

15-859N — Spectral Graph Theory and Numerical Linear Algebra. — Fall 2013

Gary Miller Euiwoong Lee

Assignment 3 Due date: Friday October 25, 2013

1 Expander better than Ahlswede-Winter

[20 points] One important property of the complete graph $K_n = (V, E)$ is *expansion*. We say that a weighted graph has c -expansion if for any subset $S \subseteq V$ with $|S| \leq \frac{n}{2}$, $|E(S, \bar{S})| \geq cn|S|$ where $E(S, \bar{S})$ is the sum of the weight of edges between S and \bar{S} . This definition is scale-variant, but all graphs considered in this problem will have the sum of weights $\Theta(n^2)$. It is also easy to see that K_n is a $\frac{1}{2}$ -expander.

1. In class, we showed that there exists a weighted graph G with $O(n \log n)$ edges such that

$$(1 - \epsilon)K_n \preceq G \preceq (1 + \epsilon)K_n$$

Show that G is a c -expander for some c , which may depend on ϵ .

2. We give an easy proof that expansion is achieved by a graph with only linear number of edges. Let $G(n, d)$ be a (slightly unusual) random graph such that

- At each vertex v , we choose d vertices u_1, \dots, u_d independently from $V \setminus \{v\}$.
- Add edges (v, u_i) for all $1 \leq i \leq d$.

Note that v 's degree may be greater than d if it is *chosen* by other vertices, and the number of edges is always nd .

Show that there exists d such that $\frac{n}{d}G(n, d)$ (so that the sum of weights is exactly n^2) is $\frac{1}{4}$ -expander with high probability.

HINT: It seems that the version of Chernoff bounds given in class is not strong enough to prove that $\frac{n}{d}G(n, d)$ is an expander. Try the following version, see Wikipedia,

Let random variables X_1, \dots, X_n be independent random variables taking on values 0 or 1. Further, assume that $\mathbf{P}(X_i = 1) = p_i$. Then, if we let $X = \sum_{i=1}^n X_i$ and μ be the expectation of X , for any $\delta > 0$

$$\mathbf{P}(X > (1 + \delta)\mu) < \left(\frac{e^\delta}{(1 + \delta)^{(1 + \delta)}} \right)^\mu.$$

Besides using this version of Chernoff bounds one should consider the random variable which is the number of edges internal to some set of vertices S . This random variable will allow you to use a large value for δ in your proof.

2 Chebyshev Polynomials

[20 points]

In this problem we will develop some important identities for Chebyshev Polynomials.

1. Consider the following rotation matrix by angle θ :

$$A_\theta = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$$

Check that A_θ^n is a rotation by $n\theta$, even if θ is a complex number.

2. We can abstract A_θ to a matrix $A = \begin{pmatrix} c & -s \\ s & c \end{pmatrix}$ where $c^2 + s^2 = 1$. Show that

$$A^n = \begin{pmatrix} T_n(c) & -sQ_n(c) \\ sQ_n(c) & T_n(c) \end{pmatrix}$$

where T_n and Q_n are polynomials in c satisfying:

$$\begin{aligned} T_0(c) &= 1 \\ T_1(c) &= c \\ T_{n+1}(c) &= cT_n(c) - (1 - c^2)Q_n(c) \end{aligned}$$

and

$$\begin{aligned} Q_0(c) &= 0 \\ Q_1(c) &= 1 \\ Q_{n+1}(c) &= cQ_n(c) + T_n(c) \end{aligned}$$

3. Use these identities to show that:

$$\begin{aligned} T_{n+1}(c) &= 2cT_n(c) - T_{n-1}(c) \\ Q_{n+1}(c) &= 2cQ_n(c) - Q_{n-1}(c). \end{aligned}$$

Thus T and Q are Chebyshev Polynomials of the first and second kind respectively. Explain why all the roots of T_n and Q_n lie in the interval $[-1, +1]$ and in this interval T returns values in this interval.

4. Show how to diagonalize A .
5. Use this diagonal form to show that

$$T_n(c) = \frac{(c + \sqrt{c^2 - 1})^n + (c - \sqrt{c^2 - 1})^n}{2} = \frac{(c + \sqrt{c^2 - 1})^n + (c + \sqrt{c^2 - 1})^{-n}}{2}$$

HINT: To get the last equality use the fact that c is $\cos \theta$ and use complex numbers.

3 Eigenvalues of Cartesian Products

[15 points]

Let $G = (V, E, w)$ and $H = (V', E', w')$ be two non-negatively weighted simple graphs. Let $G \otimes H = (\bar{V}, \bar{E}, \bar{w})$ be their Cartesian product, where:

- The vertices are $\bar{V} = V \times V'$
 - The edges are $\bar{E} = \{((x, x'), (y, y')) \mid [x = y \wedge (x', y') \in E'] \vee [x' = y' \wedge (x, y) \in E]\}$
 - $\bar{w}((x, x'), (x, y')) = w'(x', y')$ and $\bar{w}((x, x'), (y, x')) = w(x, y)$.
1. Show that the eigenvalues of $L_{G \otimes H}$ are the direct sum of those of L_G and L_H . That is if the eigenvalues of L_G are $\{\lambda_1, \dots, \lambda_n\}$ and those of L_H are $\{\mu_1, \dots, \mu_m\}$ the those of $L_{G \otimes H}$ are $\{\lambda_i + \mu_j \mid 1 \leq i \leq n, 1 \leq j \leq m\}$
 2. Show that the eigenvectors of $L_{G \otimes H}$ are the direct product of those of L_G and L_H .

4 Conjugate Directions

[15 points] Conjugate Directions is another method for solving $Ax = b$, where $A \in \mathbb{R}^{m \times m}$ is SPD. Suppose that we are given a set of search directions $\{d_{(0)}, \dots, d_{(m-1)}\}$ such that $d_{(i)}^T A d_{(j)} = 0$ for all $i \neq j$ (Conjugate Gradient is just a way of efficiently choosing such $d_{(i)}$'s using gradients). Given an initial point $x_{(0)}$, we update in each iteration such that

$$x_{(i+1)} \leftarrow x_{(i)} + \frac{d_{(i)}^T r_{(i)}}{d_{(i)}^T A d_{(i)}} d_{(i)}$$

where $r_{(i)} = b - Ax_{(i)}$. It means that in step (i) , we find $x_{(i+1)}$ such that $r_{(i+1)} \perp d_{(i)}$.

Prove that this method converges in $i \leq m - 1$ steps.

Hint: Write the initial error $e_{(0)}$ as a linear combination of $d_{(i)}$'s and show that i th step annihilates i th component.