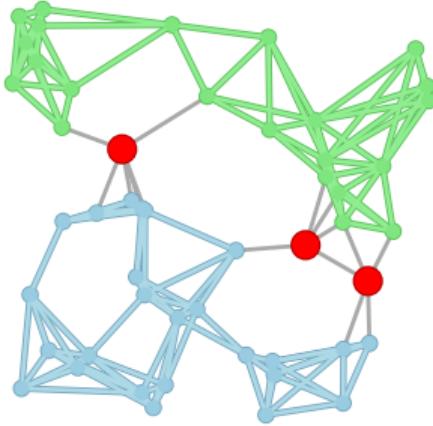
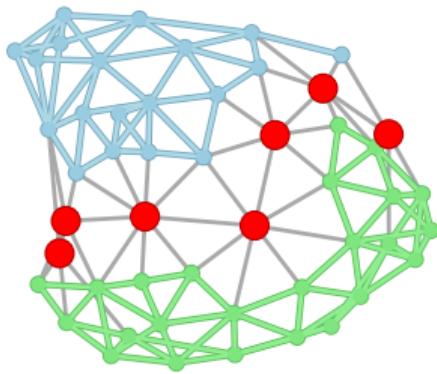
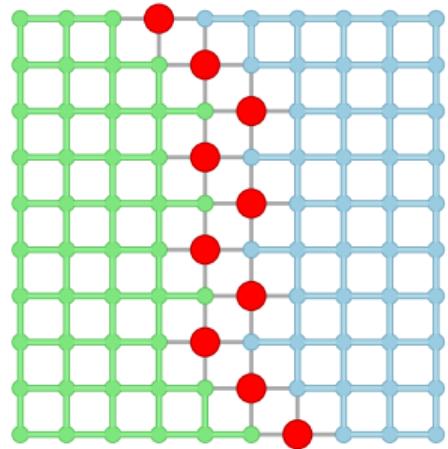


Reweighted Spectral Partitioning Works

A Simple Algorithm for Vertex Separators in Special Graph Classes

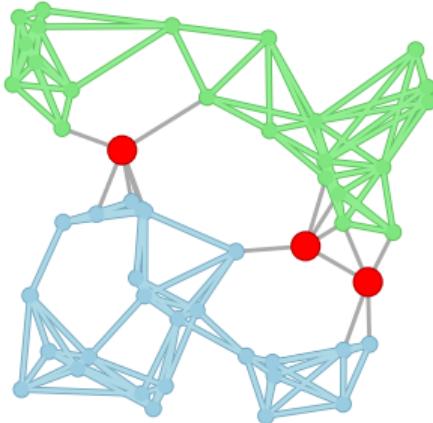
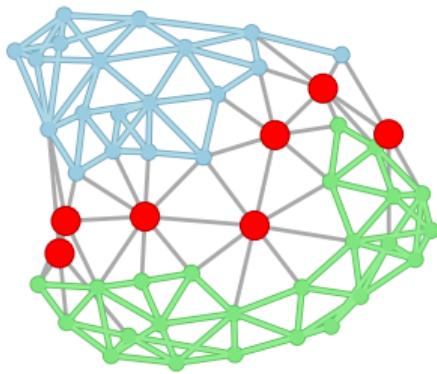
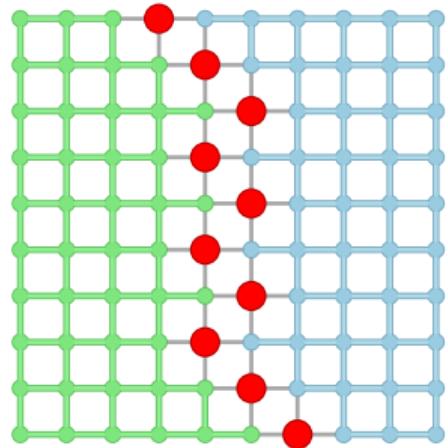
Jack Spalding-Jamieson

Balanced Vertex Separators



Vertex Separator: Small set of vertices whose removal disconnects into small components.

Balanced Vertex Separators

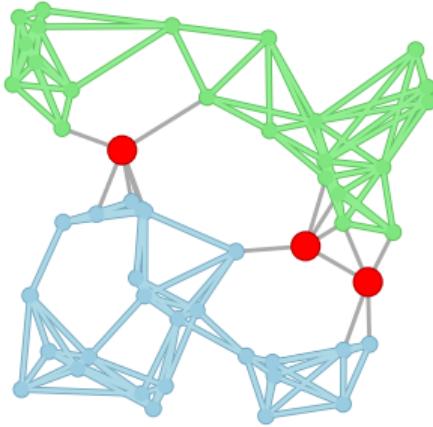
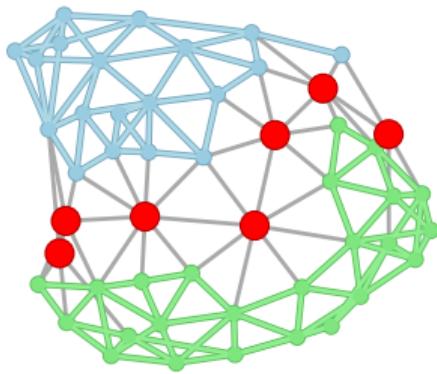
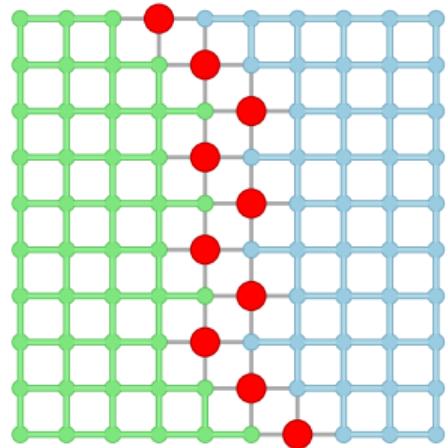


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For a planar graph G of n vertices, there is a subset S of $\mathcal{O}(\sqrt{n})$ vertices so that every connected component of $G - S$ has at most $\frac{2}{3}n$ vertices.

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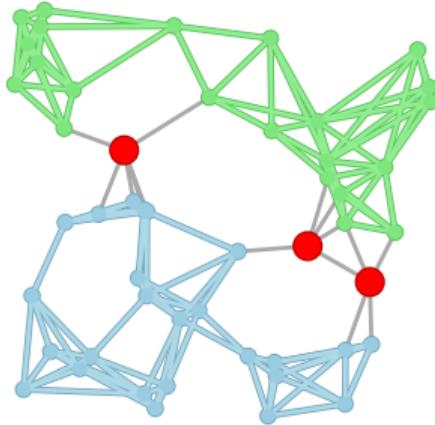
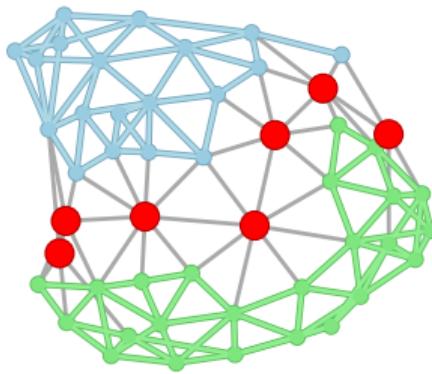
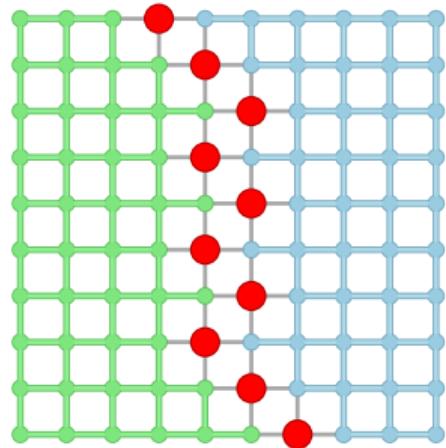


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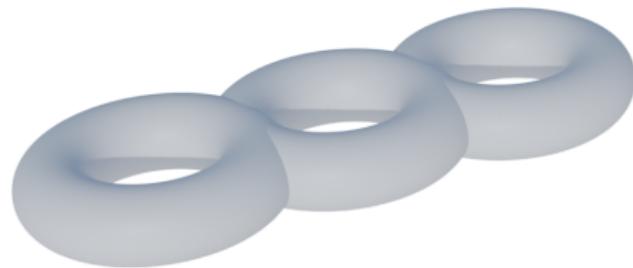
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Small separator = many fast algorithms!

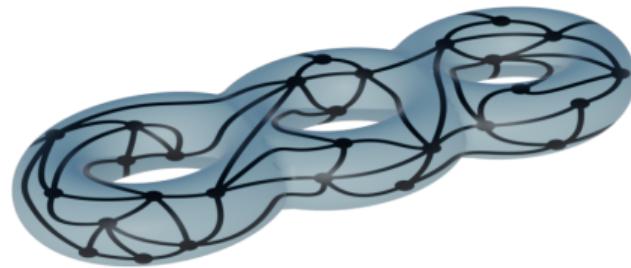
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Genus- g graph: Embeddable on genus- g surface without crossings.



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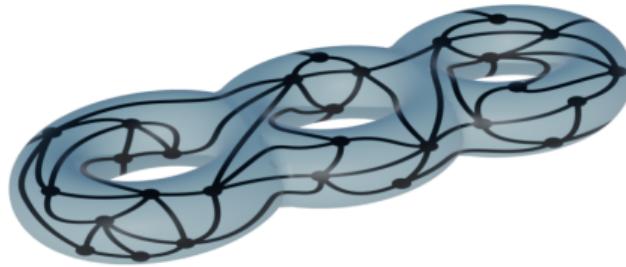


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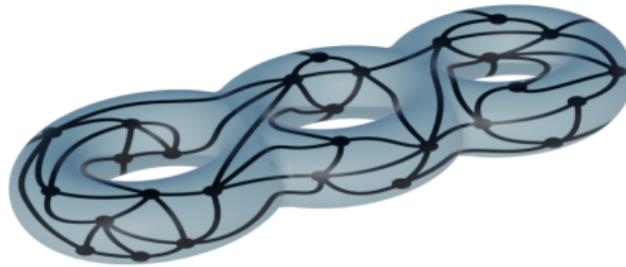


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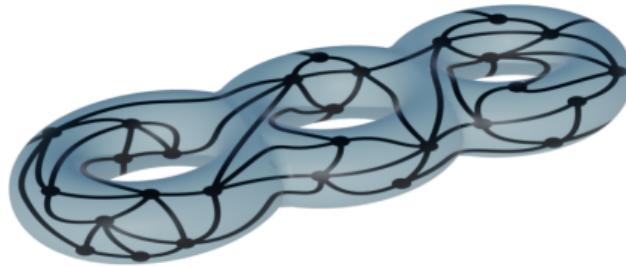
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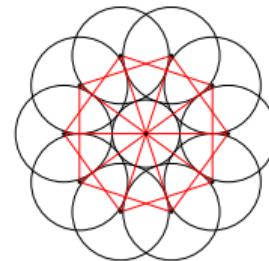
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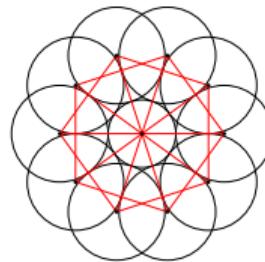
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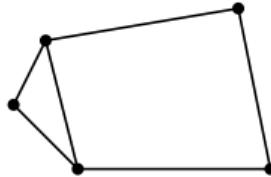
k -ply d -dimensional ball-intersection graph: Separator size $\mathcal{O}\left(dk^{\frac{1}{d}}n^{1-\frac{1}{d}}\right)$. **Can be found in $\mathcal{O}(f(d) + nd^2)$ time, for a function f , if the points are provided.**

Theorem (Improved k -ply d -dimensional ball-intersection Separator Theorem [New, Side-Result])

k -ply d -dimensional ball-intersection graph: Separator size $\mathcal{O}\left(\sqrt{\min\{d, \log \Delta\}}k^{\frac{1}{d}}n^{1-\frac{1}{d}}\right)$. **Can be found in polynomial time, if the points are provided.**

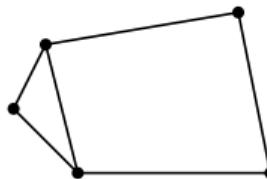
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Theorem (Improved d -dimensional k -NN Separator Theorem [New, Side-Result])

d -dimensional k -NN graph with max degree Δ : Separator size $\mathcal{O}\left(\sqrt{\min\{d, \log \Delta\}}k^{\frac{1}{d}}n^{1-\frac{1}{d}}\right)$.
Can be found in polynomial time, if the points are provided.

No additional information!

In practice: Given graph, no specialized info. Want theoretically sound guarantees of small separators.

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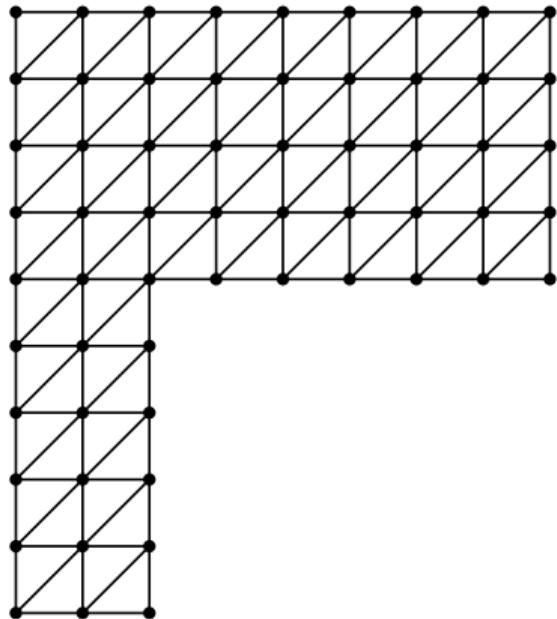
The algorithm we consider: **Reweighted Spectral Partitioning**.

Results

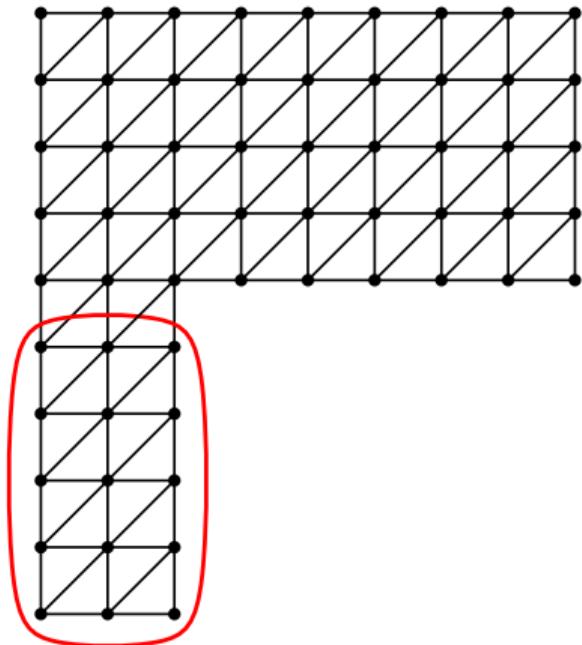
Graph class	This work	Previous work
Genus- g	$\mathcal{O}(\min\{(\log g)^2 \sqrt{gn}, \log \Delta \sqrt{gn}\})$	$\mathcal{O}(\min\{(\log g) \sqrt{gn}, \text{poly}(\Delta) \sqrt{gn}\})$
K_h -minor-free	$\mathcal{O}(\min\{\log h, \sqrt{\log \Delta}\}(h \log h \log \log h) \sqrt{n})$	$\mathcal{O}((\log h)h\sqrt{n})$
k -ply ball-intersection in \mathbb{R}^d	$\mathcal{O}(\sqrt{\log \Delta} \cdot k^{1/d} n^{1-1/d})$	$\mathcal{O}(\sqrt{\log n} \cdot dk^{1/d} n^{1-1/d})$
k -nearest-neighbour in \mathbb{R}^d	$\mathcal{O}(\sqrt{\log \Delta} \cdot k^{1/d} n^{1-1/d})$	$\mathcal{O}(\sqrt{\log n} \cdot dk^{1/d} n^{1-1/d})$

Reweighted spectral partitioning separator size guarantees (via this work)
vs. previous algorithms.

Separators, Expansion, and Cuts

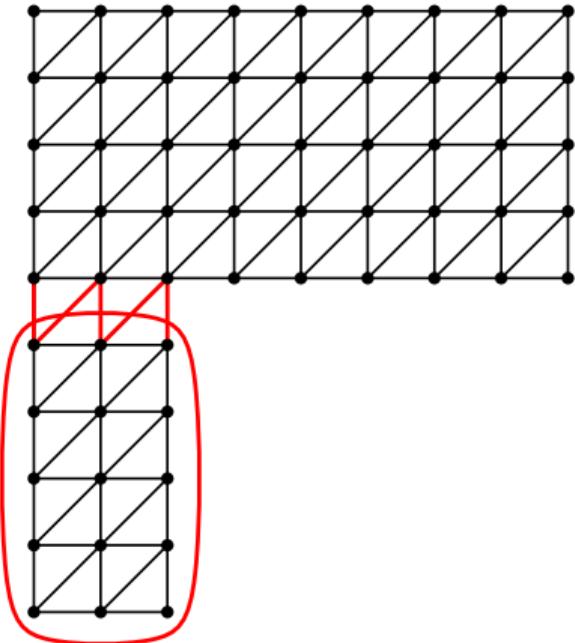


Separators, Expansion, and Cuts



Want small boundary to area ratio

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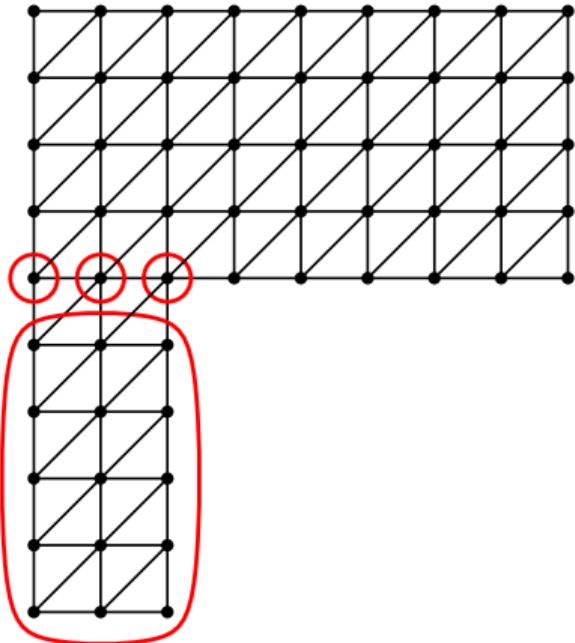


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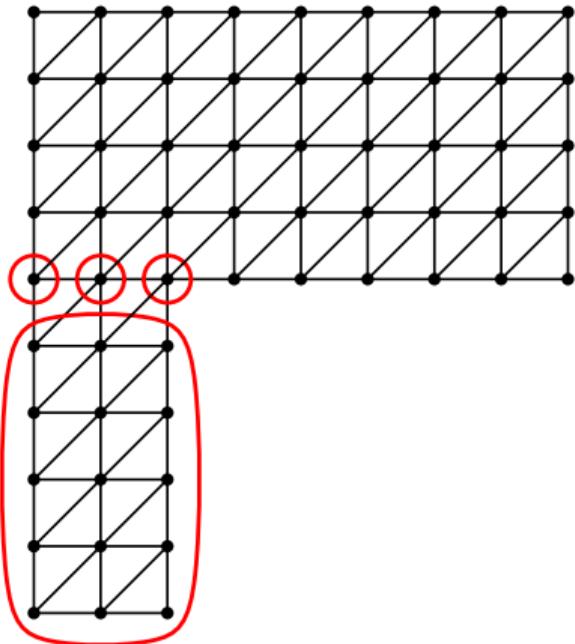
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Known algorithm:

For induced subgraph $H \subset G$, find cut S with $\psi(S) \leq \frac{\alpha}{n^\varepsilon}$
 \implies can get balanced vertex separator of size $O(\alpha n^{1-\varepsilon})$.

A Related Example: Spectral Partitioning of Graphs

Edge expansion $\phi(G) := \min_{|S| \leq \frac{n}{2}} \phi(S)$:

Small = fast algorithms.

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Similar results for many other classes (also in other works).

From Spectral Partitioning to Reweighted Spectral Partitioning

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$$\frac{\phi(G)^2}{2\Delta} \leq \lambda_2(G) \leq 2\phi(G)$$

Spectral partitioning algorithm:

Compute $\lambda_2(G)$, obtain S with $\phi(S)$ bounded.

Vertex expansion $\psi(G) := \min_{|S| \leq \frac{n}{2}} \psi(S)$: Small

= fast algorithms.

Max Reweighted Spec Gap ($\gamma^{(n)}$): A poly-time computable quantity.

Theorem (Cheeger-Style Inequality [Roc05, OTZ22, JPV22, KLT22])

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$$\frac{\psi(G)^2}{\log \Delta} \lesssim \gamma^{(n)}(G) \lesssim \psi(G).$$

Reweighted spectral partitioning algorithm:

Compute $\gamma^{(n)}(G)$, obtain S with $\psi(S)$ bounded.

Refining Reweighted Spectral Partitioning

Theorem (Refined Cheeger-Style Inequality [New])

For a graph G with n vertices and maximum degree Δ ,

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Reweighted spectral partitioning **works:** Direct class-specific upper bounds for $\gamma^{(n)}(G)$.

Graph class	$\gamma^{(n)} \leq \gamma^{(1)} \lesssim$
Planar	$\frac{1}{n}$
Genus- g	$\frac{g \min\{(\log g)^2, \log \Delta\}}{n}$
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E.g. G planar $\implies \gamma^{(n)}(G) \lesssim \frac{1}{n} \implies \psi(S) \lesssim \frac{1}{\sqrt{n}} \implies$ reproduces planar separator theorem!

Intuition for $\gamma^{(n)}(G)$

Definition

For a graph G , define:

$$\gamma^{(d)}(G) := \min_{\substack{f: V \rightarrow \mathbb{R}^d \\ y: V \rightarrow \mathbb{R}_{\geq 0}}} \frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2}$$

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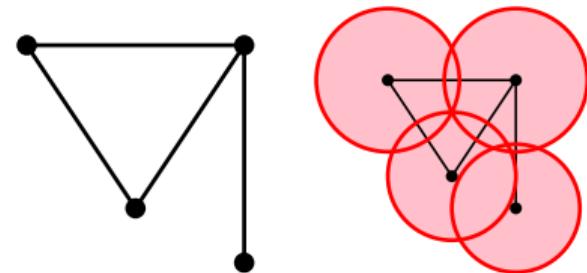
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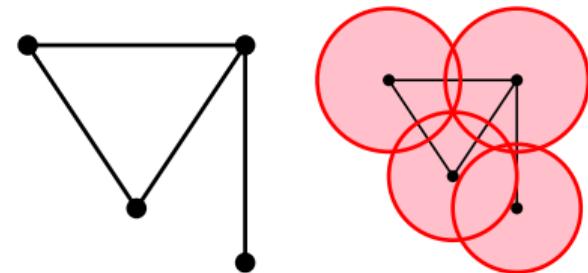
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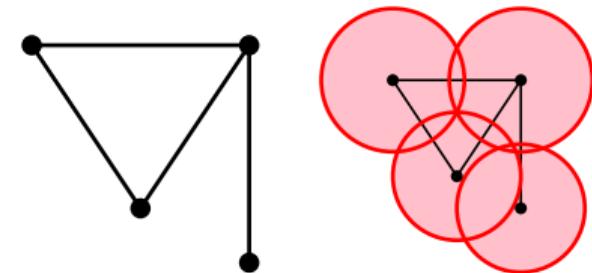
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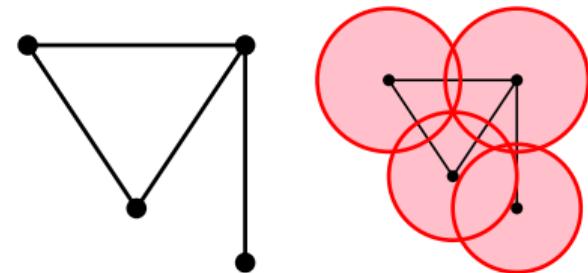
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- **Constraint:** Adjacent balls *must* intersect.



Expanding the Cheeger-Style Inequality

Theorem (Refined Cheeger-Style Inequality, expanded)

For a graph G with n vertices and maximum degree Δ ,

$$\frac{\psi(G)^2}{\min\{\log \Delta, [\alpha(G)]^2\}} \lesssim \frac{\gamma^{(1)}(G)}{\min\{\log \Delta, [\alpha(G)]^2\}} \lesssim \gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \psi(G).$$

Reminder: $\gamma^{(n)}$ is the poly-time computable quantity (it is an SDP).

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Method: Don't change sphere radii, use random projection on centres.

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Ongoing follow-up work: This is now deterministic.

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Proof Step 2: **Average 2-distortion** bound \implies normalizing denominator in objective only goes up by $\mathcal{O}(\alpha(G)^2)$.

Two kinds of upper bounds on $\gamma^{(n)}(G)$: Geometric and Combinatorial

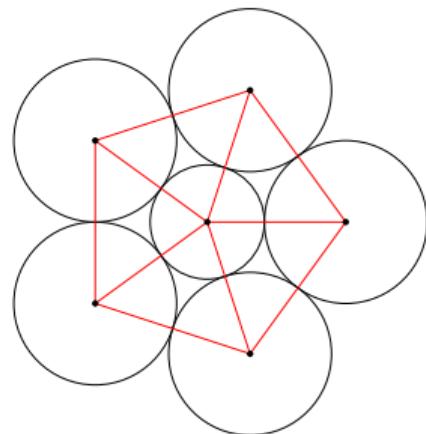
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Rich theory of **circle packings**!

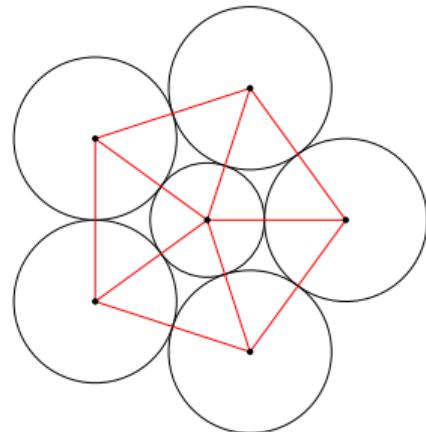


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Rich theory of **congestion bounds** via crossing numbers!

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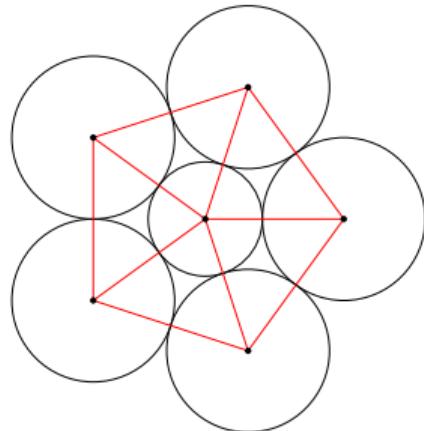
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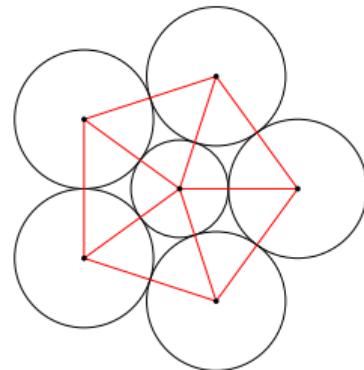
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Either kind $\implies \gamma^{(1)}(G) \lesssim \frac{1}{n}$ for G planar.

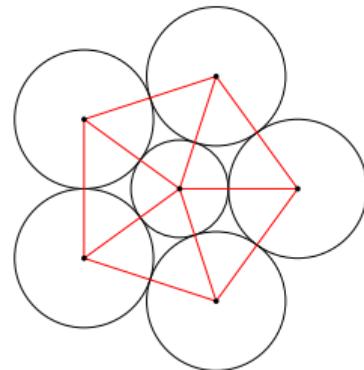
Geometric Bounds: Planar Case

Step 1: Planar circle packing theorem. Every planar graph admits touching circles representation.



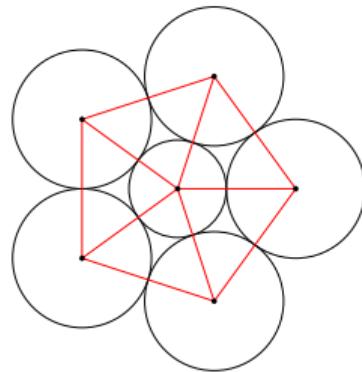
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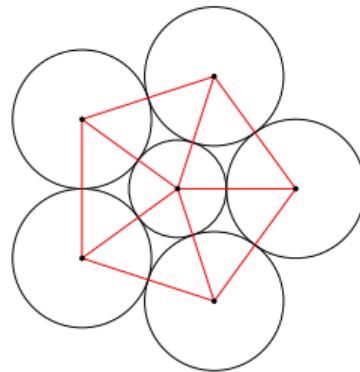
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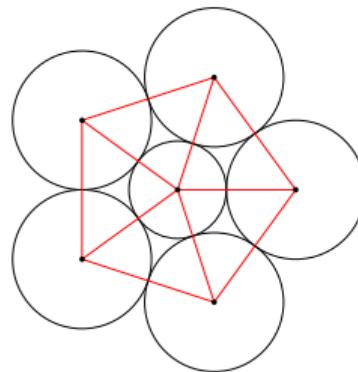
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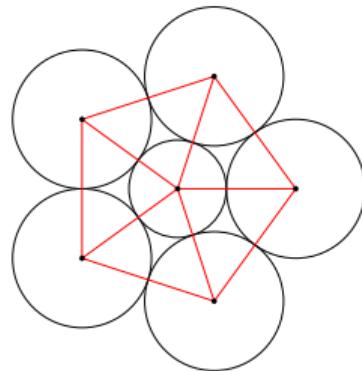
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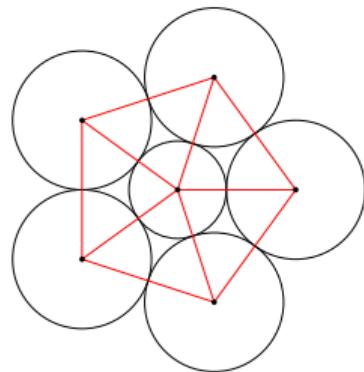
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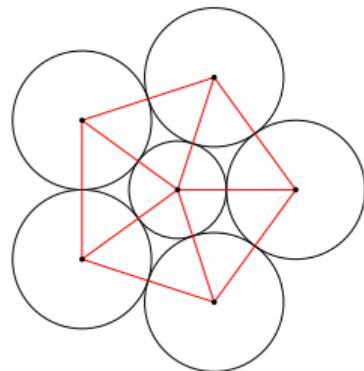
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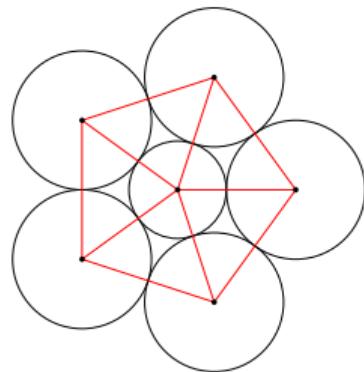
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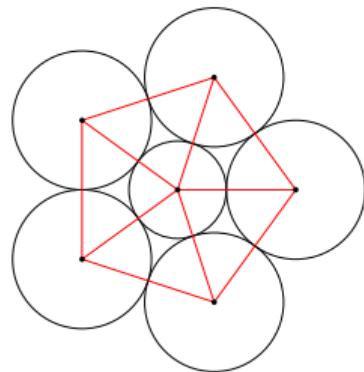
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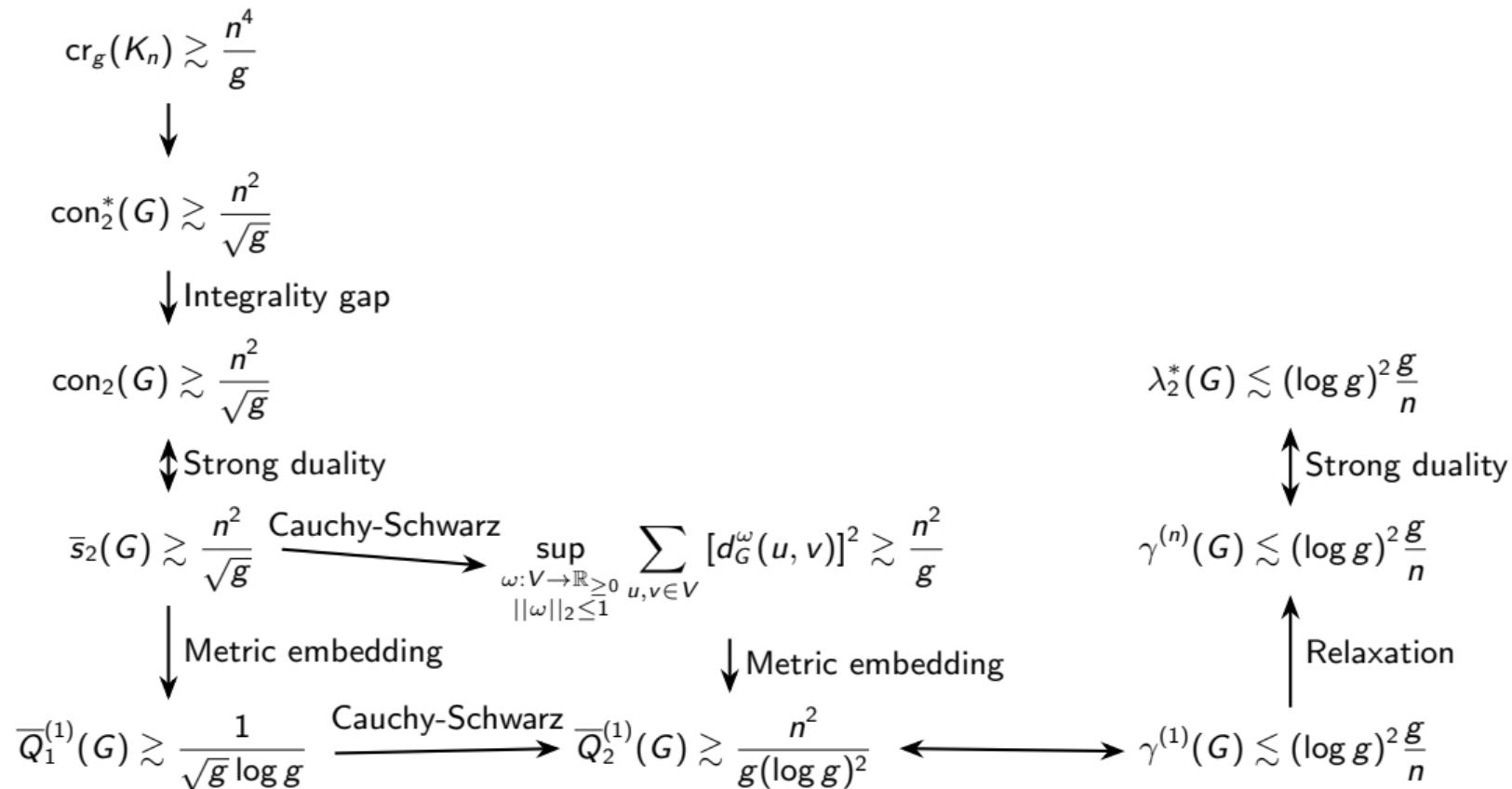
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Result: $\frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2} \lesssim \frac{1}{n}$

Combinatorial Bounds: Overview for Genus- g Graphs



Fin

**Reweighted Spectral Partitioning Works:
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<https://arxiv.org/pdf/2506.01228>

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