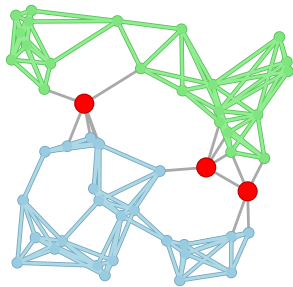
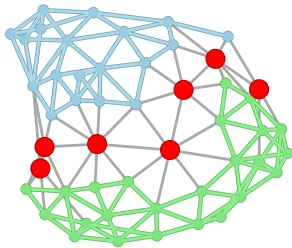
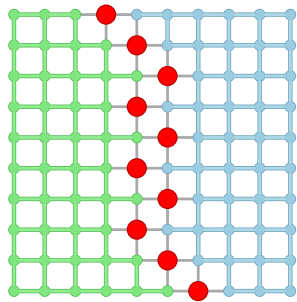


# Reweighted Spectral Partitioning Works

A Simple Algorithm for Vertex Separators in Special Graph Classes

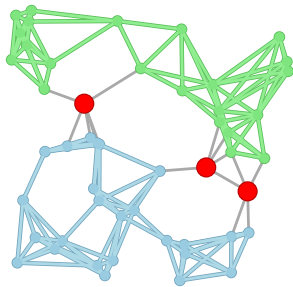
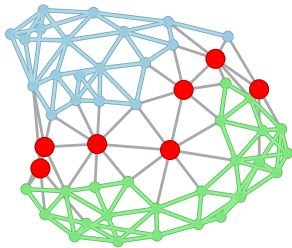
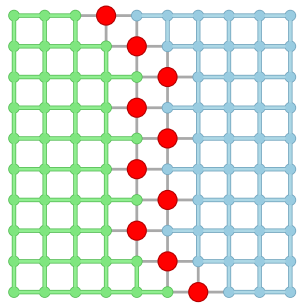
**Jack Spalding-Jamieson**

## Balanced Vertex Separators



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

# Balanced Vertex Separators

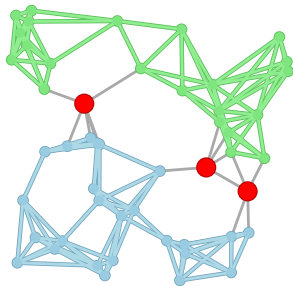
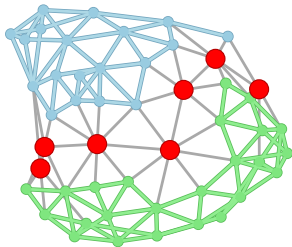
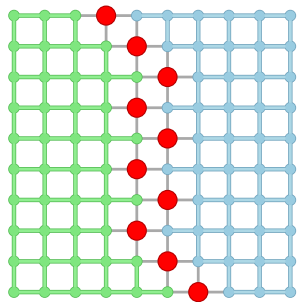


Vertex Separator: Small set of vertices whose removal disconnects into small components.

## Theorem (Planar Separator Theorem)

*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.*

# Balanced Vertex Separators

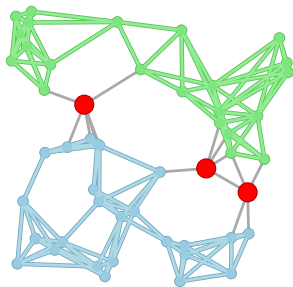
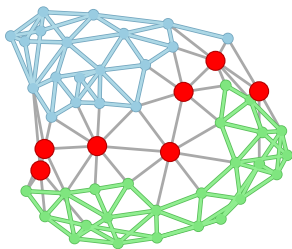
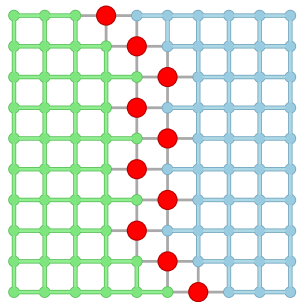


Vertex Separator: Small set of vertices whose removal disconnects into small components.

## Theorem (Planar Separator Theorem)

*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.  $S$  can be found in  $\mathcal{O}(n)$  time.*

# Balanced Vertex Separators



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

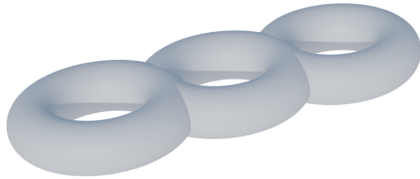
## Theorem (Planar Separator Theorem)

*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.  $S$  can be found in  $\mathcal{O}(n)$  time.*

Small separator = many fast algorithms!

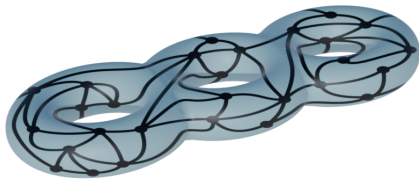
## Other Separator Theorems (1)

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



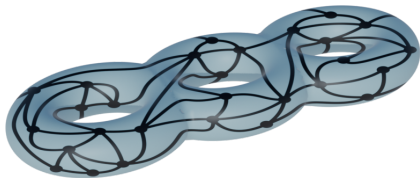
## Other Separator Theorems (1)

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



## Other Separator Theorems (1)

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



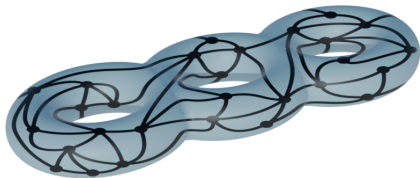
### Theorem (Genus- $g$ Separator Theorem)

*Genus  $g$  graph: Separator size  $\mathcal{O}(\sqrt{gn})$ .*



## Other Separator Theorems (1)

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

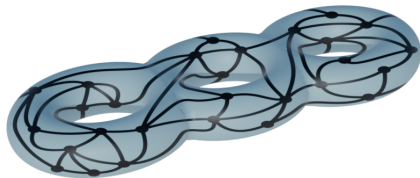


### Theorem (Genus- $g$ Separator Theorem)

Genus  $g$  graph: Separator size  $\mathcal{O}(\sqrt{gn})$ . *Can be found in  $\mathcal{O}(n)$  time, if a surface embedding is provided.*

# Other Separator Theorems (1)

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



## Theorem (Genus- $g$ Separator Theorem)

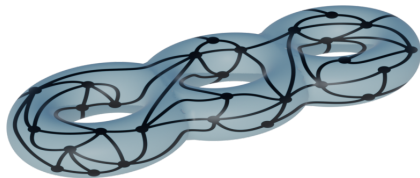
Genus  $g$  graph: Separator size  $\mathcal{O}(\sqrt{gn})$ . *Can be found in  $\mathcal{O}(n)$  time, if a surface embedding is provided.*

## Theorem ( $K_h$ -minor-free Separator Theorem)

$K_h$ -minor-free graph: Separator size  $\mathcal{O}(h\sqrt{n})$ .

# Other Separator Theorems (1)

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



## Theorem (Genus- $g$ Separator Theorem)

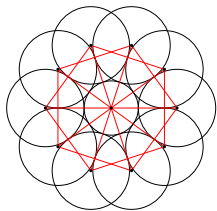
Genus  $g$  graph: Separator size  $\mathcal{O}(\sqrt{gn})$ . *Can be found in  $\mathcal{O}(n)$  time, if a surface embedding is provided.*

## Theorem ( $K_h$ -minor-free Separator Theorem)

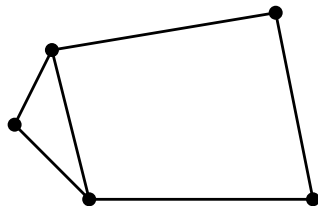
$K_h$ -minor-free graph: Separator size  $\mathcal{O}(h\sqrt{n})$ . *Can be found in  $\mathcal{O}(n^2)$  time, provided that  $h$  is constant.*

## Other Separator Theorems (2)

$k$ -ply  $d$ -dimensional sphere-intersection graph



$d$ -dimensional  $k$ -NN graph



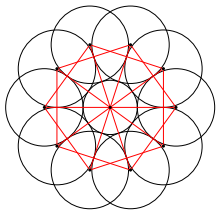
Theorem (MTTV97)

Separator size  $\mathcal{O}\left(dk^{\frac{1}{d}}n^{1-\frac{1}{d}}\right)$ .

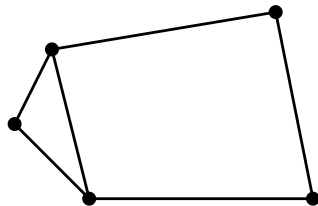
*Can be found in  $\mathcal{O}(f(d) + nd^2)$  time, for a function  $f$ , if the points are provided.*

## Other Separator Theorems (2)

$k$ -ply  $d$ -dimensional sphere-intersection graph



$d$ -dimensional  $k$ -NN graph



Theorem (**New**, Side-Result)

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.*

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

Parametrized Algorithms		
Strong per-class guarantees Complex algorithms Complex proofs Slow		

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	



# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	<b>One algorithm, many proofs</b>
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	<b>One algorithm, many proofs</b>
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

This talk is about the third kind!

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	<b>One algorithm, many proofs</b>
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

This talk is about the third kind!

- Move the difficulty from the algorithm to the proofs.

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	<b>One algorithm, many proofs</b>
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

This talk is about the third kind!

- Move the difficulty from the algorithm to the proofs.
- Implementable!

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

<b>Parametrized Algorithms</b>	<b>Approximation algorithms</b>	<b>One algorithm, many proofs</b>
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

This talk is about the third kind!

- Move the difficulty from the algorithm to the proofs.
- Implementable!
- Fast and strong per-class guarantees.

# Generic Algorithms with Many Proofs

**In practice:** Given graph, don't know class. Want guarantees if class is nice.

Three approaches:

Parametrized Algorithms	Approximation algorithms	One algorithm, many proofs
Strong per-class guarantees Complex algorithms Complex proofs Slow	Per-instance guarantees Medium-complex algos Medium-complex proofs Fast	Strong per-class guarantees Simple algorithms Complex proofs Fast

This talk is about the third kind!

- Move the difficulty from the algorithm to the proofs.
- Implementable!
- Fast and strong per-class guarantees.

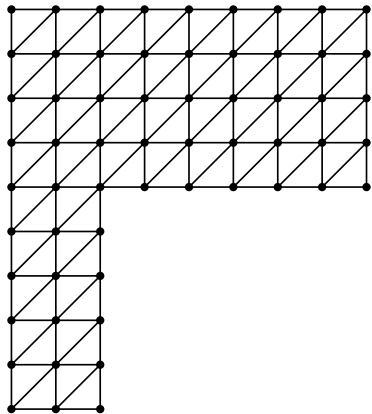
The algorithm we consider: **Reweighted Spectral Partitioning**.

# Results: Poly-time Separator Sizes

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 $\mathbb{R}^d$	$\mathcal{O}(\sqrt{\log \Delta} \cdot k^{1/d} n^{1-1/d})$	$\mathcal{O}(\sqrt{\log n} \cdot dk^{1/d} n^{1-1/d})$

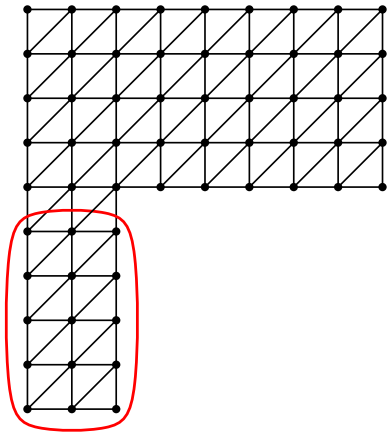
Reweighted spectral partitioning separator size guarantees (via this work)  
vs. previous algorithms.

# Separators, Expansion, and Cuts





# Separators, Expansion, and Cuts

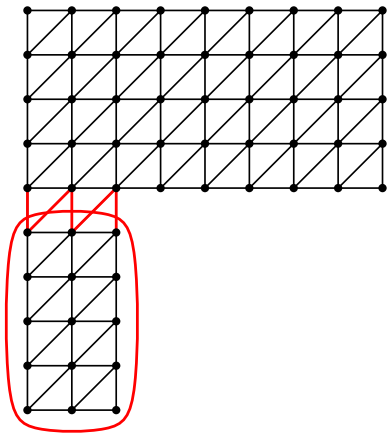


Want small boundary to area ratio

# Separators, Expansion, and Cuts

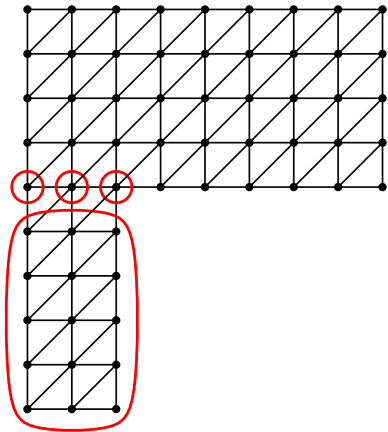
For a set  $S \subset V$ , **edge expansion** of  $S$  is:

$$\phi(S) := \frac{|E(S, S^c)|}{|S|}.$$



Want small boundary to area ratio

# Separators, Expansion, and Cuts



For a set  $S \subset V$ , **edge expansion** of  $S$  is:

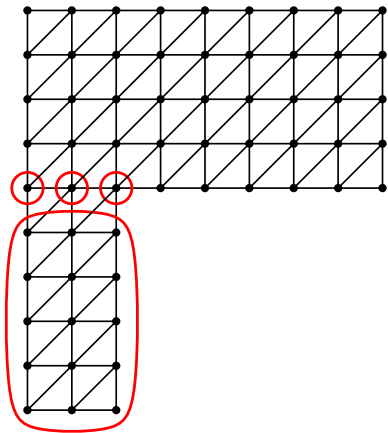
$$\phi(S) := \frac{|E(S, S^c)|}{|S|}.$$

For a set  $S \subset V$ , **vertex expansion** of  $S$  is:

$$\psi(S) := \frac{|N(S) \cap S^c|}{|S|}.$$

Want small boundary to area ratio

# Separators, Expansion, and Cuts



Want small boundary to area ratio

For a set  $S \subset V$ , **edge expansion** of  $S$  is:

$$\phi(S) := \frac{|E(S, S^c)|}{|S|}.$$

For a set  $S \subset V$ , **vertex expansion** of  $S$  is:

$$\psi(S) := \frac{|N(S) \cap S^c|}{|S|}.$$

**Known algorithm:**

For induced subgraph  $H \subset G$ , find cut  $S$  with  $\psi(S) \leq \frac{\alpha}{|H|^\epsilon}$   
 $\implies$  can get balanced vertex separator of size  $O(\alpha n^{1-\epsilon})$ .  
(Requires  $|S| \leq \frac{n}{2}$ )

## A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time  
computable “spectral” quantity.

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

## A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

hard to compute, want to approximate

## A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

easy to compute



## A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

algorithmic, generic!

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**Spectral partitioning algorithm:**

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

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

Fact for planar graphs:  $\phi(G) \lesssim \sqrt{\frac{\Delta}{n}}$ .

$\lambda_2(G)$ +Cheeger:  $\phi(S) \lesssim \sqrt{\Delta \sqrt{\frac{\Delta}{n}}}$  (weak).

## Theorem (Cheeger's inequality)

For a graph  $G$  with max degree  $\Delta$ ,

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

**Spectral partitioning algorithm:**

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

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

## Theorem (Cheeger's inequality)

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**Spectral partitioning algorithm:**

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

Fact for planar graphs:  $\phi(G) \lesssim \sqrt{\frac{\Delta}{n}}$ .

$\lambda_2(G)$ +Cheeger:  $\phi(S) \lesssim \sqrt{\Delta \sqrt{\frac{\Delta}{n}}}$  (weak).

First specialized proof:

## Spectral Partitioning Works

by Daniel Spielman and Shang-Hua Teng.

$G$  planar  $\implies \lambda_2(G) \lesssim \frac{\Delta}{n}$

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

## Theorem (Cheeger's inequality)

For a graph  $G$  with max degree  $\Delta$ ,

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

**Spectral partitioning algorithm:**

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

Fact for planar graphs:  $\phi(G) \lesssim \sqrt{\frac{\Delta}{n}}$ .

$\lambda_2(G)$ +Cheeger:  $\phi(S) \lesssim \sqrt{\Delta \sqrt{\frac{\Delta}{n}}}$  (weak).

First specialized proof:

## Spectral Partitioning Works

by Daniel Spielman and Shang-Hua Teng.

$G$  planar  $\implies \lambda_2(G) \lesssim \frac{\Delta}{n}$

Now  $\lambda_2(G)$ +Cheeger  $\implies \phi(S) \lesssim \frac{\Delta^{\frac{3}{2}}}{\sqrt{n}}$ .

# A Related Example: Spectral Partitioning of Graphs

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

## Theorem (Cheeger's inequality)

For a graph  $G$  with max degree  $\Delta$ ,

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

**Spectral partitioning algorithm:**

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

Fact for planar graphs:  $\phi(G) \lesssim \sqrt{\frac{\Delta}{n}}$ .

$\lambda_2(G)$ +Cheeger:  $\phi(S) \lesssim \sqrt{\Delta \sqrt{\frac{\Delta}{n}}}$  (weak).

First specialized proof:

## Spectral Partitioning Works

by Daniel Spielman and Shang-Hua Teng.

$G$  planar  $\implies \lambda_2(G) \lesssim \frac{\Delta}{n}$

Now  $\lambda_2(G)$ +Cheeger  $\implies \phi(S) \lesssim \frac{\Delta^{\frac{3}{2}}}{\sqrt{n}}$ .

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

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**Spectral partitioning algorithm:**

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

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**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's inequality)

For a graph  $G$  with max degree  $\Delta$ ,

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

**Spectral partitioning algorithm:**

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



# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**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])**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**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])**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

hard to compute, want to approximate

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

For a graph  $G$  with max degree  $\Delta$ ,

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

**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])**

For a graph  $G$  with max degree  $\Delta$ ,

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

easy to compute

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger's inequality)**

For a graph  $G$  with max degree  $\Delta$ ,

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

**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])**

For a graph  $G$  with max degree  $\Delta$ ,

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

algorithmic, generic!

# From Spectral Partitioning to Reweighted Spectral Partitioning

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

Small = fast algorithms.

**Fiedler Value** ( $\lambda_2$ ): A poly-time computable “spectral” quantity.

**Theorem (Cheeger’s inequality)**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**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])**

*For a graph  $G$  with max degree  $\Delta$ ,*

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

**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  $\Delta$ ,

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

## Refining Reweighted Spectral Partitioning

### Theorem (**Refined** Cheeger-Style Inequality [New])

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

$\alpha(G)$  is the worst-case modulus of padded decomposition for vertex-weighted shortest-path metrics over  $G$ .

## Refining Reweighted Spectral Partitioning

Theorem (**Refined** Cheeger-Style Inequality [New])

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

$\alpha(G)$  is the ~~worst-case modulus of padded decomposition for vertex-weighted shortest path metrics over  $G$ .~~ **intrinsic dimension** of  $G$ .



## Refining Reweighted Spectral Partitioning

### Theorem (**Refined** Cheeger-Style Inequality [New])

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

$\alpha(G)$  is the ~~worst-case modulus of padded decomposition for vertex-weighted shortest path metrics over  $G$ .~~ **intrinsic dimension** of  $G$ .

E.g.  $G$  planar  $\implies \alpha(G) \in \mathcal{O}(1)$ .

# Rewighted Spectral Partitioning **Works**

**Rewighted 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- $g$	$\frac{g \min\{(\log g)^2, \log \Delta\}}{n}$
$K_h$ -minor-free	$\frac{(h \log h \log \log h)^2}{n}$

# Rewighted Spectral Partitioning **Works**

**Rewighted 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- $g$	$\frac{g \min\{(\log g)^2, \log \Delta\}}{n}$
$K_h$ -minor-free	$\frac{(h \log h \log \log h)^2}{n}$

Graph class	$\gamma^{(n)} \leq \gamma^{(d)} \lesssim$
$(d\text{-dim})$ $k$ -ply ball-intersection	$\left(\frac{k}{n}\right)^{\frac{2}{d}}$
$(d\text{-dim})$ $k$ -NN graph	$\left(\frac{k}{n}\right)^{\frac{2}{d}}$

# Reweight Spectral Partitioning **Works**

**Reweight 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- $g$	$\frac{g \min\{(\log g)^2, \log \Delta\}}{n}$
$K_h$ -minor-free	$\frac{(h \log h \log \log h)^2}{n}$

Graph class	$\gamma^{(n)} \leq \gamma^{(d)} \lesssim$
$(d\text{-dim})$ $k$ -ply ball-intersection	$\left(\frac{k}{n}\right)^{\frac{2}{d}}$
$(d\text{-dim})$ $k$ -NN graph	$\left(\frac{k}{n}\right)^{\frac{2}{d}}$

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:

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

subject to

$$\sum_{v \in V} f(v) = \bar{0}$$
$$y(u) + y(v) \geq \|f(u) - f(v)\|_2^2 \quad \forall uv \in E$$

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

## Definition

For a graph  $G$ , define:

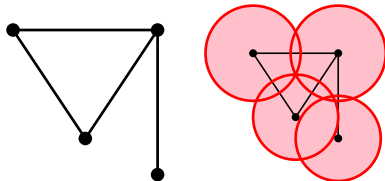
$$\gamma^{(d)}(G) := \min_{\substack{f: V \rightarrow \mathbb{R}^d \\ y: V \rightarrow \mathbb{R}_{\geq 0}}} \frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2}$$

subject to

$$\sum_{v \in V} f(v) = \bar{0}$$
$$y(u) + y(v) \geq \|f(u) - f(v)\|_2^2 \quad \forall uv \in E$$

Loose interpretation:

- For  $v \in V$ : Create a ball in  $\mathbb{R}^d$  centred at  $f(v)$ , radius  $\approx \sqrt{y(v)}$ .



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

## Definition

For a graph  $G$ , define:

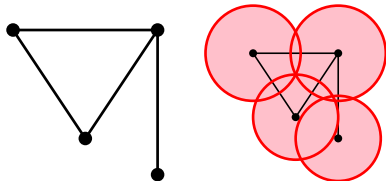
$$\gamma^{(d)}(G) := \min_{\substack{f: V \rightarrow \mathbb{R}^d \\ y: V \rightarrow \mathbb{R}_{\geq 0}}} \frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2}$$

subject to

$$\sum_{v \in V} f(v) = \bar{0}$$
$$y(u) + y(v) \geq \|f(u) - f(v)\|_2^2 \quad \forall uv \in E$$

Loose interpretation:

- For  $v \in V$ : Create a ball in  $\mathbb{R}^d$  centred at  $f(v)$ , radius  $\approx \sqrt{y(v)}$ .
- **Minimize sum of squared radii** under normalization constraints.



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

## Definition

For a graph  $G$ , define:

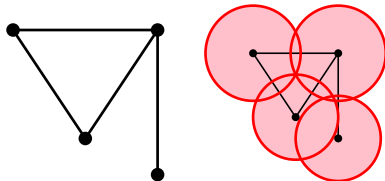
$$\gamma^{(d)}(G) := \min_{\substack{f: V \rightarrow \mathbb{R}^d \\ y: V \rightarrow \mathbb{R}_{\geq 0}}} \frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2}$$

subject to

$$\sum_{v \in V} f(v) = \bar{0}$$
$$y(u) + y(v) \geq \|f(u) - f(v)\|_2^2 \quad \forall uv \in E$$

Loose interpretation:

- For  $v \in V$ : Create a ball in  $\mathbb{R}^d$  centred at  $f(v)$ , radius  $\approx \sqrt{y(v)}$ .
- Minimize sum of squared radii **under normalization constraints**.





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

## Definition

For a graph  $G$ , define:

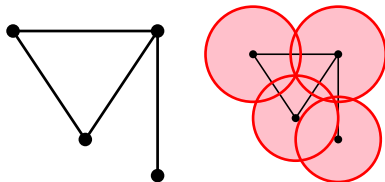
$$\gamma^{(d)}(G) := \min_{\substack{f: V \rightarrow \mathbb{R}^d \\ y: V \rightarrow \mathbb{R}_{\geq 0}}} \frac{\sum_{v \in V} y(v)}{\sum_{x \in V} \|f(x)\|_2^2}$$

subject to

$$\sum_{v \in V} f(v) = \bar{0}$$
$$y(u) + y(v) \geq \|f(u) - f(v)\|_2^2 \quad \forall uv \in E$$

Loose interpretation:

- For  $v \in V$ : Create a ball in  $\mathbb{R}^d$  centred at  $f(v)$ , radius  $\approx \sqrt{y(v)}$ .
- Minimize sum of squared radii under normalization constraints.
- **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  $\Delta$ ,*

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

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

# Expanding the Cheeger-Style Inequality

## Theorem (Refined Cheeger-Style Inequality, expanded)

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

## Lemma (OTZ22)

For a graph  $G$ ,

$$\psi(G)^2 \lesssim \gamma^{(1)}(G) \lesssim \psi(G).$$

# Expanding the Cheeger-Style Inequality

## Theorem (Refined Cheeger-Style Inequality, expanded)

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

## Lemma (OTZ22)

For a graph  $G$ ,

$$\psi(G)^2 \lesssim \gamma^{(1)}(G) \lesssim \psi(G).$$

## Lemma (Dimension-reduction step [KLT22])

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \log \Delta.$$

# Expanding the Cheeger-Style Inequality

## Theorem (Refined Cheeger-Style Inequality, expanded)

For a graph  $G$  with  $n$  vertices and maximum degree  $\Delta$ ,

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

## Lemma (OTZ22)

For a graph  $G$ ,

$$\psi(G)^2 \lesssim \gamma^{(1)}(G) \lesssim \psi(G).$$

## Lemma (Dimension-reduction step [KLT22])

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \log \Delta.$$

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

# Refining the Cheeger-Style Inequality

## Lemma (New)

*For a graph  $G$  with maximum degree  $\Delta$ ,*

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

# Refining the Cheeger-Style Inequality

## Lemma (New)

*For a graph  $G$  with maximum degree  $\Delta$ ,*

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

# Refining the Cheeger-Style Inequality

## Lemma (New)

*For a graph  $G$  with maximum degree  $\Delta$ ,*

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) :=$  radius of  $v$ . Use  $\omega$ -weighted SPs on  $G$ .



# Refining the Cheeger-Style Inequality

## Lemma (New)

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) := \text{radius of } v$ . Use  $\omega$ -weighted SPs on  $G$ .

## Theorem (Rab08, BLR10, KR10)

For a metric space  $(X, d)$ , a Monte Carlo algorithm can compute a **non-expansive** embedding of  $d$  into the line with **average 2-distortion**  $\mathcal{O}(\alpha(X, d)^2)$ .

Note: For a vertex-weighted shortest-path metric  $(X, d)$  on  $G$ ,  $\alpha(G) \leq \alpha(X, d)$ .

# Refining the Cheeger-Style Inequality

## Lemma (New)

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) := \text{radius of } v$ . Use  $\omega$ -weighted SPs on  $G$ .

## Theorem (Rab08, BLR10, KR10)

For a metric space  $(X, d)$ , a Monte Carlo algorithm can compute a **non-expansive** embedding of  $d$  into the line with **average 2-distortion**  $\mathcal{O}(\alpha(X, d)^2)$ .

Note: For a vertex-weighted shortest-path metric  $(X, d)$  on  $G$ ,  $\alpha(G) \leq \alpha(X, d)$ .

**Ongoing follow-up work:** This is now deterministic.

# Refining the Cheeger-Style Inequality

## Lemma (New)

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) := \text{radius of } v$ . Use  $\omega$ -weighted SPs on  $G$ .

## Theorem (Rab08, BLR10, KR10, unpublished follow-up work)

For a graph  $G$  with vertex-weights  $\omega : V \rightarrow \mathbb{R}_{\geq 0}$ , a deterministic algorithm can compute a **non-expansive** embedding of  $d_\omega$  into the line with **average 2-distortion**  $\mathcal{O}(\alpha(G)^2)$ .

# Refining the Cheeger-Style Inequality

## Lemma (New)

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) := \text{radius of } v$ . Use  $\omega$ -weighted SPs on  $G$ .

## Theorem (Rab08, BLR10, KR10, unpublished follow-up work)

For a graph  $G$  with vertex-weights  $\omega : V \rightarrow \mathbb{R}_{\geq 0}$ , a deterministic algorithm can compute a **non-expansive** embedding of  $d_\omega$  into the line with **average 2-distortion**  $\mathcal{O}(\alpha(G)^2)$ .

Proof Step 1: **Non-expansive** for shortest-path metric  $\implies$  partially non-expansive for original  $L_2$  metric  $\implies$  adjacent balls still intersect!

# Refining the Cheeger-Style Inequality

## Lemma (New)

For a graph  $G$  with maximum degree  $\Delta$ ,

$$\gamma^{(n)}(G) \lesssim \gamma^{(1)}(G) \lesssim \gamma^{(n)}(G) \cdot \alpha(G)^2.$$

**New method:** Embeddings of shortest-path metrics!

Let  $\omega(v) := \text{radius of } v$ . Use  $\omega$ -weighted SPs on  $G$ .

## Theorem (Rab08, BLR10, KR10, unpublished follow-up work)

For a graph  $G$  with vertex-weights  $\omega : V \rightarrow \mathbb{R}_{\geq 0}$ , a deterministic algorithm can compute a **non-expansive** embedding of  $d_\omega$  into the line with **average 2-distortion**  $\mathcal{O}(\alpha(G)^2)$ .

Proof Step 1: Non-expansive for shortest-path metric  $\implies$  partially non-expansive for original  $L_2$  metric  $\implies$  adjacent balls still intersect!

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

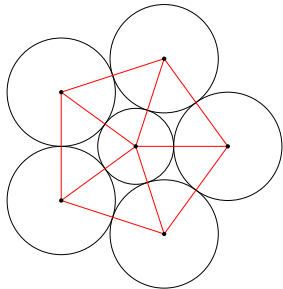
Reminder:  $\gamma^{(n)}(G)$  small for a class of graphs  $\implies$  small sparse cuts  $\psi(S)$ .

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

Reminder:  $\gamma^{(n)}(G)$  small for a class of graphs  $\implies$  small sparse cuts  $\psi(S)$ .

## Geometric Bounds on $\gamma^{(n)}(G)$

Rich theory of **circle packings**!

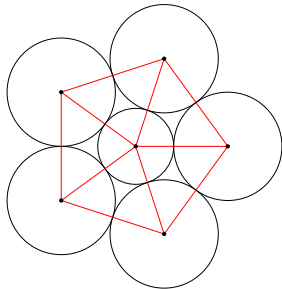


# Two kinds of upper bounds on $\gamma^{(n)}(G)$ : Geometric and Combinatorial

Reminder:  $\gamma^{(n)}(G)$  small for a class of graphs  $\implies$  small sparse cuts  $\psi(S)$ .

## Geometric Bounds on $\gamma^{(n)}(G)$

Rich theory of **circle packings**!



## Combinatorial Bounds on $\gamma^{(n)}(G)$

**Congestion bounds** via crossing numbers!

E.g., crossing number lemma:

$$\text{cr}(G) \gtrsim \frac{m^3}{n^2}.$$

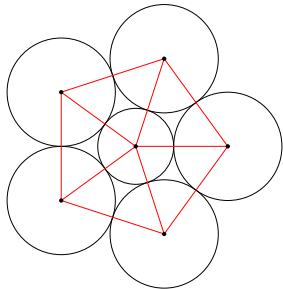


# Two kinds of upper bounds on $\gamma^{(n)}(G)$ : Geometric and Combinatorial

Reminder:  $\gamma^{(n)}(G)$  small for a class of graphs  $\implies$  small sparse cuts  $\psi(S)$ .

## Geometric Bounds on $\gamma^{(n)}(G)$

Rich theory of **circle packings**!



## Combinatorial Bounds on $\gamma^{(n)}(G)$

**Congestion bounds** via crossing numbers!

E.g., crossing number lemma:

$$\text{cr}(G) \gtrsim \frac{m^3}{n^2}.$$

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

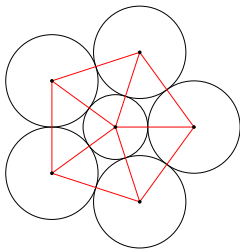
# Geometric Bounds: Planar Case

**Construction from Spielman-Teng:**

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

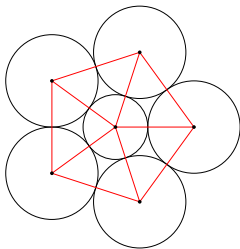
**Step 1:** Planar circle packing theorem. Every planar graph admits touching circles representation.



# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

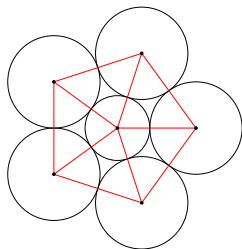
**Step 1:** Planar circle packing theorem. Every planar graph admits touching circles representation.



# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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

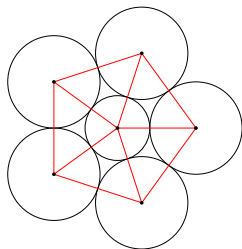


**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

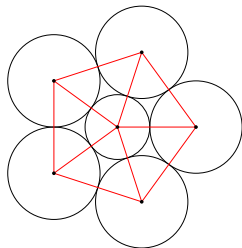
**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

Bounding  $\gamma^{(3)}$ :

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



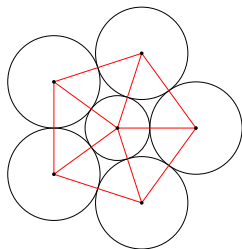
**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

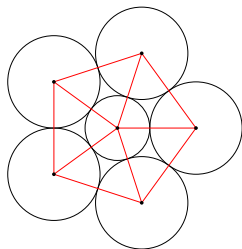
Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.



# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.

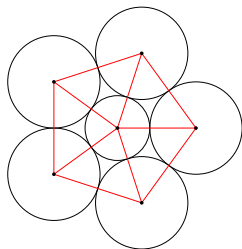
Centroid at origin:

$$\sum_{v \in V} f(v) = \bar{0}$$

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.

Centroid at origin:

$$\sum_{v \in V} f(v) = \bar{0}$$

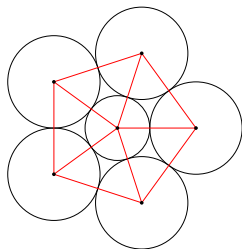
Touching circles ( $uv \in E$ ):

$$\begin{aligned} y(u) + y(v) &\geq (\text{rad}(u) + \text{rad}(v))^2 \\ &\geq \|f(u) - f(v)\|_2^2 \end{aligned}$$

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.

Centroid at origin:

$$\sum_{v \in V} f(v) = \bar{0}$$

Touching circles ( $uv \in E$ ):

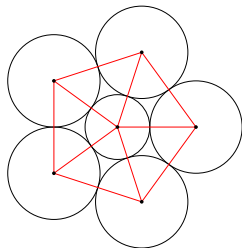
$$\begin{aligned} y(u) + y(v) &\geq (\text{rad}(u) + \text{rad}(v))^2 \\ &\geq \|f(u) - f(v)\|_2^2 \end{aligned}$$

$$\text{Unit sphere: } \sum_{x \in V} \|f(x)\|_2^2 = n$$

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.

Centroid at origin:

$$\sum_{v \in V} f(v) = \bar{0}$$

Touching circles ( $uv \in E$ ):

$$\begin{aligned} y(u) + y(v) &\geq (\text{rad}(u) + \text{rad}(v))^2 \\ &\geq \|f(u) - f(v)\|_2^2 \end{aligned}$$

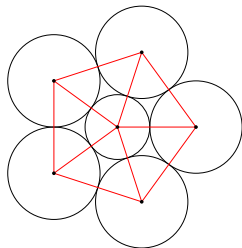
Unit sphere:  $\sum_{x \in V} \|f(x)\|_2^2 = n$

Area bound:  $\sum_{v \in V} y(v) \lesssim 1$ .

# Geometric Bounds: Planar Case

## Construction from Spielman-Teng:

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



**Step 2:** Stereographic projection: Put circle packing onto unit sphere (centroid at origin).

**Step 3:** Total area of representation  $\leq$  area of unit sphere ( $4\pi$ )

**Bounding  $\gamma^{(3)}$ :**

Use  $y(v) := 2 \cdot \text{rad}(v)^2$ ,  
 $f(v) :=$  centre of disk on sphere.

Centroid at origin:

$$\sum_{v \in V} f(v) = \bar{0}$$

Touching circles ( $uv \in E$ ):

$$\begin{aligned} y(u) + y(v) &\geq (\text{rad}(u) + \text{rad}(v))^2 \\ &\geq \|f(u) - f(v)\|_2^2 \end{aligned}$$

Unit sphere:  $\sum_{x \in V} \|f(x)\|_2^2 = n$

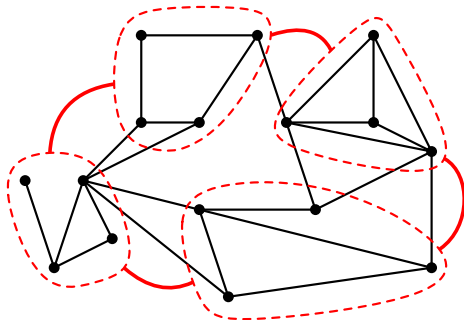
Area bound:  $\sum_{v \in V} y(v) \lesssim 1$ .

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

# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

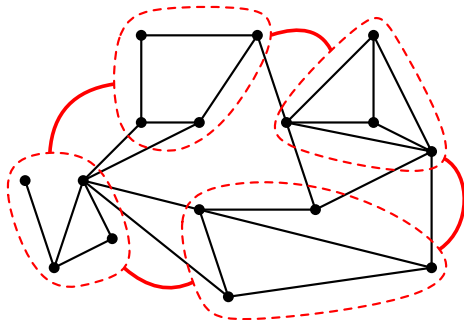
- Start with graph  $G$ .
- Will form new graph  $H$ .



# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

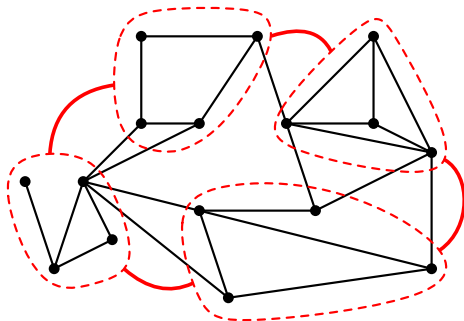
- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .



# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.

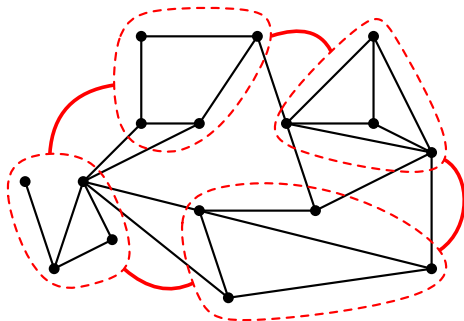




# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

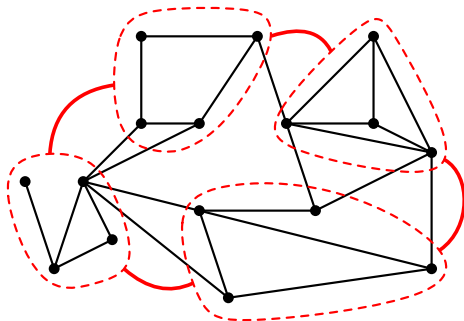
- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.



# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

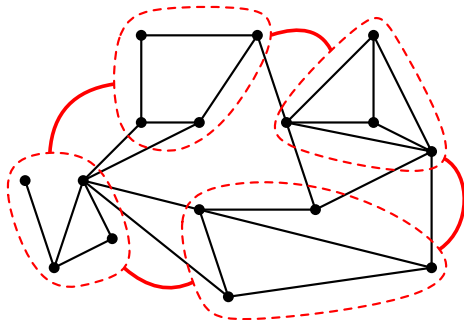
- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.



# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

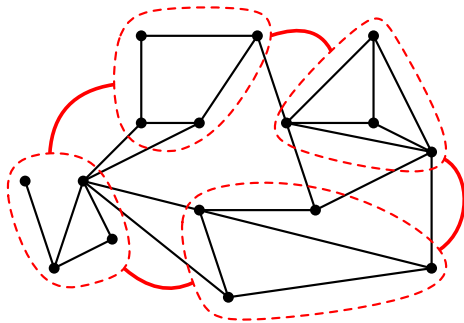
- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.



# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.

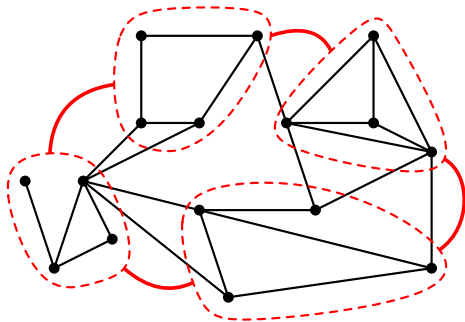


How to use:

# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.



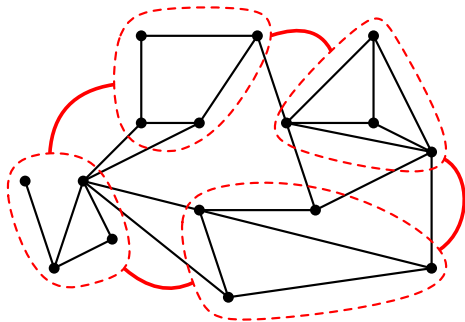
How to use:

- 1 Start with  $H$ .

# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.



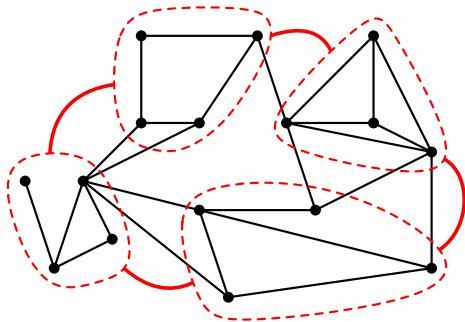
How to use:

- 1 Start with  $H$ .
- 2 Construct  $G$  that has  $H$  as uniform shallow minor.

# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.



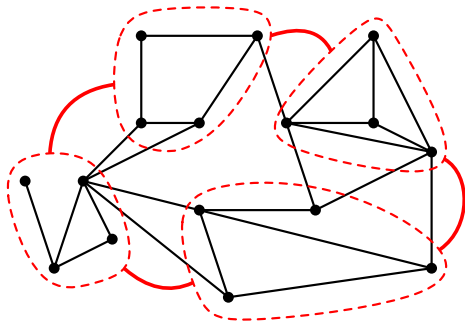
How to use:

- 1 Start with  $H$ .
- 2 Construct  $G$  that has  $H$  as uniform shallow minor.
- 3 Bound  $\gamma^{(1)}(G)$ .

# Geometric Bounds: Uniform Shallow Minors (for Genus- $g$ Graphs)

New structure: **Uniform shallow minors**.

- Start with graph  $G$ .
- Will form new graph  $H$ .
- Vertices of  $H$ : Disjoint connected subgraphs of  $G$ .
- Edges of  $H$ : Edge (optionally) exists in  $G$  between the subgraphs.
- This is a **minor**.
- **Uniform** if subgraphs form a partition with equal-sized parts.
- **Shallow** if subgraphs have bounded diameter.



How to use:

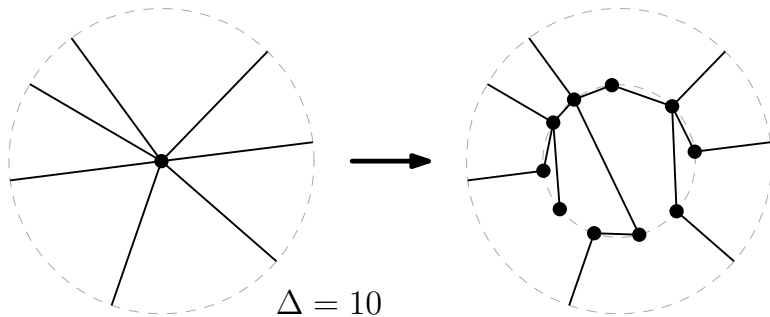
- 1 Start with  $H$ .
- 2 Construct  $G$  that has  $H$  as uniform shallow minor.
- 3 Bound  $\gamma^{(1)}(G)$ .
- 4 Relate  $\gamma^{(1)}(H)$  and  $\gamma^{(1)}(G)$ .



# Geometric Bounds: Overview for Genus- $g$ Graphs

Four steps:

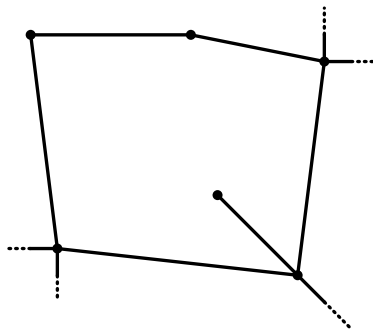
- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].



# Geometric Bounds: Overview for Genus- $g$ Graphs

Four steps:

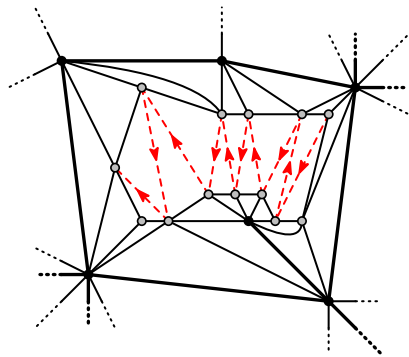
- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].
- 2 Reduce to triangulated constant-degree case  
[**uniform shallow minors**].



# Geometric Bounds: Overview for Genus- $g$ Graphs

Four steps:

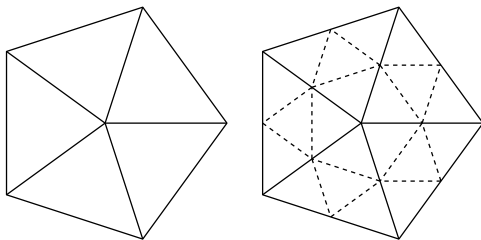
- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].
- 2 Reduce to triangulated constant-degree case  
[**uniform shallow minors**].



# Geometric Bounds: Overview for Genus- $g$ Graphs

Four steps:

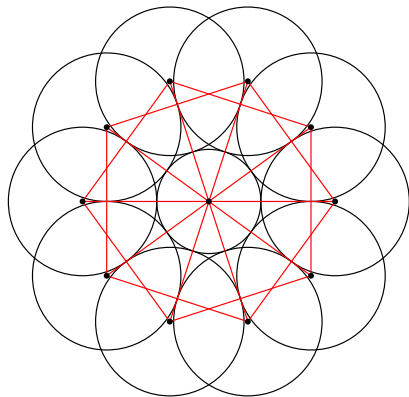
- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].
- 2 Reduce to triangulated constant-degree case  
[**uniform shallow minors**].
- 3 Reduce to highly “refined” graph  
[**adapt argument of Kelner**].



# Geometric Bounds: Overview for Genus- $g$ Graphs

Four steps:

- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].
- 2 Reduce to triangulated constant-degree case  
[**uniform shallow minors**].
- 3 Reduce to highly “refined” graph  
[**adapt argument of Kelner**].
- 4 Use circle packings with ply bounds for most points  
[**adapt argument of Kelner**].

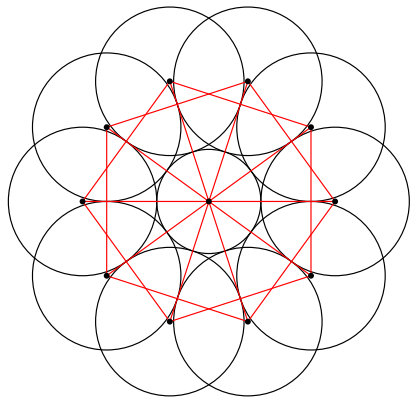


# Geometric Bounds: Overview for Genus- $g$ Graphs

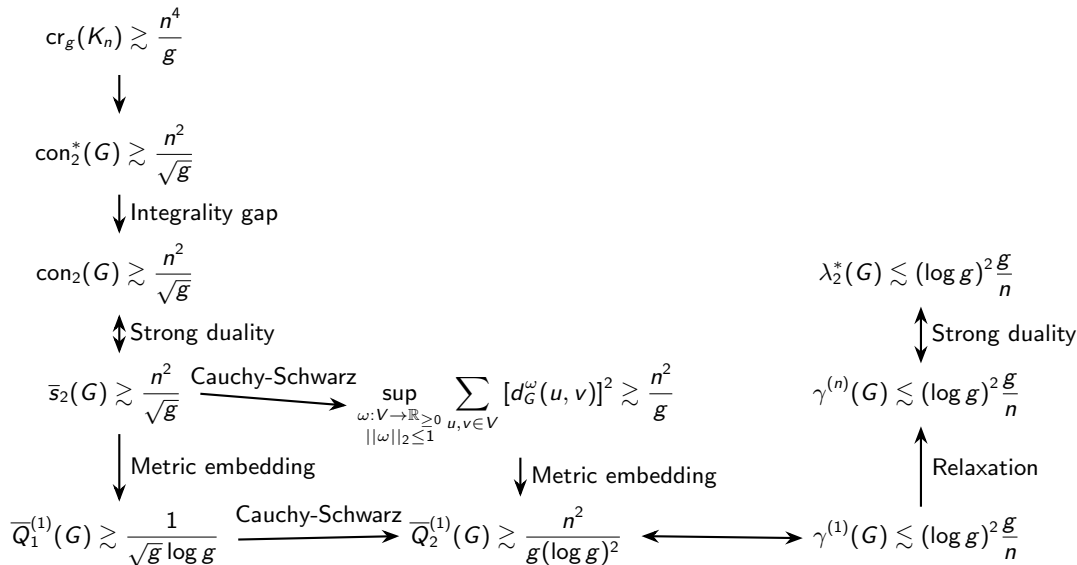
Four steps:

- 1 Reduce to constant-degree graph  
[**uniform shallow minors**].
- 2 Reduce to triangulated constant-degree case  
[**uniform shallow minors**].
- 3 Reduce to highly “refined” graph  
[**adapt argument of Kelner**].
- 4 Use circle packings with ply bounds for most points  
[**adapt argument of Kelner**].

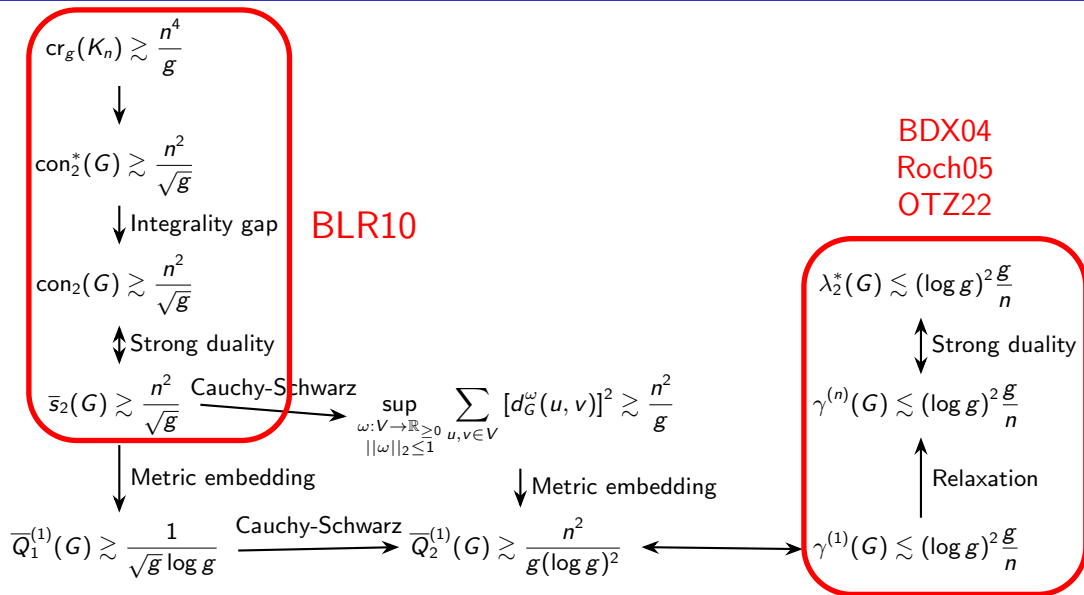
$$\text{Result: } \gamma^{(1)}(G) \lesssim \frac{g \log \Delta}{n}$$



# Combinatorial Bounds: Overview for Genus- $g$ Graphs



# Combinatorial Bounds: Overview for Genus- $g$ Graphs



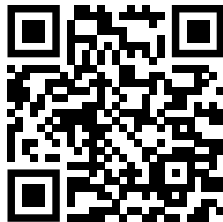


**Rewighted Spectral Partitioning Works:  
A Simple Algorithm for Vertex Separators in Special Graph Classes**

Jack Spalding-Jamieson

<https://arxiv.org/pdf/2506.01228>

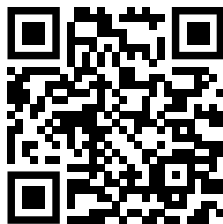
Lots more results in the paper!



**Rewighted Spectral Partitioning Works:  
A Simple Algorithm for Vertex Separators in Special Graph Classes**

Jack Spalding-Jamieson

<https://arxiv.org/pdf/2506.01228>



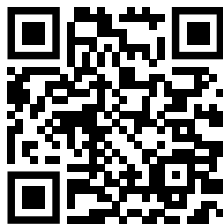
Lots more results in the paper!

- New separator theorems for some geometric graph classes.
- Other bounds on  $\gamma^{(n)}$ .
- A new bound on  $\lambda_2$  for genus- $g$  graphs.
- Fixes for a couple proofs from previous papers.

## **Reweight Spectral Partitioning Works: A Simple Algorithm for Vertex Separators in Special Graph Classes**

Jack Spalding-Jamieson

<https://arxiv.org/pdf/2506.01228>



Lots more results in the paper!

- New separator theorems for some geometric graph classes.
- Other bounds on  $\gamma^{(n)}$ .
- A new bound on  $\lambda_2$  for genus- $g$  graphs.
- Fixes for a couple proofs from previous papers.

Questions?