

## Lecture 5 (October 26, 2005)

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### 1. Reminder: Expanders

Before we get to the main topic of this section, we first restate a couple of important definitions. The expansion of a graph  $G(V, E)$  is defined as

$$\rho(G) = \min_{S \subset V} \frac{C(S, \bar{S})}{\min(|S|, |\bar{S}|)}$$

Also, the volume of a subset  $S$  is defined as

$$\text{vol}(S) = \sum_{i \in S} d_i$$

where  $d_i$  is degree  $i$ . Then define the conductance of a graph is defined as

$$\phi(G) = \min_S \frac{C(S, \bar{S})}{\min(\text{vol}(S), \text{vol}(\bar{S}))}$$

From the definitions it follows that

$$\phi(G) \leq \rho(G) \leq \phi(G)d_{max}.$$

Now here's a variant of the theorem we discussed last lecture:

**Theorem 5.1** *For all  $d \geq 3$  and  $n$  sufficiently large, there exists an  $\alpha > 0$  such that any random  $d$ -regular graph of size  $n$  has expansion  $\alpha$ .*

### 2. Spectrum of a Graph

The adjacency matrix of a graph of with  $n$  vertices is an  $n \times n$  matrix where

$$A(i, j) = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$

We will examine the eigenvalues and eigenvectors of this matrix. Another useful matrix representation of a graph is called the *Laplacian*. The Laplacian of a graph  $L(G)$  is defined as

$$L_G(i, j) = \begin{cases} d_i & \text{if } i = j \\ -1 & \text{if } i \text{ is adjacent to } j \\ 0 & \text{otherwise} \end{cases}$$

We can also define the Laplacian of a single edge as

$$L_{G(u,v)}(i, j) = \begin{cases} 1 & \text{if } i = j \in \{u, v\} \\ -1 & \text{if } i = u \text{ and } j = v \text{ or vice versa} \\ 0 & \text{otherwise} \end{cases}$$

It follows then that

$$L_G = \sum_{(u,v) \in E(G)} L_{G(u,v)}$$

It is easy to see that  $L_G$  is positive semi-definite since

$$x^T L_{G(u,v)} x = (x_u - x_v)^2$$

which implies

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

Now let  $0 \leq \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$  be the eigenvalues of  $L$ . Clearly  $\lambda_1 = 0$  since an  $n$ -vector of 1's lies in the null space.

**Claim 5.1**  $\lambda_2 > 0 \Leftrightarrow G$  is connected.

**Proof:** By contradiction, assume  $G$  is connected and  $\lambda_2 = 0$ . Then there exists a non-zero  $x$  orthogonal to  $e = \{1, \dots, 1\}^T$ , which implies  $\sum_i x_i = 0$ , such that  $x^T L x = 0$ , or equivalently

$$\sum_{(i,j) \in E} (x_i - x_j)^2 = 0.$$

This implies  $x_i = x_j$  for all  $i$  adjacent to  $j$ . But by assumption  $G$  is connected, so  $x_i = x_j$  for all  $i, j$ . This is a contradiction since the components of a constant vector cannot sum to zero unless that constant is zero. Now suppose  $G$  is disconnected; we will show that  $\lambda_2$  must be zero. Partition the vertices of  $G$  into sets  $S$  and  $\bar{S}$ . If  $S$  and  $\bar{S}$  are disconnected, then for an  $n$ -vector  $x = \alpha \mathbf{1}_S + \beta \mathbf{1}_{\bar{S}}$  we have  $x^T L x = 0$ , and we can set  $\alpha$  and  $\beta$  such that  $\|x\| = 1$  and  $x^T e = 0$ . Therefore  $\lambda_2 = 0$ . ■

**Corollary 5.1** The multiplicity of the zero eigenvalue is equal to the number of connected components in  $G$ .

The values of  $\lambda_2$  can take ranges from 0 to  $\mathcal{O}(d_{max})$ . If graph is disconnected then  $\lambda_2 = 0$  and the further  $\lambda_2$  is from 0, the better the connectedness of the graph.