

①

Generalized Hypercubes.

We already saw that H_d was a Cayley graph with $\Gamma = (\mathbb{Z}/2\mathbb{Z})^d$ and generator set $S = \{b_1, \dots, b_d \mid \text{exactly one } b_i = 1\}$.

We noticed then that (since each element is its own inverse), we could take any $S \subset \Gamma$ and still get a Cayley graph.

So suppose $S = \{g_1, \dots, g_k\}$ and let G be the Cayley graph with these generators.

②

We previously computed the eigenvectors of H_d . We now check these are also eigenvectors of G .

For each $b = (b_1 \dots b_d) \in \{0, 1\}^d$, define

$$\Psi_b(\vec{x}) = (-1)^{\langle \vec{b}, \vec{x} \rangle}$$

Lemma. The vector $\vec{\Psi}_b$ is a Laplacian matrix eigenvector with eigenvalue

$$K - \sum_{i=1}^K (-1)^{\langle \vec{b}, \vec{g}_i \rangle}$$

Proof. Observe that

$$\begin{aligned} \vec{\Psi}_b(\vec{x} + \vec{y}) &= (-1)^{\langle \vec{b}, \vec{x} + \vec{y} \rangle} = (-1)^{\langle \vec{b}, \vec{x} \rangle} (-1)^{\langle \vec{b}, \vec{y} \rangle} \\ &= \vec{\Psi}_b(\vec{x}) \vec{\Psi}_b(\vec{y}). \end{aligned}$$

(3)

Now we compute

$$(\mathbb{L} \vec{\Psi}_b)(\vec{x}) = \sum_{i=1}^K \vec{\Psi}_b(\vec{x}) - \vec{\Psi}_b(\vec{x} + \vec{g}_i)$$

$$= K \vec{\Psi}_b(\vec{x}) - \sum_{i=1}^K \vec{\Psi}_b(\vec{x} + \vec{g}_i)$$

$$= K \vec{\Psi}_b(\vec{x}) - \sum_{i=1}^K \vec{\Psi}_b(\vec{x}) \vec{\Psi}_b(\vec{g}_i)$$

$$= \vec{\Psi}_b(\vec{x}) \left[K - \sum_{i=1}^K \vec{\Psi}_b(\vec{g}_i) \right],$$

as claimed!

Now we show that if we choose random generators g_1, \dots, g_K for $K=cd$ where c is constant, it will be very likely that all eigenvalues will

be close to K . (We will need $c > 1$; maybe $c=10$, $c=2$ or $c=1+\epsilon$.)

(4)

Lemma. If $b = (b_1, \dots, b_d)$ contains at least one 1, and g is chosen at random (uniformly) from $\{0, 1\}^d$,

$$\langle \vec{b}, \vec{g} \rangle \pmod{2}$$

is uniformly distributed between $\{0, 1\}$.

~~Proof. Homework.~~

Proof. Homework.

Given the lemma,

$$\lambda_b = K - \sum_{i=1}^K (-1)^{\langle \vec{b}, \vec{g}_i \rangle}$$

= K - (a sum of independent ± 1 random variables)

⑤

We expect sums of i.i.d. ± 1 r.v.s to ^{be} concentrated around zero. Precisely,

Theorem (Simple Chernoff bounds).

Let x_1, \dots, x_k be i.i.d. ± 1 random variables (with equal probability of $+1, -1$). For all $t > 0$, we have

$$Pr \left[\left| \sum_i x_i \right| \geq t \right] \leq 2e^{-t^2/2k}$$

Thus, if $t \sim \sqrt{k}$, this becomes very small for large k .

⑥

We can combine the Chernoff bound with the union bound:

Theorem. (Boole's inequality)

For any finite (or countable) set of events A_1, \dots, A_i, \dots we have

$$\Pr \left[\bigcup_i A_i \right] = \Pr \left[\begin{array}{l} \text{at least one of} \\ \text{the } A_i \text{ occurs} \end{array} \right] \\ \leq \sum_i \Pr [A_i].$$

Notice that this is true whether or not the events A_i are correlated.

We now consider the eigenvalues of the generalized hypercube. ⑦

Suppose the dimension is d , and we choose K generators at random.

There are $2^d - 1$ nonzero eigenvectors each indexed by some $b = (b_1 \dots b_d)$ containing at least one 1.

$$\begin{aligned}\lambda_b &= K - \sum_{i=1}^K (-1)^{\langle b, \hat{g}_i \rangle} \\ &= K - \sum_{i=1}^K x_i\end{aligned}$$

where x_i is a Bernoulli ± 1 random variable.

⑧

So for each K, ϵ we have

$$\Pr[|K - \lambda_b| \geq \epsilon] = \Pr\left[\left|\sum_{i=1}^K x_i\right| \geq \epsilon\right] \leq 2e^{-\epsilon^2/2K}$$

by the Chernoff bound. Let's assume that $K = cd$ (for some c) and $\epsilon = K\sqrt{2/c}$.

$$\Pr[|K - \lambda_b| \geq \epsilon] \leq 2e^{-K^2 \frac{2}{c} / 2K}$$

$$\leq 2e^{-K/c}$$

$$\leq 2e^{-d}$$

Now there are $2^{d_{\text{eff}}} - 1$ eigenvalues, so

~~#~~

$$\Pr[\exists b \mid |K - \lambda_b| \geq K\sqrt{2/c}] \leq (2^{d_{\text{eff}}} - 1) 2e^{-d}$$

by the union bound.

9.

We observe that

$$(2^d - 1) 2e^{-d} \leq 2 \cdot \frac{2^d}{e^d} = 2 \left(\frac{2}{e}\right)^d.$$

Since $2/e < 1$, the right hand side approaches 0 exponentially fast (in d).

We have proved:

Theorem. If $K = cd$, ~~and~~ then

$$\Pr \left[\exists b \mid |K - \lambda_b| \geq K\sqrt{\frac{2}{c}} \right] \leq 2 \left(\frac{2}{e}\right)^d$$

Notice that ~~$|K - \lambda_b| \leq K$~~ $|K - \lambda_b| \leq K$ (always) because $\lambda_b \in [0, 2K]$, so this bound is useful only for $c > 2$.

Now let's ~~not~~ weight each edge (10)
of our generalized hypercube with
 $2^d/k$. Weighting edges ~~not~~ scales
eigenvalues, so

Theorem. If G is the graph with
vertex set $\{0,1\}^d$ and edges determined
by $K=cd$ random generators, each edge
with weight $2^d/k$,

$$\Pr[\exists b \mid |2^d - \lambda_b| \geq 2^d \sqrt{\frac{2}{c}}] \leq 2 \left(\frac{2}{e}\right)^d.$$

or, if v is # of vertices,

$$\Pr[\exists b \mid |v - \lambda_b| \geq \sqrt{\frac{2}{c}} v] \leq 2 \left(\frac{2}{e}\right)^d$$

Now the complete graph K_r has eigenvalues $\lambda_1, \dots, \lambda_r$, so we can rewrite our theorem as

(11)

Theorem. If G is the graph with vertex set $\{0, 1\}^d$ of $v = 2^d$ vertices, and edges determined by $K = cd = c \log_2 v$ random generators, each ~~edge~~ edge with weight $v/K = 2^d/K$,

$\Pr [G \text{ is a } (1 + \sqrt{2/c})\text{-approximation}]$
of K_r

is $\geq 1 - 2(\frac{2}{e})^d$.

This is a surprise! These graphs have degree $K = c \log_2 v \ll$ the

degree $(v-1)$ of the complete graphs K_v .

(12)

Further, the graph G has only

$$\frac{\sqrt{K}}{2} = \frac{c}{2} v \log_2 v$$

edges - much less than the

$$\binom{v}{2} = \frac{v(v-1)}{2}$$

edges in K_v .