

## Sum of squares.

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.

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

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  $\sum_i x_i = 0$ .

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

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

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

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

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

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

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

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

## 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.

## Cauchy-Schwarz Inequality

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

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:**

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

## 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  $[x_i, 0]$ .

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

## Simplify numerator.

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

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

$$\begin{aligned} \|b\|^2 &= \sum_{i,j} M_{ij} (|x_i| + |x_j|)^2 \\ &\leq \sum_{i,j} M_{ij} (2x_i^2 + 2x_j^2) \\ &= 4 \sum_i x_i^2 \end{aligned}$$

### Put together.

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:**

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

$$\leq \frac{1}{2} \sqrt{2\mu \sum_i x_i^2} \sqrt{4 \sum_i x_i^2} = \sqrt{2\mu} \sum_i x_i^2$$

Recall **Denominator:**

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

Combining:

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

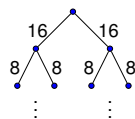
$$\frac{\mathbb{E}_{S \sim D}[\frac{1}{d}|E(S, V-S)|]}{\mathbb{E}_{S \sim D}[\min(|S|, |V-S|)]} \leq \sqrt{2\mu}$$

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

### Approximate metric using a tree.

Tree metric:

$X$  is nodes of tree with edge weights  
 $d_T(i, j)$  shortest path metric on tree.



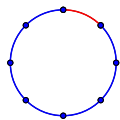
Hierarchically well separated tree metric:

Tree weights are geometrically decreasing.

**Probabilistic Tree embedding.**

Map  $X$  into tree.

- (i) No distance shrinks. (dominating)
- (ii) Every distance stretches  $\leq \alpha$  in expectation.



Distance 1 goes to  $n-1$ !  
 Bummer.

Map metric onto tree?

Fix it up chappie!

For cycle, remove a random edge get a tree.

Stretch of edge:  $\frac{n-1}{n} \times 1 + \frac{1}{n} \times (n-1) \approx 2$   
 General metrics?

### 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!

### Probabilistic Tree embedding.

**Probabilistic Tree embedding.**

Map  $X$  into tree.

- (i) No distance shrinks (dominating).
- (ii) Every distance stretches  $\leq \alpha$  in expectation.

Today: the tree will be Hierarchically well-separated (HST).

Elements of  $X$  are leaves of tree.

Useful: **use spanning tree for graphical metrics.**

The Idea:

HST  $\equiv$  recursive decomposition of metric space.

Decompose space by diameter  $\approx \Delta$  balls.

Recurse on each ball for  $\Delta/2$ .

Use randomness in selection of ball centers.  
 the  $\approx$  diameter of the balls.

### Metric spaces.

A metric space  $X$ ,  $d(i, j)$  where

$$d(i, j) \leq d(i, k) + d(k, j), d(i, j) = d(j, i), d(i, i) = 0,$$

$$\text{and } d(i, j) \geq 0.$$

Which are metric spaces?

- (A)  $X$  from  $R^d$  and  $d(\cdot, \cdot)$  is Euclidean distance.
- (B)  $X$  from  $R^d$  and  $d(\cdot, \cdot)$  is squared Euclidean distance.
- (C)  $X$ - vertices in graph,  $d(i, j)$  is shortest path distances in graph.
- (D)  $X$  is a set of vectors and  $d(u, v)$  is  $u \cdot v$ .

- (A) Obeys triangle inequality. (B)  $a^2 + b^2 \leq (a+b)^2 = a^2 + 2ab + b^2$
- (C) Shortest! (D)  $1 \cdot -1 < 0$ .

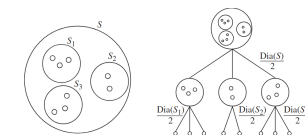
Input to TSP, facility location, some layout problems, ..., metric labelling.

Hard problems. Easier to solve on trees.

Dynamic programming on trees. Linear solving on trees.

Approximate metric on trees?

### Idea of decomposition.



## Algorithm

Algorithm:  $(X, d)$ ,  $\text{diam}(X) \leq D$ ,  $|X| = n$ ,  $d(i, j) \geq 1$

1.  $\pi$  – random permutation of  $X$ .
2. Choose  $\beta$  in  $[\frac{3}{8}, \frac{1}{2}]$  uniformly at random.

def subtree( $S, \Delta$ ):

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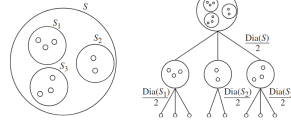
T = []
if  $\Delta < 1$  return [S]
foreach i in  $\pi$ :
    if  $i \in S$ 
        B = ball(i,  $\beta\Delta$ );  $S = S/B$ 
        T.append(B)
return map( $\lambda x$ : subtree( $x, \Delta/2$ ), T);

```

3. subtree( $X, D$ )

Tree has internal node for each level of call.  
Tree edges have weight  $\Delta$  to children.

## Analysis: no distance shrinks.



**Claim 1:**  $d_T(x, y) \geq d(x, y)$ .

When  $\Delta \leq d(x, y)$ ,  $x$  and  $y$  in diff. balls,  $\implies$  cut at  $\Delta \geq d(x, y)/2$ .

$\rightarrow d_T(x, y) \geq \Delta + \Delta \geq d(x, y)$

## Analysis: $(x, y)$

Would like  $\Pr[x, y \text{ cut by ball} | x \text{ in ball}] \leq \frac{8d(x, y)}{\Delta}$   
(Only consider cut by  $x$ , factor 2 loss.)

At level  $\Delta$

At some point  $x$  is in some  $\Delta$  level ball.  
Renummer points in order of distance from  $x$ .

If  $d(x, y) \geq \Delta/8$ ,  $\frac{8d(x, y)}{\Delta} \geq 1$ , so claim holds trivially.

Point  $j$  cuts  $(x, y)$  only if  $d(j, x) \in [\frac{3\Delta}{8}, \frac{\Delta}{2}]$ .

Call this set  $X_\Delta$ .

$j \in X_\Delta$  cuts  $(x, y)$  if..

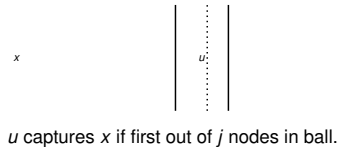
$d(j, x) \leq \beta\Delta$  and  $\beta\Delta \leq d(j, y) \leq d(j, x) + d(x, y)$   
 $\rightarrow \beta\Delta \in [d(j, x), d(j, x) + d(x, y)]$ .  
 occurs with prob.  $\leq \frac{d(x, y)}{\Delta/8} = \frac{8d(x, y)}{\Delta}$ .

And  $j$  must be before any  $i < j$  in  $\pi \rightarrow$  prob is  $\frac{1}{j}$

$\rightarrow \Pr[j \text{ cuts } (x, y)] \leq \left(\frac{1}{j}\right) \frac{8d(x, y)}{\Delta}$

$d_T(x, y)$  at level  $\Delta$  is  $4\Delta$ .  $\rightarrow E[d_T(x, y)] = \sum_{\Delta=D/2^i} \sum_{j \in X_\Delta} \left(\frac{1}{j}\right) 32d(x, y)$

## A picture.



$u$  captures  $x$  if first out of  $j$  nodes in ball.

## Analysis: idea

**Claim:**  $E[d_T(x, y)] = O(\log n)d(x, y)$ .

Cut at level  $\Delta \rightarrow d_T(x, y) \leq 4\Delta$ . (Level of subtree call.)

$\Pr[\text{cut at level } \Delta]$ ? Recall: cut at  $\beta\Delta$ , with  $\beta \in [3/8, 1/2]$ .

Would like  $\leq \frac{d(x, y)}{\Delta}$ .

$\rightarrow$  expected length is  $\sum_{\Delta=D/2^i} (4\Delta) \frac{d(x, y)}{\Delta} = 4 \log D \cdot d(x, y)$ .

Why  $\propto \frac{d(x, y)}{\Delta}$ ?

smaller the edge the less likely to be on edge of ball.  
larger the delta, more room inside ball.

random diameter  $\beta$  shifts edge across  $\Delta/8$ .

$\rightarrow \Pr[x, y \text{ cut by ball} | x \text{ in ball}] \approx \frac{d(x, y)}{\Delta/8}$

The problem?

Could be cut by many different balls.

For each probability is good, but could be hit by many.  
random permutation to deal with this

## The pipes are distinct!

$E(d_T(x, y)) = \sum_{\Delta=D/2^i} \sum_{j \in X_\Delta} \left(\frac{1}{j}\right) 32d(x, y)$

Recall  $X_\Delta$  has points with  $d(x, j) \in [3\Delta/8, \Delta/2]$

"Listen Stash, the pipes are distinct!"

Uh.. well  $X_\Delta$  is distinct from  $X_{\Delta/2}$ .

$E(d_T(x, y)) = \sum_{\Delta=D/2^i} \sum_{j \in X_\Delta} \left(\frac{1}{j}\right) 32d(x, y)$

$\leq \sum_j \left(\frac{1}{j}\right) 32d(x, y)$

$\leq (32 \ln n) (d(x, y))$ .

**Claim:**  $E[d_T(x, y)] = O(\log n)d(x, y)$

Expected stretch is  $O(\log n)$ .

We gave an algorithm that produces a distribution of trees.

The expected stretch of any pair is  $O(\log n)$ .

## Metric Labelling

Input: graph  $G = (V, E)$  with edge weights,  $w(\cdot)$ , metric labels  $(X, d)$ , and costs for mapping vertices to labels  $c : V \times X$ .

Find an labeling of vertices,  $\ell : V \rightarrow X$  that minimizes

$$\sum_{e=(u,v)} c(e)d(\ell(u), \ell(v)) + \sum_v c(v, \ell(v))$$

Idea: find HST for metric  $(X, d)$ .

Solve the problem on a hierarchically well separated tree metric.

Kleinberg-Tardos: constant factor on uniform metric.

Hierarchically well separated tree, "geometric", constant factor.

→  $O(\log n)$  approximation.