

## 1 Preliminaries

First a reminder of what the definition of a spectral expander is.

An infinite family of graphs  $\{G_n\}$  are spectral expanders if there is a constant  $c$  such that:

1.  $G_n$  is connected
2.  $G_n$  has  $O(n)$  edges
3.  $\forall n \lambda_{\min>0}(L_{G_n}) \geq c$ .

Note that the last condition is equivalent to  $L_G \succeq c \cdot I_{\text{im}_{L_G}}$ . We now derive an even simpler condition. Let  $U$  be an orthogonal matrix ( $U \cdot U^T = I$ ) with  $\frac{\vec{1}}{\sqrt{n}}$  as the last row. Then we have:

$$\begin{aligned} L_G \succeq c I_{\text{im}_{L_G}} &\iff U L_G U^T \succeq c U I_{\text{im}_{L_G}} U^T \\ &\iff \begin{pmatrix} M & 0 \\ 0 & 0 \end{pmatrix} \succeq c \begin{pmatrix} I & 0 \\ 0 & 0 \end{pmatrix} \\ &\iff M \succeq c I \\ &\iff \lambda_{\min}(M) \geq c \end{aligned}$$

Thus it makes sense to argue about  $M$  in lieu of considering the entirety of  $L_G$ .

Recall our definition  $L_G = \sum_{uv \in E(G)} y_{uv} y_{uv}^T$  where  $y_{uv} = e_u - e_v$ . Set  $v_e$  to be the first  $n-1$  components of  $U \cdot y_e$ . Note that the last component of  $U y_e$  is zero, since  $y_e^T \frac{\vec{1}}{\sqrt{n}} = 0$ . Thus  $\|v_e\|^2 = \|y_e\|^2 = 2$ . Furthermore, since  $\sum_{e \in E(K_n)} y_e y_e^T = L_{K_n} = n I_{\text{im}_{K_n}}$ , we have

$$\begin{aligned} U \left( \sum_{e \in E(K_n)} y_e y_e^T \right) U^T &= \begin{pmatrix} nI & 0 \\ 0 & 0 \end{pmatrix} \\ \iff \sum_{e \in E(K_n)} v_e v_e^T &= nI \end{aligned}$$

## 2 How to Construct an Expander

**Theorem 2.1.** Let  $w_1, \dots, w_m \in \mathbb{R}^p$  satisfy  $\sum_i w_i w_i^T = I$  and  $\|w_i\|^2 = w_i^T w_i = \frac{p}{m} \forall i$ . Choose an integer  $k > 4$  arbitrarily.

Then there exists a (multi-)set  $F \subseteq [m]$  with  $|F| = kp$  such that  $\lambda_{\min}(\sum_{i \in F} \frac{w_i w_i^T}{w_i^T w_i}) \geq k - 2\sqrt{k}$ . Furthermore, there is a deterministic, polynomial-time algorithm to find such a set  $F$ .

*Proof.* The algorithm given below produces an  $F$  with the given properties. □

To connect this theorem with expanders, let  $m$  be the number of edges in the complete graph, that is  $m = \binom{n}{2} = \frac{n(n-1)}{2}$ . Then take  $p = n - 1$  and let each vector  $w_i$  correspond to some  $v_e/\sqrt{n}$ . Then  $\sum_i w_i w_i^\top = \sum_e v_e v_e^\top/n = I$ .

Note that  $w_i^\top w_i = \frac{v_e^\top v_e}{n} = \frac{2}{n}$ , so  $\frac{w_i w_i^\top}{w_i^\top w_i} = \frac{v_e v_e^\top}{2}$ . So the algorithm outputs a (multi-)set  $F$  with  $|F| = k(n - 1)$  such that

$$\sum_{e \in F} \frac{y_e y_e^\top}{2} \geq k - 2\sqrt{k}.$$

In other words, letting  $G$  be the (multi-)graph with edge set  $F$ , we have  $\lambda_{\min_{>0}}(L_G) \geq 2k - 4\sqrt{k}$ , so  $G$  is a spectral expander.

## 2.1 Expander Algorithm

Parameters:  $\delta = \frac{1}{p}(1 - \frac{1}{\sqrt{k}})$ ,  $\varepsilon = \frac{p}{\sqrt{k}}$ ,  $l_0 = -\frac{p}{\varepsilon} = -\sqrt{k}$

Initially:  $F \leftarrow \emptyset$ ,  $A \leftarrow 0$ ,  $l \leftarrow l_0$

Potential:  $\Phi_l(A) = \text{trace}[(A - lI)^{-1}] = \sum_{i=0}^p (\lambda_i - l)^{-1}$  (where  $\lambda_i$  is the  $i^{\text{th}}$  eigenvalue of  $A$ ).

For  $j = 1, \dots, kp$ :

*Invariants:* (a)  $\lambda_{\min}(A) > l$ , (b)  $\Phi_l(A) \leq \varepsilon$

Find index  $i$  such that  $\lambda_{\min}(A + \frac{w_i w_i^\top}{w_i^\top w_i}) > l + \delta$ , and  $\Phi_{l+\delta}(A + \frac{w_i w_i^\top}{w_i^\top w_i}) \leq \Phi_l(A) \leq \varepsilon$

$F \leftarrow F \cup i$ ,  $A \leftarrow A + \frac{w_i w_i^\top}{w_i^\top w_i}$ ,  $l \leftarrow l + \delta$

End

**Claim 2.2.** The invariants hold throughout the running of the algorithm.

*Proof.* Initially  $A = 0$  and  $l = l_0$ , thus  $\lambda_{\min}(A) = 0 > l = l_0 = -\sqrt{k}$

Also  $\Phi_l(0) = \text{trace}[(-lI)^{-1}] = \text{trace}[\frac{\varepsilon}{p}I] = \varepsilon$

So the invariants are initially satisfied, and  $i$  is chosen specifically as to not violate any invariant, thus the invariants are never violated  $\square$

**Claim 2.3.** The resulting graph is a spectral expander.

*Proof.* After  $kp$  iterations the loop terminates. Thus the number of edges added is  $O(n)$ .

At this point  $l = l_0 + (kp)\delta = -\sqrt{k} + k(1 - \frac{1}{\sqrt{k}}) = k - 2\sqrt{k}$ . Thus  $\lambda_{\min}(A) > k - 2\sqrt{k} = \sum_{i \in F} \frac{w_i w_i^\top}{w_i^\top w_i}$  (this is positive since  $k > 4$ ).

This implies the graph is connected, since the kernel of its Laplacian is one dimensional.  $\square$

Similar to the previous lecture it is not clear that it is possible to find such an index at each iteration. We use a proof very similar to the one used last lecture to show that such an  $i$  always exists.

Assume that  $\lambda_{\min}(A) > l$  and  $\Phi_l(A) \leq \frac{1}{\delta}$

Define  $M := (A - (l + \delta)I)^{-1}$ ,  $N := \frac{M^2}{(\Phi_{l+\delta} - \Phi_l)(A)} - M$ .

**Observation 2.4.**  $\lambda_{\min}(A) > l + \delta$

*Proof.* Assume to the contrary that  $\lambda_{\min}(A) \in (l, l + \delta]$ . Then

$$\begin{aligned}\Phi_l(A) &= (\lambda_{\min}(A) - l)^{-1} + \dots + (\lambda_{\max}(A) - l)^{-1} \\ &> (l + \delta - l)^{-1} \\ &= \frac{1}{\delta}\end{aligned}$$

This contradicts our original assumption that  $\Phi_l(A) \leq \frac{1}{\delta}$ .  $\square$

**Observation 2.5.**  $\Phi_{l+\delta}(A) > \Phi_l(A)$ .

*Proof.*  $\Phi_{l+\delta}(A) = \text{trace}[(A - lI)^{-1}] > \text{trace}[(A - (l + \delta)I)^{-1}] = \Phi_l(A)$ .  $\square$

**Lemma 2.6.** Set  $v \in \mathbb{R}^p$  and  $t > 0$  arbitrarily. If  $\frac{1}{t} \leq v^\top N v$ , then  $\Phi_{l+\delta}(A + t v v^\top) \leq \Phi_l(A)$  and  $\lambda_{\min}(A + t v v^\top) > l + \delta$ .

*Proof.*

$$\begin{aligned}\Phi_{l+\delta}(A + t v v^\top) &= \text{trace}[(A + t v v^\top - (l + \delta)I)^{-1}] \\ &= \text{trace}[\underbrace{(A - (l + \delta)I + t v v^\top)^{-1}}_{M^{-1}}] \\ &= \text{trace}[(M^{-1} + t v v^\top)^{-1}] \\ &= \text{trace}\left[M - \frac{t M v v^\top M}{1 + t v^\top M v}\right] \quad \text{By Sherman-Morrison Formula} \\ &= \text{trace}[M] - \frac{t \cdot \text{trace}(v^\top M^2 v)}{1 + t v^\top M v} \quad \text{By linearity and cyclic property of trace} \\ &= \Phi_{l+\delta}(A) - \frac{v^\top M^2 v}{\frac{1}{t} + v^\top M v} \\ &= \Phi_l(A) + (\Phi_{l+\delta}(A) - \Phi_l(A)) - \frac{v^\top M^2 v}{\frac{1}{t} + v^\top M v}\end{aligned}$$

Thus

$$\begin{aligned}\Phi_{l+\delta}(A + t v v^\top) \leq \Phi_l(A) &\iff (\Phi_{l+\delta}(A) - \Phi_l(A)) - \frac{v^\top M^2 v}{\frac{1}{t} + v^\top M v} \leq 0 \\ &\iff \frac{1}{t} \leq \frac{v^\top M^2 v}{\Phi_{l+\delta}(A) - \Phi_l(A)} - v^\top M v = v^\top N v\end{aligned}$$

And we have  $\lambda_{\min}(A + t v v^\top) \geq \lambda_{\min}(A) > l + \delta$  by observation 2.4.  $\square$

**Lemma 2.7.**  $\text{trace}(N) \geq \frac{1}{\delta} - \varepsilon$

*Proof.*

$$\begin{aligned}
\text{trace}(N) &= \frac{\text{trace}(M^2)}{\Phi_{l+\delta}(A) + \Phi_l(A)} - \text{trace}(M) \\
&= \frac{\sum_i (\lambda_i - l - \delta)^{-2}}{\sum_i (\lambda_i - l - \delta)^{-1} - \sum_i (\lambda_i - l - \delta)^{-1}} - \sum_i (\lambda_i - l - \delta)^{-1} \\
&= \frac{\sum_i (\lambda_i - l - \delta)^{-2}}{\delta \sum_i (\lambda_i - l - \delta)^{-1} \sum_i (\lambda_i - l - \delta)^{-1}} - \sum_i (\lambda_i - l - \delta)^{-1} \\
&\leq \frac{1}{\delta} - \varepsilon
\end{aligned}$$

where the third equality uses the identity  $\frac{1}{a} - \frac{1}{a+b} = \frac{b}{a(a+b)}$ , and the inequality is a messy use of Cauchy-Schwarz. Details are in the Batson et al. paper.  $\square$

**Claim 2.8.** There is a good index.

*Proof.*

$$\begin{aligned}
\sum_i w_i^\top N w_i &= \sum_i \text{trace}(w_i^\top N w_i) \\
&= \sum_i \text{trace}(w_i w_i^\top N) \\
&= \text{trace}\left[\left(\sum_i w_i w_i^\top\right) N\right] \\
&= \text{trace}[IN] \\
&= \text{trace}[N] \\
&\geq \frac{1}{\delta} - \varepsilon
\end{aligned}$$

Then the average over the  $m$  edges is  $(\frac{1}{\delta} - \varepsilon)/m$ , and so  $\exists i$  such that:

$$\begin{aligned}
w_i^\top N w_i &\geq \frac{\frac{1}{\delta} - \varepsilon}{m} \\
&= \frac{1}{m} \left( p \left(1 - \frac{1}{\sqrt{k}}\right)^{-1} - \frac{p}{k} \right) \\
&\geq \frac{p}{m} \left[ \left(1 + \frac{1}{\sqrt{k}}\right) - \frac{1}{\sqrt{k}} \right] \\
&= \frac{p}{m},
\end{aligned}$$

where the second inequality follows from  $1/(1-x) \geq 1+x$  for all  $x \leq 1$ , by Taylor Approximation. So if we set  $t = \frac{m}{p} = \frac{\frac{n(n-1)}{2}}{n-1} = \frac{n}{2} = \frac{1}{w_i^\top w_i}$  (from our definitions above) then we can ensure the invariants are satisfied by taking  $A \leftarrow A + \frac{w_i w_i^\top}{w_i^\top w_i}$ .  $\square$

## 2.2 Comparison with the optimal

The optimal expander graphs, Ramanujan graphs, are  $d$ -regular and satisfy

$$\lambda_{\min>0}(L_G) \geq d - 2 \cdot \sqrt{d-1}.$$

So their number of edges is exactly  $\frac{d}{2}n$ .

For the sake of comparison, let us run our algorithm with  $k = d/2$ , so that  $k(n-1) \approx \frac{d}{2}n$ . Our algorithm gives us a graph  $G$  with  $k(n-1)$  edges, and

$$\lambda_{\min>0}(L_G) \geq 2k - 4\sqrt{k} = d - 2\sqrt{2} \cdot \sqrt{d}.$$

So the difference between the optimal Ramanujan graphs (which are very difficult to analyze), and the expanders constructed by our algorithm is essentially just a small  $\sqrt{2}$  factor in the coefficient of  $\sqrt{d}$ . Also, Ramanujan graphs are regular whereas  $G$  is typically not.