(\|u_q - v_p\|^2) \le \|v_p\|^2 \cdot R/2} \|v_p\|^2 &= \frac{1}{2}\sum_{p=1}^{k} \|v_p\|^2 - \frac{1}{2} \sum_{p:\min_q(\|u_q - v_p\|^2) > \|v_p\|^2 \cdot R/2} \|v_p\|^2 \\
&\ge \frac{1}{2} - \frac{1}{2} \times \sum_{p=1}^{k} \frac{2}{R} \min_q(\|u_q - v_p\|^2) \\
&\ge \frac{1}{2} - \frac{\Delta(\{u\}_q, \{v\}_p)}{R}.
\end{aligned}$$

Since the average value of $\Delta(\{u\}_q, \{v\}_p)$ over all pairs (u, v) is at most $R/4$ (see (6)), the expected size of X (for random initial vertex u) is at least $|V|/4$. □

Corollary 2.6. *If $\varepsilon/\lambda_G \le c_R$, then the size of X is greater than $|V|/8$ with probability greater than* 1/8.

Lemma 2.7. *The expected size of the cut between X and $V \setminus X$ is at most $6\varepsilon/R|E|$.*

Proof. We show that the size of the cut between X and $V \setminus X$ is at most $6\varepsilon/R|E|$ in the expectation for any choice of the initial vertex u. Fix an edge (v,w) and estimate the probability that $v \in X$ and $w \in V \setminus X$. If $v \in X$ and $w \in V \setminus X$, then S_v contains a unique state p, but S_w is empty (see Corollary 2.3) and, particularly, $\pi_{vw}(p) \notin S_w$. This happens in two cases:

- There exists p such that $i = \sigma_{vu}(p)$ is the initial state of u and $\|w_{\pi_{vw}(p)}\|^2 < t \le \|v_p\|^2$. The probability of this event is at most

$$\sum_{p=1}^{k} \|u_{\sigma_{vu}(p)}\|^2 \times \left| \frac{\|v_p\|^2 - \|w_{\pi_{vw}(p)}\|^2}{\|u_{\sigma_{vu}(p)}\|^2} \right| \le \sum_{p=1}^{k} \|v_p - w_{\pi_{vw}(p)}\|^2.$$

- There exists p such that $i = \sigma_{vu}(p)$ is the initial state of u, $t \le \|v_p\|^2$ and $\|\tilde{u}_i - \tilde{v}_p\|^2 < r \le \|\tilde{u}_i - \tilde{w}_{\pi_{vw}(p)}\|^2$. The probability of this event is at most

$$\begin{aligned}
\sum_{p=1}^{k} \|u_{\sigma_{vu}(p)}\|^2 \times \frac{\|v_p\|^2}{\|u_{\sigma_{vu}(p)}\|^2} \quad & \times \quad \left| \frac{\|\tilde{u}_{\sigma_{vu}(p)} - \tilde{w}_{\pi_{vw}(p)}\|^2 - \|\tilde{u}_{\sigma_{vu}(p)} - \tilde{v}_p\|^2}{R} \right| \\
& \le \quad \sum_{p=1}^{k} \|v_p\|^2 \times \frac{\|\tilde{v}_p - \tilde{w}_{\pi_{vw}(p)}\|^2}{R} \\
& \le \quad \sum_{p=1}^{k} \|v_p\|^2 \times \frac{2\|v_p - w_{\pi_{vw}(p)}\|^2}{R \cdot \max(\|v_p\|^2, \|w_{\pi_{vw}(p)}\|^2)} \\
& \le \quad \frac{2}{R} \sum_{p=1}^{k} \|v_p - w_{\pi_{vw}(p)}\|^2.
\end{aligned}$$

Note that the probability of the first event is zero, if $\|w_{\pi_{vw}(p)}\|^2 \ge \|v_p\|^2$; and the probability of the second event is zero, if $\|\tilde{u}_{\sigma_{vu}(p)} - \tilde{v}_p\|^2 \ge \|\tilde{u}_{\sigma_{vu}(p)} - \tilde{w}_{\pi_{vw}(p)}\|^2$.

Since the SDP value equals

$$\frac{1}{2|E|} \sum_{(v,w)\in E} \sum_{p=1}^{k} \|v_p - w_{\pi_{vw}(p)}\|^2 \le \varepsilon.$$

The expected fraction of cut edges is at most $6\varepsilon/R$.

□

Lemma 2.8. *If $\varepsilon \le \min(c_R\lambda_G, h_G R/1000)$, then with probability at least 1/16 the size of X is at least*

$$\left(1 - \frac{100\varepsilon}{h_G R}\right)|V|.$$

Proof. The expected size of the cut $\delta(X, V \setminus X)$ between X and $V \setminus X$ is less than $6\varepsilon/R|E|$. Hence, since the graph G is an expander, one of the sets X or $V \setminus X$ must be small:

$$\mathbb{E}\left[\min(|X|, |V \setminus X|)\right] \leq \frac{1}{h_G} \times \frac{\mathbb{E}\left[|\delta(X, V \setminus X)|\right]}{|E|} \times |V| \leq \frac{6\varepsilon}{h_G R}|V|.$$

By Markov's Inequality,

$$\Pr\left(\min(|X|, |V \setminus X|) \leq \frac{100\varepsilon}{h_G R}|V|\right) \geq 1 - \frac{1}{16}.$$

Observe, that $100\varepsilon/(h_G R)|V| < |V|/8$. However, by Corollary 2.6, the size of X is greater than $|V|/8$ with probability greater than $1/8$. Thus

$$\Pr\left(|V \setminus X| \leq \frac{100\varepsilon}{h_G R}|V|\right) \geq \frac{1}{16}.$$

□

Lemma 2.9. *The probability that for an arbitrary edge (v, w), the constraint between v and w is not satisfied, but v and w are in X is at most $4\varepsilon_{vw}$, where*

$$\varepsilon_{vw} = \frac{1}{2}\sum_{i=1}^{k} \|v_i - w_{\pi_{vw}(i)}\|^2.$$

Proof. We show that for every choice of the initial vertex u the desired probability is at most $4\varepsilon_{vw}$. Recall, that if $p \in S_v$ and $q \in S_w$, then $q = \sigma_{vw}(p)$. The constraint between v and w is not satisfied if $q \neq \pi_{vw}(p)$. Hence, the probability that the constraint is not satisfied is at most,

$$\sum_{p:\pi_{vw}(p) \neq \sigma_{vw}(p)} \Pr\left(p \in S_v\right).$$

If $\pi_{vw}(p) \neq \sigma_{vw}(p)$, then

$$\|\tilde{v}_p - \tilde{w}_{\pi_{vw}(p)}\|^2 \geq \|\tilde{w}_{\pi_{vw}(p)} - \tilde{w}_{\sigma_{vw}(p)}\|^2 - \|\tilde{v}_p - \tilde{w}_{\sigma_{vw}(p)}\|^2 \geq 2 - 4R \geq 1.$$

Hence, by Lemma 2.1 (5),

$$\|v_p - w_{\pi_{vw}(p)}\|^2 \geq \|v_p\|^2/2.$$

Therefore, by Lemma 2.4,

$$\sum_{p:\pi_{vw}(p) \neq \sigma_{vw}(p)} \Pr\left(p \in S_v\right) \leq \sum_{p:\pi_{vw}(p) \neq \sigma_{vw}(p)} \|v_p\|^2 \leq 2\sum_{p=1}^{k} \|v_p - w_{\pi_{vw}(p)}\|^2 = 4\varepsilon_{vw}.$$

□

Theorem 2.10. *There exists a polynomial time approximation algorithm that given a $(1 - \varepsilon)$ satisfiable instance of Unique Games on a d-expander graph G with $\varepsilon/\lambda_G \leq c$, the algorithm finds a solution of cost*

$$1 - C\frac{\varepsilon}{h_G},$$

where c and C are some positive absolute constants.

Proof. We describe a randomized polynomial time algorithm. Our algorithm may return a solution to the SDP or output a special value *fail*. We show that the algorithm outputs a solution with a constant probability (that is, the probability of failure is bounded away from 1); and conditional on the event that the algorithm outputs a solution its expected value is

$$1 - C\frac{\varepsilon}{h_G}. \tag{7}$$

Then we argue that the algorithm can be easily derandomized — simply by enumerating all possible values of the random variables used in the algorithm and picking the best solution. Hence, the deterministic algorithm finds a solution of cost at least (7).

The randomized algorithm first solves the SDP and then runs the rounding procedure described above. If the size of the set X is more than

$$\left(1 - \frac{100\varepsilon}{h_G R}\right)|V|,$$

the algorithm outputs the obtained solution; otherwise, it outputs *fail*.

Let us analyze the algorithm. By Lemma 2.8, it succeeds with probability at least 1/16. The fraction of edges having at least one endpoint in $V \setminus X$ is at most $100\varepsilon/(h_G R)$ (since the graph is d-regular). We conservatively assume that the constraints corresponding to these edges are violated. The expected number of violated constraints between vertices in X, by Lemma 2.9 is at most

$$\frac{4\sum_{(u,v)\in E}\varepsilon_{uv}}{\Pr\left(|X| \geq 100\varepsilon/(h_G R)\right)} \leq 64 \times \left(\frac{1}{2}\sum_{(u,v)\in E}\|u_i - v_{\pi_{vw}(i)}\|^2\right) \leq 64\varepsilon|E|.$$

The total fraction of violated constraints is at most $100\varepsilon/(h_G R) + 64\varepsilon$. □

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