

Lecture 22: Hyperplane Rounding for Max-Cut SDP

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1 Introduction

In the previous lectures we had seen the max-cut problem. In this lecture we will present a 0.878-approximation algorithm. We will in fact, also see that we do not have much hope of doing better.

2 Recap

Let us have quick recap of the semi-definite Programming for the max-cut problem. Figure 1 is the Quadratic Program for the Max-Cut. Figure 3 is the relaxation for the SDP.

Fact 1. *Since SDP is a relaxation of the QIP, $\text{SDP} \geq \text{QIP}$.*

We can think of SDP as a relaxation of the Integer Program, because if we add an extra constraint $\text{rank}(Y) = 1$, it will become a Quadratic Integer Program. We know from the previous lecture that,

Theorem 1. *SDP is solvable in polynomial time using ellipsoid method and a separation oracle.*

3 Vector View

Recall Cholesky Decomposition. Given $Y \succeq 0$, we can write Y as $Y = L^T D L$ where L is

Corollary 2. *We can also write $Y = L'^T L'$ where $L' = \sqrt{D}L$.*

In fact, Y contains inner product of two vectors. $y_{uv} = \langle \mathbf{w}_u, \mathbf{w}_v \rangle$. Write $L' = [\mathbf{W}_1, \mathbf{W}_1, \dots, \mathbf{W}_n]$, We have $Y_{uv} = \mathbf{w}_u^T \mathbf{w}_v$. Finally the SDP can be written as it is in Figure 3.

This Integer Program can be relaxed in the following manner.

$$\begin{aligned} \text{maximize: } & \sum_{(u,v) \in E} \frac{1 - x_u x_v}{2} \\ \text{subject to: } & x_u^2 = 1 \quad \forall u \in V \end{aligned}$$

Figure 1: Quadratic Integer Program for Max-Cut

$$\begin{aligned} \text{maximize: } & \sum_{(u,v) \in E} \frac{1 - y_{uv}}{2} \\ \text{subject to: } & y_{uv} = y_{vu} \quad \forall u, v \in V \\ & y_{uu} = 1 \quad \forall u \in V \\ & Y \succeq 1 \end{aligned}$$

Figure 2: SDP for Max-Cut

$$\begin{aligned} \text{maximize: } & \sum_{(u,v) \in E} \frac{1 - \langle \mathbf{w}_u, \mathbf{w}_v \rangle}{2} \\ \text{subject to: } & \|\mathbf{w}_u\|_2^2 = 1 \quad \forall u \in V \end{aligned}$$

Figure 3: SDP for Max-Cut

3.1 Hyperplane Rounding

The main idea is to use a random hyperplane that goes through the origin to divide the vectors in to two sets, corresponding to a cut. It can be summarized in the following steps.

1. Choose a uniform random hyperplane through the origin that divides the sphere. In other words, Choose a norm-vector with a uniform random direction; sample $\mathbf{g} = (\mathbf{g}_1, \dots, \mathbf{g}_n) \sim \mathcal{N}(0, 1)^n$.
2. Set $\mathbf{x}_u = \text{sign}(\mathbf{g}, \mathbf{w}_u) \forall u \in V$

Theorem 3. [GW95] $\mathbb{E}[\sum_{(u,v) \in E} \frac{1 - \langle \mathbf{x}_u, \mathbf{x}_v \rangle}{2}] \geq 0.878(\text{SDP})$

Proof. By linearity of expectation.

$$\begin{aligned} \text{LHS} &= \sum_{(u,v) \in E} \mathbb{E} \left[\frac{1 - \langle \mathbf{x}_u, \mathbf{x}_v \rangle}{2} \right] \\ &= \sum_{(u,v) \in E} \Pr[\mathbf{w}_u, \mathbf{w}_v \text{ separated by a random hyperplane}] \end{aligned}$$

Now for a pair of fixed u and v , let us focus on the plane containing \mathbf{w}_u and \mathbf{w}_v . By symmetry the random hyperplane's projection becomes a random line through the origin. Thus we have the following.

$$\begin{aligned} \Pr[\mathbf{w}_v \text{ and } \mathbf{w}_u \text{ are separated}] &= \frac{\angle(\mathbf{w}_v, \mathbf{w}_u)}{\pi} \\ &= \frac{\arccos(\langle \mathbf{w}_v, \mathbf{w}_u \rangle)}{\pi} \\ \implies \sum_{(u,v) \in E} \Pr[\mathbf{w}_u, \mathbf{w}_v \text{ separated by a random hyperplane}] &= \sum_{(u,v) \in E} \frac{\arccos(\langle \mathbf{w}_v, \mathbf{w}_u \rangle)}{\pi} \end{aligned}$$

Now let $\alpha_{GW} = \min_{\rho \in [-1,1]} \left\{ \frac{\arccos \rho}{(1-\rho)/2} \right\}$. Using this we have

$$\sum_{(u,v) \in E} \frac{\arccos(\langle \mathbf{w}_v, \mathbf{w}_u \rangle)}{\pi} \geq \sum_{(u,v) \in E} \alpha_{GW} \cdot \frac{1 - \langle \mathbf{w}_v, \mathbf{w}_u \rangle}{2} = \alpha_{GW} \cdot (\text{SDP})$$

Numerical results show that, $\alpha_{GW} \sim 0.87856 \dots > 0.878$ □

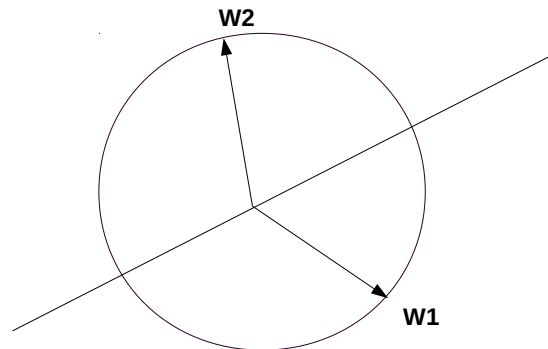


Figure 4: Hyperplane Rounding

4 Recognizing almost Bipartite Graphs

Suppose $\text{OPT} \geq (1 - \epsilon)m$. m is the number of edges ($|E|$). The graph is bipartite after removing ϵm edges. Recall that, $\mathbb{E}[\text{rounding}] \geq (1 - \epsilon)0.878m$. The question we ask here is can we do better than this?

Intuition: When $\epsilon = 0$, \exists poly-time algorithm: returns a cut with m edges (bipartite graph recognition). Let $\text{alg}(c)$ be the best found by a polytime algorithm when $\text{OPT} = c.m$. The curve of $\text{alg}(c)$ is not continuous at $c = 1$. Is this really the case? *GW* finds a cut of size $(1 - O(\sqrt{\epsilon}))m$ given $\text{OPT} = (1 - \epsilon)m$. Now we can state the following theorem.

Theorem 4. $\text{alg}(1 - \epsilon) \geq O(\sqrt{\epsilon})$

Observation: $\cos x = 1 - \frac{x^2}{2} + O(x^4) \implies \arccos(1 - y) = \sqrt{2y} + O(y)$.

Claim 1. $\arccos(1 - y) \leq 4\sqrt{y} \forall y \in [0, 2]$

Proof.

at $y = 0$: LHS = RHS = 0

at $y \in (0, 1)$: $\frac{d\text{LHS}}{dy} = \frac{1}{\sqrt{y(2-y)}} \leq \frac{1}{\sqrt{y}} \leq \frac{1}{2\sqrt{y}} = \frac{d\text{RHS}}{dy}$

at $y \in [1, 2]$: LHS $\leq \arccos(-1) = \pi$

RHS ≥ 4

□

Corollary 5. $\arccos(1 - y) = \pi - \arccos(1 - y) \geq \pi - 4\sqrt{y}$

Theorem 6. *Assuming the Unique Games Conjecture, there exists no poly-time algorithm that $(\alpha_{GW} + \delta)$ or $(1 - \epsilon, 1 - o(\sqrt{\epsilon}))$ -approximate max-cut for all $\epsilon, \delta > 0$.*

Proof.

$$\begin{aligned}
\mathbb{E}[\text{rounding}] &= \sum_{(u,v) \in E} \Pr[\mathbf{w}_u, \mathbf{w}_v \text{ separated}] \\
&= \sum_{(u,v) \in E} \frac{\arccos(\langle \mathbf{w}_u, \mathbf{w}_v \rangle)}{\pi} \\
&= \sum_{(u,v) \in E} \frac{\arccos(\epsilon_{uv} - 1)}{\pi} \\
&\geq \sum_{(u,v) \in E} \frac{\pi - 4\sqrt{\epsilon_{uv}}}{\pi} \\
&\geq m - \frac{4}{\pi} \sum_{(u,v) \in E} \sqrt{\epsilon_{uv}} (*)
\end{aligned}$$

Using Jensen's inequality we have $(*) \geq m - \frac{4}{\pi} m \sqrt{\frac{1}{m} \sum_{(u,v) \in E} \epsilon_{uv}}$ (**)

$$\begin{aligned}
\sum_{(u,v) \in E} \epsilon_{uv} &= m + \sum_{(u,v) \in E} \langle \mathbf{w}_u, \mathbf{w}_v \rangle \\
&= m + (m - 2\text{OPT}_{\text{SDP}}) \\
&\leq 2(m - \text{OPT}_{\text{QIP}}) \\
&\leq 2\epsilon
\end{aligned}$$

$$\text{Therefore, } (**) \geq m - \frac{4}{\pi} m \sqrt{2\epsilon}$$

□

5 Constraint Satisfaction Problem

In this section we talk about the Constraint Satisfaction Problems (CSP).

Domain: $\Omega = \{1, 2, \dots, q\}$

Predicates: $\Pi = \{\pi : \Omega^k \rightarrow \{0, 1\}\}$

Input: n variables x_1, \dots, x_n , m constraints in the form $(x_{i_1}, \dots, x_{i_k}, \pi \in \Pi)$

Goal: Find assignment $\sigma : \{x_1, \dots, x_n\} \rightarrow \Omega$ to maximize number of satisfied constraints.

A constraint is satisfied if and only if $\pi(\sigma(x_{i_1}), \dots, \sigma(x_{i_k})) = 1$

$$\begin{aligned}
& \text{maximize: } \sum_{a,b \in \Omega: \pi(a,b)=1} \langle \mathbf{w}_{ia}, \mathbf{w}_{jb} \rangle \\
& \text{subject to: } \langle \mathbf{w}_{i,a}, \mathbf{w}_{i,b} \rangle = 0 \quad \forall i \in [n], a, b \in \Omega, a \neq b \\
& \quad \langle \mathbf{w}_{i,a}, \mathbf{w}_{i,b} \rangle \geq 0 \quad \forall i, j \in [n], a, b \in \Omega \\
& \quad \sum_{a \in \omega} \mathbf{w}_{i,a} = \mathbf{I} \quad \forall i \in [n] \\
& \quad \|\mathbf{I}\|_2^2 = 1
\end{aligned}$$

Figure 5: Basic SDP

5.1 Basic SDP Relaxation for CSP

Here we will deal with $k = 2$, (binary CSP). For each x_i and $a \in \omega$ introduce $\mathbf{w}_{i,a}$ correspond to $\sigma(x_i) = a$. Note that in the integral solution $\mathbf{w}_{i,a} = \mathbf{I}$, if $\sigma(x_i) = a$ and $\mathbf{w}_{i,a} = 0$ otherwise. Thus we get the **Basic SDP** as in Figure 5.

Theorem 7. [Rag08] *For every CSP, \exists polynomial time rounding scheme for BasicSDP achieving the optimal approximation guarantee among all poly-time algorithms assuming the Unique Games Conjecture.*

References

- [GW95] Michel X. Goemans and David P. Williamson. Improved approximation algorithms for maximum cut and satisfiability problems using semidefinite programming. *J. ACM*, 42(6):1115–1145, November 1995.
- [Rag08] Prasad Raghavendra. Optimal algorithms and inapproximability results for every csp? In *Proceedings of the Fortieth Annual ACM Symposium on Theory of Computing*, STOC '08, pages 245–254, New York, NY, USA, 2008. ACM.