Algorithms in the Real World

Graph Separators
  - Introduction
  - Applications
An *edge separator*: a set of edges $E' \subseteq E$ which partitions $V$ into $V_1$ and $V_2$

**Criteria:**
- $|V_1|, |V_2|$ balanced
- $|E'|$ is small
An vertex separator: a set of vertices $V' \subseteq V$ which partitions $V$ into $V_1$ and $V_2$

Criteria:
- $|V_1|, |V_2|$ balanced
- $|V'|$ is small
Compared with Min-cut

**Min-cut**: as in the min-cut, max-flow theorem.

Min-cut has no balance criteria.

Min-cut typically has a source (s) and sink (t).

Min-cut tends to find unbalanced cuts.
Recursive Separation
What graphs have small separators?

**Planar graphs**: $O(n^{1/2})$ vertex separators
  - 2d meshes, constant genus, excluded minors

**Almost planar graphs**: the Internet, power networks, road networks

**Circuits**
  - need to be laid out without too many crossings

**Social network graphs**:
  - phone-call graphs, link structure of the web,
  - citation graphs, “friends graphs”

**3d-grids and meshes**: $O(n^{2/3})$
What graphs don’t have small separators

**Hypercubes:**
O(n) edge separators
O(n/(log n)^{1/2}) vertex separators

**Butterfly networks:**
O(n/log n) separators

**Expander graphs:**
Graphs such that for any U ⊆ V, s.t. |U| ≤ α |V|,
|neighbors(U)| ≥ β |U|. \(^{(α < 1, β > 0)}\)

random graphs are expanders, with high probability

It is exactly the fact that they don’t have small separators that make these graphs useful.
Applications of Separators

Circuit Layout (from 1960s)
VLSI layout
Solving linear systems
   (nested dissection)
   \( n^{3/2} \) time for planar graphs
Partitioning for parallel algorithms
Approximations to NP hard problems
   TSP, maximum-independent-set
Compact Routing and Shortest-paths
Clustering and machine learning
Machine vision

Out of core algorithms
Register allocation
Shortest Paths
Graph compression
Graph embeddings
Available Software

**METIS**: U. Minnesota
**PARTY**: University of Paderborn
**CHACO**: Sandia national labs
**JOSTLE**: U. Greenwich
**SCOTCH**: U. Bordeaux
**GNU**: Popinet

**Benchmarks**:  
• Graph Partitioning Archive
Different Balance Criteria

Bisectors: 50/50
Constant fraction cuts: e.g. 1/3, 2/3

Trading off cut size for balance (vertex separators):

\[ \text{min cut criteria: } \min_{V' \subseteq V} \left( \frac{|V'|}{|V_1| |V_2|} \right) \]

\[ \text{min quotient separator: } \min_{V' \subseteq V} \left( \frac{|V'|}{\min(|V_1|, |V_2|)} \right) \]

All versions are NP-hard
Other Variants of Separators

k-Partitioning:
Might be done with recursive partitioning, but direct solution can give better answers.

Weighted:
Weights on edges (cut size), vertices (balance)

Hypergraphs:
Each edge can have more than 2 end points common in VLSI circuits

Multiconstraint:
Trying to balance different values at the same time.
Asymptotics

If $S$ is a class of graphs closed under the subgraph relation, then

**Definition:** $S$ satisfies an $f(n)$ vertex-separator theorem if there are constants $\alpha < 1$ and $\beta > 0$ so that for every $G \in S$ there exists a vertex cut set $V' \subseteq V$, with

1. $|V'| \leq \beta f(|G|)$ cut size
2. $|V_1| \leq \alpha |G|$, $|V_2| \leq \alpha |G|$ balance

Similar definition for edge separators.
Edge vs. Vertex separators

If a class of graphs satisfies an $f(n)$ edge-separator theorem then it satisfies an $f(n)$ vertex-separator. The other way is not true (unless degree is bounded)

$|E'| = n/2$
Separator Trees

**Theorem:** For $S$ satisfying an $(\alpha, \beta)$ $f(n) = n^{1-\varepsilon}$ edge-separator theorem, we can generate a perfectly balanced separator with size

$|C| \leq k \beta f(|G|)$.

**Proof:** by picture $|C| \leq \beta n^{1-\varepsilon}(1 + \alpha + \alpha^2 + \ldots) \leq \beta n^{1-\varepsilon}(1/1-\alpha)$
Algorithms for Partitioning

All are either heuristics or approximations
- Kernighan-Lin, Fiduccia-Mattheyses (heuristic)
- Planar graph separators  
  (finds $O(n^{1/2})$ separators)
- Geometric separators  
  (finds $O(n^{(d-1)/d})$ separators in $\mathbb{R}^d$)
- Spectral (finds $O(n^{(d-1)/d})$ separators in $\mathbb{R}^d$)
- Flow/LP-based techniques  
  (give log(n) approximations)
- Multilevel recursive bisection  
  (heuristic, currently most practical)
Kernighan-Lin Heuristic

Local heuristic for edge-separators based on “hill climbing”. Will most likely end in a local-minima.

Two versions:

- Original K-L: takes $n^2$ time per pass
- Fiduccia-Mattheyses: takes linear time per pass
High-level description for both

Start with an initial cut that partitions the vertices into two equal size sets $V_1$ and $V_2$

Want to swap two equal sized sets $X \subset A$ and $Y \subset B$ to reduce the cut size.

Note that finding the optimal subsets $X$ and $Y$ solves the optimal separator problem, so it is NP hard.

We want some heuristic that might help.
Some Terminology

C(A,B) : the weighted cut between A and B

I(v) : the number of edges incident on v that stay within the partition

E(v) : the number of edges incident on v that go to the other partition

D(v) : E(v) - I(v)

D(u,v) : D(u) + D(v) - 2 w(u,v)

the gain for swapping u and v
Kernighan-Lin improvement step

KL(G,A_0,B_0)
\forall u \in A_0, v \in B_0
\quad \text{put } (u,v) \text{ in a PQ based on } D(u,v)
\quad \text{for } k = 1 \text{ to } |V|/2
\quad (u,v) = \max(\text{PQ})
\quad (A_k,B_k) = (A_{k-1},B_{k-1}) \text{ swap } (u,v)
\quad \text{delete } u \text{ and } v \text{ entries from PQ}
\quad \text{update } D \text{ on neighbors (and PQ)}
\quad \text{select } A_k,B_k \text{ with best } C_k

Note that can take backward steps ("gain" D(u,v) can be negative).
Fiduccia-Mattheyses’s improvement step

\[ FM(G,A_0,B_0) \]
\[ \forall u \in A_0 \text{ put } u \text{ in } PQ_A \text{ based on } D(u) \]
\[ \forall v \in B_0 \text{ put } v \text{ in } PQ_B \text{ based on } D(v) \]
for \( k = 1 \) to \( |V|/2 \)
\[ u = \max(PQ_A) \]
put \( u \) on \( B \) side and update \( D \)
\[ v = \max(PQ_B) \]
put \( v \) on \( A \) side and update \( D \)
select \( A_k, B_k \) with best \( C_k \)
Two examples of KL or FM

Consider following graphs with initial cut given in red.
A Bad Example for KL or FM

Consider following graph with initial cut given in red.

KL (or FM) will start on one side of the grid (e.g. the blue pair) and flip pairs over moving across the grid until the whole thing is flipped. After one round the graph will look identical?
**Boundary Kernighan-Lin (or FM)**

Instead of putting all pairs \((u,v)\) in \(Q\) (or all \(u\) and \(v\) in \(Q\) for FM), just consider the boundary vertices (i.e. vertices adjacent to a vertex in the other partition).

Note that vertices might not originally be boundaries but become boundaries.

In practice for reasonable initial cuts this can speed up KL by a large factor, but won’t necessarily find the same solution as KL.
Performance in Practice

In general the algorithms do very well at smoothing a cut that is approximately correct.

Works best for graphs with reasonably high degree.

Used by most separator packages either

1. to smooth final results
2. to smooth partial results during the algorithm
Separators Outline

Introduction:

Algorithms:
- Kernighan Lin
- BFS and PFS
- Multilevel
- Spectral
- LP-based
Run BFS and as soon as you have included half the vertices return that as the partition.

Won’t necessarily be 50/50, but can arbitrarily split vertices in middle level.

Used as substep in Lipton-Tarjan planar separators.

In practice does not work well on its own.
Picking the Start Vertex

1. Try a few random starts and select best partition found

2. Start at an “extreme” point. Do an initial DFS starting at any point and select a vertex from the last level to start with.

3. If multiple extreme points, try a few of them.
Priority-First Search Separators

Prioritize the vertices based on their gain (as defined in KL) with the current set. Search until you have half the vertices.
Multilevel Graph Partitioning

Suggested by many researchers around the same time (early 1990s).

Packages that use it:
- METIS
- Jostle
- TSL (GNU)
- Chaco

Best packages in practice (for now), but not yet properly analyzed in terms of theory.

Mostly applied to edge separators.
**High-Level Algorithm Outline**

**MultilevelPartition**\( (G) \)

If \( G \) is small, do **something brute force**

Else

**Coarsen the graph** into \( G' \) (Coarsen)

\( A', B' = \text{MultilevelPartition}(G') \)

Expand graph back to \( G \) and **project** the partitions \( A' \) and \( B' \) onto \( A \) and \( B \)

**Refine the partition** \( A, B \) and return result

Many choices on how to do underlined parts
MGP as Bubble Diagram

Coarsen

“Brute Force”

Expand, Project and Refine
Maximal Matchings

A maximal matching is a pairing of neighbors so that no unpaired vertex can be paired with an unpaired neighbor.

The idea is to contract pairs into a single vertex.
A Maximal Matching

Can be found in linear time greedily.
A side note

Compared to a **maximum** matching: a pairing such that the number of covered nodes is maximum
Coarsening
Collapsing and Weights

New vertices become weighted by sum of weights of their pair.

New edges \((u,v)\) become weighted by sum of weights of multiple edges \((u,v)\)

We therefore have to solve the weighted problem.

**Why care about weights?**
Heuristics for finding the Matching

**Random**: randomly select edges.

**Prioritized**: the edges are prioritized by weight.

Visit vertices in random order, but pick highest priority edge first.

- **Heaviest first**: Why might this be a good heuristic?

- **Lightest first**: Why might this be a good heuristic?

**Highly connected components**: (or heavy clique matching). Looks not only at two vertices but the connectivity of their own structure.
Recursively Find the Cut on the Coarsened Graph
Exanding and “Projecting”
Refining

e.g. by using Kernighan-Lin
After Refinement
**METIS**

**Coarsening**: “Heavy Edge” maximal matching.

**Base case**: Priority-first search based on gain. Randomly select 4 starting points and pick best cut.

**Smoothing**: Boundary Kernighan-Lin

Has many other options, e.g., multiway separators.
Separators Outline

Introduction:

Algorithms:
- Kernighan Lin
- BFS and PFS
- Multilevel
- Spectral
Spectral Separators

Based on the second eigenvector of the “Laplacian” matrix for the graph.

Let $A$ be the adjacency matrix for $G$.
Let $D$ be a diagonal matrix with degree of each vertex.
The **Laplacian** matrix is defined as $L = D - A$
Laplacian Matrix: Example

Note that each row sums to 0.
Fiedler Vectors

Eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_n$, real, non-negative.

Find eigenvector corresponding to the second smallest eigenvalue: $L \mathbf{x}_{n-1} = \lambda_{n-1} \mathbf{x}_{n-1}$

This is called the **Fiedler** vector.

What is true about the smallest eigenvector?
Suppose $\mathbf{x}_n = [1 \ 1 \ \ldots \ \ 1]$. $L\mathbf{x}_n = ?$
Modes of Vibration

Modes of a Vibrating String

- Lowest Frequency $\lambda$
- Second Frequency $\lambda$
- Third Frequency $\lambda$

(Picture from Jim Demmel’s CS267 course at Berkeley.)
Fiedler Vector: Example

Note that each row sums to 0.
If graph is not connected, what is the second eigenvalue? (Can we construct orthogonal vectors $x_n$ and $x_{n-1}$ such that $Lx_n=0$ and $Lx_{n-1}=0$?)

\[
L = \begin{pmatrix}
3 & 0 & -1 & -1 & -1 \\
0 & 1 & 0 & 0 & -1 \\
-1 & 0 & 2 & -1 & 0 \\
-1 & 0 & -1 & 3 & -1 \\
-1 & -1 & 0 & -1 & 3
\end{pmatrix},
\]

\[
x_{n-1} = \begin{pmatrix}
-0.26 \\
0.81 \\
-0.44 \\
-0.26 \\
0.13
\end{pmatrix}
\]

\[Lx_{n-1} = 0.83x_{n-1}\]
Finding the Separator

Sort Fiedler vector by value, and split in half.

sorted vertices: [3, 1, 4, 5, 2]
Power Method for Finding Principal Eigenvector

Every vector is a linear combination of the eigenvectors $e_1, e_2, \ldots$

Consider: $p = p_0 = a_1 e_1 + a_2 e_2 + \ldots$

Iterating $p_{i+1} = Ap_i$ until it settles will give the principal eigenvector $e_1$ (largest magnitude eigenvalue $\lambda_1$) since

$$p_i = \lambda_1^i a_1 e_1 + \lambda_2^i a_2 e_2 + \ldots$$

The more spread in the two largest eigenvalues, the faster it will settle (related to the rapid mixing of expander graphs)
The second eigenvector

Once we have the principal eigenvector, i.e., \( p_i = e_1 \) (normalized to unit magnitude) remove the component that is aligned with the principal eigenvector.

\[
p' = p - (e_1 \cdot p) e_1
\]

Now

\[
p' = a_2 e_2 + a_3 e_3 + ... 
\]

Can use random vector for initial \( p \)
Power method for Laplacian

To apply the power method to find the second smallest eigenvalue we have to reorder the eigenvalues, since we are interested in eigenvector with eigenvalue closest to zero.

\[ B = L - \lambda_1 I \] has all non-positive eigenvalues. Smallest eigenvalue of \( L \) is now largest magnitude negative eigenvalue of \( B \).

Lanczos’ algorithm is faster in practice if starting from scratch, but if you have an approximate solution, the power method works very well.
**Multilevel Spectral**

**MultilevelFiedler**(G)

If G is small, do **something brute force**
Else

**Coarsen the graph** into G’

\(e'_{n-1} = \text{MultilevelFiedler}(G')\)

Expand graph back to G and **project** \(e'_{n-1}\) onto \(e_{n-1}\)

**Refine** \(e_{n-1}\) using power method and return

To project, you can just copy the values in location i of \(e'_{n-1}\) into both vertices i expands into.

This idea is used by Chaco.