

# On the Sample Complexity of MAX-CUT

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## Abstract

We give a *simple* proof for the *sample complexity* bound  $O^{\sim}(1/\varepsilon^4)$  of absolute approximation of MAX-CUT. The proof depends on a new analysis method for linear programs (LPs) underlying MAX-CUT which could be also of independent interest.

## 1 Introduction

The purpose of this paper is to give a simple proof based on linear programs of the following theorem proven in more generality in [AFKK02].

**Theorem 1 (Main Theorem).** *For any positive  $\varepsilon$ , there exists an integer  $q \in O(\log^3(1/\varepsilon)/\varepsilon^4)$  such that for any graph  $G = \{V, E\}$  if  $Q$  is a random subset of  $V$  of cardinality  $q$  and  $G(Q)$  is the restriction of  $G$  to the sample  $Q$ , then with probability at least  $9/10$ , we have,*

$$\left| \frac{n^2}{q^2} \text{maxcut}(G(Q)) - \text{maxcut}(G) \right| \leq \varepsilon n^2.$$

where  $\text{maxcut}(G)$  is the maximum value of a cut of  $G$ .

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It is apt to rephrase this theorem by saying that the sample complexity of MAX-CUT is in  $O(\log^3(1/\varepsilon)/\varepsilon^4)$ . A more general theorem was proved in [AFKK02]. [AFKK02] uses besides integer programs also special cut-norm and cut-array framework developed for that purpose (cf. also [AN04]). The sample bound  $O\sim(\frac{1}{\varepsilon^4})$  for MAX-CUT is the best known up to date (see [AKK95], [F96], [FK99] for early approximation algorithms for that problem), although there were several attempts to improve it. Any improvement of that bound would be of course an important contribution to the area (given the fact that  $1/\varepsilon$  factors could be very large in various settings). [RV05] improved recently estimates for the *cut-norm* of random submatrices used in more generality in [AFKK02]. That however does not influence overall sampling bound  $O\sim(1/\varepsilon^4)$  for the MAX-CUT, see Errata of [RV05].

We will make essential use in our proof of the following theorem of [AFKK02]. It asserts that for a Linear Program P on  $n$  variables, each constrained to be between 0 and 1, we can make some assertion about the optimal value based on the optimal value of a small subprogram obtained by picking at random a small number of variables.

**Theorem 2.** *Suppose*

$$\begin{array}{l} \text{Max } \sum_{j=1}^n c_j x_j < \alpha \\ \sum_{j=1}^n U_j x_j \leq v \quad ; \quad 0 \leq x_j \leq 1, \end{array}$$

where each  $U_j$  is an  $m$ -vector. Suppose  $q$  is a positive integer and  $Q$  is a random subset of  $\{1, 2, \dots, n\}$  of cardinality  $q$ . Then, for any positive real number  $\lambda$ , with probability at least  $1 - 4e^{-\lambda^2/4}$ , we have :

$$\begin{array}{l} \text{Max} \sum_{j \in Q} c_j x_j \leq \frac{q}{n} \alpha + \lambda \sqrt{q} \|c\|_\infty \\ \sum_{j \in Q} U_j x_j \leq \frac{q}{n} v - \lambda \sqrt{q} \|U\|_\infty \quad ; \quad 0 \leq x_j \leq 1, j \in Q. \end{array}$$

**Proof.** See ([AFKK02]).

■

## 2 Preliminaries

Let  $G = (V, E)$  be a graph. Suppose that  $(V_L, V_R)$ ,  $V_R = V \setminus V_L$  is a bipartition of  $G$ . We use  $x_i = 0$  (resp.  $x_i = 1$ ) to indicate that the vertex  $v_i$  belongs to  $V_L$  (resp. that  $v_i$  belongs to  $V_R$ ). We let  $e_{ij}$  be the indicator function of the edges of  $G$ :

$$e_{ij} = 1 \text{ if } v_i v_j \in E, \quad e_{ij} = 0 \text{ otherwise.}$$

Then, clearly, for each  $i$ , the number of neighbours of  $v_i$  in  $V_R$ , say  $\rho_i$ , satisfies

$$\rho_i = |\Gamma(v_i) \cap V_R| = \sum_{j=1}^n x_j e_{ij}$$

The value of the cut defined by  $(V_L, V_R)$  is clearly

$$e(V_L, V_R) = \sum_{j=1}^n (1 - x_j) \rho_j.$$

For each  $j$ , let  $\rho_j^*$  denote an estimate of  $\rho_j$ . We can obtain these estimates by guessing a sample  $S \subseteq V_R$  of a certain size  $m$ , say, and putting

$$\rho_j^* = \frac{|V_R|}{|S|} |\Gamma(v_j) \cap S|$$

Of course this will entail some error. For an appropriate size  $|S|$  we may expect that the inequality

$$\rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n \tag{1}$$

holds simultaneously for all, or nearly all vertices  $v_j$ . In [AKK95], the Set  $S$  has size  $\Theta(\log n)$  and it is shown that then (1) holds with high probability for all  $v_i$  (if  $S \subseteq V_R$ ). The following is shown

**Proposition 1 ([AKK95]).** *Assume that  $(V_L, V_R)$  is an optimum cut of  $G$ . Assume that  $S$  is a random sample of  $V_R$  with size  $\Theta(\log(1/\varepsilon)\varepsilon^{-3} \log n)$ . Then, with probability at least  $2/3$ ,  $\text{maxcut}(G)$  is approximated with additive error  $O(\varepsilon n^2)$  by applying randomized rounding to the solution of the LP*

Maximize $e(V_L, V_R) = \sum_{j=1}^n (1 - x_j) \rho_j^*$ Subject to $\rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n$ $0 \leq x_j \leq 1, \quad 1 \leq j \leq n.$
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**Proof.** See ([AKK95]). ■

(Technically the sample  $S$  is taken in turn to be each of the subsets of a fixed random sample  $T$  of appropriate size so that the inclusion  $S \subseteq V_R$  need occur at least for one  $S$ .) We cannot use directly this result here since our intended sample size is only a constant (dependent on  $\varepsilon$ .) However, in this later case, we can still assert the following.

**Claim 1.** *Let  $(Q_L, Q_R)$  define an optimum cut of  $G(Q)$ . Take  $m = \lambda \log(1/\varepsilon) \varepsilon^{-2}$  and assume that  $S$  is a random subset of  $Q_R$  of size  $m$ . Then, we have that, for any fixed  $j$ , with probability at least  $1 - 2\varepsilon^{\lambda/2}$ ,*

$$\rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n \tag{2}$$

*Also, for  $\lambda \geq 3$ , the inequality (2) holds with probability at least  $(1 - \varepsilon)$  for at least  $q(1 - \varepsilon)$  vertices in  $Q$ .*

If the above condition holds we shall say that  $S$  is  $\varepsilon$ -representative with respect to  $Q_R$ .

**Proof.** Let  $q_R = |Q_R|$ ,  $k = |\Gamma(v_j) \cap Q_R|$ . Then  $|\Gamma(v_j) \cap S|$  has the hypergeometric distribution with parameters  $Q_R, k, m$  which is tighter than the Binomial distribution  $B(m, p)$  with parameters  $m$  and  $p = k/q_R$ . By a standard Hoeffding-Chernoff Bound we have

$$\begin{aligned} \Pr\left(\left| |\Gamma(v_j) \cap S| - \frac{mk}{|Q_R|} \right| \geq \varepsilon m\right) &\leq 2 \exp\left(-\frac{\varepsilon^2 q_k m}{2k}\right) \\ &\leq 2 \exp\left(-\frac{\varepsilon^2 m}{2}\right) \\ &\leq 2\varepsilon^{\lambda/2} \end{aligned}$$

Using Markov inequality we get that the number of vertices for which (2) holds is at least  $(1 - \varepsilon)q$  with probability at least  $1 - 2\varepsilon^{\lambda/2-1} \geq 1 - \varepsilon$  for  $\lambda = 4$ . ■

The following proposition will be helpful

**Proposition 2.** *Let the  $\rho_j^*$  be any fixed constants (no relation between these  $\rho_j^*$  and the graph  $G$  is assumed here) and consider the LP*

$$\begin{aligned} &\text{Maximize } \sum_{j=1}^n (1 - x_j) \rho_j^* \\ &\text{Subject to} \\ &\quad \rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n \\ &\quad 0 \leq x_j \leq 1, \quad 1 \leq j \leq n. \end{aligned}$$

*Then, if this LP is feasible, the value  $\text{val}(P)^*$  obtained by applying randomized rounding to the solution of this LP satisfies*

$$\text{val}(P)^* \leq \text{maxcut}(G) + O(\varepsilon n^2)$$

**Proof.** The proof is implicit in [AKK95]. ■

The following proposition extends Proposition 1 to the case where the approximation provided by the  $\rho_j^*$  fails on a small subset of vertices.

**Proposition 3.** *Assume that  $(V_L, V_R)$  is an optimum cut of  $G$  and assume that we have*

$$\rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n$$

*for each  $j$  in a set  $J$ , say, where  $J \subseteq \{1, 2, \dots, n\}$  has size  $|J| \geq (1 - \varepsilon)n$ . Then  $\text{maxcut}(G)$  is approximated within  $O(\varepsilon n^2)$  by applying randomized rounding to the solution of the LP*

**Program LP0**

$$\begin{aligned} &\text{Maximize } \sum_{j=1}^n (1 - x_j) \rho_j^* \\ &\text{Subject to} \\ &\quad \rho_j^* - \varepsilon n \leq \rho_j \leq \rho_j^* + \varepsilon n, \quad j \in J \text{ with } |J| \geq \varepsilon n \\ &\quad 0 \leq x_j \leq 1, \quad j = 1, \dots, n. \end{aligned}$$

We note that we do not know precisely the set  $J$ . We only have a lower bound on its cardinality.

**Proof.** Let us denote by  $x = (x_j)$  an optimum solution of LP0,  $\text{val}^*(x) =$

$\sum_{j=1}^n (1 - x_j) \rho_j^*$  its value. Define  $\text{val}(x) = \sum_{j=1}^n (1 - x_j) \rho_j$ . Then we have

$$\begin{aligned} |\text{val}(x) - \text{val}^*(x)| &\leq \sum_{j=1}^n |\rho_j - \rho_j^*| \\ &\leq \varepsilon(1 - \varepsilon)n^2 + \varepsilon n^2 \\ &\leq 2\varepsilon n^2. \end{aligned}$$

Note that we have

$$\text{maxcut}(G) \leq \max \sum_{j=1}^n (1 - x_j) \rho_j$$

which implies

$$\text{val}^*(x) \geq \text{maxcut}(G) - 2\varepsilon n^2. \quad (3)$$

Let  $y$  be obtained from  $x$  by randomized rounding. Then,  $\text{val}(y)$  is the value of the cut defined by  $y$ . From standard results we have that  $|\text{val}^*(x) - \text{val}^*(y)| \in O(\varepsilon n^2)$  w.h.p. implies with (3)

$$|\text{val}(y) - \text{maxcut}(G)| \in O(\varepsilon^2 n).$$

■

### 3 End of the proof

Let  $Q$  be a random subset of vertices of size  $q = \log^3(1/\varepsilon)\varepsilon^{-4}$ . and let  $T$  be a random subset of  $Q$  of size  $t = C \log(1/\varepsilon)\varepsilon^{-2}$  so that  $T$  is also a random subset of  $V$ . We can restrict ourselves to sets  $S$   $\varepsilon$  representative for  $G(Q)$  (since with high probability we have  $\text{cut}_S(G(Q)) = \text{maxcut}(G(Q)) + O(\varepsilon q^2)$  for such a set  $S$ .) Define

$$\text{Re}(G(Q)) = \{S \subseteq T : S \text{ is } \varepsilon - \text{representative for } G(Q)\}.$$

For each  $S \in \text{Re}(G(Q))$  we introduce the following LP's, LP1, LP2, LP3. So in each case, the estimates  $\rho_j^*$  are with reference to  $S$ . Also, we will consider in the sequel only the ordinary solutions to these programs (not the integer solutions) since randomized rounding plays a rather trivial role here.

**Program LP1**

Here the  $\rho_j$  are evaluated in  $Q$ :

$$\rho_j = \sum_{i \in Q} x_i e_{ij}$$
$$\rho_j^* = \frac{|V_R|}{|S|} |\Gamma(v_j) \cap S|$$

Maximize  $\sum_{j \in Q}^n (1 - x_j) \rho_j^*$

Subject to

$$\frac{q}{n} \rho_j^* - \frac{\varepsilon q}{2} \leq \rho_j \leq \frac{q}{n} \rho_j^* + \frac{\varepsilon q}{2}, \quad j \in J^{(Q)}$$

say

$$0 \leq x_j \leq 1, \quad j \in Q$$

and we are assuming that  $|J^{(Q)}| \geq (1 - \varepsilon)q$ .

**Program LP2**

Here the  $\rho_j^*$  are as above and the  $\rho_j$  are evaluated in  $G$ :

$$\rho_j = \sum_{i=1}^n x_i e_{ij}$$

Maximize  $\frac{n}{q} \sum_{j=1}^n (1 - x_j) \rho_j^*$

Subject to

$$\frac{n}{q} \rho_j^* - \varepsilon n \leq \rho_j \leq \frac{n}{q} \rho_j^* + \varepsilon n, \quad j \in J$$

$$0 \leq x_j \leq 1.$$

Here,  $J \subseteq \{1, 2, \dots, n\}$  is a set of indices of size  $|J| \geq (1 - 2\varepsilon)n$ .

**Program LP3**

With  $\rho_j$  and  $\rho_j^*$  as in LP1 we set here

$$\rho_j = \sum_{i=1}^n x_i e_{ij}$$

Maximize  $\frac{n}{q} \sum_{j \in Q} (1 - x_j) \rho_j^*$

Subject to

$$\rho_j^* - \frac{\varepsilon q}{2} \leq \rho_j \leq \rho_j^* + \frac{\varepsilon q}{2}, \quad j \in J^{(Q)}$$

say

$$0 \leq x_j \leq 1, \quad 1 \leq j \leq n$$

Clearly, the solution of LP3 is just equal to that of LP1 multiplied by  $\frac{n}{q}$ . Note that LP3 is a random subprogram of LP2. In view of a previous claim we need only compare, for each  $S \in \text{Re}(G(Q))$  the solutions of the programs LP3 and LP2. We use Theorem 2 in contrapositive form to assert that the value of LP2 is with sufficiently probability as big as the scaled value of LP1 and repeat this reasoning for each  $S \in \text{Re}(G(Q))$  ending with the conclusion that the assertion is true w.h.p. for all these  $S$  together and theorem (1) follows. (We also use Proposition 2 to assert that the  $\text{maxcut}(G)$  is at least nearly as big as the value of LP2.) We take  $\lambda = 4\varepsilon^{-1} \sqrt{\log(1/\varepsilon)}$  in that theorem which implies  $\lambda \sqrt{q} \leq \varepsilon q$ . Thus we can use Theorem 2 with that  $\lambda$  to assert that with probability at least  $1 - 4e^{-\varepsilon^{-2} \log(1/\varepsilon)}$ ,

$$\text{val}(LP2) - \frac{q}{n} \text{val}(LP3) \leq \varepsilon q n$$

and, with  $\text{val}(LP3) = \frac{q}{n} \text{val}(LP1)$ , we get

$$\text{val}(LP2) - \frac{q^2}{n^2} \text{val}(LP3) \leq \varepsilon q^2$$

Since there are at most  $2^{|T|} = 2^{\log(1/\varepsilon)\varepsilon^{-2}}$  distinct possible choices for  $S$ , this will be true simultaneously for all these choices with probability at least  $2/3$  for each fixed sufficiently small  $\varepsilon$ . Theorem 1 follows. ■



## Acknowledgments

We thank Ravi Kannan for stimulating remarks and discussions.

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