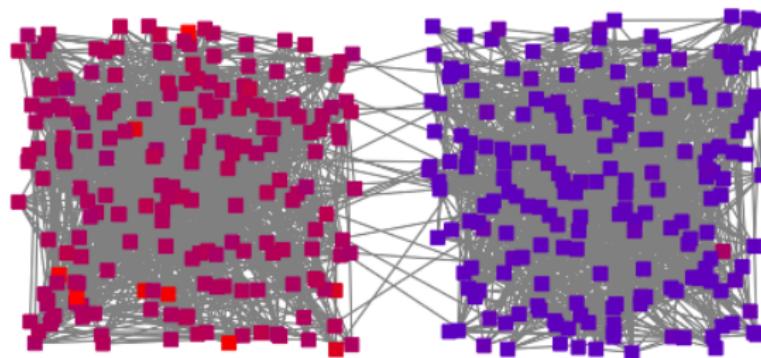


# An Algorithm for Improving Graph Partitions

Reid Andersen [Microsoft Research]  
–joint work with–  
Kevin Lang [Yahoo! Research]

# Graph Partitioning

Divide vertex set into groups, with few edges between groups.

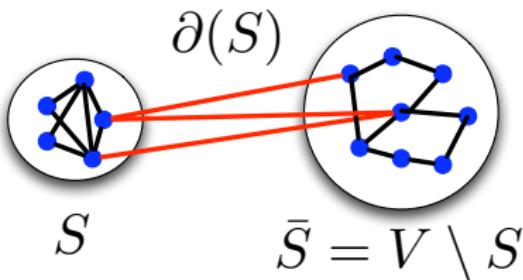


Applications:

- Divide-and-conquer algorithms for graphs
- Parallel computing, VLSI layout
- Image processing, finding communities

# The Minimum Quotient Cut Problem

Find a set  $S \subseteq V$  minimizing the *quotient cost*  $Q(S)$ .



## Quotient cost

$$Q(S) = \frac{\partial(S)}{\min(\pi(S), \pi(\bar{S}))} = \frac{\text{\# edges between } S \text{ and } \bar{S}}{\text{weight of vertices in } S}$$

## Vertex weights

Let each vertex have a nonnegative integer weight  $\pi(v)$ .  
 $\pi(S)$  is the total weight of vertices in  $S$ .

# Algorithms for finding quotient cuts

The Minimum Quotient Cut problem is NP-hard.

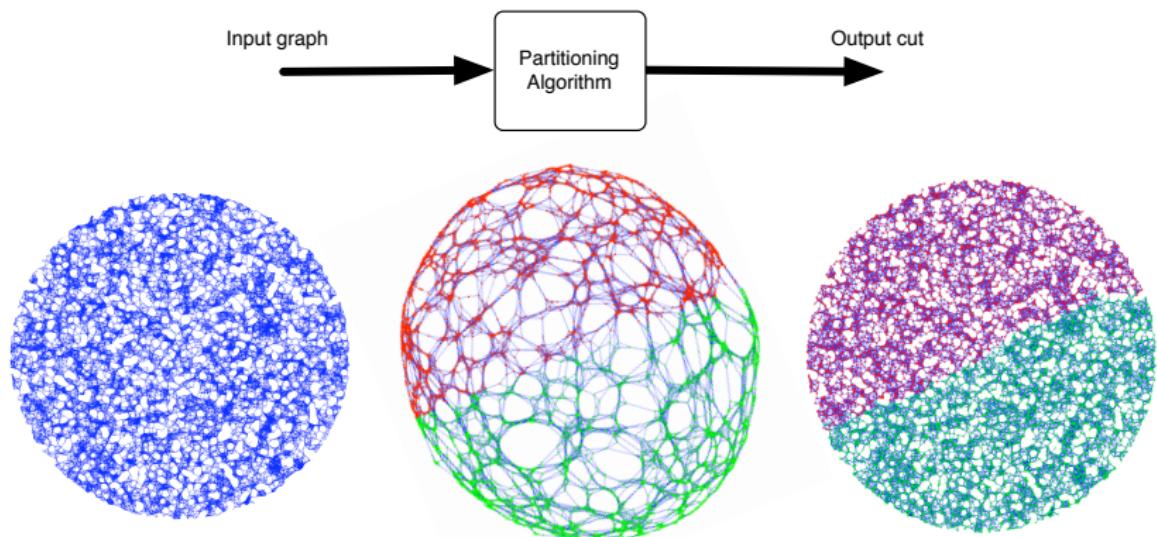
## Approximation algorithms

- Spectral Partitioning [Fiedler 72]
- Leighton Rao [LR 88]
- Arora Rao Vazirani [ARV 04]  
(Best approximation algorithm known, with ratio  $O(\sqrt{\log n})$ )

## Effective heuristics

- Local search [Kernighan,Lin 70] [Fiduccia,Mattheyses 82]
- Multilevel methods (METIS) [Karypis, Kumar 98]

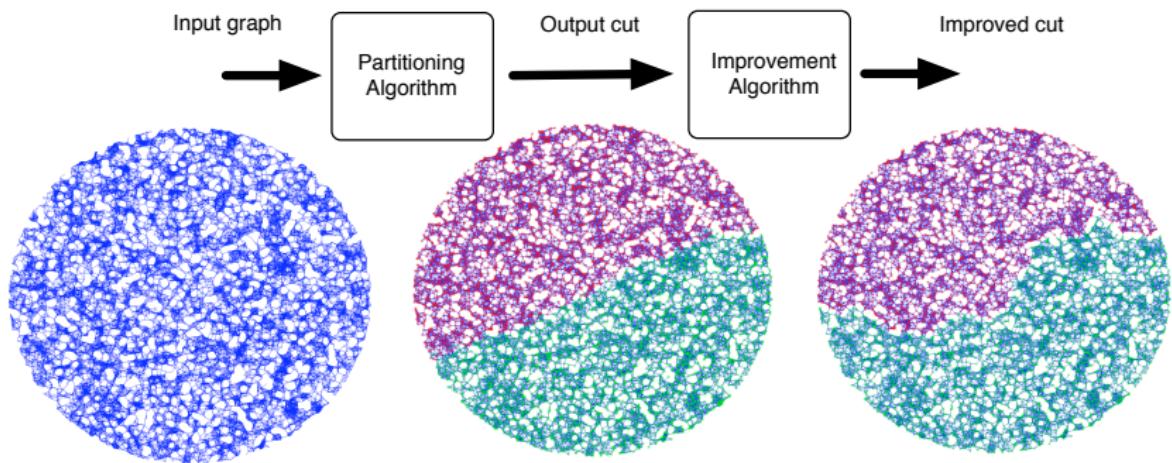
# A partitioning algorithm



# Improving the proposed cut

This talk is about an algorithm called Improve.

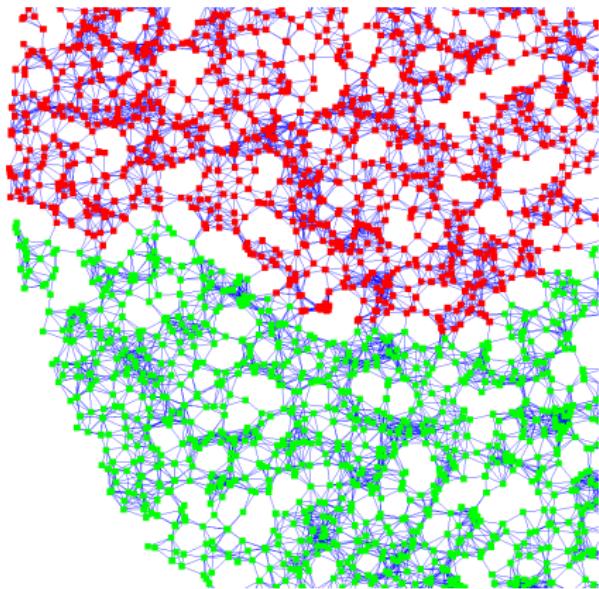
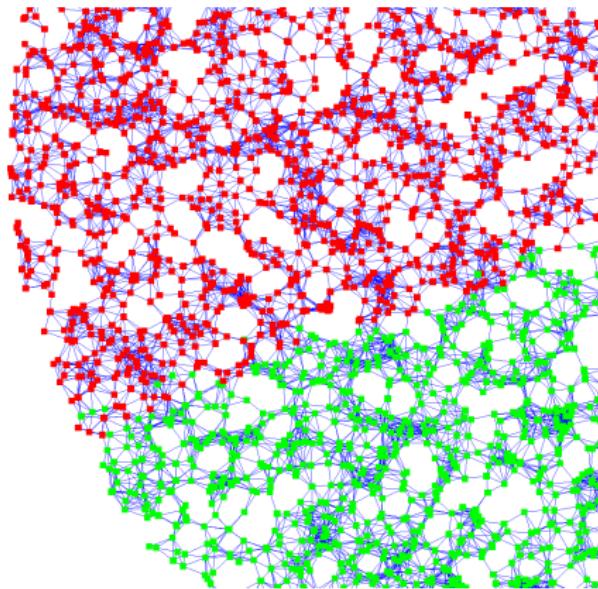
We apply it to the cut proposed by the partitioning algorithm to obtain a cut with better quotient score.



$$Q(\text{Proposed cut}) = 0.108400 = (542 \text{ edges} / 5000 \text{ nodes})$$

$$Q(\text{Improved cut}) = 0.040085 = (189 \text{ edges} / 4715 \text{ nodes})$$

## Detail of proposed cut and improved cut



# Previous work: methods for improving partitions

## Swapping vertices

- greedy hill-climbing, simulated annealing
- local search: Kernighan-Lin, Fiduccia-Mattheyses
- Flow algorithms can find a block of vertices to swap for a big greedy improvement.

There is a [powerful known method](#) for improving the quotient cost, based on [parametric flow](#) ...

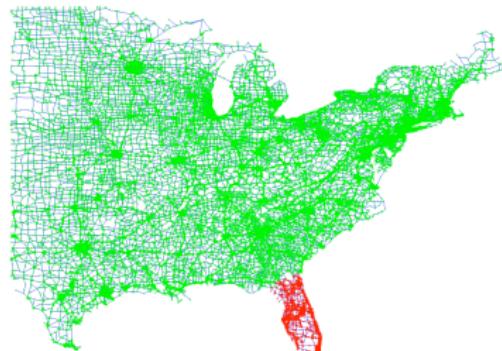
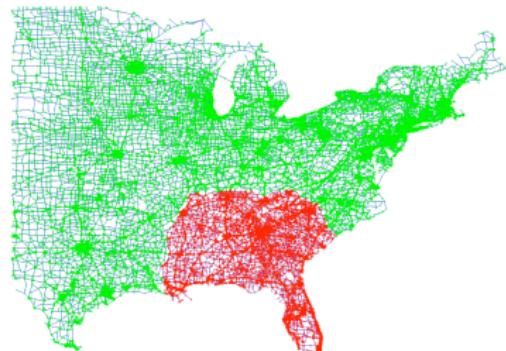
- Described in [Gallo Grigoriadis Tarjan 89].
- Key tool in the polylog approximation algorithm for minimum bisection [Feige Krauthgamer 01].
- Lang and Rao [LR 04] demonstrated its practical utility.

# Previous work: parametric flow improvement algorithm

## PFI algorithm

**Input** : a proposed set  $A$  with weight  $\pi(A) \leq \pi(\bar{A})$ .

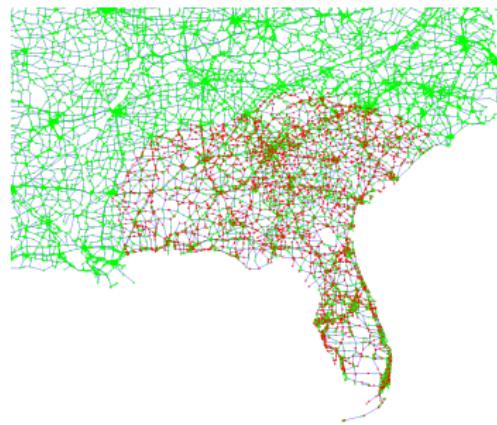
**Output** : the subset of  $A$  with the smallest quotient cost.



- Finds the optimal cut that can be obtained by *removing* vertices from the proposed cut.
- Works by solving a sequence of  $s - t$  min cut problems, or one parametric flow problem. [Gallo Grigoriadis Tarjan 89]

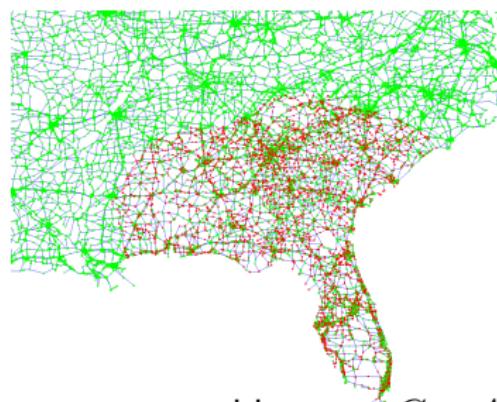
# Motivation for the Improve algorithm

What if there exists a great cut  $C$ ,  
and the proposed cut  $A$  contains a significant fraction of  $C$ ,  
but not all of it?



# Motivation for the Improve algorithm

What if there exists a great cut  $C$ ,  
and the proposed cut  $A$  contains a significant fraction of  $C$ ,  
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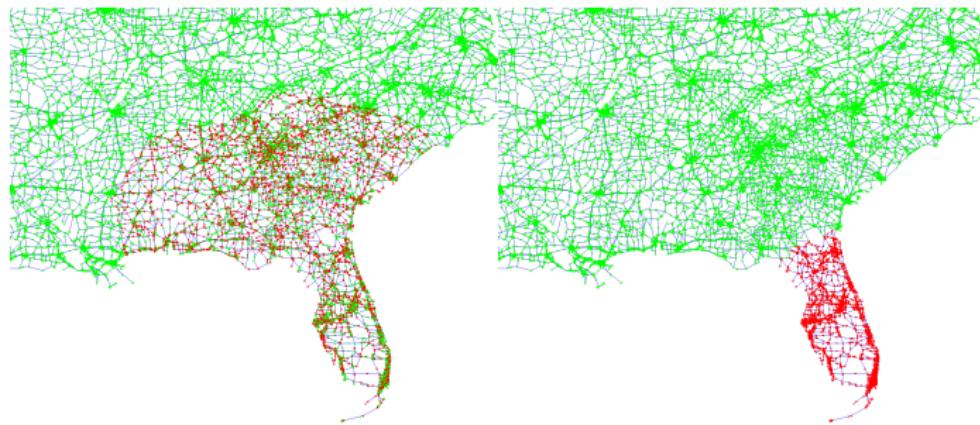
- PFI could return  $C \cap A$ , but that cut might be terrible.
- PFI cannot “fill in the holes” by adding nodes from outside  $A$ .

# The Improve algorithm

## Improve

**Input** : a proposed set  $A$  with  $\pi(A) \leq \pi(\bar{A})$

**Output** : a set  $S$



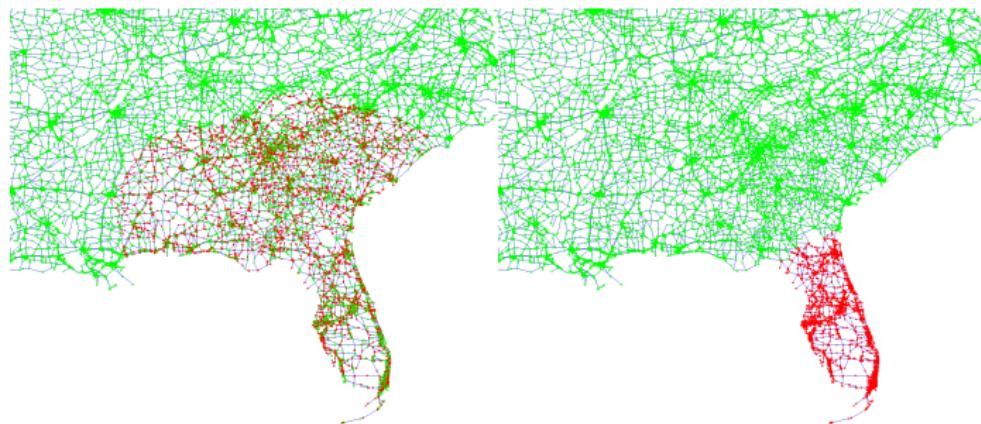
- Adds and removes vertices from the proposed cut.
- Works by solving a sequence of  $s - t$  min cut problems, that cannot be cast as a parametric flow problem.

# The Improve algorithm

## Improve

**Input** : a proposed set  $A$  with  $\pi(A) \leq \pi(\bar{A})$

**Output** : a set  $S$



- Main theorem: to find a cut nearly as good as  $C$ , the proposed set just needs to have a larger intersection with  $C$  than a randomly chosen set.

# Main theorem about Improve

## Improve

**Input** : a proposed set  $A$  with  $\pi(A) \leq \pi(\bar{A})$

**Output** : a set  $S$

## Theorem (part 1)

- Improve runs in polynomial time.
- The set returned by Improve has quotient cost at least as small as the best subset of  $A$ ,

$$Q(S) \leq \min_{C \subseteq A} Q(C).$$

# Main theorem about Improve

## Theorem (part 2)

Let  $C$  be any set whose intersection with the proposed set  $A$  satisfies

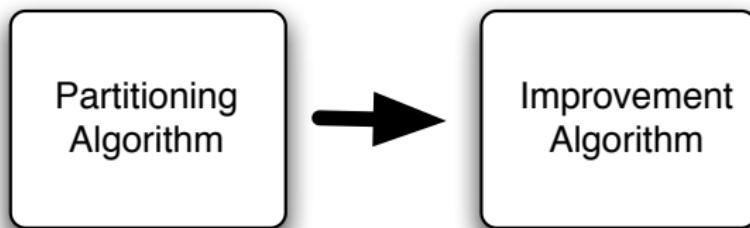
$$\frac{\pi(A \cap C)}{\pi(C)} \geq \frac{\pi(A)}{\pi(V)} + \epsilon.$$

Then the set  $S$  output by Improve has quotient cost almost as small as  $C$ ,

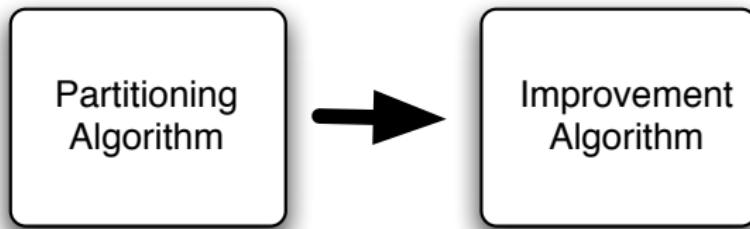
$$Q(S) \leq \frac{1}{\epsilon} Q(C).$$

- If the fraction of  $C$  contained in the proposed set  $A$  is larger than you would expect if  $A$  were chosen randomly, then Improve will return a cut almost as good as  $C$ .

# The role of partitioning and improvement algorithms



# The role of partitioning and improvement algorithms



# Techniques

## Modified quotient cost

We define a modified quotient cost relative to  $A$  that penalizes sets for including vertices outside of  $A$ .

## Iterated minimum cut computations

Improve computes and outputs a set minimizing the modified quotient cost.

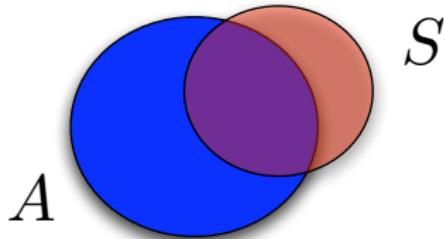
It does this by constructing and solving a sequence of s-t minimum cut problems in an augmented graph.

# Weight function relative to the proposed cut

This modified weight function gives you credit for including vertices in  $A$ , and penalizes you for including vertices outside of  $A$ .

Given a proposed set  $A \subseteq V$ , define

$$D_A(S) = \pi(S \cap A) - \pi(S \cap \bar{A}) \left( \pi(A)/\pi(\bar{A}) \right).$$



## Remarks

- The modified weight  $D_A(S)$  is at most the true weight  $\pi(S)$ .
- It can be zero or negative.

## Quotient cost relative to the proposed cut

The modified quotient cost uses the weight relative to the proposed cut as the denominator, instead of the true weight.

### Quotient cost relative to $A$

Given a set  $A \subseteq V$  that satisfies  $\pi(A) \leq \pi(\bar{A})$ , define

$$\tilde{Q}_A(S) = \begin{cases} \partial(S)/D_A(S) & \text{if } D_A(S) > 0. \\ +\infty & \text{if } D_A(S) \leq 0. \end{cases}$$

#### Remark:

- Defined for all subsets of  $V$ .

# Relating the relative quotient cost to the true quotient cost

Lemma (Relative quotient cost is bigger than true quotient cost)

Assume  $\pi(A) \leq \pi(\bar{A})$ .

- 1 For any set  $S \subseteq V$ , we have  $\tilde{Q}_A(S) \geq Q(S)$ .

Lemma (Upper bounds on the relative quotient cost)

- 1 If  $C \subseteq A$ , then  $\tilde{Q}_A(C) = Q(C)$ .
- 2 If  $C$  is a set for which the intersection of  $A$  with  $C$  satisfies

$$\frac{\pi(A \cap C)}{\pi(C)} \geq \frac{\pi(A)}{\pi(V)} + \epsilon \frac{\pi(\bar{A})}{\pi(V)},$$

then  $\tilde{Q}_A(C) \leq \frac{1}{\epsilon} Q(C)$ .

# Sketch of the main theorem

Proof sketch of Theorem 1.

`Improve`( $A$ ) outputs a set  $S$  that minimizes  $\tilde{Q}_A$ .

If  $C$  and  $A$  have a large intersection, say  $\pi(C \cap A) \geq (\frac{1}{2} + \epsilon)\pi(C)$ , then

$$\tilde{Q}_A(C) \leq \frac{1}{\epsilon} Q(C).$$

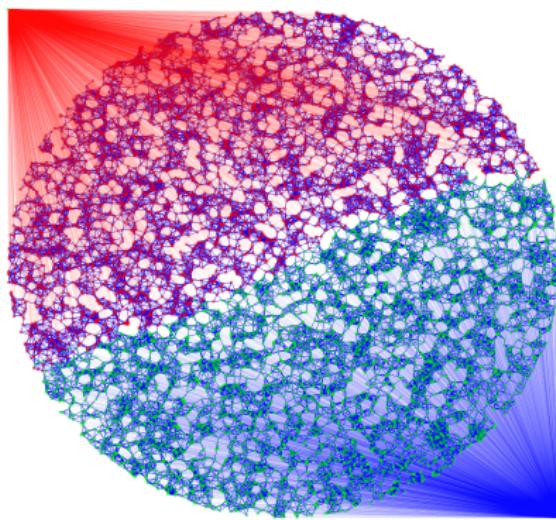
That gives us an upper bound on the true quotient cost of the set output by `Improve`,

$$Q(S) \leq \tilde{Q}_A(S) \leq \tilde{Q}_A(C) \leq \frac{1}{\epsilon} Q(C).$$



# Augmented graph construction

The augmented graph  $G_A(\alpha)$  depends on the input graph  $G$ , on the proposed set  $A$ , and on a parameter  $\alpha \in [0, \infty)$



- Keep the nodes and edges in  $G$  with their original weights.
- Add a source node  $s$  and sink node  $t$ .
- Add edges from  $s$  to each node  $v$  in  $A$ , with weight  $\alpha\pi(v)$ .
- Add edges from  $t$  to each node  $v$  in  $\bar{A}$ , with weight  $\alpha\pi(v)f(A)$ , where  $f(A) = \pi(A)/\pi(\bar{A})$ .

# How to use the augmented graph cuts

Let  $\text{cost}_{A,\alpha}(S)$  be the cutsize of  $\{\mathbf{s}\} \cup S$  in the augmented graph.

By construction,

$$\text{cost}_{A,\alpha}(S) = \alpha\pi(A) + (\partial(S) - \alpha D_A(S)).$$

By computing the minimum cut, you answer the following question:

Is there a set of vertices in the graph for which  $\frac{\partial(S)}{D_A(S)} < \alpha$ ?

# Improve pseudocode

This is a simple iterative procedure for finding the set that minimizes  $\tilde{Q}_A$ .

- **Input.** a set  $A \subseteq V$  satisfying  $\pi(A) \leq \pi(\bar{A})$ .
- **Initialization.** Let  $S = A$  and let  $\alpha = Q(A)$ .
- **Main loop.**
  - 1 Compute the minimum  $s - t$  cut in the graph  $G_A(\alpha)$ .
  - 2 Let  $S'$  be the set of vertices on the source side.
  - 3 Let  $\alpha' = \tilde{Q}_A(S')$  be the new value of  $\alpha$ .
  - 4 If  $\alpha' < \alpha$ , continue the loop. Otherwise, halt and output  $S$ .

# Number of iterations required

To bound the number of iterations, we show that  $\tilde{Q}_A(S_i)$ ,  $D_A(S_i)$ , and  $\partial(S_i)$  strictly decrease at each step.

## Corollary

- If the vertex weights  $\pi(v)$  are integers, the algorithm halts after at most  $\pi(V)^2$  iterations.
- If the edges of the graph are unweighted, the algorithm halts after at most  $m$  iterations, where  $m$  is the number of edges in the graph.

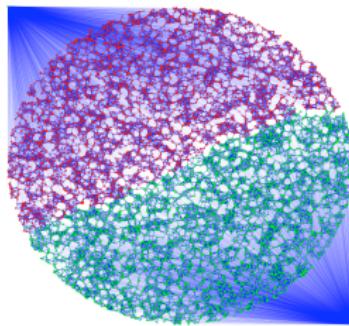
## In our experiments...

- The average number of flow computations required was 4.
- No instance required more than 10 flow computations.

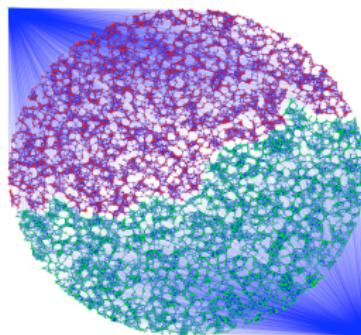
## Details from each iteration

iteration	cutsize	numnodes	swap-ins	denom	$Q(S)$	$\tilde{Q}_A(S)$
0	542	5000	0	5000	0.108400	0.108400
1	198	4908	133	4642	0.040342	0.042654
2	189	4715	132	4451	0.040085	0.042462

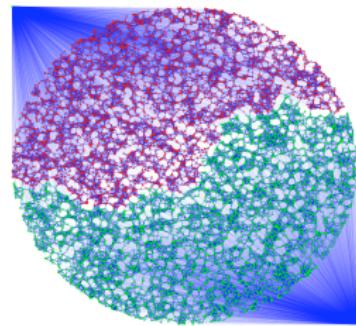
Original cut



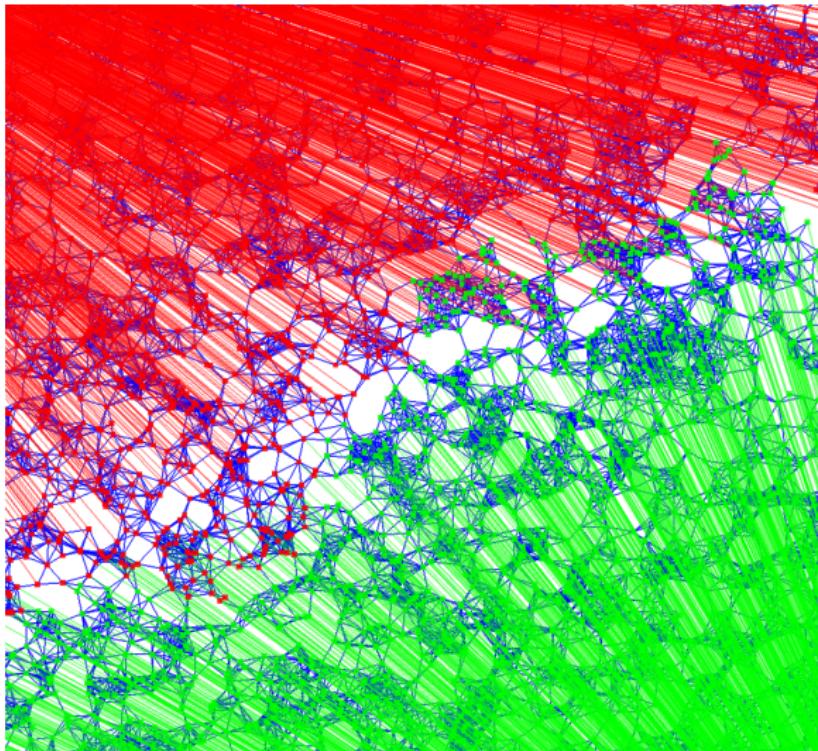
After 1 iteration



After 2 iterations  
(done)



# Detail of the set minimizing the relative quotient cost



# Experiments

We ran off-the-shelf partitioning algorithms  
(spectral partitioning and METIS)  
on three different families of graphs.

We want to compare:

Partitioning algorithm alone

Partitioning algorithm + PFI

Partitioning algorithm + Improve

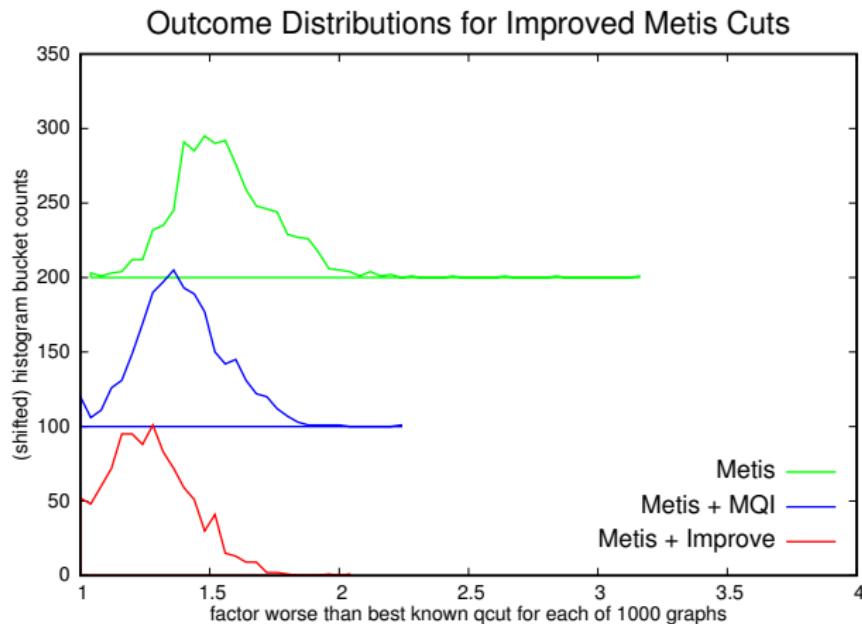
First family of test graphs:

random geometric graphs plus random edges.

We generated 1000 random graphs from this distribution.

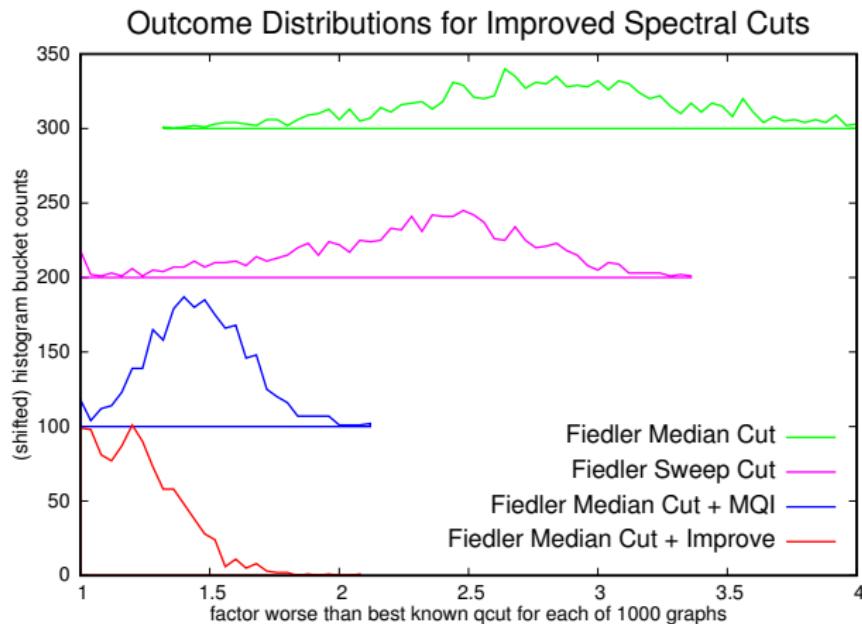
# Improved METIS cuts

Histogram: for each of the 1000 graphs, how much worse is the resulting cut from the best cut we could find?



# Improved spectral cuts

Solution quality histograms for 4 different methods for finding a cut from the Fiedler eigenvector.



# Improve vs PFI on benchmark graphs

**Test graphs** Benchmark meshlike graphs from the graph partitioning archive (run by Chris Walshaw).

**Experiment** For each graph we ran METIS many times, improved the cuts using Improve and PFI, and took the best qcut cost over all runs.

**Table 1** Improve always beats or ties PFI.  
The table shows how many times it beats it.

name	n_nodes	Improve vs PFI		
		wins	ties	losses
wing	62032	3914	2378	0
fe_tooth	78136	1970	625	0
fe_rotor	99617	1794	241	0
598a	110971	1263	181	0
144	144649	999	14	0
wave	156317	1132	0	0
m14b	214765	605	27	0

# Improve vs PFI on benchmark graphs

Table 2

This table shows the ratio between the best balanced qcut obtained by METIS+Improve and the best balanced cut from the graph partitioning archive.

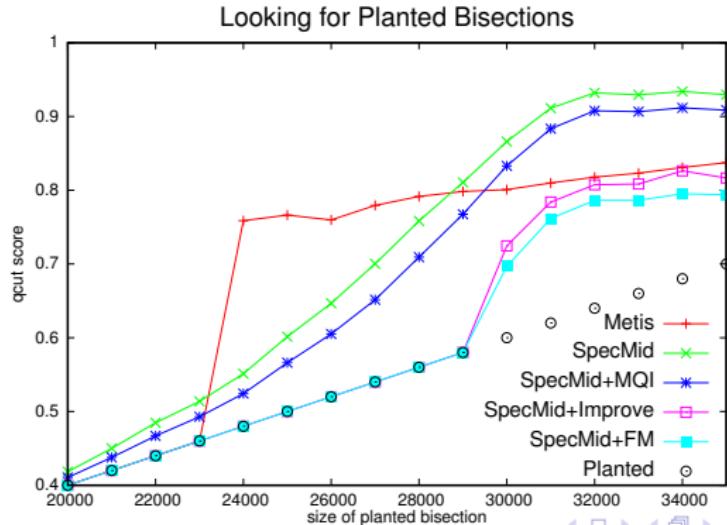
Both cuts are required to contain at least 47.5% of the graph

name	best qcut found with at least 475:525 balance	compared to archive cut
wing	0.025504 = 791 / 31015	1.000032
fe_tooth	0.097809 = 3821 / 39066	0.992518
fe_rotor	0.041964 = 2004 / 47755	1.036868
598a	0.043219 = 2398 / 55485	1.000000
144	0.089733 = 6488 / 72303	0.999982
wave	0.111400 = 8702 / 78115	1.001702
m14b	0.035723 = 3836 / 107382	1.000000

# Random graphs with planted bisections

**Test graphs** Take two random 4-regular graphs with  $50k$  nodes and  $100k$  edges, then add  $c$  random edges between the two sides.

**Experiment** Generate 16 graphs with varying values of  $c$ .  
Compare the qcuts found by 5 algorithms.



# Concluding remarks