Hardy-Muckenhoupt Bounds for Laplacian Eigenvalues

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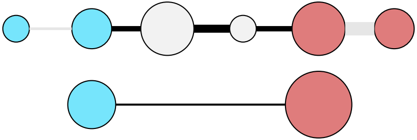
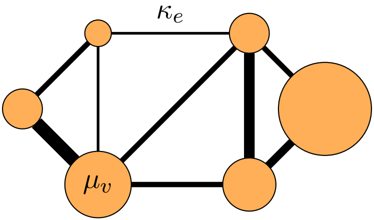
APPROX 2019



Graphs and the Laplacian



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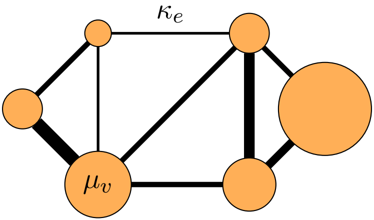

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- Mass, $\mu \in \mathbb{R}^V_{>0}$

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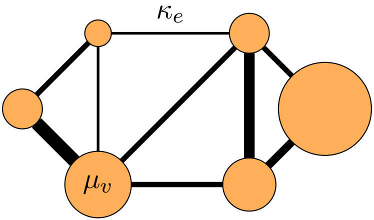

- Weighted connected graph, $G = (V, E, \mu, \kappa)$
- Mass, $\mu \in \mathbb{R}^V_{>0}$
- Edge weights, $\kappa \in \mathbb{R}^E_{>0}$

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\begin{aligned}
x^\top L x &= \dots \\
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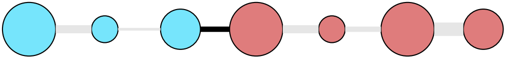
- Numerical linear algebra?
- Goal: give good bounds for λ_2 in terms of graph structure

Cuts and Cheeger's inequality

- Sparsest cut, Φ

$$\Phi(G) = \min_{A} \left\{ \frac{\sum_{e \in E(A,\bar{A})} \kappa_e}{\min(\mu(A), \mu(\bar{A}))} \;\middle|\; A, \bar{A} \neq \varnothing \right\}$$



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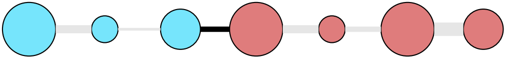


Theorem (Cheeger's Inequality)

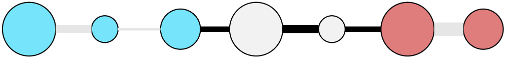
If $\mu_v = d_v$,

$$\frac{\Phi^2}{2} \leq \lambda_2 \leq 2\Phi.$$

Our work

- Neumann content, Ψ_2

$$\Psi_2(G) = \min_{A,B} \left\{ \frac{\kappa_{\mathsf{eff}}(A,B)}{\left(\mu(A)^{-1} + \mu(B)^{-1}\right)^{-1}} \,\middle|\, A, B \neq \varnothing,\ A \cap B = \varnothing \right\}$$



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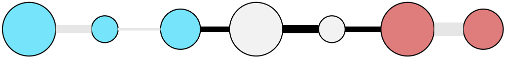

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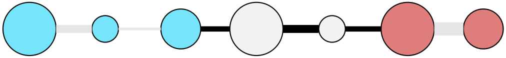

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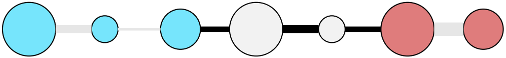

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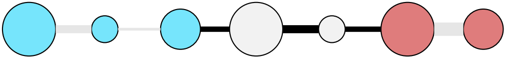

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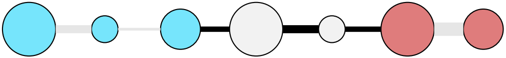

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Theorem ([MWW19])

Let G be a weighted connected graph. Then

$$\frac{\Psi_2}{4} \leq \lambda_2 \leq \Psi_2.$$

Furthermore, all constants are tight.

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- Let G be a path graph on $2n$ vertices with $\kappa = \mu = 1$

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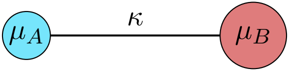
- [MWW19] $\Longrightarrow$ $\lambda_2 \approx \frac{1}{n^2}$
- $\Phi \approx 1/n$
- Cheeger's inequality $\Longrightarrow$ $\frac{1}{n^2} \lesssim \lambda_2 \lesssim \frac{1}{n}$

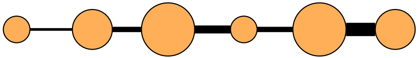
Graphs with two vertices



- Can compute

$$\lambda_2 = \frac{\kappa}{\left(\mu_A^{-1} + \mu_B^{-1}\right)^{-1}} = \Psi_2.$$

Graphs with more vertices



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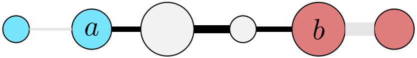

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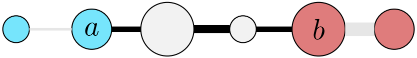

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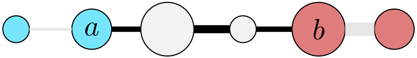

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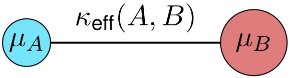

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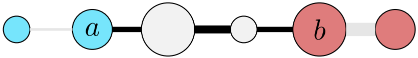

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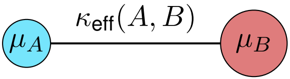

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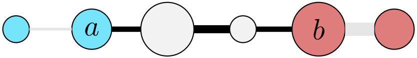

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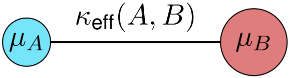

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- Then,

$$\Psi_2 = \min_{a<b} \frac{\kappa_{\text{eff}}(A, B)}{\left(\mu_A^{-1} + \mu_B^{-1}\right)^{-1}}$$

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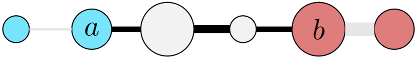

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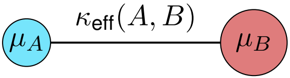

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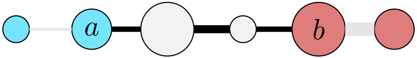

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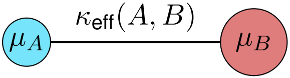

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Ψ_2 is λ_2 for the best two-vertex approximation of G

Summary

- Neumann content

$$\Psi_2 = \min_{A,B} \left\{ \frac{\kappa_{\text{eff}}(A,B)}{(\mu(A)^{-1} + \mu(B)^{-1})^{-1}} \,\middle|\, A, B \neq \varnothing,\ A \cap B = \varnothing \right\}$$

- Showed

$$\frac{\Psi_2}{4} \leq \lambda_2 \leq \Psi_2$$

- Quadratic improvement on Cheeger's inequality in some cases
- Generalizations
- Thanks for listening! Questions?