Counting and sampling minimum cuts in weighted planar graphs

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Input: a positively weighted (directed) planar graph G=(V,E) and two vertices s,t

Output: the number of minimum (s,t)-cuts of G



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Earliest cut-counting works: network reliability problems

- Min-cuts / Disconnecting two vertices:

- number of min (s,t)-cuts useful in estimating the probability of disconnecting the network, e.g., [Colbourn '05]

- efficient poly-time counting in (unweighted) planar (multi-) graphs when s,t are on the same face [Ball and Provan '83]

Other, recent, motivation: computer vision

e.g.: [Boykov & Veksler '06], [Boykov, Veksler, & Zabih '01],
[Vicente, Kolmogorov, & Rother '08], [Zeng, Samaras, Chen, & Peng '08]

Motivation & related work

Other, recent, motivation: computer vision

- the simplest case: image segmentation
 where image represented by a planar graph
- user selects two points, the graph cut represents
 the segmentation
- currently in use only min-cut algorithms
 (optimization version), using an arbitrary min-cut



http://path.upmc.edu/cases/case123.html

- many advantages of counting (and the related sampling) versions, e.g.:
 - statistical tests
 - user can choose from several cuts

- can be used to compute the partition function that can be used to estimate model parameters

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Output: the number of contiguous minimum (s,T)-cuts



Weight(S) = 6+1+2+6 = 15

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Back to image segmentation:

- what about thin objects ?

user selects several points to guide
 the segmentation algorithm



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contiguity requirements [connectivity priors]



Recent progress in flow/cut algorithms for planar graphs [optimization problems, not counting/sampling]:

- [Borradaile & Klein '09]: O(n log n) single-source-single-sink acyclic max.flow

- [Borradaile, Sankowski, & Wulff-Nilsen '10]: fast computation of a minimum single-source-single-sink cut, for a sequence of given source-sink pairs

- [Italiano, Nussbaum, Sankowski, & Wulff-Nilsen '11]: undirected planar graphs, algos below O(n log n) time barrier

- [Borradaile, Klein, Mozes, Nussbaum, & Wulff-Nilsen '11]: O(n log³ n) multi-source-multi-sinks max. flow

Hardness results in general graphs:

- [Ball & Provan '83]: counting minimum (s,t)-cuts is #P-complete

- [Dyer, Goldberg, Greenhill, Jerrum '03]: AP-reduction between counting independent sets in bipartite graphs and counting upper sets of a poset

Thm 1: An $O(dn + n \log n)$ algorithm counting all minimum (s,t)-cuts in weighted planar graphs, where n is the number of vertices, and d is the distance from s to t in the unweighted graph.

Thm 2: An $O(n^3)$ algorithm counting all contiguous minimum single-source multi-sink cuts in weighted planar graphs.

[Can be used to find a contiguous minimum (s,T)-cut.]

In both cases:

After this preprocessing time, we can produce a uniformly random minimum (s,t)-cut, resp. contiguous minimum (s,T)-cut, in linear time.

Flow network:

- a directed graph with positive capacities on the edges, and
- two vertices s (the source) and t (the sink)



Flow f: flow amount on every edge satisfying:

- for every edge e: flow amount $f(e) \leq capacity c(e)$, and
- for every vertex v (except s,t):

flow amount into v = flow amount out of v

- flow value: amount out of s minus amount into s



Review of network flows

Residual graph of a flow f:

- **forward edges**: weight = capacity flow
- **backward edges**: weight = flow



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Review of network flows

Residual graph of a flow f:

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- **backward edges**: weight = flow

(only edges with positive weight)



Ford-Fulkerson Thm:

value of max s-t flow = value of min s-t cut

Note: flow is max iff no s-t path in the residual graph



- 1. Find a max flow and construct the residual graph
- 2. Contract strongly connected components
- 3. Compute # "forward-cuts" in the DAG

(forward-cuts = upper set / maximal antichains in the poset)



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Contract(t)

Ball & Provan's reduction

"Forward-cut:" a set of vertices S such that:

- contains Contract(s) and not Contract(t), and
- for every vertex in S, all successors also in S


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Given an unweighted (multi-)graph and vertices s,t:

- 1. Find a max flow and construct the residual graph
- 2. Contract strongly connected components
- 3. Compute # "forward-cuts" in the DAG



Contract(t)



Observe: Planar input graph -> planar DAG

Goal: count "forward-cuts" (or maximal antichains)



- split the outer face into the "top" and the "bottom" face
- count all "top"-"bottom" paths in the dual graph



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- find a contract(t)-contract(s) path
- construct the dual, except no edges cross the path
- sum # paths between faces sharing an edge on the path



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Sampling minimum (s,t)-cuts

- Choose a red edge proportionally to the corresponding path count.
- Starting at the corresponding **end** vertex, choose a predecessor vertex proportionally to the stored value
- Continue until get to the start vertex



Running time

Reduction to forward cuts:

- O(n log n) to find a (acyclic) max-flow in planar graphs
 [Borradaile-Klein '09]
- O(n) to find and contract the strongly connected components

Counting forward cuts:

- O(n) find the path, construct the dual graph
- O(n) compute #paths between two end-points in the dual
- O(dn) overall computation of paths, at most d end-point pairs where d
 = length of the s-t path

TOTAL: $O(dn + n \log n)$

Contiguous set of vertices: can be separated from the other vertices by a simply connected planar region that intersects every edge at most once



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Back to the Ball & Provan's reduction

- Every minimum cut separating s and t is contiguous



- does the reduction "preserve" contiguous cuts?

Back to the Ball & Provan's reduction

Does the reduction preserve contiguous cuts?



NO...

All edges weight ∞ , except for blue edges: weight 1.

Blue edges used up to their capacity, other edges not -> Only blue edges survive in the contracted residual graph:



Back to the Ball & Provan's reduction

Does the reduction preserve contiguous cuts?



NO...









only bottom contiguous

The new reduction and counting

 A new reduction: creates a different DAG where contiguous forward (T',s')-cuts are in bijection with contiguous (s,T)-cuts in G

Computing the number of contiguous forward (T',s')-cuts:
 dynamic programming across a tree-structure connecting
 T' with s' in the dual graph

Tours in the dual graph

Cut is not a simple cycle !

-> a tour in the dual graph.



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A non-crossing tour:

For every face visited by the tour, its edges must be "cut" in the clockwise order when traversing the tour.



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Lemma:

Contiguous forward (T,s)-cuts are in 1-1 correspondence with non-crossing tours in the dual of the graph obtained from the new reduction.



Goal: count non-crossing tours



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Idea: build a tree from T to s:



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Idea: build a tree from T to s:

Then, compute #paths between a "left" and a "right" edge in a "wedge".



Generalize to larger wedge distance (of the left and the right edge) via dynamic programming.

Many open problems:

- multi-source multi-sink min cuts: counting (contig or not)
- multi-source multi-sink contig. min cuts: find
- other notions of contiguity

- graphs arising in computer vision (e.g., high-dimensional grids)
- non-planar graphs ? (unweighted or weighted)
- sampling all cuts proportionally to their weights