

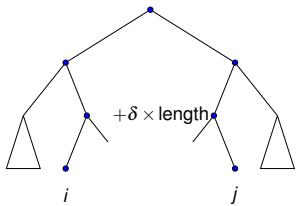
## Tree

Path:  $G = (V, E)$ ,  $V = \{1, \dots, n\}$ ,  $E = \{(i, i+1) : i \in \{1, n-1\}\}$

Init:  $f(e) = 0, \forall e \in G$ .

Update( $i, j, \delta$ )  
 $\forall k \in \{i, \dots, j-1\}, f(i, i+1) = f(i, i+1) + \delta$

Lookup( $i, j$ )  
 Return  $\sum_{k=i}^{j-1} f(k, k+1)$ .



Leaves are edges.  
 Update: find common ancestor.  
 For left path:  
 Add  $\delta \times \text{length}$  to edge.  
 Reflect for right path.

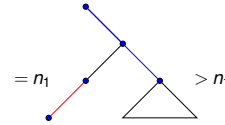
Lookup: Exercise.

$O(\log n)$  update/lookup.

## Path Decomposition of Tree

Given tree  $T$ .

Decomposition Procedure:  
 Longest path from root to leaf.  
 From root, go towards heavier side.  
 Remove. Recurse



Decomposition Property:  
 Where a root to leaf path in tree only sees  $O(\log n)$  paths.

Proof Idea:  
 Every path change, doubles number of vertices.

$O(\log^2 n)$  update time for updating flow values on tree edges!

## What's going on?

Geometric View.

Cycles are constraints.

Flow around cycle = 0.

Each cycle update is approximate projection  
 into subspace defined by constraint.

Solution is intersection of cycle constraints and flow conservation.  
 Kirchhoff's Laws.

Algorithmic Power.

Algebra: Solving exactly on tree.

Calculus: make a local move th decreases potential.

Better Algorithm:

Recursive algorithm give  $O(m\sqrt{\log n})$  iterations to halve error.

Preconditioner uses tree to make sparse version of graph.

Correspondence to Practice:

Random sparsification of Cholesky factorization.

(Kyung-Sachdeva)

Tree pre-conditioner.

Laplacian Systems are quite general:

Climate, physics, SDD-matrices.

## Next

Rayleigh quotient.

$$\lambda_2 = \max_{x \perp 1} \frac{x^T M x}{x^T x}.$$

Eigenvalue gap:  $\mu = \lambda_1 - \lambda_2 = \frac{1}{d} \lambda_{\min}(L)$ .

Recall:  $h(G) = \min_{S, |S| \leq |V|/2} \frac{|E(S, V-S)|}{|S|}$

$$\frac{\mu}{2} = \frac{1-\lambda_2}{2} \leq h(G) \leq \sqrt{2(1-\lambda_2)} = \sqrt{2\mu}$$

Today: the right hand inequality.

## Sum of squared differences.

Quotient Rayleigh:  $\max_{x \perp 1} \frac{x^T M x}{x^T x}$ .

Alternatively:  $\mu = \min_{x \perp 1} \frac{x^T (L/d)x}{x^T x}$ .

$L = dI - A$  or  $L/d = I - A/d = I - M$ .

Also:

$$\begin{aligned} x^T L x &= \sum_i d x_i^2 - \sum_{e=(i,j)} 2 x_i x_j \\ &= \sum_{e=(i,j)} (x_i^2 + x_j^2 - 2 x_i x_j) \\ &= \sum_{e=(i,j)} (x_i - x_j)^2. \end{aligned}$$

Denominator:

$$\sum_i |x_i|^2 = |x|^2. \text{ Normalize to 1.}$$

Also note:

$$\sum_{i,j} (x_i - x_j)^2 = \sum_{i,j} x_i^2 + x_j^2 - 2 x_i x_j = 2n |x|^2.$$

Since  $x_j \sum_i x_i = 0$  for  $x \perp 1$ .

Rayleigh Quotient:

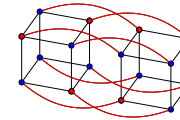
embedding to line

that minimizes ratio of Average edge length/(avg pair length)

## Hypercube

$V = \{0, 1\}^d$  ( $x, y \in E$  when  $x$  and  $y$  differ in one bit.

$|V| = 2^d$   $|E| = d 2^{d-1}$ .



Good cuts? "Coordinate cut":  $d$  of them.

Edge expansion:  $\frac{2^d - 1}{d 2^{d-1}} = \frac{1}{d}$

Ball cut: All nodes within  $d/2$  of node, say  $00 \dots 0$ .

Vertex cut size:  $\binom{d}{d/2}$  bit strings with  $d/2$  1's.

$$\approx \frac{2^d}{\sqrt{d}}$$

Vertex expansion:  $\approx \frac{1}{\sqrt{d}}$ .

Edge expansion:  $d/2$  edges to next level.  $\approx \frac{1}{2\sqrt{d}}$

Worse by a factor of  $\sqrt{d}$

## Eigenvalues of hypercube.

Anyone see any symmetry?

Coordinate cuts. +1 on one side, -1 on other.

$$(Mv)_i = (1 - 2/d)v_i.$$

Eigenvalue  $1 - 2/d$ .  $d$  Eigenvectors. Why orthogonal?

Next eigenvectors?

Delete edges in two dimensions.

Four subcubes: bipartite. Color  $\pm 1$

Eigenvalue:  $1 - 4/d$ .  $\binom{d}{2}$  eigenvectors.

Eigenvalues:  $1 - 2k/d$ .  $\binom{d}{k}$  eigenvectors.

## Slow vector.

Find  $x \perp \mathbf{1}$  with Rayleigh quotient,  $\frac{x^T Mx}{x^T x}$  close to 1.

$$x_i = \begin{cases} i - n/4 & \text{if } i \leq n/2 \\ 3n/4 - i & \text{if } i > n/2 \end{cases}$$

Hit with  $M$ .

$$(Mx)_i = \begin{cases} -n/4 + 1/2 & \text{if } i = 1, n \\ n/4 - 1 & \text{if } i = n/2 \\ x_i & \text{otherwise} \end{cases}$$

$$\rightarrow x^T Mx = x^T x(1 - O(\frac{1}{n^2})) \rightarrow \lambda_2 \geq 1 - O(\frac{1}{n^2})$$

$$\mu = \lambda_1 - \lambda_2 = O(\frac{1}{n^2})$$

$$h(G) = \frac{2}{n} = \Theta(\sqrt{\mu})$$

$$\frac{\mu}{2} = \frac{1-\lambda_2}{2} \leq h(G) \leq \sqrt{2(1-\lambda_2)} = \sqrt{2\mu}$$

Tight example for upper bound for Cheeger.

## Back to Cheeger.

Coordinate Cuts:

Eigenvalue  $1 - 2/d$ .  $d$  Eigenvectors.

$$\frac{\mu}{2} = \frac{1-\lambda_2}{2} \leq h(G) \leq \sqrt{2(1-\lambda_2)} = \sqrt{2\mu}$$

For hypercube:  $h(G) = \frac{1}{d} \lambda_1 - \lambda_2 = 2/d$ .

Left hand side is tight.

Note: hamming weight vector also in first eigenspace.

Lose "names" in hypercube, find coordinate cut?

Find coordinate cut?

Eigenvector  $v$  maps to line.

Cut along line.

Eigenvector algorithm gets a linear combination of coordinate cuts.

Something like ball cut.

Find coordinate cut?

## Eigenvalues of cycle?

Eigenvalues:  $\cos \frac{2\pi k}{n}$ .

$$x_i = \cos \frac{2\pi ki}{n}$$

$$(Mx)_i = \cos \left( \frac{2\pi k(i+1)}{n} \right) + \cos \left( \frac{2\pi k(i-1)}{n} \right) = 2 \cos \left( \frac{2\pi k}{n} \right) \cos \left( \frac{2\pi ki}{n} \right)$$

Cuz:  $\cos(x+y) + \cos(x-y) = 2 \cos x \cos y$ .

cuz:  $e^{i(x+y)} = e^{ix} e^{iy}$ .  $e^{ix} = \cos x + i \sin x$ . ....

Eigenvalue:  $\cos \frac{2\pi k}{n}$ .

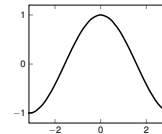
Eigenvalues: vibration modes of system. Fourier basis.

$$\cos x \approx 1 + \sin(0)x - \cos(0) \frac{x^2}{2}.$$

$$\cos \frac{2\pi}{n} \approx 1 + \sin(0)x - \cos(0) \frac{x^2}{2}.$$

Second biggest eigenvalue:  $\approx 1 - \frac{2\pi^2}{n^2}$ .

$$h(G) = \frac{2}{n} \leq \frac{\pi}{n} \approx \sqrt{2\mu}.$$



## Cycle

Tight example for Other side of Cheeger?

$$\frac{\mu}{2} = \frac{1-\lambda_2}{2} \leq h(G) \leq \sqrt{2(1-\lambda_2)} = \sqrt{2\mu}$$

Cycle on  $n$  nodes.

Will show other side of Cheeger is tight.

Edge expansion: Cut in half.

$$|S| = n/2, |E(S, \bar{S})| = 2$$

$$\rightarrow h(G) = \frac{2}{n}.$$

Show eigenvalue gap  $\mu \leq \frac{1}{n^2}$ .

Find  $x \perp \mathbf{1}$  with Rayleigh quotient,  $\frac{x^T Mx}{x^T x}$  close to 1.

## Random Walk.

$p$  - probability distribution.

Probability distribution after choose a random neighbor.  
 $Mp$ .

Converge to uniform distribution.

Power method:  $M^i x$  goes to highest eigenvector.

$$M^i x = a_1 \lambda_1^i v_1 + a_2 \lambda_2^i v_2 + \dots$$

$\lambda_1 - \lambda_2$  - rate of convergence.

$\Omega(n^2)$  steps to get close to uniform.

Start at node 0, probability distribution,  $[1, 0, 0, \dots, 0]$ .

Takes  $\Omega(n^2)$  to get  $n$  steps away.

Recall drunken sailor.

## Other views

Quotient Rayleigh:  $\max_{x \perp \mathbf{1}} \frac{x^T M x}{x^T x}$ .

Alternatively:  $\mu = \min_{x \perp \mathbf{1}} \frac{x^T (L/d)x}{x^T x}$ .

$L = dI - A$  or  $L/d = I - A/d = I - M$ .

Also:

$$\begin{aligned} x^T L x &= \sum_i d x_i^2 - \sum_{e=(i,j)} 2 x_i x_j \\ &= \sum_{e=(i,j)} (x_i^2 + x_j^2 - 2 x_i x_j) \\ &= \sum_{e=(i,j)} (x_i - x_j)^2. \end{aligned}$$

## Random threshold.

$$\mu = \min_{x \perp \mathbf{1}} \frac{\sum_e M_{ij} (x_i - x_j)^2}{\sum_{i,j} (x_i - x_j)^2}$$

Conductance  $\phi(G) = n \frac{E(S, \bar{S})}{|S| |V - S|}$ .

Idea: pick random threshold.

Average number of edges cut compared to pairs is  $\mu$ .

True if "length" corresponded to  $|x_i - x_j|$ .

Off when length is  $(x_i - x_j)^2$ .

Off by average length of edges.

For path:

edges have  $|x_i - x_j|$  being  $1/n$  of that for pairs.

For expanders:

edges go a constant fraction of what random pairs do.

## Warmup exercise: no larger eigenvalue on cycle.

Consider  $x$  for path.

Sort by  $x$ -value:  $x_1, \dots, x_n$ .

Let  $x_1^2 + x_n^2 = 1$ . Shift so that  $x_{n/2} = 0$ .

Now, since any cut  $\geq 1$

$$x^T L x \geq 1 \times \sum_i (x_i - x_{i+1})^2.$$

Cuz:  $\geq$  one edge "crossing" over the interval  $[x_i, x_{i+1}]$ .

Take  $a = (x_i - x_{i+1})$  and  $b = 1/\sqrt{n}$ .

Cauchy-Schwartz  $|a||b| \geq a \cdot b$ .

Yields:  $\sum_i (x_i - x_{i+1})^2 \geq (x_1 - x_n)^2 / n$

Furthermore:  $\sum_i x_i^2 \leq n(x_1^2 + x_n^2) \leq n(x_1^2 + x_n^2 - 2x_1 x_n) = n(x_1 - x_n)^2$ .

$$\rightarrow \mu = \frac{x^T L x}{x^T x} \geq 1/n^2.$$

Argument uses cut size to lower bound eigenvalue.

Or use eigenvalue to upper bound on cut size.

Is  $\mu \geq 2/n^2$ ?

## Cheeger Hard Part.

Now let's get to the hard part of Cheeger  $h(G) \leq \sqrt{2(1 - \lambda_2)}$ .

**Idea:** We have  $1 - \lambda_2$  as a continuous relaxation of  $\phi(G)$

Take the  $2^{nd}$  eigenvector  $x = \operatorname{argmin}_{x \in \mathbb{R}^V - \operatorname{Span}\{\mathbf{1}\}} \frac{\sum_{i,j} M_{ij} (x_i - x_j)^2}{\frac{1}{n} \sum_{i,j} (x_i - x_j)^2}$

Consider  $x$  as an embedding of the vertices to the real line.

Round  $x$  to get a  $x \in \{0, 1\}^V$

**Rounding:** Take a threshold  $t$ ,

$$\begin{cases} x_i \geq t & \rightarrow x_i = 1 \\ x_i < t & \rightarrow x_i = 0 \end{cases}$$

What will be a good  $t$ ?

We don't know. Try all possible thresholds ( $n-1$  possibilities), and hope there is a  $t$  leading to a good cut!

## Interpretation of quadratic form

Consider  $\mu = \min_{x \perp \mathbf{1}} \frac{x^T L x}{x^T x}$ .

$\sum_i x_i = 0$

Claim:  $n \sum_i x_i^2 = \frac{1}{n} \sum_{i \leq j} (x_i - x_j)^2$

$\sum_i (2(n-1)x_i^2 - 2x_i \sum_{j \neq i} x_j)$

$-2x_i \sum_{j \neq i} x_j = -2x_i((\sum_i x_i) - x_i) = 2x_i^2 + x_i \sum_i x_i = 2x_i^2$

$\sum_i n x_i^2 - (\sum_i x_i)(\sum_i x_i)$

Claim:  $x^T L x = \sum_{e=(i,j)} M_{ij} (x_i - x_j)^2$

$$\mu = \min_{x \perp \mathbf{1}} \frac{\sum_e M_{ij} (x_i - x_j)^2}{\frac{1}{n} \sum_{i,j} (x_i - x_j)^2}$$

Ratio of average edge "length" to pair length.

Conductance  $\phi(G) = n \frac{E(S, \bar{S})}{|S| |V - S|}$ .

Idea: pick random threshold.

Average number of edges cut compared to pairs is  $\mu$ ?

## Sweep Cut Algorithm

Input:  $G = (V, E)$ ,  $x \in \mathbb{R}^V$ ,  $x \perp \mathbf{1}$

Sort the vertices in non-decreasing order with respect to  $x$   
WLOG  $V = \{1, \dots, n\}$   $x_1 \leq x_2 \leq \dots \leq x_n$

Let  $S_i = \{1, \dots, i\}$   $i = 1, \dots, n-1$

Return  $S = \operatorname{argmin}_{S_i} h(S_i)$

**Main Lemma:**  $G = (V, E)$ ,  $d$ -regular

$$x \in \mathbb{R}^V, x \perp \mathbf{1}, \mu = \frac{\sum_{i,j} M_{ij} (x_i - x_j)^2}{\sum_{i,j} (x_i - x_j)^2}$$

If  $S$  is the output of the sweep cut algorithm, then  $h(S) \leq \sqrt{2\mu}$

**Note:** Applying the Main Lemma with the  $2^{nd}$  eigenvector  $v_2$ , we have  $\mu = 1 - \lambda_2$ , and  $h(G) \leq h(S) \leq \sqrt{2(1 - \lambda_2)}$ . Done!

## Proof of Main Lemma

WLOG  $V = \{1, \dots, n\}$   $x_1 \leq x_2 \leq \dots \leq x_n$

Want to show

$$\exists i \text{ s.t. } h(S_i) = \frac{\frac{1}{d} |E(S_i, V - S_i)|}{\min(|S_i|, |V - S_i|)} \leq \sqrt{2\mu}$$

**Probabilistic Argument:** Construct a distribution  $D$  over  $\{S_1, \dots, S_{n-1}\}$  such that

$$\frac{\mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)|]}{\mathbb{E}_{S \sim D}[\min(|S|, |V - S|)]} \leq \sqrt{2\mu}$$

$$\rightarrow \mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)| - \sqrt{2\mu} \min(|S|, |V - S|)] \leq 0$$

$$\exists S \quad \frac{1}{d} |E(S, V - S)| - \sqrt{2\mu} \min(|S|, |V - S|) \leq 0$$

## The distribution $D$

WLOG, shift and scale so that  $x_{\lfloor \frac{n}{2} \rfloor} = 0$ , and  $x_1^2 + x_n^2 = 1$

Take  $t$  from the range  $[x_1, x_n]$  with density function  $f(t) = 2|t|$ .

$$\text{Check: } \int_{x_1}^{x_n} f(t) dt = \int_{x_1}^0 -2t dt + \int_0^{x_n} 2t dt = x_1^2 + x_n^2 = 1$$

$$S = \{i : x_i \leq t\}$$

Let  $D$  be distribution over  $S_1, \dots, S_{n-1}$  from the above process.

## Denominator.

$$\text{Goal: } \frac{\mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)|]}{\mathbb{E}_{S \sim D}[\min(|S|, |V - S|)]} \leq \sqrt{2\mu}$$

**Denominator:**

Let  $T_i =$  indicator for “ $i$  is in the smaller set of  $S, V - S$ ”

Can check

$$\mathbb{E}_{S \sim D}[T_i] = \Pr[T_i = 1] = x_i^2$$

Idea:  $i$  in smaller set if  $\tau \in [0, x_i]$  or  $[x_i, 0]$ .

$$\begin{aligned} \mathbb{E}_{S \sim D}[\min(|S|, |V - S|)] &= \mathbb{E}_{S \sim D}[\sum_i T_i] \\ &= \sum_i \mathbb{E}_{S \sim D}[T_i] \\ &= \sum_i x_i^2 \end{aligned}$$

## Numerator

$$\text{Goal: } \frac{\mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)|]}{\mathbb{E}_{S \sim D}[\min(|S|, |V - S|)]} \leq \sqrt{2\mu}$$

**Numerator:**

Let  $T_{i,j} =$  indicator for  $i, j$  is cut by  $(S, V - S)$

$$\begin{cases} x_i, x_j \text{ same sign:} & \Pr[T_{i,j} = 1] = |x_i^2 - x_j^2| \\ x_i, x_j \text{ different sign:} & \Pr[T_{i,j} = 1] = x_i^2 + x_j^2 \end{cases}$$

A common upper bound:  $\mathbb{E}[T_{i,j}] = \Pr[T_{i,j} = 1] \leq |x_i - x_j|(|x_i| + |x_j|)$

$$\begin{aligned} \mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)|] &= \frac{1}{2} \sum_{i,j} M_{ij} \mathbb{E}[T_{i,j}] \\ &\leq \frac{1}{2} \sum_{i,j} M_{ij} |x_i - x_j| (|x_i| + |x_j|) \end{aligned}$$

## Cauchy-Schwarz Inequality

$|a \cdot b| \leq \|a\| \|b\|$ , as  $a \cdot b = \|a\| \|b\| \cos(a, b)$

Applying with  $a, b \in \mathbb{R}^{n^2}$  with  $a_{ij} = \sqrt{M_{ij}} |x_i - x_j|$ ,  $b_{ij} = \sqrt{M_{ij}} (|x_i| + |x_j|)$

**Numerator:**

$$\begin{aligned} \mathbb{E}_{S \sim D}[\frac{1}{d} |E(S, V - S)|] &= \frac{1}{2} \sum_{i,j} M_{ij} \mathbb{E}[T_{i,j}] \\ &\leq \frac{1}{2} \sum_{i,j} M_{ij} |x_i - x_j| (|x_i| + |x_j|) \\ &= \frac{1}{2} a \cdot b \\ &\leq \frac{1}{2} \|a\| \|b\| \end{aligned}$$

## Simplify numerator.

Recall  $\mu = \frac{\sum_{i,j} M_{ij} (x_i - x_j)^2}{\frac{1}{n} \sum_{i,j} (x_i - x_j)^2}$ ,  $a_{ij} = \sqrt{M_{ij}} |x_i - x_j|$ ,  $b_{ij} = \sqrt{M_{ij}} (|x_i| + |x_j|)$

$$\begin{aligned} \|a\|^2 &= \sum_{i,j} M_{ij} (x_i - x_j)^2 = \frac{\mu}{n} \sum_{i,j} (x_i - x_j)^2 \\ &= \frac{\mu}{n} \sum_{i,j} (x_i^2 + x_j^2) - \sum_{i,j} 2x_i x_j \\ &= \frac{\mu}{n} \sum_{i,j} (x_i^2 + x_j^2) - 2 \left( \sum_i x_i \right)^2 \\ &\leq \frac{\mu}{n} \sum_{i,j} (x_i^2 + x_j^2) = 2\mu \sum_i x_i^2 \\ \|b\|^2 &= \sum_{i,j} M_{ij} (|x_i| + |x_j|)^2 \\ &\leq \sum_{i,j} M_{ij} (2x_i^2 + 2x_j^2) \\ &= 4 \sum_i x_i^2 \end{aligned}$$

### Put together.

$$\text{Goal: } \frac{\mathbb{E}_{S \sim D}[\frac{1}{d}|E(S, V-S)]}{\mathbb{E}_{S \sim D}[\min(|S|, |V-S|)]} \leq \sqrt{2\mu}$$

**Numerator:**

$$\begin{aligned} \mathbb{E}_{S \sim D}[\frac{1}{d}|E(S, V-S)] &\leq \frac{1}{2} \|a\| \|b\| \\ &\leq \frac{1}{2} \sqrt{2\mu \sum_i x_i^2} \sqrt{4 \sum_i x_i^2} = \sqrt{2\mu} \sum_i x_i^2 \end{aligned}$$

Recall **Denominator:**

$$\mathbb{E}_{S \sim D}[\min(|S|, |V-S|)] = \sum_i x_i^2$$

We get

$$\frac{\mathbb{E}_{S \sim D}[\frac{1}{d}|E(S, V-S)]}{\mathbb{E}_{S \sim D}[\min(|S|, |V-S|)]} \leq \sqrt{2\mu}$$

Thus  $\exists S$ , such that  $h(S) \leq \sqrt{2\mu}$ , which gives  $h(G) \leq \sqrt{2(1-\lambda)}$   $\square$

### Kind of a proof.

$$G = (V, E), h = h(G).$$

Claim:

From  $S \subset V$  of vertices,  $|E(N_{1/h}(S))| \geq 2|E(S)|$ .

Claim': there are  $\Omega(h|S|)$  paths of length  $\ell = 1/h$  in  $N_{1/h}(S)$ .

Cut size is  $\geq h(G)|S| \implies$  flow of value  $h(G)|S|$ .

Max flow-min cut theorem.

From path argument:  $\implies \mu \geq \frac{1}{\ell^2} = h(G)^2$ .

Run argument over sets of size  $2^i$  and one gets the upper bound.

Why no  $\log n$  factor?

The mass splits, and **every level** has  $\mu_i \geq h(G)^2$ .

Cheeger proof magically does this!