CSCI5160 Approximation Algorithms — Spring 2022

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Notes 11: Cheeger–Alon–Milman inequality

1. Local sweep cut

We now prove the hard direction of Cheeger–Alon–Milman inequality from the previous lecture.

Theorem 1.1 (Cheeger–Alon–Milman)**.** $\varphi(G) \leqslant \sqrt{2\lambda_2}$.

The proof is a "rounding algorithm" that converts any $y \in \mathbb{R}^V$ with small Rayleigh quotient $R(y) = \dfrac{y^\top L y}{y^\top D y} = \dfrac{\sum_{(i,j)\in E} w_{ij}(y_i - y_j)^2}{\sum_{i\in V} d(i) y_i^2}$ into a subset S with small conductance.

Lemma 1.2. *Given any $y \in \mathbb{R}^V$, there is an algorithm to find $S \subseteq \operatorname{supp}(y)$ with $\varphi(S) \leqslant \sqrt{2R(y)}$.*

Here $\operatorname{supp}(y) = \{i \in V \mid y_i \neq 0\}$ denotes the support of y.

How to turn $y \in \mathbb{R}^V$ into a subset? We saw from last lecture that if y is the indicator $\mathbb{1}_T$ of some subset $T \subseteq V$, then $R(y) = \varphi(T)$. It is natural to consider rounding by thresholding: Choose threshold $t \in \mathbb{R}$ and output $S_t = \{i \in V \mid y_i > t\}$.

The algorithm instead output $S_t = \{i \in V \mid y_i^2 > t\}$. The squaring allows us to relate conductance to Rayleigh quotient, which involves squared terms $(y_i - y_j)^2$ and y_i^2 in the numerator and denominator, respectively.

Proof of Lemma 1.2. Imagine threshold t increases from zero to infinity, and $S_t = \{i \in V \mid y_i^2 > t\}$ shrinks from $\operatorname{supp}(y)$ to $\emptyset$. The cut weight $w(S_t, \overline{S}_t)$ and total degree $d(S_t)$ also changes as t grows.

We will assume all $|y_i| \leqslant 1$, as scaling y by a constant does not affect $R(y)$. We will also pick $t \in [0,1]$ uniformly at random. We now analyze the expected cut weight $\mathbb{E}_t[w(S_t, \overline{S}_t)]$ and expected total degree $\mathbb{E}_t[d(S_t)]$.

$$\begin{aligned}
\mathop{\mathbb{E}}_t[w(S_t, \overline{S}_t)] &= \sum_{(i,j)\in E} w_{ij} \mathop{\mathbb{E}}_t[\mathbb{1}((i,j) \text{ is cut by } S_t)] \\
&= \sum_{(i,j)\in E} w_{ij}(y_j^2 - y_i^2) \qquad \text{assuming } y_i^2 \leqslant y_j^2 \\
&= \sum_{(i,j)\in E} w_{ij}(y_j - y_i)(y_j + y_i) \leqslant \sqrt{\sum_{(i,j)\in E} w_{ij}(y_j - y_i)^2} \sqrt{\sum_{(i,j)\in E} w_{ij}(y_j + y_i)^2}
\end{aligned}$$

The inequality is Cauchy–Schwarz. The first term under square-root is the numerator of the Rayleigh quotient. For the second term under square-root,

$$\sum_{(i,j)\in E} w_{ij}(y_i + y_j)^2 \leqslant \sum_{(i,j)\in E} w_{ij} 2(y_i^2 + y_j^2) = 2\sum_{i\in V} d(i) y_i^2 \ .$$

Altogether,

$$\mathop{\mathbb{E}}_t[w(S_t, \overline{S}_t)] \leqslant \sqrt{\sum_{(i,j)\in E} w_{ij}(y_j - y_i)^2} \sqrt{2\sum_{i\in V} d(i) y_i^2} \ .$$

Now for the expected total degree,

$$\mathop{\mathbb{E}}_t[d(S_t)] = \sum_{i\in V} d(i) \mathop{\mathbb{E}}_t[\mathbb{1}(i \in S_t)] = \sum_{i\in V} d(i) y_i^2 \ .$$

So their ratio satisfies

$$\frac{\mathbb{E}_t[w(S_t, \overline{S}_t)]}{\mathbb{E}_t[d(S_t)]} \leqslant \sqrt{2R(y)} \ .$$

By the following proposition, there must be some choice of $t = t_*$ such that

$$\varphi(S_{t_*}) = \frac{w(S_{t_*}, \overline{S}_{t_*})}{d(S_{t_*})} \leqslant \sqrt{2R(y)} \ . \qquad \square$$

Proposition 1.3. *Let f and g be arbitrary real-valued integrable functions. There must be some choice of t_* such that*

$$\frac{f(t_*)}{g(t_*)} \leqslant \frac{\mathbb{E}_t[f(t)]}{\mathbb{E}_t[g(t)]} \,.$$

Proof. Let $C = \mathbb{E}_t[f(t)] / \mathbb{E}_t[g(t)]$, so that

$$0 = \mathop{\mathbb{E}}_t[f(t)] - C \mathop{\mathbb{E}}_t[g(t)] = \mathop{\mathbb{E}}_t[f(t) - Cg(t)] \,.$$

There must be some choice of $t = t_*$ such that the term in the expectation is nonpositive:

$$f(t_*) - Cg(t_*) \leqslant 0 \qquad \Longleftrightarrow \qquad \frac{f(t_*)}{g(t_*)} \leqslant C = \frac{\mathbb{E}_t[f(t)]}{\mathbb{E}_t[g(t)]} \,. \qquad \square$$

The algorithm in Lemma 1.2 can find small conductance S_{t_*} deterministically: Simply try all thresholds t that lead to different $S_t = \{i \in V \mid y_i^2 > t\}$, and output the one with the smallest conductance. There are at most n choices for t once vertices are sorted according to y_i^2.

2. From orthogonality to small support

Does Lemma 1.2 prove Theorem 1.1? Not yet, the subset S_{t_*} produced need not contain at most half of the total degree. It may even be the case that $S_{t_*} = V$.

But we also did not exploit the orthogonality condition: that $\sum_{i \in V} d(i) y_i = 0$. In this section, given $y \in \mathbb{R}^V$ with small Rayleigh quotient and satisfying the orthogonality condition, we will produce two vectors z_- and z_+ both with "small support", and apply the algorithm in previous section to z_- or z_+.

Note that the numerator of the Rayleigh quotient does not change if all entries of y are shifted by the same $c \in \mathbb{R}$. Among all shifts $z = y + c\mathbb{1}$, the denominator of the Rayleigh quotient is minimized when $\sum_{i \in V} d(i) z_i = 0$, because the quadratic form

$$z^\top D z = \sum_{i \in V} d(i) z_i^2 = \sum_{i \in V} d(i) (y_i + c)^2$$

has derivative (with respect to c) $2 \sum_{i \in V} d(i) y_i$.

Assume without loss of generality that y is sorted, so that $y_1 \leqslant \ldots \leqslant y_n$. Find the smallest j such that $\sum_{1 \leqslant i \leqslant j} d(i) \geqslant d(V)/2$. We will then shift y by $c = -y_j$ to obtain $z = y - y_j \mathbb{1}$. The previous paragraph implies that $R(z) \leqslant R(y)$, because the numerator stays the same but the denominator can only increase after the shift.

Note that $z_j = 0$. The above choice of j ensures *both* sets $S_- = \{i \in V \mid y_i < y_j\} = \{i \in V \mid z_i < 0\}$ and $S_+ = \{i \in V \mid y_i > y_j\} = \{i \in V \mid z_i > 0\}$ contain at most half of the total degree of V. We will take the positive and negative part of z to get z_+ and z_-:

$$z_- = \begin{cases} z_i & z_i < 0 \\ 0 & \text{otherwise} \end{cases} \qquad \text{and} \qquad z_+ = \begin{cases} z_i & z_i > 0 \\ 0 & \text{otherwise} \end{cases} \,.$$

We now show z_- or z_+ has Rayleigh quotient at most that of z.

Lemma 2.1. $\min\{R(z_-), R(z_+)\} \leqslant R(z)$.

Proof. $z^\top D z = z_+^\top D z_+ + z_-^\top D z_-$, because left-hand-side is a weighted sum of z_i^2, and each nonzero z_i^2 is counted in z_+ or z_-.

$z^\top L z \geqslant z_+^\top L z_+ + z_-^\top L z_-$, because left-hand-side is a weighted sum of $(z_i - z_j)^2$ over edges, and every edge that contribute to left-hand-side, it either get dropped if z_i and z_j have opposite signs, or is retained otherwise.

We have therefore shown $\dfrac{z_-^\top L z_- + z_+^\top L z_+}{z_-^\top D z_- + z_+^\top D z_+} \leqslant R(z)$. The result follows once we can show $\min\left\{\dfrac{A}{C}, \dfrac{B}{D}\right\} \leqslant \dfrac{A+B}{C+D}$. And it is implied by Proposition 1.3. $\square$

3. Discussion

The task of finding subset of smallest conductance is known as Sparsest Cut. This problem is NP-hard, so we settle for an approximation algorithm.

By the above arguments, an algorithm to find a set S of small conductance is as follows:

(1) Compute an eigenvector y to the second smallest eigenvalue of $\mathcal{L}$
(2) Sort all entries of y so that $y_{i_1} \leqslant \ldots \leqslant y_{i_n}$, i.e. vertex i_1 has the smallest value, i_n the largest
(3) Try all cut of the form $S = \{i_1, \ldots, i_j\}$ (or $\overline{S}$, whichever has smaller total degree)

By both sides of Cheeger–Alon–Milmon, this algorithm is guaranteed to find a subset S with $\varphi(S) \leqslant 2\sqrt{\varphi(G)}$.

The approximation guarantee is quite bad if $\varphi(G)$ is very small, say order of $1/n$.

There are other approximation algorithm with better guarantee. There is an SDP-based approximation algorithm by Arora–Rao–Vazirani with approximation ratio $O(\sqrt{\log n})$.