

Lecture 9: May 1, 2013

Madhur Tulsiani

Scribe: Shweta Jain

We know that given the adjacency matrix A of a d -regular graph, the eigenvalues of A have the relation

$$d = \mu_1 \geq \mu_2 \geq \mu_3 \geq \dots \geq \mu_n = -d$$

and if $N = I - \frac{1}{d}A$ is the normalized Laplacian then the eigenvalues of N are

$$0 = \lambda_1 \leq \lambda_2 \leq \lambda_3 \leq \dots \leq \lambda_n \leq 2$$

where $\lambda_i = 1 - \frac{1}{d}\mu_i$.

1 Quadratic form of a matrix

Let $L = dI - A$. For $x \in \mathbb{R}^n$,

$$x^T N x = \frac{1}{d} \sum_{(i,j) \in E} (x_i - x_j)^2$$

$$\lambda_1 = \min_{x \in \mathbb{R}^n} \frac{x^T N x}{x^T x}$$

is the Rayleigh Quotient of x , denoted by $R(x)$ and

$$\lambda_2 = \min_{x \in \mathbb{R}^n, x \perp \mathbf{1}} R(x)$$

If $\lambda_2 = 0$ then G has at least 2 connected components.

2 Cheeger's Inequality

Let $S \subseteq V$, $\varphi(S) = \frac{|E(S, \bar{S})|}{d|S|} = \mathbb{P}_{\text{random}(i,j) \in E} (j \in \bar{S}, i \in S)$

where $|E(S, \bar{S})|$ = number of edges going out of S

(for general graphs, $\varphi(S) = \frac{|E(S, \bar{S})|}{\sum \text{deg}(i)}$ where $\sum \text{deg}(i)$ is also known as the "volume of the graph").

and $\Phi_G = \min_{|S| \leq \frac{n}{2}} \varphi(S)$ be the expansion of the graph.

Then Cheeger's inequality says: $\frac{\lambda_2}{2} \leq \Phi_G \leq \sqrt{2\lambda_2}$

Proof:

Proof 1: To prove: $\frac{\lambda_2}{2} \leq \Phi_G$

Let (S, \bar{S}) be a cut in the graph s.t. $|S| \leq \frac{n}{2}$ and $\varphi(S) \leq \beta$. Then $\exists x \in \mathbb{R}^n, x \perp \mathbf{1}$ s.t. $R(x) \leq 2\beta$.

Consider the vector $\frac{1}{|S|}$ from S and the vector $\frac{-1}{|\bar{S}|}$ from \bar{S} . Then $\sum x_i = |S| \cdot \frac{1}{|S|} + |\bar{S}| \cdot \left(\frac{-1}{|\bar{S}|}\right) = 0$ i.e. orthogonal to $\mathbf{1}$.

Now $R(x) = \frac{\sum_{(i,j) \in E} (x_i - x_j)^2}{d \cdot x^T x}$.

For any edge in $S, x_i = x_j$ so contribution in the sum = 0. Similarly for $|\bar{S}|$. Therefore the only contribution is that of edges going across which is $= \frac{1}{d} \frac{|E(S, \bar{S})| \cdot \left(\frac{1}{|S|} + \frac{1}{|\bar{S}|}\right)^2}{|S| \cdot \frac{1}{|S|^2} + |\bar{S}| \cdot \frac{1}{|\bar{S}|^2}} = \frac{1}{d} \frac{|E(S, \bar{S})| \cdot |S| + |\bar{S}|}{|S| \cdot |\bar{S}|} \leq$

$\beta \cdot 2$ i.e. 2β . Hence proved.

Proof 2: To prove: $\varphi_G \leq 2\sqrt{\lambda_2}$ (slightly worse bound)

Claim 2.1 Given $x \perp \mathbf{1}$, we can find S s.t. $|S| \leq \frac{n}{2}$ and $\varphi_G \leq 2\sqrt{R(x)}$.

Proof: Our proof is algorithmic (a linear time algorithm known as spectral partitioning)

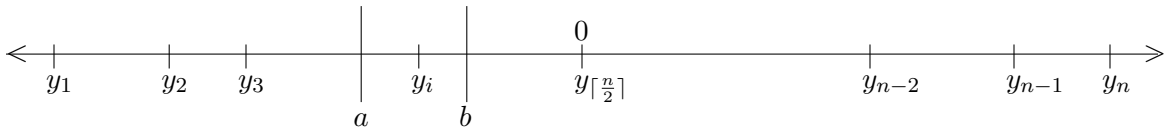
Observation 1:

Multiplying x by a constant c does not change $R(x)$.

Adding c to x :

Let $y = x + c\mathbf{1}$. Then $R(y) \leq R(x)$ This is because: $y^T N y = x^T N x$ (numerators are same) and $\|y\|^2 = \|x + c\mathbf{1}\|^2 = \|x\|^2 + cn$ since x is orthogonal to $\mathbf{1}$ i.e. denominator of LHS is greater than that of RHS. Thus $R(y) \leq R(x)$.

Choose a c such that $y_{\lceil \frac{n}{2} \rceil} = 0$ i.e. let the median be at 0. We know that x gives a real number for each vertex on the number line. We cut this line.



Here a and b are cuts and there are n such cuts possible.

Claim 2.2 One of these cuts is good enough for us.

Proof: We notice that every edge will be looked at only twice. If we know the value for cut a , then to find the value for the next cut b , we only need to look at what happens to edges of y_i i.e. the vertex between a and b .

To avoid having to remember which side of the cut is $\leq \frac{n}{2}$, let

$\forall i, z_i^{(1)} = \max\{y_i, 0\}$ i.e. the positive part of y and

$z_i^{(2)} = \min\{y_i, 0\}$ i.e. the negative part of y . At least one of $z^{(1)}$ and $z^{(2)}$ must be non-zero.

Fact 2.3 $(z^{(1)})^T(z^{(1)}) + (z^{(2)})^T(z^{(2)}) = y^T y$

Fact 2.4 $(z^{(1)})^T N(z^{(1)}) \leq y^T N y$

This is because LHS = $\frac{1}{d} \sum_{(i,j) \in E} (z_i^{(1)} - z_j^{(1)})^2$ whereas the RHS is just the sum of absolute values. Same argument applies for $(z^{(2)})^T N(z^{(2)})$. Combined with the earlier fact we get that at least one of $(z^{(1)})^T(z^{(1)})$ and $(z^{(2)})^T(z^{(2)})$ must be $\leq \frac{y^T y}{2}$. Therefore $R(z^{(1)})$ or $R(z^{(2)})$ must be $\leq 2R(y)$ ■

Given $z \in [-1, 1]^n$, $\exists S \subseteq \{i : z_i \neq 0\}$ s.t. $\varphi(S) \leq \sqrt{2R(z)}$ We will apply this to $z^{(1)}$ and $z^{(2)}$.

- choose random number $t \in [0, 1]$ with uniform distribution
- let $S = \{i : z_i^2 \geq t\}$, then $\mathbb{P}(\text{we choose the } i^{\text{th}} \text{ vertex}) = z_i^2$

Claim 2.5 $\frac{\mathbb{E}[|E(S, \bar{S})|]}{d \mathbb{E}[|S|]} \leq \sqrt{2R(z)}$

if this is true then since LHS is a positive quantity,

$$\mathbb{E} \left[|E(S, \bar{S})| - d \sqrt{2R(z)} |S| \right] \leq 0 \Rightarrow \exists t \text{ s.t. } |E(S, \bar{S})| - d \sqrt{2R(z)} |S| \leq 0.$$

Proof: Proof of claim:

$$\text{Let } Y_i = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{then } \mathbb{E}[|S|] = \sum_i \mathbb{E}[Y_i] = \sum_i z_i^2$$

$$\mathbb{E}[|E(S, \bar{S})|] = \sum_{(i,j) \in E} |z_i^2 - z_j^2|$$

$$= \sum_{(i,j) \in E} |z_i - z_j| |z_i + z_j|$$

$$\leq \sqrt{\sum_{(i,j) \in E} |z_i - z_j|^2} \sqrt{\sum_{(i,j) \in E} (z_i + z_j)^2}$$

(by Cauchy Schwartz)

$$\leq \sqrt{\sum_{(i,j) \in E} |z_i - z_j|^2} \sqrt{\sum_{(i,j) \in E} (2z_i^2 + 2z_j^2)}$$

$$= \sqrt{\sum_{(i,j) \in E} |z_i - z_j|^2} \sqrt{2d \sum_{(i,j) \in E} z_i^2}$$

Therefore
$$\frac{\mathbb{E}[|E(S, \bar{S})|]}{d \mathbb{E}[|S|]} \leq \frac{1}{d} \frac{\sqrt{\sum_{(i,j) \in E} |z_i - z_j|^2} \sqrt{2d \sum_{(i,j) \in E} z_i^2}}{\sum_{(i,j) \in E} z_i^2}$$

$$= \sqrt{R(z)}$$
 ■

We are getting 2 outside root, we will try to get it inside now.

To prove: $\exists S \subseteq V$ s.t. $|S| \leq \frac{n}{2}$ and $\varphi(S) \leq \sqrt{2R(y)}$.

Let $y_{\frac{n}{2}} = 0$ and $y_1^2 + y_n^2 = 1$. Choose $t \in [y_1, y_n]$ where t is a random variable with density $2|t|$ defined only between y_1 and y_n .

Let $S = \{i : y_i \leq t\}$. Then for $a \geq y_1$ and $b \leq y_n$,

$$P(t \in [a, b]) = \int_a^b 2|r| dr$$

$$= \text{sgn}(b) \cdot b^2 - \text{sgn}(a) \cdot a^2$$

Claim 2.6
$$\frac{\mathbb{E}[|E(S, \bar{S})|]}{d \mathbb{E}[\min(|S|, |\bar{S}|)]} \leq \sqrt{2R(y)}$$

After this proof same as above.

Proof of claim:

$$\mathbb{E}[|E(S, \bar{S})|] = \sum_{(i,j) \in E} P(t \in (y_i, y_j))$$

$$= \sum_{(i,j) \in E} |\text{sgn}(y_i) y_i^2 - \text{sgn}(y_j) y_j^2|$$

$$= \sum_{(i,j) \in E} |\text{sgn}(y_i) y_i^2 - \text{sgn}(y_j) y_j^2|$$

Claim 2.7 $|\text{sgn}(y_i) y_i^2 - \text{sgn}(y_j) y_j^2| \leq |y_i - y_j|(|y_i| + |y_j|)$

If this is true then we continue the same process as above.

Proof of claim:

If same signs: obvious

If different signs then it is $= |y_i - y_j|(|y_i| + |y_j|) - (|y_i| + |y_j|)^2$

Hence proved.

Let

$$Y_i = \begin{cases} 1 & \text{if } (i \in S \text{ and } |S| \leq \frac{n}{2}) \text{ OR } (i \in \bar{S} \text{ and } |\bar{S}| \leq \frac{n}{2}) \\ 0 & \text{otherwise.} \end{cases}$$

i.e.

$$Y_i = \begin{cases} 1 & \text{if } y_i \leq t \leq 0 \text{ OR } y_i \geq t \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

Then $\mathbb{E}[\min(|S|, |\bar{S}|)] = \sum_i \mathbb{E}[Y_i]$

$$\begin{aligned}
&= \sum_i y_i^2 \\
\text{So } &\frac{1}{d} \frac{\mathbb{E} [|E(S, \bar{S})|]}{\mathbb{E} \left[\min_i (|S|, |\bar{S}|) \right]} \\
&\leq \frac{\sqrt{2 \sum (y_i - y_j)^2} \sqrt{2d \sum_i y_i^2}}{d \sum_i y_i^2} \\
&= \sqrt{2R(y)}
\end{aligned}$$

Thus $\varphi_G \leq \sqrt{2\lambda_2}$

Hence Proved. ■

3 Some generalizations of Cheeger's inequality

Here we found sets S_1, S_2 s.t. $S_2 = \bar{S}_1$, $\varphi(S_1) \leq \sqrt{2\lambda_2}$ and $\varphi(S_2) \leq \sqrt{2\lambda_2}$

We can also find sets S_1, \dots, S_k that are disjoint s.t. $\forall i \varphi(S_i) \leq O(k^2) \sqrt{\lambda_k}$

Later results also showed that we can find $S_1, S_2, \dots, S_{\frac{k}{2}}$ s.t. $\varphi(S_i) \leq O(\sqrt{\lambda_k \log k})$ (cannot do better than $\log k$)

Dirichlet Boundary Conditions:

Find vectors $z^{(1)}, z^{(1)} \dots z^{(k)}$ s.t. $\forall i, j \{i : z^{(i)} \neq 0\} \cap \{j : z^{(j)} \neq 0\} = \emptyset$ and $\forall i, R(z^{(i)}) = O(k^4) \cdot \lambda_k$

How to find z_i ?

Arrange the k eigenvectors in a matrix and read them row wise. We get vectors $\in \mathbb{R}^k$. Cluster them.