

Isolating Cuts - Min Cut Differentity

- Another way to use randomness to find min cuts in graphs
- more recent, maybe generalizable in different ways.

• Basic Subroutine:

Min Isolating Cuts: given graph G , "terminal" set $R \subseteq V$

Find $\text{cuts}(S_v, V \setminus S_v)$ for each $v \in R$

that is a minimum cut separating v from $R \setminus v$.

$$\text{i.e. } S_v = \arg \min_{S: S \cap R = \{v\}} |2S|$$

Also works with non-negative edge weights, ignoring here.

Theorem: given (G, R) can find all R ^{min} isolating cuts in time needed to run $O(\log n)$ max-flows in some ~~vertex~~ ^{graph} $|V|$ and $|E|$ edge.

[Li Panigrahi '21]

[Since recent results show that max-flows can be done in near-linear time, this is also near-linear algo for isolating cuts].

Note: if $R = \{s, t\}$ then isolating cuts = min s - t cut.

if $R = V$ then isolating cuts are just "degree" cuts $S_v = \{v\}$.

But R being intermediate gives other structures.

Q1: How to prove above theorem?

Q2: How does this help find global min cut?

Clearly can use $R = \{s, t\}$ ^{and} to enumerate over all t to find

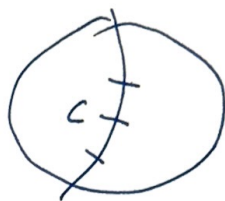
global mincut with $n-1$ ~~cuts~~ isolating cuts.

Better?

Let's do D2 first (uses randomisation!)

Suppose C is the minimum (global) cut in G .

Suppose also that $|C| \leq |V|/k$.
and it has k vertices.



Now suppose R is obtained by picking each vertex in V w.p. $1/k$ indep.

$$Pr[|R \cap C| = 1] = \sum_{x \in C} Pr[R \cap C = \{x\}]$$

$\uparrow$
 $\binom{k}{1} (1 - \frac{1}{k})^{k-1} \approx \frac{1}{k} \approx \frac{1}{|C|}$

Also works OK if
we sample w.p. $[\frac{1}{2k}, \frac{2}{k}]$

$\Rightarrow \sum_{x \in C} \frac{1}{|C|}$ is approx $1/|C|$. (constant prob)

$\Rightarrow$ if we repeat this experiment $\Theta(\log n)$ times,
 $Pr(\text{we fail each time}) \leq 1 - 1/n^{10}$.

Good: so with high probability, $\exists$ one sample R
s.t. $|R \cap C| = 1$. (say $R \cap C = x$ for some x).

Now: C isolates x from $R \setminus x$
and is a global min-cut. So it is isolate cut too!

— x —

~~Then~~ But we don't know the size of C . (needed to sample @ rate $1/k$)
 $= 1/|C|$

Try them all (in powers of 2).

Constant factors change the probability of success only slightly.

So final Algorithm (Min Cut using Isolating Cuts)

for each size class $k = 1, 2, 2^2, 2^3, \dots, 2^{\log n}$

~~for each~~ $\log(\log n)$ repetitions

~~pick min~~ sample $R \leftarrow$ pick each vertex in V independently w.p. $1/k$.

find min isolating cuts for (G, R)

Return the smallest cut found.

Thm: Algo above finds min cut w.p. $1 - 1/\text{poly}(n)$.

[Pf: for right choice of k , succeed w.p. $1 - 1/\text{poly}(n)$ in finding the min-cut.
 $\uparrow$
 $k \in [1, 2|V|]$ □

Great. How about finding min-isolating cuts? (Q1 above)

Very nice idea using the "submodularity" of the cut function.

Def: call a function $f: 2^V \rightarrow \mathbb{R}$ (which maps subsets of vertices to reals) submodular if

$$f(A \cup B) + f(A \cap B) \leq f(A) + f(B)$$

$$\forall A, B \subseteq V$$

Equivalent but more informative defn:-

$$\forall A \subseteq B \subseteq V \text{ and } e \notin B,$$

$$f(A \cup \{e\}) - f(A) \geq f(B \cup \{e\}) - f(B)$$

e adds more value to a subset A than to superset B .

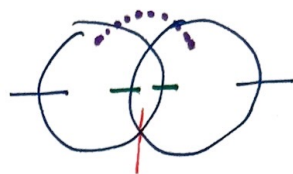
decreasing marginal returns.

Notation: Let $d(S) = |\partial S|$ # of edges crossing $(S, V \setminus S)$

if nonnegative weights $w_e \Rightarrow d(S) = \sum_{e \in \partial S} w_e$ also works.

Lemma 1: d is submodular.

Pf: by picture. ☺



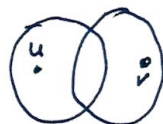
Lemma 2: d also satisfies $d(A) + d(B) \geq d(A \setminus B) + d(B \setminus A)$.

Pf: similar picture ☺

Lemma 3: can choose min isolating cuts $\{S_v\}_{v \in R}$ st these sets S_v are disjoint

Pf. Sp. $S_u \cap S_v \neq \emptyset$.

define $S'_u = S_u \setminus S_v$, $S'_v = S_v \setminus S_u$. also isolating cuts!



(*) Submodularity says.

$$d(S_u) + d(S_v) \geq d(S'_u) + d(S'_v)$$

(**) because of minimality $d(S_u) \leq d(S'_u)$, $d(S_v) \leq d(S'_v)$

$$\Rightarrow d(S'_u) + d(S'_v) \geq d(S_u) + d(S_v)$$

$\Rightarrow$ all must be equalities and hence S'_u, S'_v also min isolating.

Repeat until all disjoint



Great: this shows that we can describe

min isolating cuts using only near-linear # of bits



But: can we find them fast?

Yes. Clever use of submodularity!

Fix inclusion-wise smallest isolating cuts

$$\{S_x^*\}_{x \in R}$$

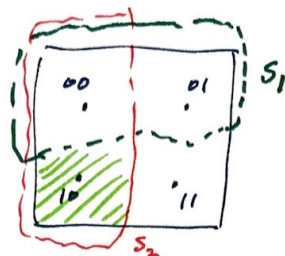
Label

~~At the~~ vertices in R using $\log R$ bits

Let $R_i = \{v \in R \mid \text{ith bit of } v\text{'s label has } 1\}$

Find $C_i \subseteq V$ such that ∂C_i is minimum cut separating R_i from $R \setminus R_i$

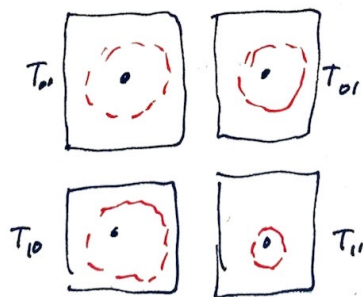
Delete all these edges.



Causes all these terminals to be separated from each other.

Let T_x be piece containing $x \in R$

(so T_{10} is marked in green highlight).



Claim: $S_x^* \subseteq T_x$. $\forall x \in R$

pf: sps not.

(S_x^* is smallest ^{min} isolating cut sep. x from $R \setminus x$)

① S_x^* is min isolating cut so $d(S_x) \leq d(T_x)$.
 T_x is some isolating cut

Assume that $x \in C_i$ $\forall$ iterations i (else flip C_i and $V \setminus C_i$).

If $S_x^* \subseteq C_i$ $\forall i \Rightarrow S_x^* \subseteq T_x$.

so suppose $S_x^* \not\subseteq C_i$.

Now: $S_x^* \cap C_i$ also isolating. since S_x^* minimal $\Rightarrow d(S_x^* \cap C_i) \geq d(S_x^*)$

$$\text{but } d(S_x^*) + d(C_i) \geq d(S_x^* \cap C_i) + d(S_x^* \cup C_i)$$

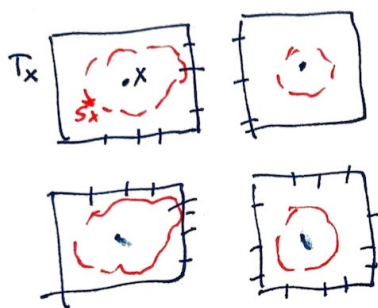
$$\Rightarrow d(S_x^* \cup C_i) < d(C_i)$$

but $S_x^* \cup C_i$ contains the same terminals as C_i (i.e. R_i)

which would violate the fact that C_i is a min cut

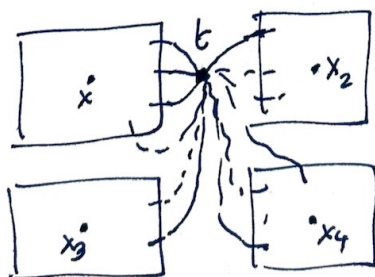
□

Great: the picture looks like



So now just need to separate x from the boundary of T_x for each $x \in R$.

Can just combine into one graph with $O(VE)$ ~~extra~~ edges.



And run ~~shortest~~ max-flow/min-cut on this combined instance!

————— x —————

Good: to recap

① can find min isolating cuts in $O(\log n)$ max-flows!

② can use isolating cuts routine $O(\log^2 n)$ times to find global min cut! (whp)

← deterministic!

← randomized!